IRRODL

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International **R**eview of **R**esearch in **O**pen and **D**istributed **L**earning
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Editorial – Volume 26, Issue 1

Terry Anderson
Professor Emeritus, Athabasca University

I have been blessed in retirement by the knowledge that some of the projects I worked on over the years have outlived my time in academia. Thus, the invitation to co-author an article on IRRODL's 25 years of publication, as well as a chance to get "back in the saddle" and write this editorial is less a task and more a privilege.

The issue begins with the article "A celebration of IRRODL's 25-year history." Founding Editor Peter Cookson, subsequent editors Rory McGreal and myself, and Managing Editor Serena Henderson co-authored the article, providing an overview of the accomplishments and challenges of publishing a pioneering online journal. We document issues and opportunities faced by IRRODL as the technology and the interest in distributed and open education expanded from the fringes to a viable and sometimes essential component of education systems. After reviewing the first draft, I noted to Rory McGreal that the article was too much a "brag rag," so we tuned it down a bit. However, I am sure you realize that those directly involved in production, as well as the numerous scholars and students who have used IRRODL over these 25 years, have a great deal to be proud of.

IRRODL is a success story, partly because it was in the right place (fully digital) at the right time (an explosion of interest in distributed education) with the right tools (unprecedented access to personal composition, publication, research, and networking technologies) and at the right price (free and open for both readers and authors). When we published the first issue, there were many (including my PhD supervisor) who believed that publishing in an electronic journal had about much scholarly value as mailing the work to a friend. Times changed. I recall boxing up those old paper journals for the recycler. These works retain relevant and historic value, but the paper format makes them unretrievable by even subscribers, much less accessible by the multitude of new students and scholars globally.

IRRODL would not have succeeded, much less flourished, without the ongoing support of Athabasca University. Though the focus of IRRODL matches the delivery mode of the University, many larger open and distance education institutions have not supported full-and part-time staff to edit, mange, and produce a quality international journal focussed on their core business – quality distributed teaching and learning.

By contrast, one can imagine if IRRODL had chosen or been forced to gain support from one of the large academic publishing giants. Just last month, we heard of the mass resignation of editors from *The Journal of Human Evolution*. This journal has been managed for decades by Elsevier. In recent years, copy editor and special issue editors have been let go, the number of articles published severely limited, and an astounding Article Processing Charge (APC) of $3,990 USD ($5,727 CAD) assessed to authors if they wish—

or are forced—to publish their article open-source. These cost-cutting measures were necessary for a company that earned profits of $3.23 billion CAD in 2023!

IRRODL's success has also benefited from the pioneering work of John Willinsky and Simon Fraser University, which created the Public Knowledge Project (PKP). This open-source toolset manages the submission, review, editing, publication, and archiving of IRRODL and most of the other open access journals around the world.

Of course, IRRODL could not have succeeded without the contributions of thousands of scholars from many countries of the world. Many of these authors' efforts have been rewarded by the thrill of seeing their work reviewed and published in a globally read, high-quality academic journal. Another rewarding experience is receiving notification from Google Scholar or other indexing systems that the work has been read and cited by other researchers.

We also recognize the efforts of thousands of authors whose work was not accepted for publication. We hope that the comments from editors and reviewers have been helpful to these scholars and served as a springboard for publication in other journals.

Perhaps the biggest thank you goes out to the thousands of anonymous IRRODL reviewers. These scholars have taken time from their busy days to critically review and help improve the work of others–most of whom they have never met and whose names they do not know. Of course, they do this work voluntarily. I am confident that not one of the 1,304 articles published in IRRODL during these 25 years that has not been edited, either in small or major ways, to enhance its quality and readability.

To conclude, all of us at IRRODL extend a heartfelt thank-you to everyone who has helped make these 25 years of quality scholarly research freely accessible to all.

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As we celebrate this milestone, we are delighted to present the first article in this issue under the *Research Articles* section:

"Predicting online learners' performance through ontologies: A systematic literature review"

At the time we were starting IRRODL, we devoted time and effort trying to understand the semantic web, the ontologies underlying the technology, and their application in *educational objects* and *educational modelling languages*. Subsequent developments in whole language models and search engine efficiencies have made this work appear somewhat obsolete. However, it is interesting to observe how the semantic web and the roll of ontologies remain relevant and can still be used successfully to predict learners' performance.

"The impact of switching intention of teachers' online teaching in the COVID-19 era: The perspective of push-pull-mooring"

Academic publishing (as well as practice) was profoundly affected by the COVID-19 lockdown. Many students, teachers, and institutions realized that it was distance education or no education at all. Some teachers were given the choice to move their work online, driven by both push factors (e.g., institutional mandates) and pull factors (e.g., students' need for access). This article itemizes and quantifies these push and pull factors, evaluating and measuring their effects.

"Automatic classification of online learner reviews via fine-tuned BERTs"

MOOCs continue to provide learning opportunities to millions of users, offering a "massive" source of data collection. Using 365,000 student reviews of courses from Class Central, the authors use an AI technique of natural language processing known as Bidirectional Encoder Representations from Transformers (BERTs). While the research methods may be complex, particularly for those without a technical background, the applications of these tools in addressing both large and small educational challenges are widely valued. The intricate procedures yield simplified recommendations for comparing and improving MOOCs across various subject domains.

"Impact of simulation-based learning on learning loss among nursing students: A quasi-experimental study"

One of the projects I worked on during retirement was a part of a team from Harvard University investigating the impact of distributed health-related simulations on student performance. My initial understanding of simulations was based on computerized processes used to demonstrate and measure natural or scientific processes. However, I quickly learned from this experience, as highlighted in this article, that a medical simulation is viewed as a medical intervention conducted by teachers or students on human actors posing as or simulating patients. Additionally, this study posits that the emergency cessation of on-campus education and the shift to online learning during the pandemic resulted in "learning loss" in optimal learning. It demonstrates how simulations can help mitigate some of this "learning loss." Unfortunately, the quasi-experimental component of the study compares those receiving remedial simulations face-to-face with those watching the simulations on video tapes—a media comparison study often yielding minimal differences in performance.

"Self-, peer, and tutor assessment in online microteaching practice and doctoral students' opinions"

Similar to the concept of "simulation training" used by medical researchers, microteaching involves a student teaching a short segment of a class to peers. In this paper, the microteaching was conducted online, with the process recorded for feedback. This study examined the concordance among self, peer, and tutor assessments in online microteaching practices, along with students' views on their online microteaching experiences.

"Peculiarities of the development of students' musical skills under the influence of modern software"

I love educational experiments like the one described in this article that enrolls students located in four different countries. The course is also innovative as music education is exploding as technical tools enhance the possibilities for creative expression. Finally, the article details and measures student perceptions of the value associated with use of digital and distributed music creation tools.

"Implementation of an on-the-job training method in a distance education environment"

As an ex-hobby beekeeper, I couldn't help but enjoy this emergency distance education application focused on teaching student beekeepers effective techniques for spring colony management. Unlike some hastily assembled emergency online delivery, I appreciated the systematic evaluation of the tasks and the thoughtful way they were taught at a distance—especially under the pressures and constraints of pandemic education. We are seeing ongoing need for vocational skill training and retraining, and while this presents extra challenges for distributed education, we have decades of experience developing learning designs and new innovative tools emerging monthly to teach and learn practical skills.

"Evaluating AI-personalized learning interventions in distance education"

The holy grail of education has always been personalized feedback, tailored learning designs, and motivation to allow each individual to learn at their optimal effectiveness. Theoretically, with AI continually customizing instruction at an individual level, one should see improved learning outcomes. This study puts this to the test by comparing an experimental group provided with customized practice activities to a control group offered conventional online learning material. As expected, "the experimental group who interacted with personalized AI-based learning materials showed significant improvements in fluency, accuracy, and overall effectiveness." AI is rapidly transforming many aspects of teaching and learning. Given differences in age, local context, and learner expectation, these AI tutors may be more effective at assisting learners at a distance than those gathered in-person. Education is more than individual learning—it is also about learning how to interact with and engage socially within a community.

"The impact of a learning analytics based feedback system on students' academic achievement and self-regulated learning in a flipped classroom"

This study also compared the performance of students when provided with ai-generated feedback based on their learning performance, alongside a control group that used only online learning materials produced by the instructor. Similar to the previous study, this research revealed only small changes in learning outcomes between the two groups. However, it is important to note that we are still in the early days of using AI-generated student feedback.

"Analyzing learning sentiments on a MOOC discussion forum through epistemic network analysis"

This is a fascinating, if not entirely convincing, use of network analysis to identify so-called "learning sentiments." Our decision not to include some form of affective presence in the now well-known Community of Inquiry model continues to spark discussion among researchers. At a conference, I once flippantly responded to this concern by noting that you have to remember that the Community of Inquiry (COI) was developed by three males from Alberta, and that cowboys are not known for their affinity with affect.

The results from this study of learning sentiment are intriguing, if not surprising. They caused me to reflect on over 25 years of analyzing text-based interactions and the evolving use of AI analytic techniques to alleviate the arduous task of manual analysis. The traces left by networked education continue to present exciting opportunities for researchers to explore teaching and learning processes.

"A categorical confirmatory factor analysis for validating the Turkish version of the self-directed online learning scale (SDOLS-T)"

The importance of self-directed learning has long been recognized as critical in all types of formal education, especially those delivered at a distance where instructor presence is often reduced. This study employs advanced analytics to evaluate the effectiveness of a Turkish translation of a robust instrument originally developed in English. As anticipated, factor analysis confirmed the theoretical foundation of the instrument. The study further demonstrates the positive impact of using this instrument in diagnosing and supporting learners to gain self-direction in their formal learning.

"Comparative effectiveness of approaches to students' labour education in universities in the new era with the use of information technologies"

This study focusses on the importance of employees being highly motivated and aware of the role, needs, and rewards of engagement in the workforce. The study compared two different methods—one involving hands-on practical activities and the other featuring more theoretical teaching methods. The two groups were assessed on their resulting attitudes towards work, with interesting though somewhat contradictory results.

Following the insightful research articles in this issue, we are pleased to share a contribution under the *Research Notes* section:

"Manuscript selection in a literature review: "Free-full-text-or-next" as a new criterion"

One of the strengths of IRRODL is that a MEd student from Australia can have their work and thinking promoted through an international journal. In this article, the author examines the increasingly important systematic literature review process that strives to insure we continue to "build upon the shoulders of others." AI-assisted online access allows researchers to easily select relevant papers and their contexts from a large and ever-growing archive of reviewed work. One of the critical steps in doing a systematic review is selecting the articles that meet the criteria relevant to the research questions. In this case, the author suggests that reviewers check if the article is available freely in full text—if not then "next," and the article is rejected from for the review. It took me a few reads to understand what "Free-Full-Text-or-Next" even meant, but I eventually got it. The author makes a good argument illustrating the inclusive value of full-text access for all scholars. However, I wasn't convinced. If possible, I want a review of all the relevant articles—even those hidden behind paywalls.

Rounding out this issue, we share with you two insightful contributions under the *Literature Reviews* section:

"Facilitating students' emotional engagement in synchronous online learning: A systematic literature review"

The easiest distance education system to implement in emergency contexts is to substitute synchronous videoconference classes for those formerly conducted face-to-face in a classroom. Thus, there has been a surge of interest in using and measuring the impact of this technology, with a special focus on engagement. This study employed a grounded theory approach using data collected from a systematic review of the literature. Factors influencing engagement using this medium were grouped into four categories: (a) instructor actions (e.g., interacting informally before and after class, encouraging the expression of ideas), (b) learner behaviors (e.g., building rapport with peers, recognizing individual accountability), (c) environment characteristics (e.g., creating a supportive atmosphere, selecting communication modes), and (d) activity design (e.g., using breakout rooms, embedding diverse elements. This sounds to me much like the characteristics of good teaching in any context.

"Bibliometric insights into the open education landscape"

The popularity and diverse contexts of use of open education has resulted in a rich research literature focussed on various components and contexts of open education. This study stands out for its quantitative approach in mapping the current academic topics and focus of open education, providing insights into the dynamic interplay between technology, policy, and pedagogy.

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Twenty-Five Years of Innovation and Knowledge Sharing: The Legacy and Future of the International Review of Research in Open and Distributed Learning

Terry Anderson[1], Peter S. Cookson[2], Serena Henderson[1], and Rory McGreal[1]
[1]Athabasca University, [2]Delaware State University

Abstract

Since its founding in 2000 by Athabasca University, the *International Review of Research in Open and Distributed Learning* (IRRODL) has emerged as a leading platform for the dissemination of scholarly work in open and distributed learning. This article revisits IRRODL's foundational goals, the institutional support that facilitated its creation, and its evolution over 25 years. Through this retrospective, we celebrate the journal's achievements and examine its future as a freely accessible repository of information and knowledge for practitioners and researchers in open and distributed learning.

Keywords: online journal, open access, open source, publication

Introduction

IRRODL is a leading voice in the field of open and distributed learning, helping shape the discourse on open education and online learning theory and practice. With its commitment to open access, IRRODL provides a platform for researchers worldwide to share research results thereby fostering a global community of scholars and practitioners. Its comprehensive coverage of topics—ranging from open practices and pedagogical innovations to emerging technologies— ensures its relevance to academics and educators seeking evidence-based insights, best practices, and strategies. By bridging theoretical advancements with practical insights, IRRODL has become a force and resource—helping shape the future of open and distributed learning.

Open access (OA) ensures that scholarly research is freely accessible to all, breaking down barriers to information due to subscription costs or institutional access limitations. This democratization of knowledge fosters equity, enabling researchers, educators, policymakers, and the public worldwide to engage with research findings without financial hindrance. Open access distribution facilitates collaboration, innovation, and the adaptation of research for and from diverse contexts—empowering institutions and individuals to improve practices and outcomes. By removing paywalls, OA promotes transparency and accelerates the global exchange of ideas, vital for addressing challenges including sustainability, health crises, and education and research disparities.

The rise of online education has transformed teaching and learning paradigms. These changes are fueled by advancements in technology and the demand for flexible, inclusive access to education—even in times of war and epidemic. Online educational practices emphasize interactivity, learner autonomy and self-direction, and accessibility, while theoretical frameworks have expanded to address issues such as openness, digital equity, attrition, engagement in virtual environments, and the design of learning-centered curricula. This evolution has created opportunities and challenges as researchers explore digital tools and platforms to measure if they enhance learning effectiveness and address diverse learning needs.

Bridging the gap between theory and practice is essential for advancing education. While theoretical frameworks provide foundational understanding, their real-world application ensures relevance and impact. Educators and institutions are challenged to translate scholarly insights into actionable strategies that address challenges in open and distributed education. This dynamic exchange between research and practice fosters innovation, improves teaching effectiveness, and enhances learning outcomes. Extending scholarship to practice also enriches research, as practical applications often reveal new areas of inquiry, leading to a continuous cycle of knowledge generation and refinement.

IRRODL Founding and Early Days

Institutional Context

In 1970, Athabasca University (AU) was initially conceived as a traditional, campus-based institution. However, a pivotal shift occurred just two years later, transforming AU into an open university focused on distance education. Through innovative correspondence courses and the early adoption of digital technologies, AU led the way in online learning in Canada. By the late 1990s, AU had already leveraged advancements using the Internet and online learning platforms, while adopting both synchronous and asynchronous digital learning modes enabling students to overcome geographic and temporal limitations.

The establishment of the *International Review of Research in Open and Distance Learning* (IRRODL) in 2000 was a natural extension of AU's commitment to broadening access to education. With AU's institutional support, the journal was born digital and so was able to harness online platforms to publish research that reaches a worldwide audience of scholars and practitioners in distance education. The flexibility and accessibility that digital dissemination provided made IRRODL a crucial resource for overcoming barriers to educational research sharing, echoing AU's motto as "Canada's Open University."

Choice of Journal Title

The journal's name, *International Review of Research in Open and Distance Learning*, reflects its commitment to inclusivity, diversity, and rigorous scholarship in the field:

1. *International*: The journal welcomes and actively supports submissions from a wide array of international contributors, with the aim of fostering a global exchange of ideas and practices in distance education, with a focus on encouraging contributions from the global south.

2. *Review:* IRRODL encourages submissions that go beyond traditional research to include systematic reviews and comparative studies, that provide comprehensive insights into specific interests in distributed education. Review also relates to the validation of the research published All submissions are comprehensively blind reviewed by peers in the field.

3. *Research:* The journal prioritizes original manuscripts grounded in systematic inquiry and evidence-based, along with articles that focus on theory and best practices.

4. *Open and Distance Learning:* Encompassing flexible, independent, and technology-mediated modes of education, IRRODL embodies the broad spectrum of open and distance education through its varied content.

The title thus encapsulates IRRODL's mission of advancing global knowledge on distributed education and expanding access to research for all readers.

In 2016, with support from UNESCO and with a growing understanding of changes in the field of distance education, IRRODL widened its focus to include articles on open educational resources (OER) and open practices (OP) as well as the growing number of hybrid and blended courses becoming available from traditional institutions. In recognition of this expansion, the journal name was changed to refer to *distributed* learning, replacing the term *distance* in the title, and became the *International Review of Research in Open and Distributed Learning*.

Institutional and Editorial Support

The initial success of IRRODL was significantly bolstered by institutional backing from AU. Key contributors included the former Associate Vice-President for Research and Institutional Studies, Dr. Peter Cookson, who served as the founding editor, and a part-time Managing Editor responsible for implementing essential submission and publication processes. Additionally, AU's International Consortium for the Advancement of Academic Publication provided technical support, solidifying IRRODL's operational foundation.

Choosing the First Editorial Board

To reinforce AU's commitment to establish a journal whose content was truly international, we invited an internationally diverse group of leading distance education theorists, researchers, and practitioners to serve on IRRODL's Editorial Board or as Consulting Editors. To that end, we sought high profile distance educators (people who constituted a virtual who's who of contributors to the growth of distance education in their countries and/or internationally). Seventeen outstanding distance educators from 12 countries agreed to serve on the Editorial Board. Twenty-nine distance educators from 19 countries agreed to serve as Consulting Editors. Beginning with the inaugural issue, members of both groups were instrumental in enabling IRRODL's goal of geographical diversity of contributors and contributions.

Funding and Sustaining IRRODL

Diamond OA journals are those that do not require payment of article processing charges (APCs) or other fees from either authors or readers. Although the term *diamond OA* has been coined only recently, IRRODL has been diamond from its inception, and it has been awarded the Directory of Open Access Journals (DOAJ) Seal for best practices in open access publishing.

IRRODL was the first journal in Canada to be released as open access, charging no fees for subscriptions or for general readers and no publication charges to authors. IRRODL's open access model aligns with AU's mission as an open university. The journal's financial sustainability at first depended solely on support from AU. Later, the journal received ongoing triennial grants from the Canadian Social Sciences and Humanities Research Council (SSHRC). In 2016, IRRODL also received one-time funding from UNESCO to increase its mandate to include OER and OP as well as distributed forms of education. These funds have been crucial for supporting innovations and for covering operational expenses, including technical infrastructure and managing the submission and publication processes.

Inaugural Issue and Editorial Strategy

The first issue of IRRODL set the stage for a new approach to scholarly publishing. It featured a two-part structure: a Main Section dedicated to in-depth articles on theory, research, and practice, and a Notes section with news on developments in open and distance learning. Under the theme "The Problems and the Promise: Into the New Century," the issue included contributions from internationally respected scholars, quickly establishing IRRODL as a platform for the global discourse in the evolving field of distance education. Over the years IRRODL has experimented with a variety of specially focussed sections, including technology reviews, leadership articles, book reviews and special issues.

Fight for Open Access Funding

When IRRODL was founded, the Canadian research funding agency, SSHRC, did not support open access journals. Even though IRRODL had more than two thousand subscribers, it was not eligible for funding because SSHRC insisted that they must be paying subscribers, which of course was anathema to an open access journal. As a result of this policy, IRRODL put out a plea for a voluntary payment of $10 Canadian to all subscribers and within a week received more than 100 positive responses. This information was conveyed to SSHRC, but they still did not allow IRRODL to qualify for funding. However, for the next call, SSHRC altered its rules to allow open access journals to participate, and IRRODL began receiving funding that continues to the present. IRRODL, as the first open access journal in Canada, was also the first to receive SSHRC funding. Ironically, in 2015 SSHRC reversed its policy and now only funds open access journals!

Innovations and Challenges

Transition to New Media Formats

With the departure of founding editor Peter Cookson, Terry Anderson took over as editor in IRRODL's third year. His tenure coincided with a period of rapid technological advancement, enabling IRRODL to introduce multiple article formats, including MP3 audio, as well as PDF, HTML, and EPUB. A translation widget was added, enabling articles to be read in multiple languages.

Ensuring Scholarly Credibility

As open access journals gained traction and popularity a host of predatory journals emerged to exploit article processing charges thus creating a shady business model. For IRRODL, this meant that maintaining credibility was paramount. To preserve high standards, IRRODL rigorously enforced peer review, with all articles subject to double-blind evaluation by two or more reviewers. Double-blind peer review is widely recognized as an effective method to ensure objective feedback and rigorous evaluation. In this system, neither the authors nor the reviewers know each other's identities, theoretically eliminating bias. However, this approach also comes with challenges: the anonymity it affords can reduce accountability; and, the volunteer nature of reviewing can lead to inconsistent quality and timeliness in the review process. Finding quality reviewers remains a challenge, especially given the constraints on volunteer labour in academia. To address this, IRRODL became one of the first to implement the Public Knowledge Project's (PKP) Open Journal System (OJS). This system supports journal management, administration, and distribution and importantly, allows editors to assess reviewer quality and track their expertise.

Special Issues

Continuous innovation and adaptation is important as IRRODL seeks to maintain its leadership position in scholarly publishing. IRRODL's approach has evolved over time to remain responsive to the changing needs of the academic community. Special issues allow IRRODL to focus on contemporary topics, offering readers in-depth insights into pressing issues while fostering editorial growth and expertise. Special issues also provide unique advantages to both the editorial team and the broader scholarly community. They offer cohesive focal points on specific themes and draw attention to areas of emerging importance within ODL. Expert contributions from scholars who may not otherwise submit to the journal help broaden IRRODL's reach and influence. Some special issues on enduring topics like student support, cost issues, and the future of open universities remain highly relevant years after publication.

Canadian Initiative for Distance Education Research (CIDER)

CIDER sponsors a variety of professional development activities designed to increase the quantity, quality, and distribution of distance education research. CIDER, founded by the IRRODL editor, was designed to promote professional development in online learning and teaching by delivering monthly webinars. The CIDER sessions are online, open, and free, providing a forum in which researchers or research groups can present their work to a broad audience of fellow researchers, practitioners, and students from across Canada and internationally.

OER Knowledge Cloud

Another initiative of IRRODL, originally sponsored by UNESCO, is the *OER Knowledge Cloud*. It is a repository of more than 2,800 scholarly articles and reports related to open educational resources, including MOOCs and open practices. It houses searchable records of journal articles, reports (e.g., from government or industry), books and other items in any digital format. These articles and reports are available either directly from the cloud repository or by links to their sources.

Public Commenting and Continuous Publication

Two notable innovations that were trialed include public commenting and continuous publication, both of which yielded important lessons. Public commenting was enabled through the OJS application. This allowed readers to leave public comments on published articles, with the aim of promoting open dialogue and community engagement. However, this innovation did not prove to be popular with the community and very few comments were recorded. Academic readers, often constrained by their own publishing demands and time, simply did not engage in public critique or discussion of others' work—at least not directly and publicly in our journal. This experiment underscored that while public commenting is a popular obsession, it requires scholarly commitment, quality control, as well as a significant cultural shift in academia.

Another innovation was IRRODL's move toward continuous publication. Traditionally, journals follow an issue-based model where all articles are published simultaneously on a regular, if not scheduled basis. IRRODL's experiment with continuous publication aimed to reduce the time between submission and publication by releasing articles individually as they completed the review and editing processes. Although this approach had the advantage of faster publication, it presented challenges in terms of article visibility, promotional efforts, peer acceptance, and editorial workload. In response to these challenges, IRRODL returned to the scheduled publication of issues. However, it continues to refine its publication processes, demonstrating a commitment to evolving in line with best practices and the needs of its contributors.

Achieving Recognition and Navigating Open Access Challenges

Citation Index Inclusion and Impact Factor

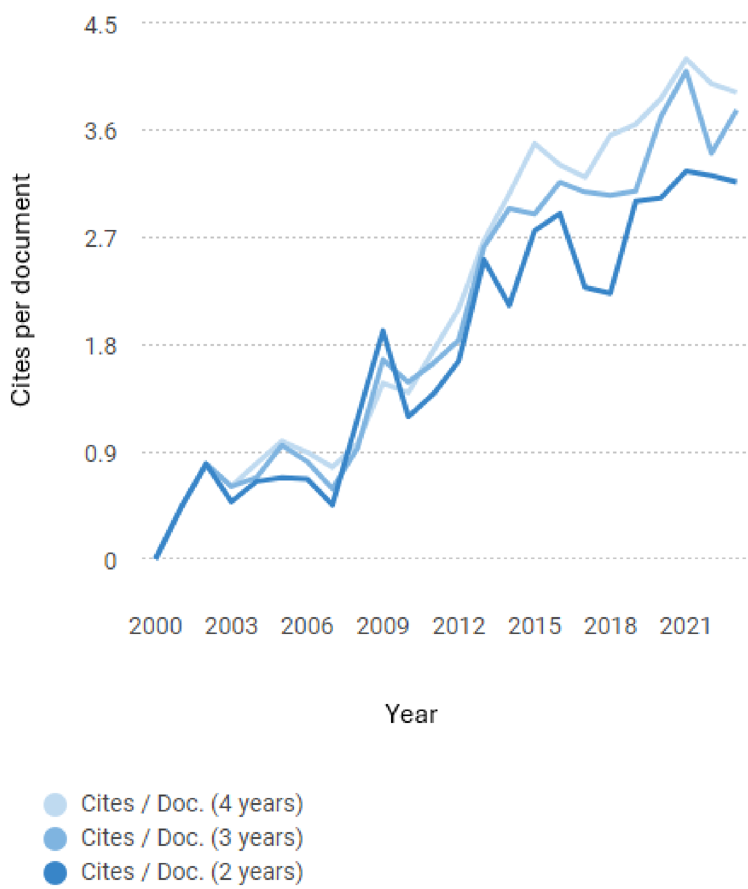
The journal's credibility and impact grew significantly when IRRODL achieved inclusion in prestigious citation indexes such as the Thomson Reuters Social Science Citation Index (SSCI) in 2009. This milestone marked IRRODL's acceptance into the global academic mainstream, making it a more attractive venue for submissions from researchers worldwide. With subsequent indexing by Scopus and the Directory of Open Access Journals (DOAJ), IRRODL established itself as a leading source of information in the field of distance education.

IRRODL *Expansion*

Citation indexes such as *Scopus* and *Google Scholar* place IRRODL as the most cited Canadian education journal and in the top 20 educational technology journals published globally. A measure of academic importance of both individual articles and research journals is the number of times an article or a journal is cited by other authors, indicating the relative influence of the work on the scholarly community. Data from this metric are shown in Figure 1. IRRODL has been rated among the highest impact distributed learning journals and in the top ten of educational technology journals.

Figure 1

Citations Per IRRODL *Article Over Time*



Note. Citation numbers were determined by dividing the total number of IRRODL citations by the number of published articles. The lines show the growth in the average number of times that articles from the past 2, 3, and 4 years were cited in the current year. The two-year line, shown in dark blue, represents IRRODL's impact factor.

Adapted from "International Review of Research in Open and Distance Learning," by Scimago Journal & Country Rank, 2024 (https://www.scimagojr.com/journalsearch.php?q=17781&tip=sid&clean=0).

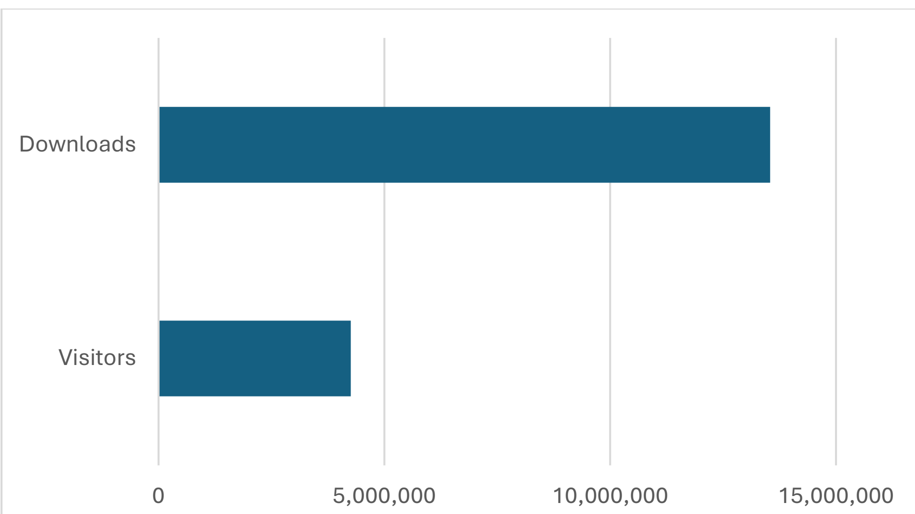
However, citations alone cannot reflect all the value. Practitioners, as opposed to researchers, may find an article very useful or insightful, and yet, as they are not active authors, the value of the work for them is not reflected in number of citations. We know from discussions and from our own presentations at practitioner conferences that IRRODL is widely read. Its openness is critical for those without access to research libraries and databases.

An easy metric of a journal's relevance is to count the number of page views and downloads, or the number of subscribers—those who are notified when a new issue is released, keeping in mind that robot crawlers can inflate these numbers. To further complicate download counts, as an open access journal, copies of IRRODL articles are routinely posted online by governments, institutions, and authors. Regardless, Figure 2 shows that views and downloads are measured in the millions.

As shown in Figure 2, IRRODL has attracted over four million visitors and recorded more than 13 million downloads since 2011, indicating a significant engagement rate with its content. This suggests that visitors find the journal's offerings highly valuable, with each visitor downloading an average of over three articles. This level of interaction implies a strong reputation and relevance of a journal within its field, evidencing that it is a critical platform for disseminating research. IRRODL's high download figures could also reflect the accessibility of content, possibly through open access or appealing topics. These metrics underscore the journal's influence on the broader field of educational technology.

Figure 2

Visitors to and Downloads From IRRODL *Since 2011*

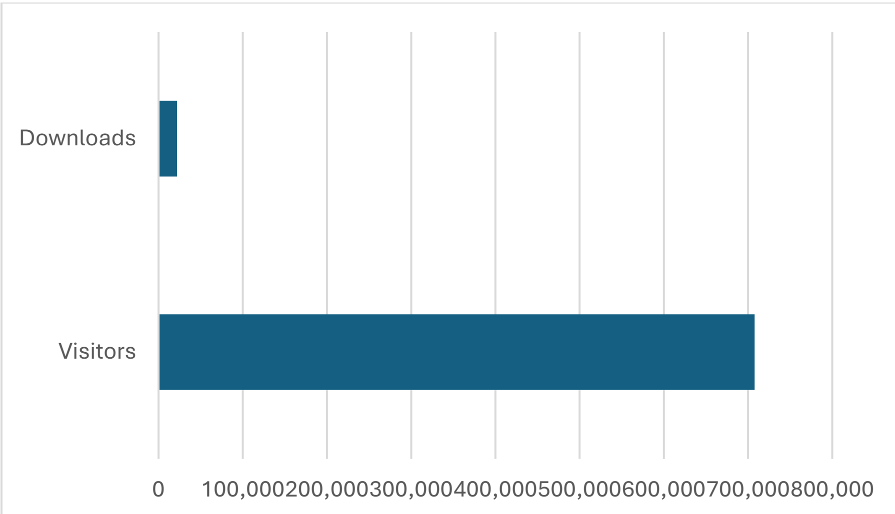


Note. Downloads include all formats available on the site: PDF, EPUB, HTML, and MP3; exact number of downloads is 13,539,958 and visitors are 4,254,355.

The number of IRRODL article visits (707,778) and downloads (21,945) since 2023, according to the *Érudit* website, is also impressive. See Figure 3.

Figure 3

Downloads and Visitors Since 2023 According to the Érudit Website

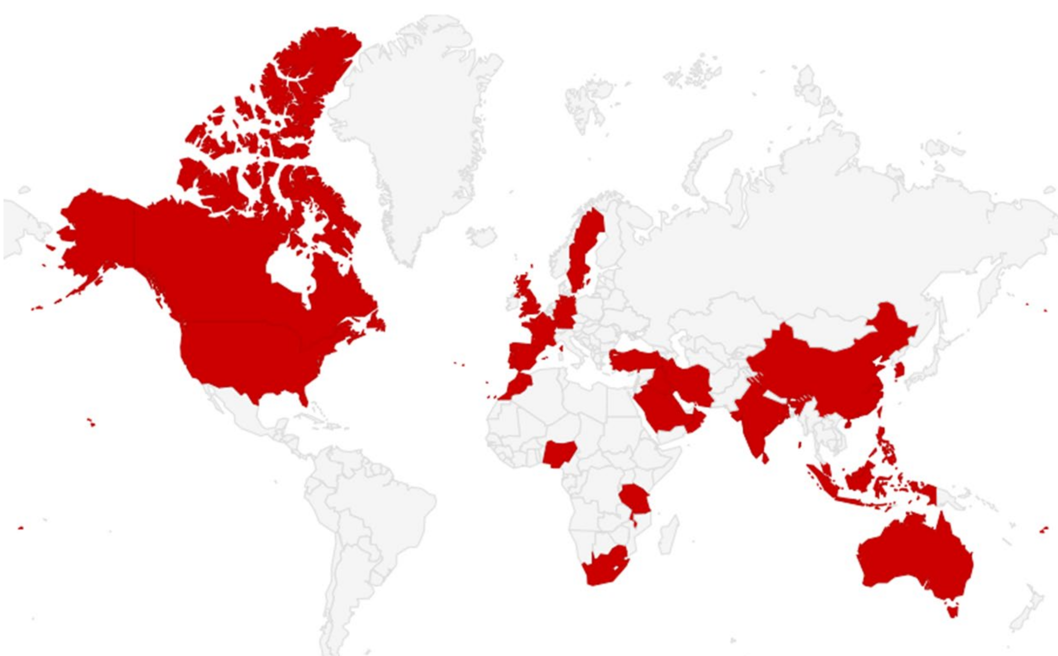


Note. Downloads include only PDF documents.

Figure 4 shows that authors come from many countries—and Figure 5 reveals that the majority of readers are from the Global South—thus demonstrating the international nature of the journal. Between 2023 and 2024, IRRODL published research articles from 31 different countries, highlighting its commitment to educational innovation and access.

Figure 4

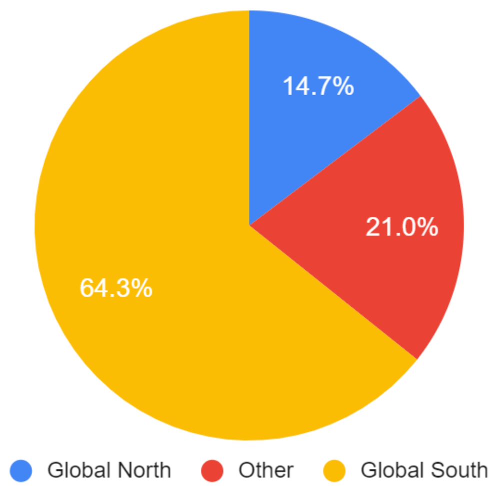
Number of Articles Published by Country (2023–2024)



IRRODL demonstrates a strong global user base with 64.3% of its audience from the Global South, 21% from the Global North, and the remaining 14.7% from unidentified regions. See Figure 5. This distribution highlights the journal's broad international reach while also revealing the dominance of the Global North. Rather than demonstrating greater interest in open and distributed learning in the North, the disparity is probably driven by the North's stronger digital infrastructure and research investments. Conversely, the lower engagement from the Global South indicates that there are barriers such as limited Internet access, resource constraints, or awareness gaps.

Figure 5

IRRODL *Website Visitors/Readership*



The journal also draws reviewers from around the globe by requesting IRRODL authors to participate as reviewers. This helps the journal achieve balanced and globally relevant reviewer perspectives. In addition to maintaining geographical diversity, IRRODL has invested in accessibility options for its readers, expanding beyond traditional publication formats. This commitment to accessibility has been a guiding principle, ensuring that IRRODL's content is available and adaptable to various audience needs.

International Readership and Engagement

In addition to its substantial citation and download metrics, IRRODL enjoys a diverse and geographically widespread readership. Between 2011 and 2024, Google Analytics recorded a total of 4,254,355 visitors to irrodl.org (Figure 6). The countries with the highest number of views were:

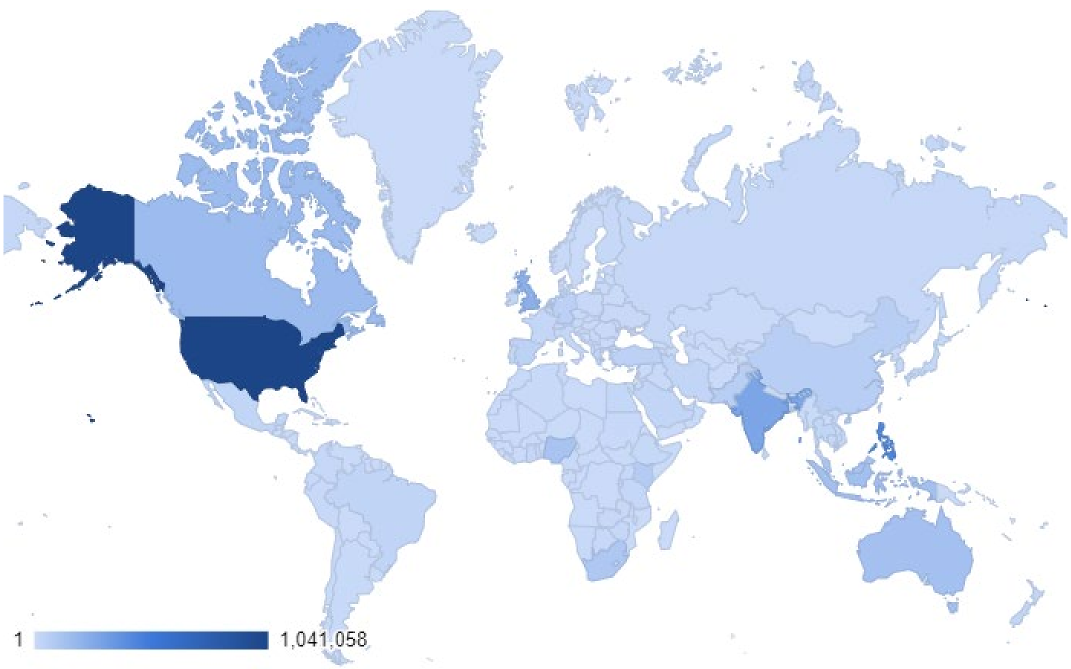
1. United States
2. Philippines
3. India
4. United Kingdom

5. Canada
6. Indonesia
7. Australia
8. Nigeria
9. Malaysia
10. South Africa

This further reinforces IRRODL's broad international impact, particularly in regions such as the Philippines, India, and Nigeria, where open and distance learning plays a crucial role in overcoming educational barriers.

Figure 6

Total Number of Visitors to irrodl.org Between 2011-2024



Challenges of Success

At its peak, IRRODL published up to six issues annually, with as many as 115 articles each year, requiring the editorial team to oversee a demanding review, assessment, and editorial process. Technically, this involved and still involves producing each article in multiple formats—HTML, PDF, and EPUB. From 2006 through 2019, IRRODL also included an MP3 audio version of each article, which was very helpful for visually impaired users. However, by 2019, text-to-speech applications had become ubiquitous. Because producing MP3 files is very time-consuming, the decision to stop their production was made beginning in 2020.

The IRRODL team's focus on quality reviews, accessibility, and professional formatting was important for ensuring the journal's reach and accessibility to a global audience.

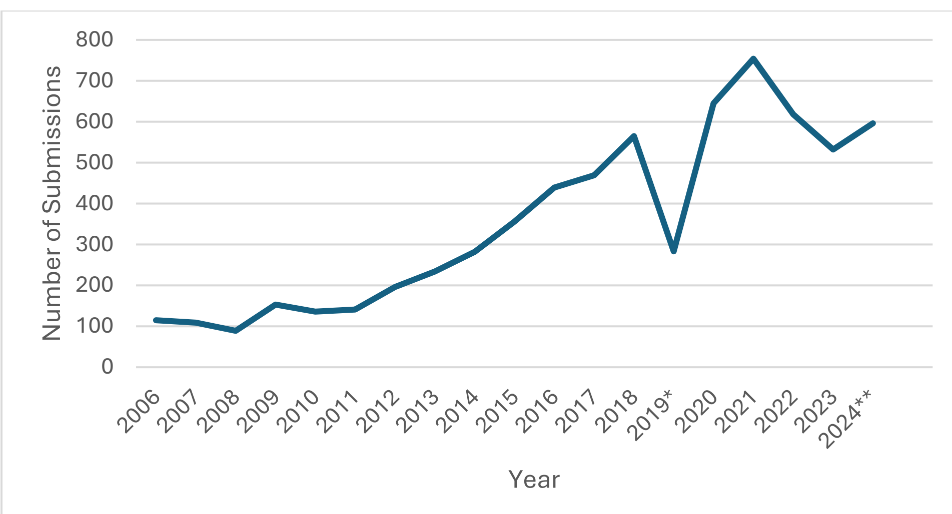
By 2020, the rising demands led IRRODL's editorial team to reassess their position. Coping with the success of the journal had become problematic. The continued processing of so many submissions was unsustainable. At the same time, IRRODL was moved organizationally within the university to AUPress, the first open access publisher in Canada. A committee formed by AUPress advised the editorial team to limit issues to four per year and the total number of published research articles was limited to 40 per year. The Managing Editor position was increased to full time and more copyeditors, research assistants, graduate students, and technical staff were engaged to streamline operations. This enabled the Managing Editor to concentrate on enhancing editorial quality rather than solely managing volume. In addition, a statistician was put on contract to assist in reviewing articles that contained complex quantitative research. These measures were designed to create a sustainable framework for maintaining and improving high publication standards. Later, IRRODL also agreed to be hosted on the Érudit website. Érudit is the largest host of Canadian open access research *publications*, primarily in the humanities and social sciences.

IRRODL has now become a leading journal for research in open and distributed learning. As an open access leader, from 2001 through 2024, IRRODL received 6,679 submissions, of which 1,304 were accepted, reflecting an overall acceptance rate of about 19.5%.

Figure 7 shows the number of submissions from 2006 to 2024.

Figure 7

Total Annual Submissions to IRRODL, *2006–2024*



Note. *Only 4 months of this year were open for submissions. **Date includes up to October 27, 2024.

Adapting to Evolving Workflows: The Role of the Managing Editor

The surge in submissions has significantly increased the demands on the Managing Editor. This role now requires extensive expertise in the pre-review vetting of submissions for subject relevance, APA style, article length, and originality; post-review editing and digital publication process; and quality control to uphold international publication standards. Additionally, the Managing Editor coordinates complex publication logistics and oversees the entire submission to publication process, demonstrating leadership in the global landscape of open scholarly publications.

Innovations in the Peer Review Processes

The peer review process is essential in maintaining a journal's credibility. However, securing timely, high-quality reviews in a specialized field such as open and distributed learning poses a persistent challenge as peer reviewers often face significant time constraints. To address this, IRRODL's editorial team normally requires at least two quality reviews per submission before making publication decisions. This practice, while necessary for upholding IRRODL's standards, has sometimes resulted in delays in the publication process.

From the beginning, one of IRRODL's most pressing challenges has been balancing the pace of publication with the need for rigorous peer review. To address this problem, IRRODL not only solicits experts in the field, but also asks authors, on publication of their article, to become peer reviewers. In recent years, IRRODL's editorial team has also actively recruited peer reviewers at academic conferences and professional gatherings, building a network of skilled reviewers.

By tightening acceptance criteria for submissions, and instituting a cap on annual publications, the journal has created an environment where only the most rigorously reviewed articles proceed to publication. The Managing Editor rejects submissions that do not adhere to the guidelines or are not within the ODL scope of the journal. This limits the number of articles sent to editors. This strategy not only supports the journal's reputation for quality, but also helps ensure a manageable workload for reviewers, thereby improving the peer review experience. Reviewers are normally sent no more than two articles per year. This is important for attracting and keeping good reviewers. Using the OJS application, all reviewers are rated on a scale ranging from excellent to unacceptable or no response. Although reviews are almost always undertaken by PhD level academics, we also realize the learning that occurs when one reviews an article and later sees the reviews of that same article by 2^{nd} and 3^{rd} reviewers. To leverage this learning, we have allowed doctoral level students to review some articles and found that they can provide acceptable reviews. It remains a continuing challenge to obtain good reviews in a timely manner. This challenge has caused significant delays for some authors awaiting decisions on their submissions.

Summary

The journey of IRRODL as a pioneer of innovative practices in open access and publication reflects a journal willing to evolve to meet the demands of an ever-changing academic landscape. Special issues have enabled IRRODL to focus on timely and relevant topics, offering comprehensive coverage that benefits researchers, practitioners, and policymakers alike. The creation of CIDER and the OER Knowledge Cloud as IRRODL-related initiatives, demonstrates the journal's leadership in taking full advantage of the evolving digital environment. Even the experiments with public commenting and continuous publication underscore

IRRODL's role as a trailblazer in open access scholarly publishing, willing to challenge traditional models in pursuit of greater transparency, timeliness, and quality.

While challenges in reviewer selection, accountability, and volunteer management persist, IRRODL's successes in these areas underscore its resilience and adaptability. As the field of ODL continues to grow, the lessons IRRODL has learned through its innovative practices will undoubtedly shape future advancements in academic publishing.

The evolution of IRRODL can be seen as a response to broader shifts in academic publishing, that highlights the growing complexity of running a leading scholarly journal. By restructuring, implementing workflow efficiencies, and fostering international and diverse scholarship, IRRODL has set a high standard for open access academic publishing. As the journal continues to adapt to new challenges and opportunities, Athabasca University and AUPress will continue to ensure that IRRODL's contributions to scholarly discourse are timely, relevant, and accessible to a global audience. Through these efforts, IRRODL reaffirms its commitment to advancing knowledge in open and distributed learning and supporting the broader open-access movement.

In its first 25 years, IRRODL has been a successful diamond open access journal, internationally recognized platform for evaluating, distributing, and curating research in open and distributed education. By fostering a diverse and global community of readers, contributors, and reviewers, IRRODL has helped to shape the discourse on distributed learning and expand the availability of research for practitioners and scholars worldwide.

Future Directions and Challenges

As IRRODL enters its second quarter-century, it remains committed to removing barriers to knowledge sharing and to advancing innovative research and best practices. Future efforts will focus on sustaining financial viability and expanding IRRODL's reach, while maintaining the rigorous scholarly standards that have defined the journal since its inception. IRRODL continues to push the boundaries of open-access publishing by exploring the integration of artificial intelligence (AI) in academic publishing workflows, enhancing accessibility options for readers, and promoting the open-access model globally with a greater focus on the Global South. The editorial team plays a crucial role in these initiatives, providing strategic insights into how new technologies and editorial practices can sustain IRRODL's legacy as a diamond open access journal in the educational technology field.

Acknowledgements

The continuing support of Athabasca University and SSHRC have been critical to the success of the journal. A special thanks is also extended to our contributors and reviewers. Finally, we acknowledge the editors, associate editors, managing editors, editorial board members, copy editors, and technical support that have contributed to the IRRODL's continuing success.

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Predicting Online Learners' Performance Through Ontologies: A Systematic Literature Review

Safa Ridha Albo Abdullah* and Ahmed Al-Azawei
*Department of Software, College of Information Technology, University of Babylon, Babel, Iraq; *Corresponding author*

Abstract

This systematic review sheds light on the role of ontologies in predicting achievement among online learners, in order to promote their academic success. In particular, it looks at the available literature on predicting online learners' performance through ontological machine-learning techniques and, using a systematic approach, identifies the existing methodologies and tools used to forecast students' performance. In addition, the environment for generating ontologies, as considered by academics in the field, is likewise identified. Based on the inclusion criteria and by adopting PRISMA as a research methodology, seven studies and two systematic reviews were selected. The findings reveal a scarcity of research devoted to ontologies in the prediction of learners' achievement. However, the research outcomes suggest that building an ontological model to harness machine-learning capabilities could help accurately predict students' academic performance. The results of this systematic review are useful for higher education institutes and curriculum planners. This is especially pertinent in online learning settings to avoid dropout or failure. Also highlighted in this study are numerous possible directions for future research.

Keywords: data mining, decision tree, education, ontology, Semantic Web, classification algorithm

Introduction

Online learning has been established as an alternative to traditional face-to-face learning, representing a close fusion of contemporary education and information technology (IT). Moreover, it is regarded by some scholars as crucial to the advancement of educational equity (Hussain et al., 2018). It should be made clear that online learning, open and distributed learning (ODL), and distributed education (DE) are not synonyms. Although online learning is concerned with the delivery of education via digital means, open and distributed learning (ODL) refers to educational approaches that enable access to learning materials and opportunities independent of a geographical location. Distributed education (DE), on the other hand, is an educational method that emphasizes offering learning experiences and materials across places and platforms, frequently using technology to support learning that is not limited to traditional classroom environments (Prinsloo et al., 2022).

Online learning is extensively employed worldwide due to its high degree of flexibility in terms of time and place, low bar for knowledge acquisition, and abundance of learning resources (Qiu et al., 2022). Platforms enable students to access a variety of learning activities, including reading, downloading, submitting papers, uploading content, and designing and delivering presentations, all achievable from any location at any time (Chweya et al., 2020). The adoption of online learning has therefore been growing, due to its benefits in comparison with conventional learning systems. Without being required to attend a class, students can access learning materials via online learning systems (El Aissaoui & Oughdir, 2020).

Nevertheless, this does not mean that online learning is without limitations. The lack of direct interaction has been indicated as a factor of academic failure or unsatisfactory grades among significant numbers of students in online learning environments (Mogus et al., 2012). Moreover, the student dropout rate is higher in online learning courses than in more traditional settings. This is especially evident in developing countries, since there are still many obstacles to the successful implementation of online learning in the developing world, such as low student motivation, difficulties with direct teacher-student connection, and poor access to the online learning environment (Al-Azawei, 2017; Al-Azawei et al., 2017).

Consequently, there is a need for efficient approaches to reduce the risk of failure by predicting learners' performance at an early stage (Aslam et al., 2021). Early prediction is a recently recognised phenomenon that involves forecasting outcomes to help educational institutions understand how to help students complete their online courses successfully. However, an accurate prediction of students' academic success necessitates a thorough comprehension of the variables and characteristics that could affect their achievement (Yağcı, 2022). Moreover, according to the literature (Sultana et al., 2019), predicting students' success is a complicated task because of the massive amounts of data kept in contexts such as educational and learning management databases. Earlier research, therefore, attempted to identify features that could lead to enhancing the prediction of online learners' performance (Abdullah & Al-Azawei, 2024; Al-Masoudy & Al-Azawei, 2023). Online learning performance refers to the efficacy in which students attain educational goals in a digital learning environment, so it includes a variety of measures, including engagement, completion rates, exam scores, and overall course satisfaction (Kara, 2020). However, the emergence of the Semantic Web has facilitated this process.

The Semantic Web is an extension of the traditional Web, serving as an invaluable tool for expanding and deepening the comprehension of information between people and computers (Pelap et al., 2018), consequently revolutionizing online and distance learning. To enhance the quality of educational content and provide learning activities that are tailored to the needs of each student, education systems employ Semantic Web technologies such as ontologies and semantic rules. The objective of an ontology in this instance is to help learners achieve their learning objectives by enabling them to transfer their learner profiles between the components of an e-learning system (Bolock et al., 2021).

In the education context, ontologies have been developed to gather data and categorise learning content, thereby facilitating human-machine communication (Zeebaree et al., 2019). Thus, there are numerous advantages to be gained by implementing ontologies in online or e-learning, such as enhancing students' retention, implementing timely interventions to assist students at risk of failure, determining the factors that influence students' academic performance, and improving the quality of education in practice (Al-Yahya et al., 2015). In another study (Icoz et al., 2015), ontologies were proposed to create conceptual maps to expose students to different experiences. However, there is still a dearth of systematic reviews concerning the use of ontologies to predict academic achievement among online learners, especially within the context of ODL. Ontological approaches can provide novel solutions to improve the ODL experience. By organizing educational data, ontologies enable the design of individualized and adaptable learning routes, based on each learner's particular pace and demands. Ontologies can also increase the accessibility of educational materials by ensuring that learning content is structured in a way that is easy to locate, regardless of learner's individual background, guaranteeing that each learner can succeed in ODL contexts (Wang & Wang, 2021). Hence, the present study is one of the first to undertake a systematic review of the available literature on the use of ontologies to predict students' academic performance. Eight questions were formulated to address this research gap:

RQ1. How can an ontology model be built to predict students' academic performance?

RQ2. Which techniques and learning platforms enable the prediction of students' academic performance based on ontologies?

RQ3. What are the primary research objectives of the chosen studies?

RQ4. What features are used, and what are the contexts of these studies?

RQ5. Which evaluation techniques are used?

RQ6. What are the key benefits of implementing ontologies to predict online learners' academic performance?

RQ7. In which countries were the experiments in the included papers conducted?

RQ8. When were the previous experiments on ontologies conducted?

Specifically, this paper looks at the ontologies used across a number of fields, together with previous systematic reviews on the implementation of ontologies in e-learning. It includes an outline and justification of the methodology adopted in this systematic review and reports the research findings. The key outcomes of this study are then discussed, with a concluding section that highlights the main concepts extracted and the research limitations.

What Is an Ontology?

An ontology is a modeling tool that deploys a standard vocabulary to define and represent domains in a formal manner (Rami et al., 2018). Ontologies and the Semantic Web have been deployed in online learning in wide-ranging ways, including to convey domain knowledge, offer metadata for significant ideas and entities, promote richer definition and retrieval of educational content, enable the definition, sharing, and exchange of learning content, develop curricula, and measure learning quality (Al-Yahya et al., 2015). In short, ontologies are essential Semantic Web technologies that are regarded as the backbone of the Web (Raad & Cruz, 2015). Furthermore, they constitute one of the most successful means of organizing a body of knowledge (Al-Chalabi & Hussein, 2020).

Ontologies have been employed in numerous applications and disciplines and can be used to organize content in any field (Zeebaree et al., 2019). They are used, for example, to store the data from learning objects, actions, behaviors, feelings, and models created by students. Ontology models are composed of many different classes or sub-ontologies derived from a range of data sources (Rahayu et al., 2022). Within online learning, ontologies are frequently used to describe its services and components for collaboration between diverse systems (Al-Yahya et al., 2015). However, building an ontology is an expensive, time-consuming, and error-prone task, especially in an online learning environment (Al-Chalabi & Hussein, 2020). This is because the process of creating an ontology requires extensive skills and human experience in knowledge engineering. Hence, the acquisition of ontological knowledge in the e-learning context requires an expert in the field (George & Lal, 2019).

Previous Systematic Reviews on the Implementation of Ontologies in Online Learning

Earlier literature on the research topic did not adopt taxonomies for the educational objective of assessing how well students met their educational goals or achieved high academic performance. Moreover, while this review identified a number of related articles, it also detected a research gap, with few articles found to cover the combined use of computational ontologies and learning analytics. For example, Costa et al. (2018) investigated 21 journal articles published between 2010 and 2018, with a focus on the ways in which education analytics and computational ontologies led by taxonomy and learning goals can help evaluate academic performance.

Furthermore, Costa et al. (2020) reviewed 31 journal articles published between 2010 and 2019. These studies were analyzed from two perspectives, specifically in terms of learning analytics, computational ontologies, taxonomies of educational objectives, and the relationship between these components and academic performance. However, in both Costa et al. (2018) and Costa et al. (2020), a research gap may be noted with regard to computational ontologies and learning analytics in the online learning context. Conversely, unlike these systematic reviews and others in the research context, the present study explores the contribution of ontological techniques to the prediction of online learners' performance.

The rationale for this study was to build an ontological model that would leverage machine-learning capabilities and help accurately predict academic achievement, while also recommending a more general approach based on concepts rather than specific features of a particular course. Therefore, this systematic literature review is expected to fill the identified research gap and inform future trends in the use of ontological techniques to predict the academic achievement of online students.

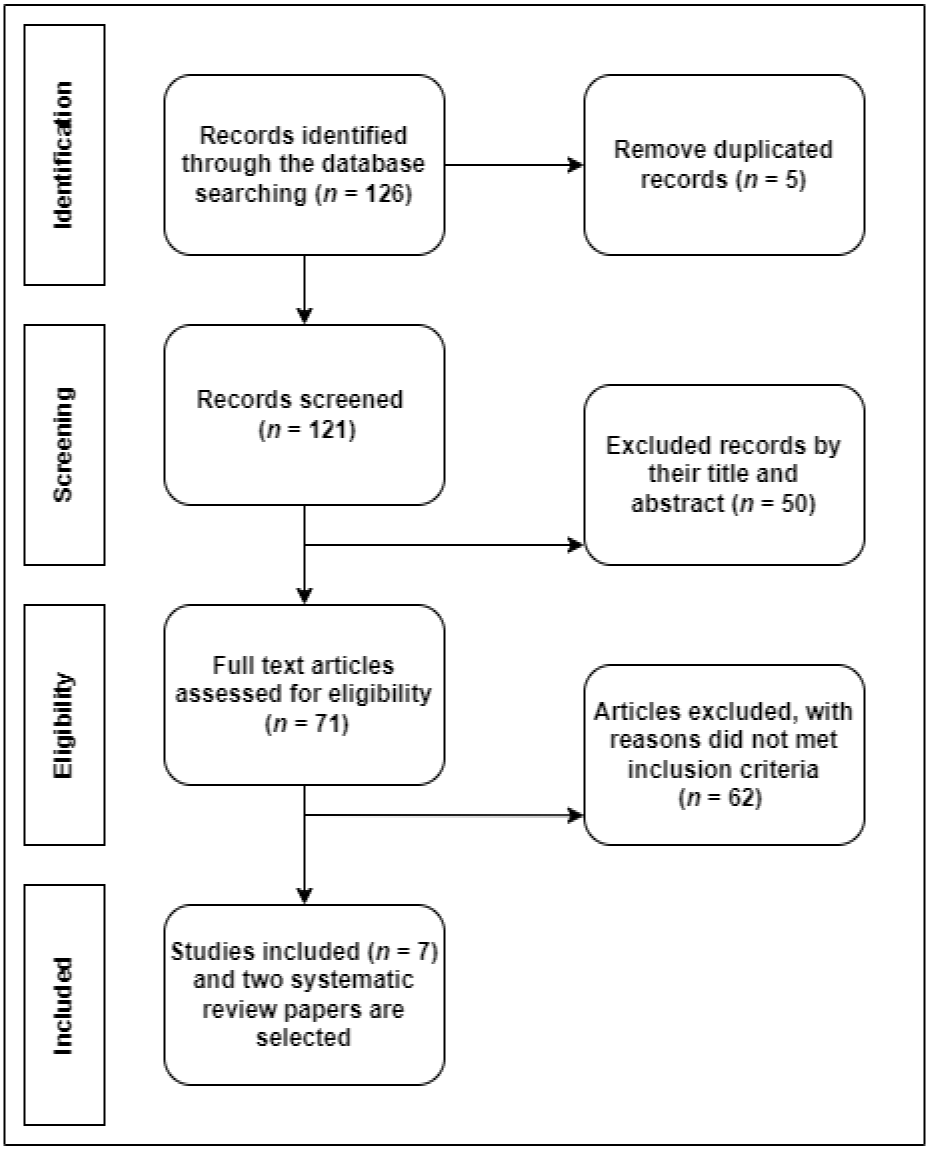
Methodology

For this study, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flow diagram was selected to find, select, evaluate, and synthesize research in the field. The PRISMA flow diagram has been widely used in several fields since its initial publication in 2009. The rationale behind the adoption of PRISMA over other protocols includes two reasons. First, it is a recognized approach in several academic disciplines because of its comprehensiveness and acceptance in the academic community (Liberati et al., 2009; Zainuddin et al., 2024). Second, PRISMA can help researchers ensure that their literature evaluation is conducted in a systematic manner (Liu et al., 2024). The current study adopts the PRISMA checklists technique to highlight the application of ontologies in e-learning and learning technologies within the education sector (Liberati et al., 2009).

The most recent iteration of PRISMA (the 2020 statement) was adopted in this study as a guide for setting the criteria (Page et al., 2021). Several checklists are included in PRISMA, encompassing eligibility criteria (exclusion and inclusion), search strategy, data-gathering procedures, method of selecting studies, synthesis approach, and synthesis results. Figure 1 presents the key steps of the PRISMA research methodology.

Figure 1

Flow of Studies From Identification to Inclusion



Note. Adapted from "The PRISMA 2020 Statement: An Updated Guideline for Reporting Systematic Reviews," by M. J. Page, J. E. McKenzie, P. M. Bossuyt, I. Boutron, T. C. Hoffmann, C. D. Mulrow, L. Shamseer, J. M. Tetzlaff, E. A. Akl, S. E. Brennan, R. Chou, J. Glanville, J. M. Grimshaw, A. Hróbjartsson, M. M. Lalu, T. Li, E. W. Loder, E. Mayo-Wilson, S. McDonald, ... D. Moher, 2021, *BMJ*, *372*(71), 5. (https://doi.org/10.1136/bmj.n71). CC BY 4.0.

Eligibility Criteria

The papers included in this systematic review were evaluated and selected based on precise inclusion and exclusion criteria. These inclusion and exclusion criteria are set out in Table 1.

Table 1

Inclusion and Exclusion Criteria

Inclusion criteria	Exclusion criteria
Research involving ontology and the prediction of online learners' performance.	Research including an ontology that was not used to predict online learners' performance.
Research studies written in English.	Research studies written in a language other than English.
Research with empirical findings, regardless of geographical boundaries.	Research involving an ontology used in circumstances related to learning as a whole, but not for predicting the achievement of online learners.
Research published between 2010 and 2023.	Research published before 2010.
Research published in peer-reviewed journals.	Research published in journals, etc., with no peer-review process.

Search Strategy

This study involved a systematic review of literature in seven leading databases and search engines, namely IEEE, Scopus, ACM, ERIC, Science Direct, Springer, and Google Scholar. The review was conducted between January and March 2023. However, the papers sourced were published between 2010 and 2023, as illustrated in Table 2. The keywords used for the database search were "e-learning," "Semantic Web," "ontology," "prediction of online learners' performance," and "learners' performance."

Table 2

Number of Studies by Database or Search Engine and Year of Publication

Database or Search Engine	*n*		
	2010–2016	2017–2023	Total
Scopus	5	11	16
IEEE	17	8	25
Science Direct	11	10	21
Google Scholar	15	8	23
Springer	10	11	21
ACM	7	11	18
ERIC	6	5	11
Total	71	55	126

Selection of Related Articles

After deleting duplicates (n = 5), 121 peer-reviewed papers were initially obtained. The researcher carefully analysed the abstracts and conclusions of these papers and scanned the content to determine which studies satisfied the inclusion criteria. In the screening stage, fifty articles were excluded based on title/abstract. This led to reviewing with a total of 71 papers. In the eligibility step, 62 articles were removed because they did not meet the inclusion criteria. Such articles did not include empirical findings or merely offered a framework for integrating ontologies. Finally, only seven papers and two systematic reviews were included.

Quality Assessment

Along with inclusion and exclusion criteria, another element that may be employed in the selection of studies for a systematic review is the quality rating of an article. The quality evaluation checklist used in this study defined nine criteria for evaluating the quality of the research retained for further analysis. For each of the nine criteria, a study received one point for "yes" and zero points for "no." A total score ranging from 0 to 9 was then awarded to each study, with a higher score indicating that the study was of good quality. The nine criteria include the following:

Q1. Have the goals of the study been outlined?

Q2. Were the research goals described?

Q3. Is the methodology understandable?

Q4. Was the research empirically tested?

Q5. Have all techniques and resources been well defined?

Q6. Were the findings satisfying?

Q7. Does the study increase researchers' comprehension or knowledge?

Q8. Have the data collection techniques been sufficiently described?

Q9. Do the researchers explain the problems?

Table 3 displays the results of the quality assessment checklist for the selected studies. Based on these results, these seven studies are of a high enough quality that would make them suitable for future investigation.

Table 3

Results of the Quality Assessment on the Selected Studies

Study	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Total
El-Rady (2020)	1	1	1	1	1	1	1	1	1	9
Costa et al. (2021)	1	0	1	0	1	0	0	1	1	5
El-Rady et al. (2017)	1	1	1	1	1	1	1	1	1	9
Boufardea & Garofalakis (2012)	1	1	1	1	1	0	0	1	1	7
Grivokostopoulou et al. (2014)	1	1	1	1	1	1	1	1	1	9
Hamim et al. (2021)	1	1	1	1	1	1	0	1	1	8
López-Zambrano et al. (2022)	1	1	1	1	1	1	1	1	1	9

Results and Discussion

The results presented in this systematic review are based on the nine research objectives extracted from the selected studies, published between 2010 and 2023.

Building an Ontology Model

The first research question (RQ1) asked: How can an ontology model be built to predict students' academic performance? This study found that the prediction model in the primary studies used an ontology as a learning model. Moreover, an ontological model of prediction was designed or implemented in many tools and settings (Grivokostopoulou et al., 2014). The studies identified the Protégé tool as a popular environment for creating and developing ontologies, as shown in Table 4. The result demonstrates widespread adoption of ontology language standards.

Although the World Wide Web Consortium (W3C) provides many language standards, the Web Ontology Language (OWL) was employed in nearly half the primary research selected for this study. Moreover, Table 4 reveals that ontology languages were used in the prediction models (El-Rady, 2020; Costa et al., 2021; El-Rady et al., 2017; Boufardea & Garofalakis, 2012; Grivokostopoulou et al., 2014; Hamim et al., 2021; López-Zambrano et al., 2022). In El-Rady et al. (2017), Grivokostopoulou et al. (2014), and Hamim et al. (2021), the Protégé tool was used to build each rule in the Semantic Web Rule Language (SWRL), based on a decision tree. The rules were then converted to SWRL and added to the ontology. In other experiments, ontologies were combined with an intelligent recommendation system. López-Zambrano et al. (2022) presented a new technique using Semantic Web resources. This technique creates an ontology based on an activity taxonomy to capture how students engage with the Moodle learning management system. Another study found that an ontology learning goal was used to generate knowledge corresponding to the cognitive level of Bloom's revised learning objective taxonomy (Costa et al., 2021). Because it typically takes a long time to build an ontology, it was proposed that METHONTOLOGY could be used to build a learner ontology model (El-Rady, 2020), but the environment for creating ontologies was not specified (Costa et al., 2020).

Table 4

Construction of Ontologies in the Selected Studies

Study	Ontology language	Tool
El-Rady (2020)	OWL	Protégé
Costa et al. (2021)	RDF/XML	Protégé
El-Rady et al. (2017)	OWL	Protégé
Boufardea & Garofalakis (2012)	RDF/XML	Protégé
Grivokostopoulou et al. (2014)	-	Protégé
Hamim et al. (2021)	OWL\DL	Protégé
López-Zambrano et al. (2022)	-	Protégé

Note. OWL = Web Ontology Language; RDF = Resource Description Framework; XML = Extensible Markup Language; DL = Description Logic.

Effective Techniques and Learning Platforms

The second research question (RQ2) asked: Which techniques and learning platforms enable the prediction of students' academic performance based on ontologies? Table 5 tabulates the machine-learning techniques used with the ontologies. The review found that various machine-learning techniques were implemented alongside ontologies to predict academic performance. This indicates that the studies selected either used a decision tree algorithm alone or in combination with other machine-learning techniques.

Three studies solely employed the decision tree technique (Boufardea & Garofalakis, 2012; Grivokostopoulou et al., 2014; López-Zambrano et al., 2022), three studies used different machine-learning techniques (El-Rady, 2020; Costa et al., 2021; El-Rady et al., 2017), and one study implemented linear and logistic regression algorithms (Costa et al., 2021). Regarding the type of platform used, six studies (Costa et al., 2021; El-Rady et al., 2017; Boufardea & Garofalakis, 2012; Grivokostopoulou et al., 2014; Hamim et al., 2021; López-Zambrano et al., 2022) did not specify the type of platform, whereas one study clearly mentioned the use of Moodle (El-Rady, 2020).

Table 5

Machine-Learning Algorithms Used in the Selected Studies

Study	Technique
El-Rady (2020); El-Rady et al. (2017)	Bayes Net, Naive Bayes, random forest, AdTree, J48, IB1, KSTAR, JRip, OneR, SMO, SimpleLogistics, LWL, simple CART
Costa et al. (2021)	Linear and logistic regression algorithms
Boufardea & Garofalakis (2012)	J48, C4.5
Grivokostopoulou et al. (2014)	J48 and the CART (decision tree)
Hamim et al. (2021)	C5.0
López-Zambrano et al. (2022)	J48 (decision tree)

Table 5 presents various machine learning algorithms that were used in earlier research for the classification tasks. This includes, but are not limited to, decision trees, Bayesian networks, and ensemble methods. For further details, researchers can refer to a research study conducted by Tan, Steinbach, and Kumar (2016).

Primary Research Objectives

RQ3 asked: What are the primary research objectives of the chosen studies? In response, each paper was classified into one of four categories: (a) predicting final performance to help tutors obtain deeper insights; (b) tracing the achievement of students who are underperforming or in danger of failing; (c) presenting apposite references and recommendations to each student to promote their success on a course and drive broader pedagogical improvement, and (d) improving prediction model portability in terms of predictive accuracy.

Table 6 shows that the majority of studies selected traced underperforming students (n = 6). The second-highest number (n = 4) offered sound recommendations and appropriate advice. One study measured students' understanding and improved the portability of prediction models, whereas another evaluated students' academic performance, and a further study monitored the status of students' knowledge.

Table 6

Objectives of the Selected Studies

Objective	Studies
Predicting final performance	El-Rady, (2020); Costa et al. (2021); El-Rady et al. (2017); Boufardea & Garofalakis(2012); Grivokostopoulou et al. (2014); Hamim et al. (2021); López-Zambrano et al. (2022)

Tracing students' achievement	El-Rady, (2020); Costa et al. (2021); El-Rady et al. (2017); Grivokostopoulou et al. (2014); Hamim et al. (2021)
Presenting apposite references and recommendations	Costa et al. (2021); Boufardea & Garofalakis(2012); Grivokostopoulou et al. (2014)
Improving the portability of the prediction model	López-Zambrano et al. (2022)

Features and Context

The fourth research question (RQ4) was: What are the features used and what are the contexts of these studies? Table 7 shows the features used in all the articles collected, revealing that they were conducted using educational datasets or learning environments based on online learning or e-learning modes (El-Rady, 2020; Costa et al., 2021; El-Rady et al., 2017; Boufardea & Garofalakis, 2012; Grivokostopoulou et al., 2014; Hamim et al., 2021; López-Zambrano et al., 2022).

In some educational domains, while the datasets are too small (El-Rady, 2020; Costa et al., 2021; El-Rady et al., 2017; Boufardea & Garofalakis, 2012; Grivokostopoulou et al., 2014; Hamim et al., 2021; López-Zambrano et al., 2022), in others, they are usually large enough (El-Rady, 2020; Hamim et al., 2021; López-Zambrano et al., 2022). Moreover, only one of the studies reviewed failed to mention the features of the dataset used (Costa et al., 2021).

Table 7

Contexts and Features Used in the Selected Studies

Study	Features used to build ontologies	Context
El-Rady, (2020)	Average number of comments, posts and likes submitted by the learner on Facebook groups for the course, learner's age, address, gender, learner's activities (related or unrelated to the curriculum), number of sessions attended, grades for exercises, mid-term grades, family members, average time spent on learning, number of previous failures, final grade	E
Costa et al. (2021)	Not mentioned	E
El-Rady et al. (2017)	Number of sessions attended, grades for exercises, mid-term grades, learner's activities, learner's age, learner's address, average number of comments, gender, family members, average time spent learning, number of previous failures, learner's activities, posts and likes submitted by learner on Facebook groups for the course	O

Boufardea & Garofalakis(2012)	Grades for projects, grades for exams, the type of exam, student's gender, student's age, student's marital status, and educational background	O
Grivokostopoulou et al. (2014)	Marks in tests, student's gender, academic year, marks in final exams for the course	O
Hamim et al. (2021)	Personal identity, social identity, digital identity, family background, personality, professional experience, physical limitations, knowledge profile, learning profile, academic background, cognitive profile	O
López-Zambrano et al. (2022)	Questionnaires, quizzes, surveys, forums, glossaries, assignments, databases, chats, choice, lessons, workshops, scorepackages, wikis	O

Note. E = e-learning; O = online learning.

Evaluation Techniques

The next research question (RQ5) was: Which evaluation techniques are used? Table 8 illustrates the techniques used to evaluate the proposed ontologies with machine-learning algorithms. There was no specific evaluation methodology to assess the quality of the ontologies developed. The studies variously applied an evaluation matrix (El-Rady, 2020; El-Rady et al., 2017; Boufardea & Garofalakis, 2012; Grivokostopoulou et al., 2014; Hamim et al., 2021) or other evaluation techniques (López-Zambrano et al., 2022). Only one study implemented interviews and questionnaires to assess the quality of the suggested architecture's viability, taking into account how it would affect the teaching and learning process (Costa et al., 2021).

Table 8

Evaluation Techniques in the Selected Studies

Study	Evaluation technique
El-Rady, (2020); El-Rady et al. (2017); Boufardea & Garofalakis (2012); Grivokostopoulou et al. (2014); Hamim et al. (2021)	Accuracy, precision, recall, accuracy matrix
Costa et al. (2021)	Interviews, questionnaires
López-Zambrano et al. (2022)	Area under AUC loss, ROC curve

Note. AUC = Area Under the Curve; ROC = Receiver Operating Characteristic.

Table 9 illustrates the outcomes of assessing the performance of the various methods adopted in the selected studies. Data-mining techniques, such as the J48 algorithm, yielded better accuracy and performance (87%; Grivokostopoulou et al., 2014). The random forest algorithm was used to predict whether students would pass or fail based on a dataset, attaining 91.36% accuracy (El-Rady et al., 2017). In another study, the C5.0 algorithm achieved 83.6% accuracy (Hamim et al., 2021). Similarly, in Boufardea & Garofalakis (2012), the C5.0 algorithm outperformed other studies (85.2%), and the AUC metric was found to yield 0.63% accuracy

(López-Zambrano et al., 2022). Ultimately, El-Rady, (2020) achieved the best accuracy (95.8%), using the J48 and random forest algorithms.

Table 9

Overall Accuracy of the Algorithms as Reported in the Included Studies

Study	Techniques	Accuracy, %
El-Rady, (2020)	Random forest and J48 algorithm	95.8
El-Rady et al. (2017)	Random forest algorithm	91.36
Boufardea & Garofalakis (2012)	C5.0 algorithm	85.2
Grivokostopoulou et al. (2014)	J48 algorithm	87
Hamim et al. (2021)	C5.0 algorithm	83.6
López-Zambrano et al. (2022)	J48 algorithm (decision tree)	0.63

Key Benefits

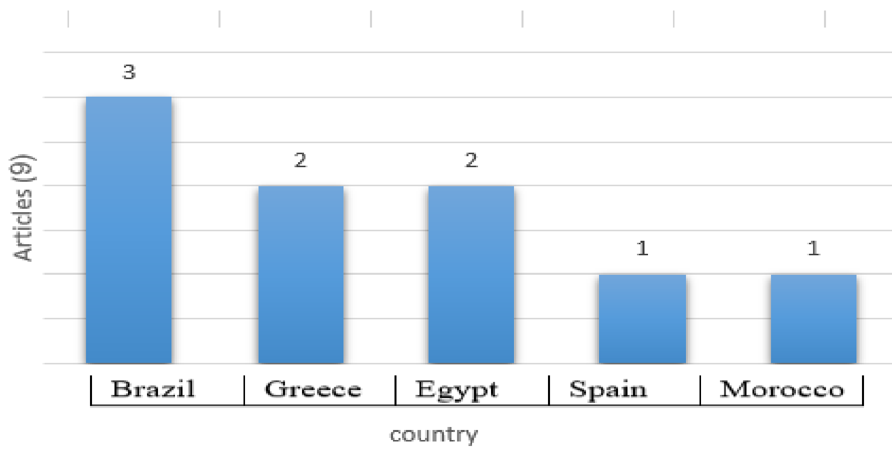
Research question six (RQ6) asked: What are the key benefits of implementing ontologies to predict online learners' academic performance? In response, this research found that ontological machine-learning techniques were successfully implemented in online learning. Each student in the selected studies had received learning activities via ontologies, which also helped improve the quality of the curriculum. Moreover, ontologies were used to represent students' characteristics and the teaching domain (Grivokostopoulou et al., 2014). In El-Rady et al. (2017) and Boufardea & Garofalakis (2012), the aim was to predict learners' progress or status and generate information about students' final performance. The application of ontologies was also aimed at predicting students' failure, success, and dropout rate (Hamim et al., 2021). In terms of predictive accuracy, the use of ontologies appeared to enhance the portability of the prediction models, as ontological models developed on one course could be used for other course goals at different levels of application, without sacrificing their prediction accuracy (López-Zambrano et al., 2022). Additionally, some of the included papers emphasised how the ontology model could help identify students who required extra help and make appropriate recommendations to close the gaps in students' learning and lower the student failure ratio (Grivokostopoulou et al., 2014).

Country Context

The next research question (RQ7) asked: In which countries were the experiments in the included papers conducted? Figure 2 depicts the articles' distribution across countries, indicating that the studies took place in Brazil (n = 3), Greece (n = 2), Egypt (n = 2), Spain (n = 1), and Morocco (n = 1).

Figure 2

Distribution of Articles Across Countries

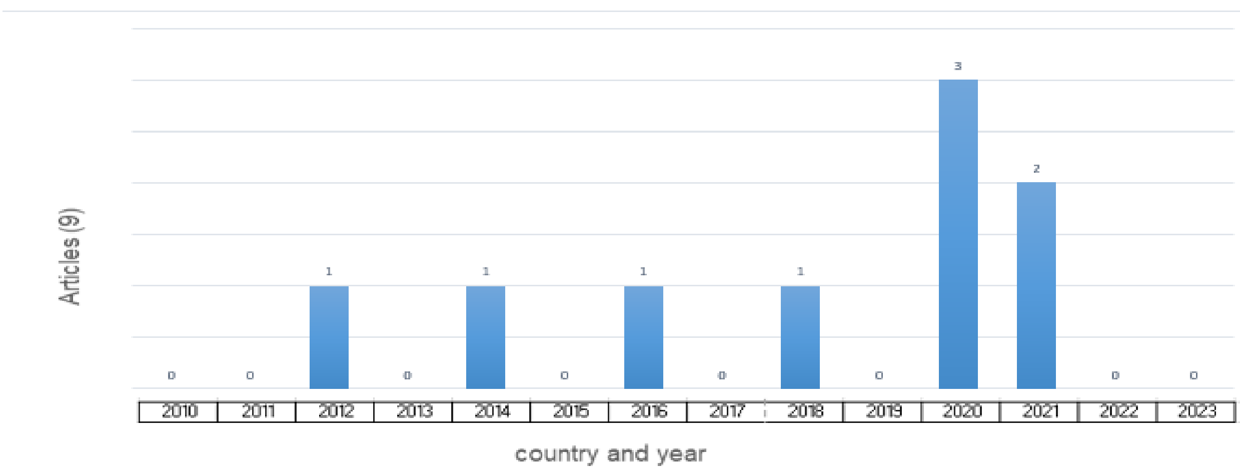


Time of Previous Experiments

The final research question (RQ8) asked: When were the previous experiments on ontologies conducted? Figure 3 presents the selected studies organized by year of publication. This classification served to build a clearer picture of the distribution of publications for the past 13 years and a summary of the research output in this field.

Figure 3

Distribution of Selected Articles According to Year of Publication



It is clear from Figure 3 that from 2010 to 2023, there was no substantial increase in the number of publications on ontological techniques for forecasting the success of online learners. In eight of those years, no such papers were published. In 2012, 2014, 2016, and 2018, one journal article on this topic was published for each year, whereas in 2020, there were three. This increase may be attributed to the evolution in associated areas such as Web 3.0 and e-learning, or the widespread use of online learning during the COVID-19 pandemic.

The use of ontological approaches to predict online academic success provides a novel way to understand and promote students' progress. This approach can open the door for more flexible, responsive, and successful educational systems as it can help define learners' characteristics and then improve customization of the learning experience.

This research highlights how most of the ontological methods reported in the literature employed Protégé software to create ontologies, but two studies failed to define the environment for ontology creation. The OWL representation language was identified as a common tool for encoding ontologies, whereas the RDF representation language was less frequently used; three studies used an OWL representation and two used an RDF representation language, as shown in Table 4. Conversely, other selected studies did not mention the representation language used.

Among the machine-learning techniques mentioned in the selected studies, the decision tree technique was found to be the most commonly deployed. Meanwhile, different machine-learning techniques were applied in three of the studies, but two studies omitted to specify the technique used to forecast students' academic performance, as shown in Table 5. The findings show there was no substantial increase in the number of journal articles published between 2010 and 2023 on the topic of ontology-based techniques for predicting academic performance. This means that related research may still be facing some issues in implementing ontological prediction techniques. The purpose of most of the studies shown in Table 6 was to investigate the accuracy of using ontologies to predict students' performance. However, some studies were designed to serve more than one purpose.

To evaluate the research findings, several techniques were employed: a convolution matrix, AUC loss, area under the ROC curve, interviews in five of the studies reviewed, and a questionnaire in one study. In contrast, three studies omitted to mention any evaluation technique, as illustrated in Table 8. Among the machine-learning techniques used in the selected studies, the highest accuracy (95.8%) was achieved with the random forest and J48 algorithms, as displayed in Table 9.

Regarding the location of these studies, three were carried out in Brazil, two in Greece, two in Egypt, one in Spain, and one in Morocco, as shown in Figure 2. Furthermore, there was no substantial rise in the number of publications on ontology-based techniques for predicting academic performance between 2010 and 2023. See Figure 3.

Despite the advantages of implementing ontologies to predict students' academic achievement, there remain many research gaps. First, experiments and prediction models should be trained on large datasets. In addition, artificial datasets might not reflect students' actual performance or behaviour (Boufardea & Garofalakis, 2012). Second, most of the included studies employed machine-learning algorithms (López-Zambrano et al., 2022). However, the use of deep learning algorithms with an ontology could help improve the prediction of academic performance. Third, a common factor among the reviewed studies was that they all relied solely on the original features of the datasets, whereas generating new features could lead to better prediction accuracy (Al-Azawei & Al-Masoudy, 2020). Fourth, some researchers have mainly used Protégé with a Pellet reasoner, but there are many other reasoners that could be used. Reasoners that also support Protégé are Snorocket, RACER, FACT++, HermiT, CEL, ELK SWRL-IQ, and TrOWL (Nafea et al., 2016). Furthermore, although this systematic review was conducted across several databases, only a few studies were found to have implemented ontological techniques to predict students' performance. This could signify that the research area requires further empirical investigation to identify its key advantages in predicting academic performance.

Finally, evaluating the performance of ontological approaches was clearly lacking from this body of literature, which could be attributed to the absence of relevant evaluation standards. In nearly half the reviewed studies, no clear evaluation techniques appear to have been implemented, which could affect the overall reliability of those ontologies. Khalilian (2019) suggested that evaluating the quality of an ontology is crucial to determine the most suitable ontology for a specific purpose.

Conclusion

This article presents a systematic review, conducted to explore the role of ontologies in predicting learners' academic achievement. The PRISMA methodology was used to collect possible research papers. Seven studies and two systematic reviews published between 2010 and 2023 were selected. This research therefore provides an inclusive review of ontological methods of predicting online students' achievement.

The reviewed papers were classified according to the techniques implemented, ontology language represented, learning platform used, classification applied, location of affiliations, year of publication, datasets implemented, number of participants, and evaluation methods deployed. This systematic review provided a clear analysis of the research gaps and limitations, in order to inform possible future trends. It is envisaged that this review will broaden the boundaries of knowledge and provide relevant literature for scholars who are interested in furthering the topic of inquiry. It also highlighted the influence of ontologies on DE and ODL theories. This lies in the fact that the use of ontology can provide tools for organizing, integrating, and analyzing educational information and processes. It can also improve the efficacy and theoretical underpinning of educational models by contributing to curriculum design, interoperability, scalability, and flexibility. Hence, such integration can lead to promoting innovation and increasing outcomes of both learners and educational institutions.

Regardless of the importance of this work, a number of research limitations should be mentioned. The first is that no repeat searches for pertinent research were conducted after a set length of time, which could mean that some papers were disregarded or released later. Second, only specific databases were used, so papers published elsewhere might not have been retrieved. Third, the results did not include research written in other languages. Fourth, the only keywords used to identify relevant studies were "online learning," "Semantic Web," "ontology," and "learners' performance." Employing additional keywords could have yielded more accurate and comprehensive results. Finally, the included studies did not explore the influence of ontologies on personalizing online learning platforms according to learners' needs and characteristics. As such, further research is invited to investigate the relationship between these two concepts.

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The Impact of Switching Intention of Teachers' Online Teaching in the COVID-19 Era: The Perspective of Push-Pull-Mooring

Chien-Liang Lin[1], Jun-Yan Liu[2], Chi-Heng Li[3], Yu-Sheng Su[4,5*], and Juan Zhou[6]
*[1]Department of Information Management, Ming Chuan University, Taiwan; [2]Department of Marketing and Logistics Management, National Pingtung University, Taipei, Taiwan; [3]Graduate Institute of Applied Science and Technology, National Taiwan University of Science and Technology, Taiwan; [4]Department of Computer Science and Information Engineering, National Chung Cheng University, Taiwan; [5]Department of Computer Science and Engineering, National Taiwan Ocean University, Taiwan; [6]Graduate School of Environmental and Information Studies Environmental and Information Studies, Tokyo City University, Japan; *Corresponding author*

Abstract

In response to the COVID-19 pandemic, many educational institutions switched to online learning to maintain learning activities. With the global pandemic, the educational environment was forced to shift from traditional face-to-face teaching or blended learning to a fully online learning model. In February 2020, China took the lead in announcing the implementation of online learning, encouraging most teachers to use it. Exploring the potential of online learning to replace traditional face-to-face teaching is a topic deserving consideration. This study explored the factors that influenced teachers' intention to switch to online learning during the pandemic, using a push-pull-mooring model. The study analyzed 283 valid responses gathered through an online questionnaire and found that push effects, pull effects, and habits significantly impact teachers' intention to switch from offline to online teaching. The findings provide additional insights into the future of higher education after the pandemic.

Keywords: COVID-19, migration behavior, online learning, push-pull-mooring model

Introduction

COVID-19 changed the teaching mode in many schools, especially during the first 2 years of the pandemic. To avoid interruption to university learning, educational institutions in various countries stopped face-to-face teaching and encouraged teachers and students to switch to online teaching to achieve the "study must not stop" goal (Chen et al., 2020). Before the pandemic, many countries had a certain degree of understanding and use of online learning, but some teachers may not have had much online teaching experience (Chen et al., 2020). The emergency policies adopted by various countries in response to the pandemic inevitably forced many teachers and students to start the switch. This transition from in-person to online classes caught many inexperienced teachers and students off guard (Carrillo & Flores, 2020). Most past users of online learning and teaching had positive learning or educational motivations based on their personal favorite courses and common technology (Çınar et al., 2021). However, the urgent change in learning modes during the pandemic led to a situation in which teachers experienced great risks and anxiety, as well as barriers to their teaching, all of which differed from their previous teaching habits (Liu et al., 2022). This could have caused teachers' negative emotions about online teaching, possibly turning into teaching obstacles and leading to poor teaching quality (MacIntyre et al., 2020). Many users were forced to learn how to use online teaching platforms quickly and widely, which may have affected them during the conversion process (Chen & Keng, 2019), inducing anxiety about teaching (Liu et al., 2022). Therefore, under the influence of COVID-19, the efforts teachers made to meet the educational goal of "study must not stop" became a dilemma (Lin et al., 2021).

In past research, the push-pull-mooring model (PPM) was primarily used to study behavior when changing from offline to online environments (Hou & Shiau, 2019). There were many topics covered in previous studies discussing the behavior of students switching from face-to-face to online learning (Nayak et al., 2022). Research on teachers has the same value, especially since the PPM model is a crucial theory in studying migration behavior, and its variables are not fixed in any structural framework. Researchers need to define the impact of push, pull, and mooring factors on migration behavior (Handarkho & Harjoseputro, 2020). In previous PPM studies, dissatisfaction was the main push factor (Tang & Chen, 2020), and alternative attraction was the main pull factor (Al-Mashraie et al., 2020). However, in terms of mooring factors, there are still many external factors that influence users' willingness to switch (Hou & Shiau, 2019). This study applied the PPM model to explore teachers' behaviors, identifying security risk (SR) and service quality (SQ) as push factors, and challenge motivation (CM), task-technology fit (TTF), and teaching self-efficacy (TSE) as pull factors. Habits were the main mooring factor. Analyzing 283 valid responses, the study shows how these factors influenced teachers' willingness to move to online platforms. The research integrates the stress caused by the pandemic and policy changes, providing a comprehensive understanding of the transition to online education. The findings emphasize the need to support educators through such changes to enhance the sustainability of online teaching. These findings can help policymakers and administrators develop strategies for smooth transitions to blended or fully online learning environments.

Literature Review and Hypotheses

Teachers' Study During the Pandemic

During the pandemic, in order to control the spread of the virus, governments around the world announced they would stop face-to-face classes, asking teachers to switch to online teaching (Cao et al., 2021). Due to the urgency of the health crisis and the fact that many countries had never had a national unified online teaching experience, many teachers needed to rapidly switch to online platforms, creating a great challenge (Carrillo & Flores, 2020). Previous studies have suggested that when teachers' emotions are affected, it will likely lead to changes in self-cognition and self-efficacy, in which stress will have a major impact (Beserra et al., 2022). The research regarding COVID-19 has mentioned that teachers may encounter facilitators or deterrents in teaching, such as stress, fatigue, support, and workplace well-being, which may affect their self-efficacy (Stang-Rabrig et al., 2022). Pressley and Ha (2021) adopted the self-efficacy theory to examine teachers' perceptions of online instruction and noted in their study of teachers' self-efficacy that even teachers with abundant face-to-face teaching experience may suffer increased stress or anxiety associated with online instruction. This may reduce their self-efficacy and thus their effectiveness. Daumiller et al. (2021) employed the achievement goal theory to discuss the research on teachers' abrupt transition to online teaching. The results indicated that achievement goals could change teachers' attitudes toward online teaching. Positive challenges that lead to good performance goals would bring more positive attitudes and less stressful rejection. MacIntyre et al. (2020) explored the influence of pressure on teachers' switching to online teaching and showed that positive versus negative emotions would affect teachers' acceptance. However, when the stress level is high, the negative effects of anxiety may be reduced by student and parental support, thereby increasing teachers' self-efficacy (Bruggeman et al., 2022). According to Wong et al. (2021), when the learning and teaching motivation of students and teachers are both positive, it will enhance positive feedback and views on online teaching from both parties, which will increase teachers' willingness to teach online.

During the pandemic, the difficulties encountered in teaching in response to the crisis catalyzed teacher innovation and development, and such changes brought innovative thinking in emergency management contexts (Moorhouse & Wong, 2022). Liu et al. (2022) noted that when teaching online courses during the pandemic, there may have been sudden interruptions from school colleagues or family members, which caused teachers to feel anxious and then affected the efficiency of online courses.

In previous studies on COVID-19, teachers' emotions, stress, self-efficacy, interaction, and anxiety during the pandemic were the main focus. However, this study argues that when using an online teaching platform during a pandemic, in addition to teachers' factors, other important factors brought about by the environment or platform services should also be considered. As discussed in previous literature, this study suggests that the PPM model is an important theory to help analyze factors affecting the transfer of in-person classes to online course platforms.

The Push-Pull-Mooring Framework

PPM is a theoretical framework for studying people's migration behaviors. It can be traced back to a concept proposed by Lee (1966), who argued that the concept of migration should have both positive and negative factors, forming the basis of the push-pull model. Essentially, the negative concept is a push force motivating people to leave their original living environment, while the positive concept is a pull force attracting people to move to a different place. However, since the push-pull model was unable to explain the role of individual determinants in migration behavior, Moon (1995) argued that mooring factors should be introduced into migration behavior, further proposing the PPM model. Mooring is a factor that can increase or decrease push or pull, and so can further influence people's decisions. Researchers in the field of marketing and information systems have indicated that user switching behavior is similar to the concept of population migration (Fu et al., 2021; Tang & Chen, 2020). Users move from existing services (e.g., social media, information system platforms, online learning) to other services, which is the migration behavior of service platforms (Li, 2018). Similarly, migration behavior can be used to describe a transition in the classroom environment in teaching. When the PPM model was proposed, it was adopted to explain the impact of context and environment. Chen and Keng (2019) explored students' possible transfer factors for online English teaching, and Liao et al. (2019) investigated the transfer factors in social network learning. Previous studies found that when the situation in which PPM was employed differed, the conformations of push, pull, and mooring would follow. As mentioned by Xu et al. (2014), special attention must be paid to the particularity of the research background when using the PPM model to aid in understanding the possible elements of PPM in various situations. In order to fully understand teachers' willingness to switch to online teaching during the COVID-19 pandemic in China, this study adopted the PPM model to find the variables of push, pull, and mooring affecting teachers' switching behaviors.

Push Factors

Push factors are often the negative causes that force people to leave their original place of residence and find another livable or acceptable offsite location (Lee, 1966). Push factors have been further interpreted as the cause of moving away from existing services (Tang & Chen, 2020). Lin et al. (2021) demonstrated that SR is a push factor and suggested that when users are concerned about the uncontrollable SR of the original service, they may move to avoid the problem. Liu et al. (2020) stated that when the user perceives the SR to be uncontrollable or unacceptable, they will seek out and transfer to alternative services. Chen and Keng (2019) reported that when users perceive that SQ is unsatisfactory, they are forced to shift to better services. Previous PPM studies have confirmed SQ as one of the push factors (Chen & Keng, 2019; Tang & Chen, 2020). This study argues that during the pandemic, SR should be defined as security issues related to the transmission of viruses during physical delivery, forcing teachers to move to an online platform. Similarly, for the purposes of this study, SQ should be defined as teachers being forced to move to an online platform when they experienced dissatisfaction with face-to-face instruction during the pandemic. Therefore, we considered SQ and SR as push factors and proposed the following hypothesis:

> H1: The higher the service quality and security risk, the higher the willingness of teachers to switch from face-to-face to online teaching.

Pull Factors

Pull factors are interpreted in migration studies as the attraction of a different location when the idea of leaving one's place of residence begins (Lee, 1966). Zhang et al. (2020) explained that when students perceive that the online platform provides more satisfying results than face-to-face learning, they may be motivated to switch. TTF is considered to be the primary consideration for the functionality of an information system, which influences whether the user can successfully complete the task and continue to use it (Goodhue & Thompson, 1995). CM is composed of intrinsic and extrinsic motivation. Extrinsic motivation is interest or a sense of challenge, while intrinsic motivation is achieving a goal or desire (Amabile, 1997). TSE is defined as the teacher's ability to realize active participation and good learning outcomes for students in spite of difficulties or problems (Tschannen-Moran & Hoy, 2001). This study argues that there are three dimensions to be considered from the perspective of technology services. First, teachers should consider choosing a proper platform to fit their own pedagogy (i.e., technology fit) in order to fulfill pedagogical goals (i.e., tasks) assigned by their government's ministry of education or the school. Second, teachers face significant challenges in the urgent transition to online teaching, which can lead to a decrease in their self-efficacy. Conversely, if teachers are able to achieve the challenging goal, their self-efficacy will increase (Culp-Roche et al., 2021). Finally, TSE increases when teachers are willing to focus on their students and demonstrate good engagement and learning outcomes. In conclusion, we classified CM, TTF, and TSE as pull factors, formulating the following hypothesis:

> H2: The higher challenge motivation, TTF, and teaching self-efficacy are, the more teachers will switch from face-to-face courses to online teaching.

Mooring Factors

Mooring may increase or decrease push and pull (Moon, 1996). In previous PPM studies, habits were defined as a form of mooring (Lin et al., 2021; Xu et al., 2017). Habits are a norm accumulated by experience, turning into laziness (Wang et al., 2019). They are difficult to change, but if there is dissatisfaction with the current situation, people often would be willing to try to change (Polites & Karahanna, 2012). When old habits are dissatisfying and there is a willingness to change, there is a high probability that new habits will be formed (Chen & Keng, 2019). This study suggests that during the pandemic, teachers relied on old habits because of great pressure. They were accustomed to their old teaching style, which may have prevented them from developing new habits, including using online platforms to teach, thus affecting their motivation to switch to online teaching. Therefore, based on past literature, we considered habits as the main mooring factor and formulated the following hypotheses.

> H3: The stronger the habit, the weaker the teachers' intentions to switch from face-to-face to online instruction.

> H3a: The stronger the past habits, the weaker the relationship between the push influence and switching intentions.

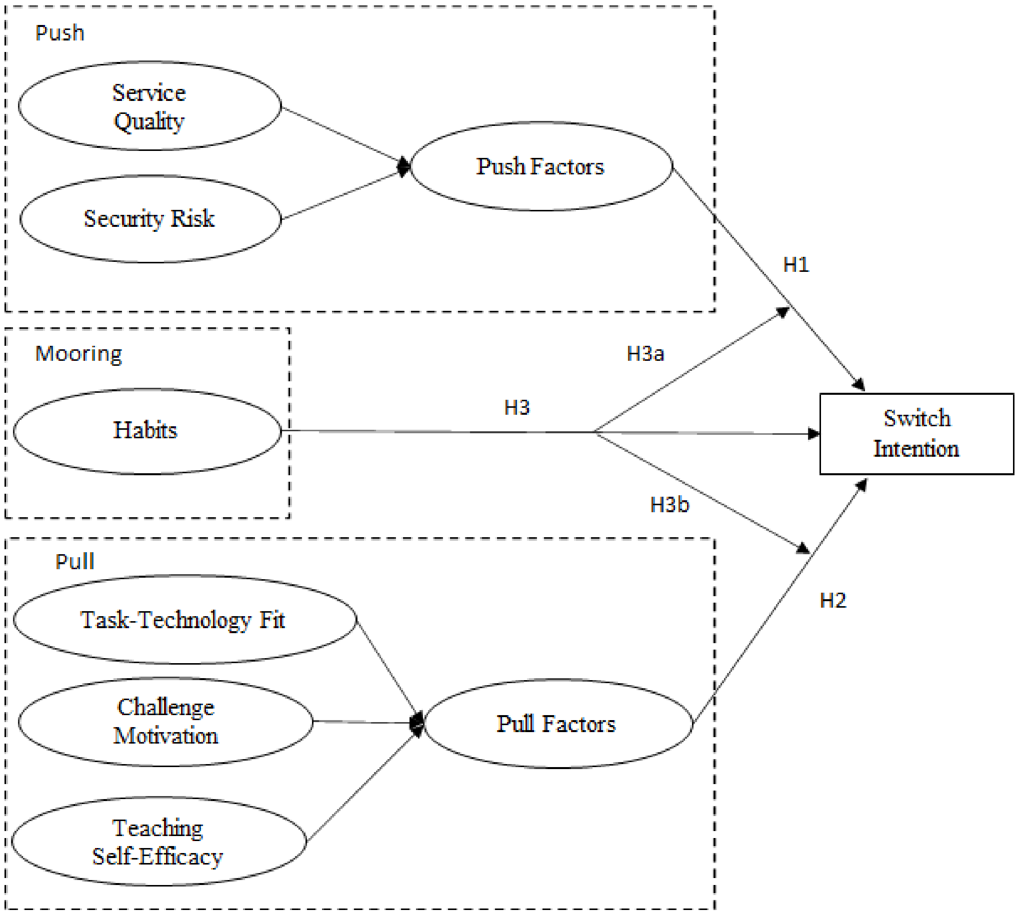
> H3b: The stronger the past habits, the weaker the relationship between the pull influence and switching intentions.

Research Model

Based on previous literature on the PPM model, we constructed a research model of Chinese university teachers' conversion behaviors influenced by COVID-19, and defined the possible orientations of push, pull, and mooring based on the online teaching context. On the basis of the model, we identified three main orientations: push (SR and SQ), pull (TSE, TTF, and CM), and habits, as presented in Figure 1.

Figure 1

Research Model and Structure



Note: H = hypothesis.

Data Collection

In this study, a pretest was conducted, following Mokkink et al.'s (2010) methodology, to ensure the validity of the questionnaire. University professors engaged in online teaching during the pandemic evaluated the initial questionnaire to verify its content and quality. Based on their feedback, necessary corrections were made before finalizing the questionnaire. The Questionnaire Star platform (https://www.wjx.cn/) was used for online distribution in the context of the COVID-19 pandemic to secure effective response collection. The study participants were university teachers in China affected by the pandemic. The survey was conducted in summer 2020, following the shift to online classes in Chinese universities.

We employed an online snowball sampling method, as our target population was university teachers using online teaching platforms. Initially, researchers sent the survey link to acquaintances who met the criteria, who then forwarded the link to others within their social and professional networks, thus increasing coverage. This method quickly gathered a large number of responses, enhancing the sample's diversity and reach (Turk et al., 2022). However, snowball sampling can introduce selection bias, as the sample is drawn from the networks of the original respondents. To mitigate these issues, the study combined convenience sampling and sought to ensure diversity in the initial pool of respondents. Indeed, many researchers in education studies also use snowball and convenience sampling methods to collect samples (Mourlam et al., 2020; Nagar & Talwar, 2023). We collected 300 questionnaires, of which 283 were deemed valid after filtering for quality and consistency. The sample size was determined based on previous studies using partial least squares structural equation modeling (PLS-SEM), supporting the robustness of our analysis given the exploratory nature of the research. To ensure the quality and validity of the collected questionnaires, we used five criteria to assess validity based on studies by Cheng et al. (2019) and Lin et al. (2021) during the pandemic:

1. We confirmed whether the teachers were using an online platform at the time of the pandemic. If not, the questionnaire was considered invalid.

2. Questionnaires in which all responses received the same score (all 1 or 7) were considered invalid.

3. A new question was added to identify respondents who completed the questionnaire in the reverse direction, in order to prevent them from completing it indiscriminately.

4. The questionnaire was only available to respondents with an account. If there was a duplicate account, the questionnaire was considered invalid.

In terms of basic demographic characteristics, 139 (49.11%) males and 144 (50.89%) females were recruited, with the same results for both genders. Regarding educational qualifications, 182 teachers had a PhD, while 101 had a master's degree, a ratio of 2:1. This indicates that a high proportion of teachers in mainland Chinese universities do not hold a PhD. In terms of the types of institutions from which these samples were drawn, 52 were from 985/211 universities, 161 were from national universities, and 70 were from private universities, reflecting the current situation of public and private universities in China. In terms of teachers' ages, 80 (28.27%) were under 35 years old, 100 (35.33%) were between 36 and 45, 51 (18.02%) were between 46 and 50, and 52 (18.37%) were over 50 years old. As for their positions, 34 (12.01%) questionnaires were returned by full professors, 128 (45.23%) by associate professors, 89 (31.45%) by assistant professors, and 32 (11.31%) by lecturers. Regarding the teacher background in China, the ratio of full/associate professors to assistant professors and below reflects the current situation in China, indicating that the sample distribution accurately reflects the actual situation. Finally, in the survey on whether they had used online teaching before the pandemic, 178 (62.9%) had never used it, while only 27 (9.54%) had used online learning platforms for more than 2 years, and 78 (27.56%) had used them for less than 2 years. The result of the basic demographic information shows that the popularity of online learning among university teachers was low before the pandemic. To ensure that there were no significant biases in the data analysis, we examined differences in teachers' intentions to switch to online teaching based on gender, education level, and age. The results of the PLS-SEM data analysis indicated that none of these factors reached statistical significance ($p > .05$). Results suggested that teachers' intentions to switch from face-to-face courses to online teaching were consistent regardless of gender, education level, or age.

Results

The selection of PLS-SEM as the methodological approach for this study was primarily informed by its exploratory and theoretically-oriented character, necessitating subsequent analysis of potential variables (Shiau et al., 2019). Given that push and pull factors were conceptualized as second-order constructs in this investigation, traditional techniques such as analysis of moment structures (AMOS), which only support reflective indicators for the examination of second-order formation models, were deemed insufficient. On the other hand, PLS-SEM is capable of accommodating both reflective and formative indicators (Huang & Shiau, 2017), making it a more suitable method for this study. Consequently, SmartPLS (Version 3.3.4; https://www.smartpls.com/) was employed for the analysis of data and testing of hypotheses in the context of this research.

Common method variance (CMV) can cause errors if it arises from measurement methods rather than the items themselves. To reduce CMV, the survey was paginated with brief breaks between pages. Harman's one-way test showed that CMV was within acceptable limits, with a total explained variance of 41.34% and no construct exceeding 50% (Shiau et al., 2019).

Straub et al. (2004) emphasized content validity's significance in model construction. By aligning with previous operational definitions, this study ensured construct integrity, thus avoiding measurement errors (Petter et al., 2007). Consequently, second-order model constructs were defined as formative indicators, with pull factors comprising two reflective dimensions: SQ and SR, while push factors included CM, TTF, and TSE.

Measurement Model

In the stage of evaluating reliability and validity, we needed to analyze factor loading, composite reliability (CR), average variance extracted (AVE), and discriminant validity according to the suggestions of Hair et al. (2017). Cronbach's α and factor loading were used to evaluate and analyze the reliability of each project. The factor loading in this study was based on the suggestion put forward by Shiau et al. (2019). The result values on factor loading of all facets were over .7, while α values for all facets were greater than the recommended .7 proposed by Hair et al. (2019). The CR of all facets was greater than the suggested value of .7 proposed by Hair et al. (2017). Additionally, the AVE of the construct itself was greater than the previously recommended value of > 0.5 (Shiau et al., 2019). The research results all exceeded the values suggested in the literature, indicating strong consistency and convergence of the measurement model in this study. The statistical results are shown in Table 1.

Table 1

Reliability and Validity of Study Constructs

Construct	Factor loading	α	CR	AVE	VIF
Service quality (SQ)	.794*** .823*** .894*** .864*** .882***	0.905	0.930	0.726	1.029

Security risk (SR)	.934*** .953*** .895***	0.919	0.949	0.861	1.029
Task-technology fit (TTF)	.926*** .902*** .918*** .801***	0.910	0.937	0.789	2.271
Challenge motivation (CM)	.820*** .818*** .725*** .790*** .759***	0.842	0.888	0.614	2.254
Teaching self-efficacy (TSE)	.853*** .893*** .925*** .797***	0.890	0.924	0.753	2.332
Habits (HA)	.887*** .819*** .706*** .839***	0.837	0.887	0.665	1.040
Switching intention (SI)	.856*** .900*** .884*** .902***	0.908	0.936	0.785	DV

Note. CR = composite reliability; AVE = average variance extracted; VIF = Variance inflation factor.

****p* < 0.001; DV= Dependent Variable.

The formative indicators of the second-order constructs were evaluated according to their effective significance ($p < .05$), and their contribution to the corresponding second-order constructs was indicated. As shown in Table 2, SQ, SR, TTF, CM, and TSE of the push and pull constructs all showed significant results, which had strong explanatory power even at the second level. We used the validation and testing mentioned in the previous theory in the sample; the control results fully supported the second-order concept of push and pull.

Table 2

The Measurement Results of Formative Indicators

Construct	Sub-construct	Weight
Push factor	Service quality (SQ)	0.355***
	Security risk (SR)	0.877***
Pull factor	Task-technology fit (TTF)	0.381***
	Challenge motivation (CM)	0.368***
	Teaching self-efficacy (TSE)	0.374***

Note: ***$p < .01$

Hair et al.'s (2017) approach was used to evaluate discriminant validity. It involved ensuring that the square root of the AVE for each construct surpassed the correlation coefficients between constructs, thereby confirming discriminant validity across all constructs (Table 3).

Table 3

Discriminant Validity (Fornell & Larcker's Method)

	HA	TTF	TSE	SR	CM	SQ	SI
HA	**0.815**						
TTF	-0.057	**0.888**					
TSE	-0.151	0.694	**0.868**				
SR	-0.090	-0.319	-0.279	**0.928**			
CM	-0.135	0.681	0.692	-0.331	**0.783**		
SQ	0.008	-0.558	-0.525	0.167	-0.573	**0.852**	
SI	-0.187	0.676	0.687	-0.360	0.699	-0.538	**0.886**

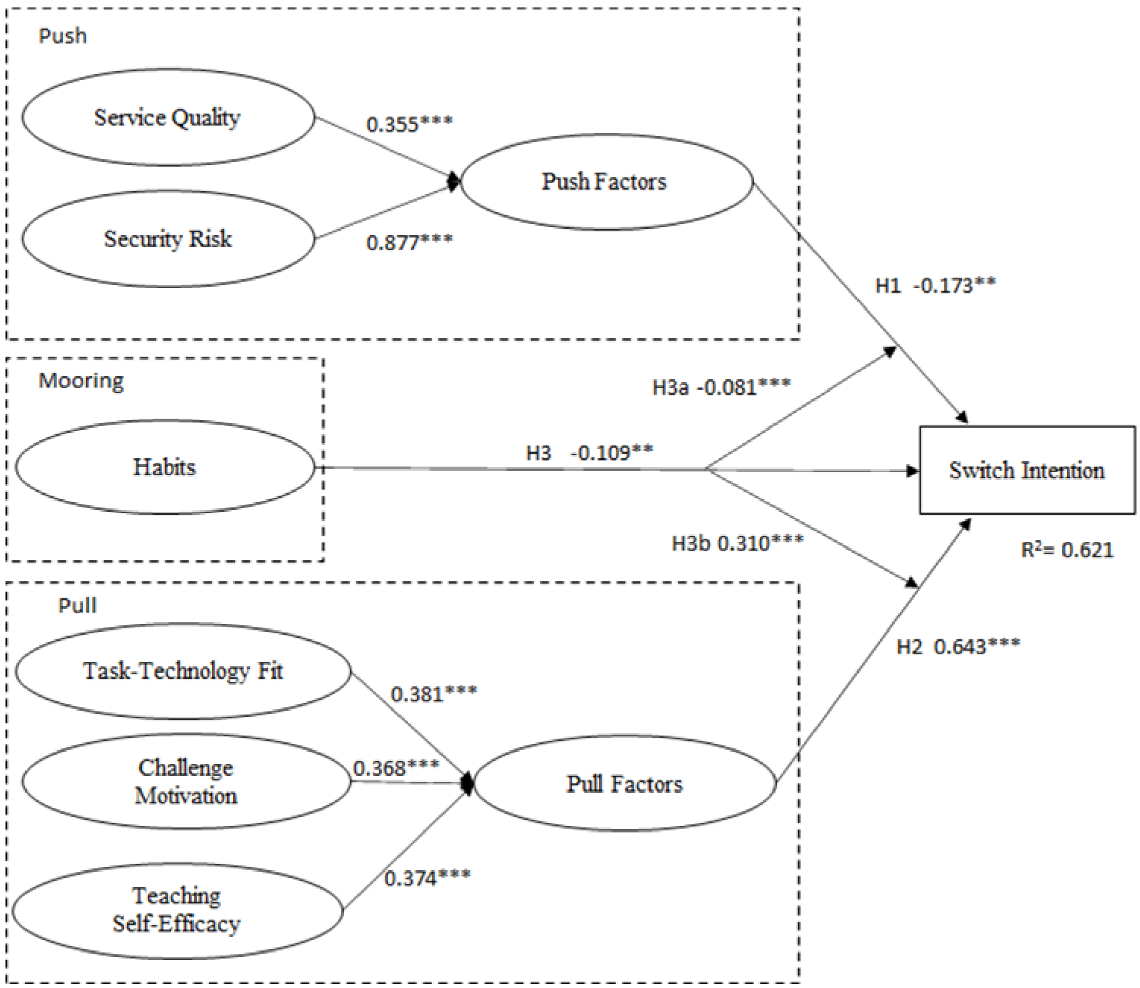
Note. HA = habits; TTF = task-technology fit; TSE = teaching self-efficacy; SR = security risk; CM = challenge motivation; SQ = service quality; SI = switching intention. Figures in bold represent the square root of the average variance extracted (AVE).

Structural Model

These figures indicate that the proposed hypothesis model has good fitness. As for the analysis of the results, we tested the model using the bootstrapping resampling technique with 5,000 resamples (Hair et al., 2017). The analysis results of the structural model are shown in Figure 2. Based on the analysis results, the overall explanatory power of this study was 62.1%, showing that the model had good predictive power. In terms of the results for H1, pull factors had a negative significant influence on switching intention (β = -0.173, p < .01), while for H2, pull factors had a positive significant impact on switching intention (β = 0.310, p < .001). Subsequently, habits had a negative significant effect on switching intention (β = -0.109, p < .01), so H3 was supported. Finally, regarding regulatory effects, H3a exhibited a negative significant relationship (β = -0.081, p < .001), which is inconsistent with Li and Ku's (2018) study. However, for H3b, habits (β = 0.310, p < .001) had a positive regulatory effect on pull and switching intention (Chen & Keng, 2019), suggesting that prior habits could affect pull factors.

Figure 2

Analysis Results of the Research Model



Note. **p < .01; ***p < .001.

Conclusion

Discussion

According to the results of testing related to H1, push factors had a significant negative influence on teachers' willingness to switch from face-to-face to online delivery. Faced with the environmental uncertainty of COVID-19, teachers refused to continue face-to-face teaching due to concerns over SQ and SR. These findings are consistent with Lee's (1966) PPM model, which suggests that negative factors lead individuals to leave existing services. Consistent with previous studies by Chen and Keng (2019) and Lin et al. (2021), our findings indicated that when teachers are dissatisfied with both SR and SQ, they are more likely to seek alternative solutions. Among the push factors, SR emerged as the most influential, followed by SQ. Security concerns, particularly in the context of a pandemic, played a critical role in prompting teachers to abandon face-to-face courses. Environmental uncertainties heightened fears about the ability of schools to effectively prevent contagion among teachers and students during face-to-face interactions. Similarly, the importance of SQ as a push factor is supported by previous research showing that inadequate SQ drives the shift from face-to-face to online learning (Chen & Keng, 2019). During the pandemic, the Ministry of Education of China's policies restricting face-to-face teaching forced teachers to switch to online teaching to meet students' educational needs. This transition highlighted the need for stable and high-quality online teaching platforms to manage emergency teaching scenarios. Future strategies should include robust real-time online emergency service mechanisms to promptly address the problems faced by teachers and students. By improving the SQ and ensuring adequate security measures, educators will be more willing to move to online platforms in times of crisis.

Regarding the results of testing related to H2, pull factors were found to have a significant positive influence on teachers' willingness to switch from face-to-face to online teaching. Pull factors, such as CM, TTF, and TSE, increased teachers' willingness to switch to online delivery. This finding is consistent with Lee's (1966) PPM model, which posits that positive attractions motivate individuals to change services. Among the pull factors, TTF emerged as the most influential, followed by TSE and CM. These findings are consistent with previous studies. For example, Wu and Chen (2017) found that TTF significantly influenced users' willingness to use online platforms. During the pandemic, meeting students' learning needs through appropriate online teaching methods became a critical task for teachers. Consequently, the willingness to switch to online teaching depends heavily on the platform's ability to meet pedagogical requirements and support students' learning needs. The influence of CM is consistent with Fulmer and Frijters' (2011) finding that positive motivation in the face of challenges enhances willingness to adopt new methods. During the pandemic, a lack of consistent online teaching experience was a significant challenge for teachers. However, those who were motivated to find suitable online platforms and pedagogies to meet students' needs were more likely to switch from face-to-face to online teaching. TSE also played a crucial role, supporting the findings of Ismayilova and Klassen (2019). The urgency of the pandemic-induced transition placed a heavy burden on teachers. However, those who focused on student engagement and learning outcomes demonstrated perseverance and increased their willingness to transition to online teaching. For future online teaching, it is important to ensure that the platform's functionality is aligned with teachers' needs. Features such as assignment grading, report grading, and evaluation comments should be linked directly to the school's teaching database to reduce administrative burden. Encouraging teachers through positive feedback and supportive comments from students can further enhance their motivation and effectiveness in online teaching.

From the results of testing connected to H3, previous habits had a negative effect on teachers' intention to switch, consistent with findings from previous PPM studies (Nayak et al., 2022). Teachers are typically accustomed to face-to-face teaching, but the pandemic caused them to reconsider these habits due to concerns about personal safety and SQ. Habit is a deeply ingrained behavior that cannot be changed immediately. However, when new habits address dissatisfaction with original practices, individuals are more willing to change (Chen & Keng, 2019; Polites & Karahanna, 2012). In our study, the pandemic created a unique context where teachers were forced to shift to online platforms. This shift was motivated by the need to ensure personal safety and maintain SQ. The negative impact of existing habits on switching intentions underlines the resistance to change that many teachers experienced. Nevertheless, the need to adapt to new conditions facilitated the formation of new teaching habits. For future emergency teaching scenarios, habits must be considered as a critical factor. While face-to-face teaching has many advantages, online platforms also offer significant benefits, especially during a pandemic. Reinforcing and promoting the advantages of online platforms can help establish new teaching habits. Encouraging teachers to embrace these new practices can facilitate a smoother transition and enhance their effectiveness in online teaching environments.

Theoretical Implications

This study makes a unique contribution to the literature on teachers' behavior change during the pandemic by integrating the theory of self-efficacy (Pressley & Ha, 2021) and achievement goal theory (Daumiller et al., 2021; MacIntyre et al., 2020). Unlike most studies that focus on teachers' abilities, emotions, and barriers, this research adopted the push-pull-mooring (PPM) model to explain contextual change behaviors, incorporating teachers' individual competencies and integrating concepts from self-efficacy and TTF theories. This approach provides a comprehensive understanding of teachers' behavior change during emergency management in Chinese universities under the influence of the COVID-19 pandemic. Notably, no previous PPM studies have combined self-efficacy and TTF within the PPM framework, making this study a valuable addition to the transition behavior literature by applying a new perspective on PPM, self-efficacy, and TTF.

Practical Implications

The practical implications of this study are important for guiding educational policy, practice, and future research. Educational policymakers should prioritize the development of safe and high-quality online teaching environments, implement stringent security measures, and ensure high SQ of online platforms to create a more conducive environment for online teaching. Educational institutions should provide comprehensive training and resources to enhance teachers' self-efficacy and ensure that online teaching platforms are well-aligned with teaching tasks, thus supporting teachers in effectively meeting the challenges of online education. Additionally, educational leaders should promote the advantages of online platforms to help teachers develop new teaching habits, facilitate smoother transitions, and improve the efficiency of online teaching environments. These practical insights enhance the relevance and impact of the study, providing actionable guidance for educators, policymakers, and researchers.

Limitations and Future Research

This study integrates the theories of self-efficacy and TTF into the push-pull-mooring (PPM) model, providing a novel framework for examining behavior change in educational settings. However, the data collection methods, primarily questionnaire-based and using snowball and convenience sampling, may introduce biases such as overrepresentation of certain demographic groups. Future studies should consider a randomized sampling approach to enhance generalizability. Additionally, the study was conducted during the COVID-19 pandemic, making it difficult to determine whether teachers' behaviors changed after the pandemic. Researchers should conduct follow-up studies to assess any changes in teacher behavior. The current study's statistical results on teachers' willingness to switch from face-to-face to online teaching may not fully address all emergency-related issues. Therefore, future research should include qualitative approaches to explore additional switching factors. Longitudinal studies are recommended to assess the evolution of these factors over time and their long-term impact on teaching practices. By continuing to explore important factors from the PPM perspective when discussing emergency issues, researchers can further understand the dynamics of online teaching adoption and provide deeper insights into effective teaching practices.

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Automatic Classification of Online Learner Reviews Via Fine-Tuned BERTs

Xieling Chen[1], Di Zou[2], Haoran Xie[3], Gary Cheng[4], Zongxi Li[5], and Fu Lee Wang[6]
[1]School of Education, Guangzhou University, Guangzhou, China; [2] Department of English and Communication, The Hong Kong Polytechnic University, Hong Kong SAR; [3] School of Data Science, Lingnan University, Hong Kong SAR; [4]Department of Mathematics and Information Technology, The Education University of Hong Kong, Hong Kong SAR; [5]School of Data Science, Lingnan University, Hong Kong SAR; [6]School of Science and Technology, Hong Kong Metropolitan University, Hong Kong SAR

Abstract

Massive open online courses (MOOCs) offer rich opportunities to comprehend learners' learning experiences by examining their self-generated course evaluation content. This study investigated the effectiveness of fine-tuned BERT models for the automated classification of topics in online course reviews and explored the variations of these topics across different disciplines and course rating groups. Based on 364,660 course review sentences across 13 disciplines from Class Central, 10 topic categories were identified automatically by a BERT-BiLSTM-Attention model, highlighting the potential of fine-tuned BERTs in analysing large-scale MOOC reviews. Topic distribution analyses across disciplines showed that learners in technical fields were engaged with assessment-related issues. Significant differences in topic frequencies between high- and low-star rating courses indicated the critical role of course quality and instructor support in shaping learner satisfaction. This study also provided implications for improving learner satisfaction through interventions in course design and implementation to monitor learners' evolving needs effectively.

Keywords: learner-generated content, automatic classification, fine-tuned, BERTs, course evaluation

Introduction

Online education has experienced a substantial surge in popularity, offering individuals the flexibility to learn without the constraints of physical classroom attendance. Massive open online courses (MOOCs), as a widely adopted mode of digital learning, have provided distance learners with abundant learning materials, interactive environments, and the freedom to select their study schedules (Liu et al., 2023); thus, an increasing number of educational institutions have developed MOOC courses.

MOOCs have offered opportunities for students to exchange perspectives on their learning experiences by writing course reviews, resulting in large-scale learner-generated content available for online educational data analytics (Chen et al., 2024) that offers insights into learners' learning experiences and preferences (Hew et al., 2020).

One common approach to analysing online course reviews has involved categorizing review content into specific features using coding categories. For instance, Hew (2016) developed a coding system based on quantitative content analysis (QCA) of 4,466 course reviews to pinpoint factors contributing to MOOC learners' engagement. While QCA effectively analyses small amounts of textual data, it is challenging to deal with large-scale course reviews. Furthermore, QCA cannot offer timely feedback on learners' experiences to instructors and designers for their decision-making about interventions to increase completion rates of MOOCs.

Given the limitations of QCA, several automated classifiers have been developed to automatically identify topics within online course reviews. For instance, Li et al. (2022) employed an ontology of key topics and associated keywords to analyse the proportion of reviews mentioning these topics in order to establish a foundational understanding of learner feedback. Similarly, Chen et al. (2024) developed classifiers based on deep learning methods such as convolutional neural networks (CNNs) for the automatic examination of course evaluation texts. Although these methods have reduced labour costs and enabled automatic detection, their performance has relied heavily on distinct manually-created characteristics, and has been constrained by obstacles such as imbalanced sample sizes and unregistered words.

Compared to the aforementioned traditional machine learning and deep learning algorithms, bidirectional encoder representations from transformers (BERTs) can reduce the necessity for laborious feature engineering and have gained wide application and contributed significantly to enhancing performance in various natural language processing (NLP) tasks (El-Rashidy et al., 2023). With the ability to continuously pretrain on a large domain-specific corpus, BERT has shown promise for facilitating the classification of topics within MOOC course reviews.

However, there has been limited research on fine-tuned BERTs combined with text mining for MOOC review analytics. Thus, this study aimed to propose a hybrid approach for analysing online reviews in MOOCs to predict learner preferences and aid instructors in decision-making. Specifically, we first introduced a BERT-BiLSTM-Attention model specific to MOOC review analysis and explored its performance in identifying review topics. The model used BERT as an encoder to represent the review texts by incorporating the position and context of a word in a sentence, with BiLSTM (bidirectional long short-term memory network) and attention mechanisms for capturing review texts' global contextual information to predict review topics. Based on the prediction results, we further exploited statistical modelling to understand topic distributions across disciplines and course rating groups. Accordingly, we addressed three research questions:

> RQ1: To what extent is the use of BERT models effective in identifying review topics within online course review data?
>
> RQ2: What level of effectiveness does the employment of BERT models exhibit in categorizing reviews into various topic categories?
>
> RQ3: How do review topic categories differ across various disciplinary domains and course rating groups?

Our contributions included four aspects. First, we developed a BERT-BiLSTM-Attention model for analysing the thematic orientation of online course reviews by exploiting BERTs to represent review textual features, BiLSTM to capture global review context, and attention mechanisms to facilitate feature extraction and improve classification. Second, we empirically validated BERT-BiLSTM-Attention's effectiveness against 10 baselines based on a dataset comprising 364,660 review sentences from 401 courses across 13 disciplines. Furthermore, we highlighted the practical utility of pre-trained language models (PLMs) for big MOOC review textual data analytics to facilitate precise identification of learners' experiences and timely interventions. Finally, we provided domain-specific insights by revealing variations of learner concerns across disciplines and course groups, shedding light on influential factors for learner satisfaction.

Theoretical Perspectives

Following previous MOOC review analysis studies (e.g., Chen et al., 2024; Hew et al., 2020), we used Moore's theory of transactional distance (Moore, 2013) as an initial conceptual framework to promote decision-making concerning MOOC design; however, we did not forcefully impose the three variables (i.e., course structure, learner autonomy, and dialogue) of the theory onto our data corpus.

In Moore's theory, course structure involves features of course design and organization (e.g., information presentation, course content) used to help learners plan, organize, and manage learning activities. Second, learner autonomy involves learners' sense of freedom to engage in learning and a degree of control over learning. Finally, dialogue is explained from three dimensions—learner-content, learner-instructor, and learner-learner interaction—focusing on learning content reflection, interaction with teachers, and peer interaction, respectively.

Literature Review

Online Course Review Classification

To explore factors affecting online learner experiences, systematic analysis has been broadly used to translate review texts into specific categories through coding analysis involving code development and course review analysis conducted by trained coders (Hew, 2016). However, coding analysis of online course reviews relies heavily on manual efforts to train eligible coders and ensure reliability among them. Additionally, coding itself is a time-consuming endeavour; thus, instructors and course designers may have to wait for an extended period to receive feedback on learners' learning experiences. Therefore, a model capable of automatically and swiftly classifying a vast amount of online course review texts into appropriate categories while providing prompt feedback would represent a viable solution.

Automatic classification, wherein machines autonomously categorize data into predefined groups, has been shown to be swifter and more cost-efficient compared to manual classification (Chen et al., 2024). The primary automated review topic classification methods have relied largely on traditional text-mining features (e.g., keyword frequencies) and machine learning algorithms. For instance, Li et al. (2022) employed a top-down approach that drew upon subject matter expertise to establish the ontology of main topics and associated keywords for analysing course review topics, and computed the percentage of reviews mentioning these main topics to obtain a basic overview of learner reviews.

In recent times, scholars have employed deep learning methodologies to manage extensive textual data from MOOCs to automatically analyse the topics discussed in online course reviews. For example, Chen et al. (2024) used deep learning approaches such as CNNs to train classifiers for the automatic classification of course review content; the recurrent convolution neural network classifier exhibited an $F1$-score of 0.780.

The aforementioned approaches have successfully minimized labour costs and enabled automated detection; however, their performance has been affected by challenges such as imbalanced sample sizes and unregistered words, as well as the need for manual extraction of multifaceted and high-dimensional text features. BERT, as a prominent and valuable PLM capable of achieving remarkable performance even with limited and imbalanced datasets compared to traditional machine learning models, has been an effective solution to the above-mentioned challenges encountered by traditional machine learning and deep learning approaches. The training process of BERTs comprises pre-training and fine-tuning, during which BERT acquires comprehensive semantic representations from a substantial volume of text data through self-supervised learning and refines its understanding of domain-specific knowledge through a specialized text classification dataset. Hence, it was worth exploiting BERT's potential for automating the classification of review topics within MOOCs.

BERTs and Their Application in Education

For word embedding models like Word2vec and FastText, regardless of the word's context, the embedding remains unchanged; thus, these methods generate a unified global portrayal for every word, disregarding its surrounding context. Conversely, BERT offers word representations that adapt according to the surrounding context based on contextual embeddings capable of capturing diverse syntactic and semantic characteristics across language contexts.

BERT, as a pre-trained language representation model that amalgamates the strengths of both embeddings from language models (ELMs) and generative pre-trained transformer (GPT), employs a layered transformer structure for training weights in transfer learning like GPT to enhance its ability to handle long-term dependencies. Similar to ELMs, it uses both left-to-right and right-to-left language models to capture more profound semantics and generate potent sequence representations that excel across a multitude of downstream tasks.

In recent years, the use of the BERT model has expanded into the realm of education, promoting significant advancements across various intelligent education applications. For instance, Wulff et al. (2023) applied BERT to categorize segments of preservice physics instructors' reflective texts in accordance with elements outlined in a reflection-supporting model, revealing BERT's superior performance over alternative deep learning models and traditional learning approaches for reflective writing segment classification. Cavalcanti et al. (2023) explored BERT's application in classifying Portuguese feedback texts of teachers and showcased a 35.71% improvement regarding Cohen's kappa compared to Cavalcanti et al. (2020) who used the random forest as a classifier.

In the context of MOOCs, based on a dataset encompassing 2,394 learning objectives, Sebbaq and El Faddouli (2022) employed transfer learning via BERTs to automate MOOCs pedagogical annotation at scale, focusing on the cognitive levels outlined in Bloom's taxonomy. Their findings revealed that opting for a more intricate classifier did not enhance classification performance significantly; instead, using a model built upon BERT layers, in conjunction with dropout and the rectified linear unit activation function, resulted in the highest accuracy.

Despite notable performance in NLP tasks, the exploration of BERT models for classifying course review topics within MOOC learning contexts has remained relatively limited. Hence, this study concentrated on BERTs for enhancing the efficacy of online course review classification.

Research Methodology

Research Design

Based on Chen et al.'s (2024) MOOC dataset, this study used BERT-BiLSTM-Attention to automatically categorize MOOC learners' review topics within their course feedback. The study unfolded through seven steps, as depicted in Figure 1 and outlined below.

Step 1: The original dataset with extensive course review data and course metadata was collected from the Class Central platform.

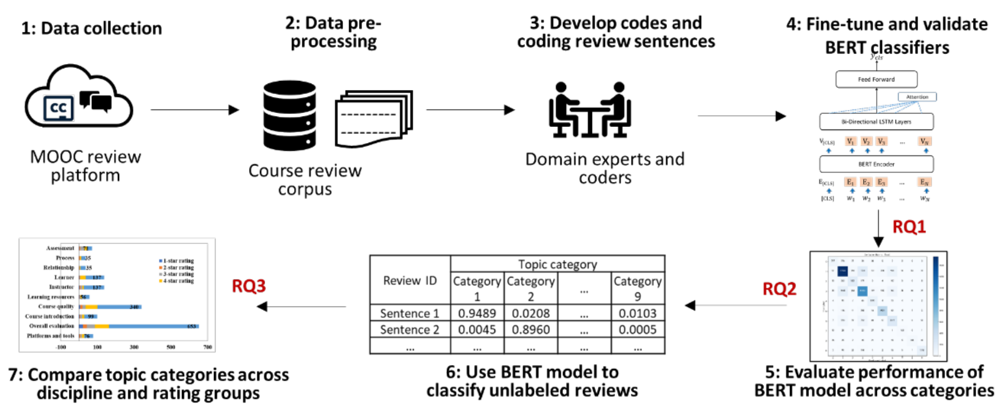
Step 2: For the original dataset, Chen et al. (2024) used NLP tools for data pre-processing and excluding private information to construct the MOOC-Corpus that contained proper nouns and terms pertinent to MOOCs. To mitigate potential bias arisen, we included domain experts to manually review a sample of the dataset to ensure the pre-processing preserved the essential characteristics of the MOOC reviews.

Step 3: Domain experts and coders devised codes and categorized the review sentences in the MOOC-Corpus according to their associated topic categories.

Step 4: This step addressed RQ1. The BERT-BiLSTM-Attention model and the other 10 baseline models underwent pre-training and fine-tuning on the annotated MOOC-Corpus. Their classification performance was evaluated before and after fine-tuning using accuracy, precision, recall, and *F*1-score.

Figure 1

Research Design



Step 5: RQ2 was addressed in this step. The fine-tuned BERT-BiLSTM-Attention model's performance across different topic categories was evaluated using the four metrics. Visualization was achieved through plotting confusion matrices.

Step 6: The fine-tuned BERT-BiLSTM-Attention model from Step 4 was employed to automatically categorize unlabelled course review sentences with topic category labels.

Step 7: This step addressed RQ3. The distribution of review topic categories across discipline domains and course rating groups was analysed and compared in order to reveal differences in learners' engagement with different disciplines and course groups, as well as learners' perceptions regarding learning in MOOCs.

Data Collection and Pre-Processing

As Chen et al. (2024) had already removed learner privacy information, the MOOC-Corpus used in this study did not contain sensitive data that could compromise learner privacy. We further segmented the review texts in the MOOC-Corpus into individual words, rectified spellings, and eliminated stop words using the Natural Language Toolkit. This process yielded 364,660 course review text sentences, sourced from 401 courses spanning 13 disciplines.

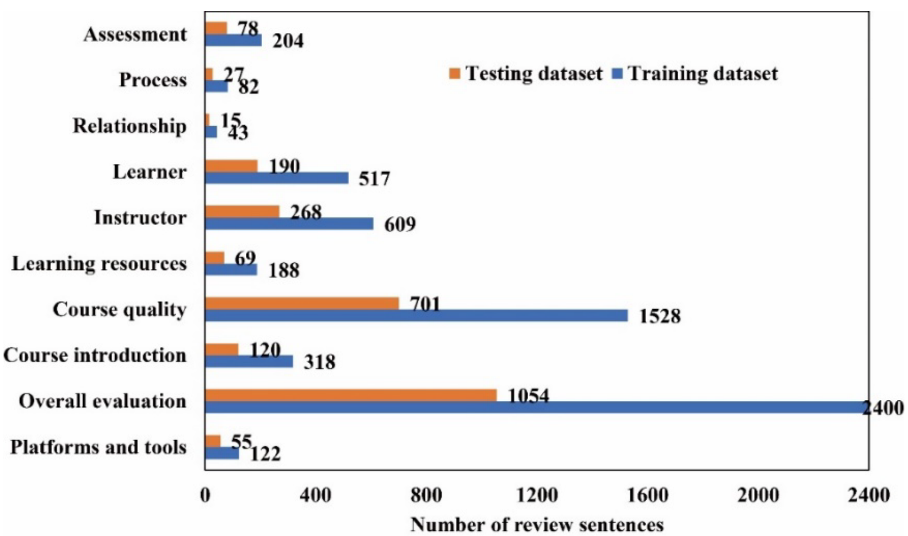
Coding Analysis

To annotate the MOOC-Corpus for training and assessing the model, two proficient domain specialists devised codes for topic categories in MOOC course reviews (see Appendix), drawing insights from synthesized findings in previous literature (e.g., Chen et al., 2024; Hew et al., 2020). Manual categorization of course review topics was performed by the two specialists based on nine topic categories. To enhance coding precision, we analysed individual sentences, considering them to encapsulate a singular meaning.

While multiple codes could be assigned to each review sentence, instances of the same code within a single instance were tallied only once. Initially, a random sample of 1,000 review sentences was selected for independent screening by two coders who had previously been trained to calibrate their understanding and application of the coding scheme to minimize discrepancies and align their assessments. Throughout the screening, regular cross-checks and feedback on the coding scheme were conducted to monitor consistency and allow for timely refinements. The coding outcome yielded a Cohen's kappa value of 0.930. Any discrepancies were thoroughly deliberated until a consensus was reached. In cases where consensus was not reached, a domain expert, as the third coder, was involved to re-evaluate and make the final decision. Finally, each coder individually labelled the remaining course review sentences. The annotated review data corpus results are presented in Figure 2, comprising 9,996 annotated review sentences.

Figure 2

Number of Review Sentences in Testing and Training Datasets

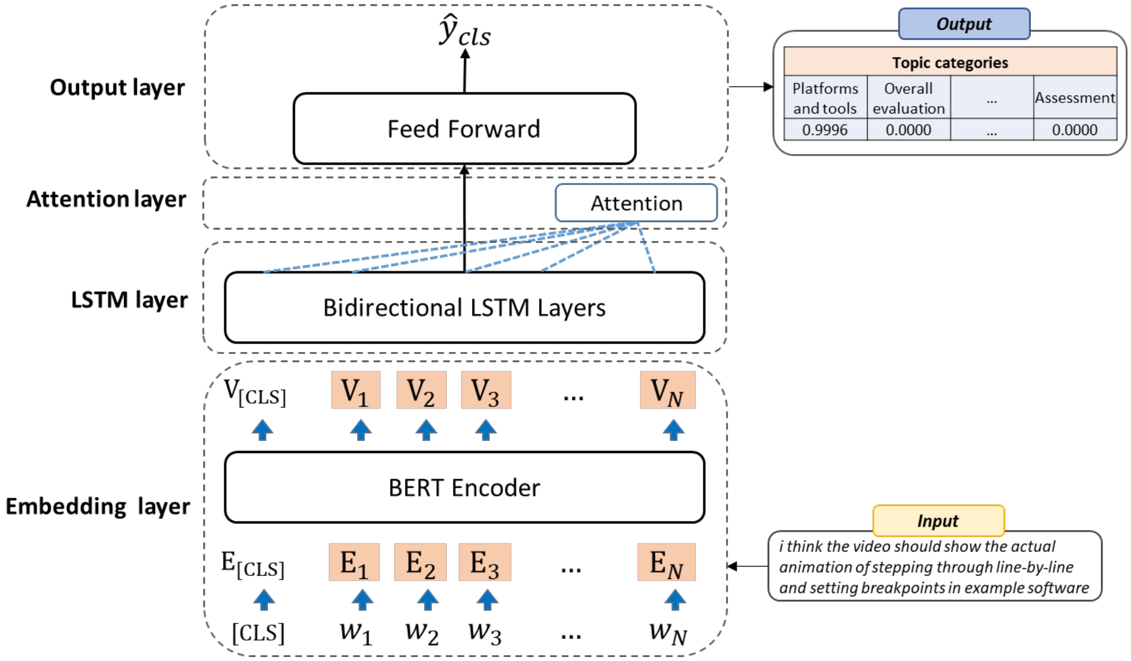


Automatic Classification Based on BERT-BiLSTM-Attention

BERT-BiLSTM-Attention was introduced for categorizing online course reviews into distinct categories based on their semantic meanings. The architecture of BERT-BiLSTM-Attention is shown in Figure 3. The embedding layer transformed the review texts into numerical vector spaces using distributed representations of the embedded words. The second component employed a BiLSTM network to grasp the broader context of the online course reviews. To attain bidirectional semantic dependencies, this study concatenated the hidden states of both the forward and backward LSTMs, allowing for a comprehensive understanding of global contextual semantics by encompassing semantic data from historical and forthcoming contexts.

Figure 3

Architecture of the BERT-BiLSTM-Attention Model



In the attention layer, the attention mechanism calculated word weight and subsequently summed up the hidden states of words in order to capture significant words in the text semantics. Through a Softmax function, the hidden states of the online course reviews in each target and source were standardized between zero and one. The attention weight signified the correlation among the target's and source's hidden states, while the context vector represented the source states' weighted mean. After merging the context vector and the target hidden state, an attention vector was generated, which contained details pertaining to the current focus of attention. The output layer employed a Softmax activation function to compute the probability distributions of categories in order to determine the predicted category with the greatest probability.

Fine-Tuning Strategies, Model Evaluation, and Data Analysis

The BERT-BiLSTM-Attention model was fine-tuned, tailored to a specific task focused on automatically classifying course review topics. According to Liu et al. (2023), employing a proper fine-tuning approach enhanced a BERT-BiLSTM-Attention model's performance in subsequent tasks. A comparison of classification performance was conducted between the BERT-BiLSTM-Attention model and 11 baseline methods. These baselines, commonly used in classification studies (e.g., Chen et al., 2024; Liu et al., 2023) can be categorized into two groups. One set of baselines that used BERT for encoding the review texts (i.e., BERT, BERT-CNN, BERT-CNN-BiLSTM, and BERT-BiLSTM) was selected to assess how combining BERT's contextual embeddings with different neural network structures impacted performance. The other set of baselines that employed Word2Vec for encoding the online course review texts were included to evaluate performance with word embeddings that were less context-aware than BERT. These baseline models included Word2vec-CRNN, Word2vec-TextCNN, Word2vec-BiLSTM, Word2vec-CRNN-Attention, Word2vec-BiLSTM-CNN, and Word2vec-BiLSTM-Attention.

All experiments were carried out using a single NVIDIA RTX3080 (16GB) GPU, which can also be replaced by commonly available multiple lower-tier GPUs such as GTX 1080. Researchers may also seek support from institutions in the field of computer science to access the necessary computational power. For baselines utilizing Word2Vec, we configured the batch size to 256 with a dropout rate of 0.5 to train the model with cross-entropy loss. We employed the Adam optimizer with an initial learning rate ranging from 1e-2 to 1e-5 and retained the model exhibiting the best performance. Specifically, the initial learning rate means the starting value used by the optimization algorithm (i.e., the Adam optimizer in this study) to control the step size during model training. The 1e-2 and 1e-5 represent the range of values for the learning rate, where 1e-2 is scientific notation for 0.01 and 1e-5 for 0.00001. Regarding BERT-based models, we followed Liu et al.'s (2023) process to determine parameters by first using a smaller batch size of eight to efficiently fit the model into GPU memory, and subsequently adopted Adam with a dropout probability of 0.1 to optimize the cross-entropy loss. Finally, we fine-tuned BERTs in five epochs with the learning rates of 3e-5 (i.e., 3×10^{-5}) and 3e-6 (i.e., 3×10^{-6}) and selected the former that demonstrated the highest $F1$-score through experimentation. Across all models, the hidden size was fixed at 256 for the recurrent modules, while the number of kernels was set to 256 for the convolutional modules.

To address RQ1, we assessed the effectiveness of models in categorizing topics within online course reviews. Before comparison, we partitioned the 9,996 annotated review sentences into the training and testing dataset. Specifically, 6,997 instances (70%) were assigned arbitrarily to the training dataset to train classifiers, and 2,999 instances (30%) constituted the testing dataset to gauge the model performance. In our experiments, we used four widely employed metrics: accuracy, precision, recall, and $F1$-score to assess classification performance.

To investigate RQ2, we employed the fine-tuned BERT-BiLSTM-Attention model to categorize 354,664 unlabelled review sentences according to predefined topic categories. Subsequently, we assessed the BERT-BiLSTM-Attention classifier's performance using the four metrics and a confusion matrix to gain insights into its classification capabilities across different topic categories.

To investigate RQ3, we employed descriptive analysis and statistical modelling to examine how various review topic categories were distributed across different discipline domains and course rating groups. These analyses aimed to discern potential variations in learners' review topics based on their academic disciplines and the overall course rating levels. Specifically, the low-star rating group consisted of courses with an overall star rating score of one or two, while the high-star rating group comprised courses with a rating score of four or five. Subsequently, a multivariate analysis of variance (MANOVA) was carried out to evaluate if notable variances existed in the frequency distributions of various topic categories between the low- and high-star rating groups.

Results

Classification Performance of BERT Models (RQ1)

The fine-tuned BERT-BiLSTM-Attention model's performance was compared with 10 baseline methods. The results for these 11 models before fine-tuning are depicted in Table 1, while Table 2 illustrates their performance after fine-tuning. Overall, BERT-based models generally outperformed traditional Word2vec-based classification models in predicting MOOC review categories. Among the models before fine-tuning, those employing Word2vec-CRNN demonstrated the weakest performance across the four metrics. However, after fine-tuning, the Word2vec-CRNN-Attention model exhibited the lowest performance among all models. Focusing on the fine-tuned models, the BERT-BiLSTM-Attention model demonstrated superior predictive capability for categorizing learner-generated course evaluation text, achieving the highest $F1$ value of 0.7626 and recall value of 0.7578 compared to baseline models. Additionally, BERT-BiLSTM achieved the highest accuracy value of 0.8117, while BERT attained the highest precision value of 0.7843, representing slight improvements of 0.43% and 1.70%, respectively, over the BERT-BiLSTM-Attention model.

Table 1

Performance of BERT-BiLSTM-Attention Against Baselines Before Fine-Tuning as Measured by Accuracy, Recall, Precision, and F1-score

Model	Accuracy	Recall	Precision	$F1$-score
Word2vec-CRNN	0.5805	0.5805	0.5116	0.5202
Word2vec-TextCNN	0.6671	0.6671	0.6115	0.6243
Word2vec-BiLSTM	0.7400	0.7400	0.7369	0.7318
Word2vec-CRNN-Attention	0.6306	0.6306	0.5421	0.5745
Word2vec-BiLSTM-CNN	0.7253	0.7253	0.7110	0.7061
Word2vec-BiLSTM-Attention	0.7338	0.7338	0.7478	0.7294
BERT	0.8090	0.7441	0.7757	0.7572
BERT-CNN	0.8089	0.7407	0.7858	0.7589
BERT-CNN-BiLSTM	0.8037	0.7310	0.7671	0.7449
BERT-BiLSTM	0.8062	0.7385	0.7704	0.7488
BERT-BiLSTM-Attention	0.8053	0.7554	0.7681	0.7582

The training process involved multiple epochs to train the classifiers using the training dataset, followed by an assessment using the testing dataset. The training and testing loss, as well as accuracy values for the fine-tuned BERT, fine-tuned BERT-BiLSTM, and fine-tuned BERT-BiLSTM-Attention models, are depicted in Figure 4. All three models with the same Transformer structure showed comparable accuracies on the testing dataset.

Table 2

Performance of BERT-BiLSTM-Attention Against Baselines After Fine-Tuning as Measured by Accuracy, Recall, Precision, and F1-score

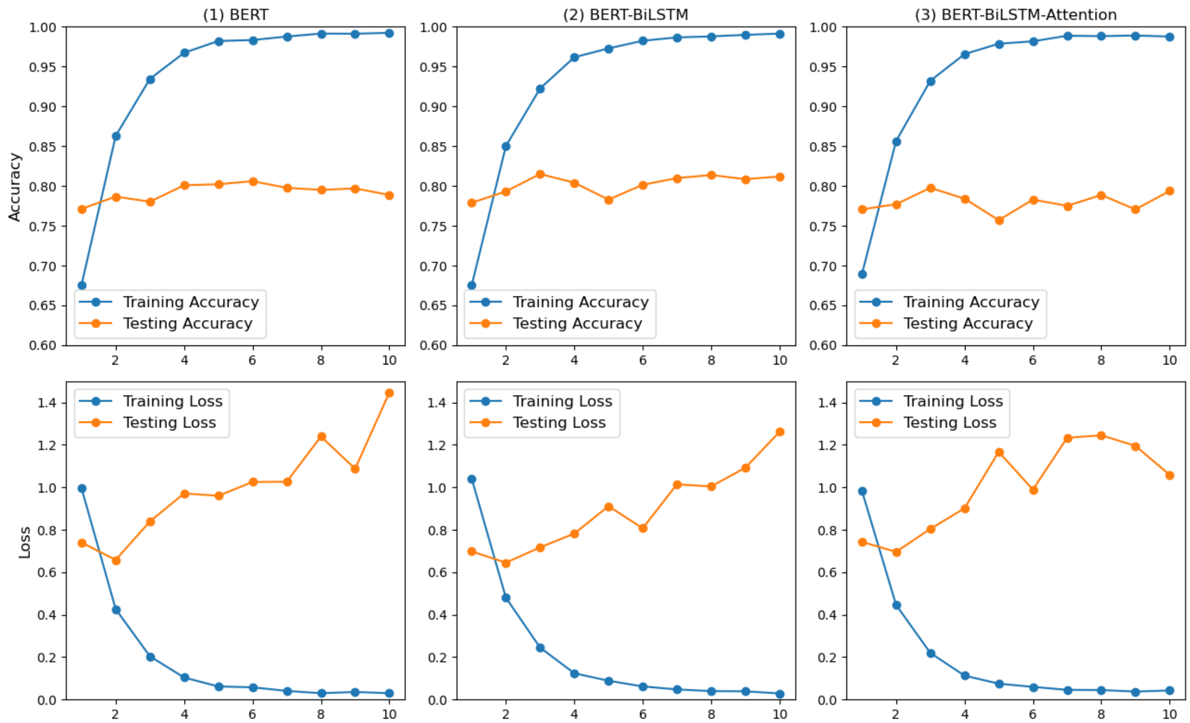
Model	Accuracy	Recall	Precision	*F*1-score
Word2vec-CRNN	0.6088	0.6088	0.6134	0.6099
Word2vec-TextCNN	0.6570	0.6570	0.6523	0.6513
Word2vec-BiLSTM	0.7334	0.7334	0.7306	0.7296
Word2vec-CRNN-Attention	0.5894	0.5894	0.5231	0.5380
Word2vec-BiLSTM-CNN	0.7225	0.7225	0.7336	0.7245
Word2vec-BiLSTM-Attention	0.7354	0.7354	0.7383	0.7335
BERT	0.8105	0.7440	**0.7843**	0.7591
BERT-CNN	0.8105	0.7420	0.7794	0.7535
BERT-CNN-BiLSTM	0.8025	0.7336	0.7593	0.7403
BERT-BiLSTM	**0.8117**	0.7538	0.7642	0.7561
BERT-BiLSTM-Attention	0.8082	**0.7578**	0.7712	**0.7626**

Note. Figures in bold indicate the highest values achieved for each evaluation metric.

By adding the BiLSTM and attention layers over BERT, the BERT-BiLSTM-Attention model yielded better robustness over BERT—the testing loss went up steadily at the early stage of the training, showing that it suffered less from overfitting. It is worth noting that BERT-BiLSTM-Attention achieved the highest *F*1-score but not the highest accuracy score, which may be explained by the fact that the dataset is highly skewed (as shown in Figure 2) with some categories having many more samples than others. *F*1-score measuring the model performance with imbalanced data indicated that BERT-BiLSTM-Attention could better handle the imbalanced data.

Figure 4

Comparing Training Loss, Testing Loss, and Accuracy of BERT, BERT-BiLSTM, and BERT-BiLSTM-Attention Models



Classification Performance Across Topic Categories (RQ2)

Table 3 displays the BERT-BiLSTM-Attention model's performance across the nine review topic categories. Notably, precision values of 0.9264, 0.9005, and 0.8911 were achieved for the assessment, process, and instructor categories, respectively, positioning them as the top three in this metric. Regarding recall, the leading categories were instructor, learning resources, and overall evaluation, with values of 0.9317, 0.9130, and 0.8149, respectively.

Table 3

Performance of the Fine-Tuned BERT-BiLSTM-Attention Model Across Categories as Measured by Precision, Recall, and F1-score

Category	Precision	Recall	*F*1-score
Platforms and tools	0.7669	0.6818	0.7218
Overall evaluation	0.8697	0.8149	0.8414
Course introduction	0.6916	0.7158	0.7035
Course quality	0.7745	0.8093	0.7915
Learning resources	0.6213	0.9130	0.7394

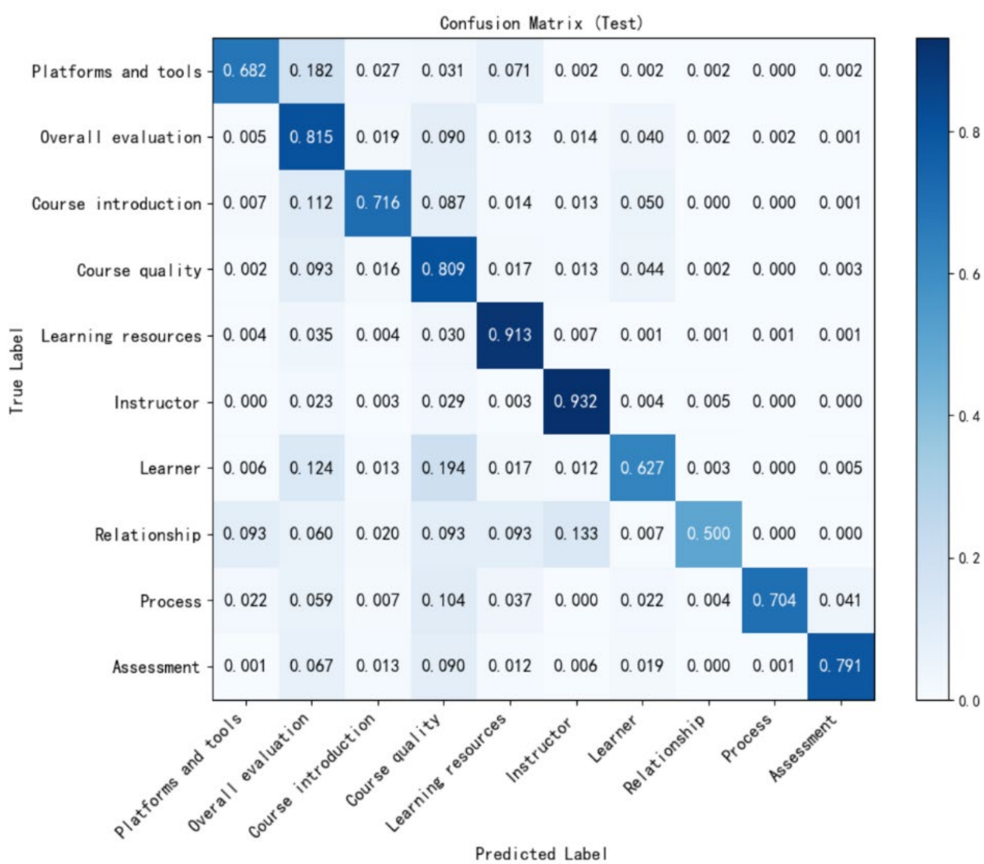
Instructor	0.8911	0.9317	0.9110
Learner	0.5911	0.6268	0.6084
Relationship	0.5769	0.5000	0.5357
Process	0.9005	0.7037	0.7900
Assessment	0.9264	0.7910	0.8534

Regarding *F*1-scores, instructor, assessment, and overall evaluation took the lead with scores of 0.9110, 0.8534, and 0.8414, respectively. Notably, the instructor category exhibited the highest accuracy value of 93.17%. In summary, the BERT-BiLSTM-Attention model demonstrated effectiveness in distinguishing various categories within learner-generated course evaluation text, including instructor, learning resources, overall evaluation, and assessment. Nevertheless, it displayed relatively weaker performance in categories like learner and relationship.

To demonstrate the model's performance across different categories, we created a confusion matrix specific to the BERT-BiLSTM-Attention classifier (see Figure 5). In this matrix, the x-axis donated predicted categories, and the y-axis indicated the actual categories.

Figure 5

Confusion Matrix for the Fine-Tuned BERT-BiLSTM-Attention Model

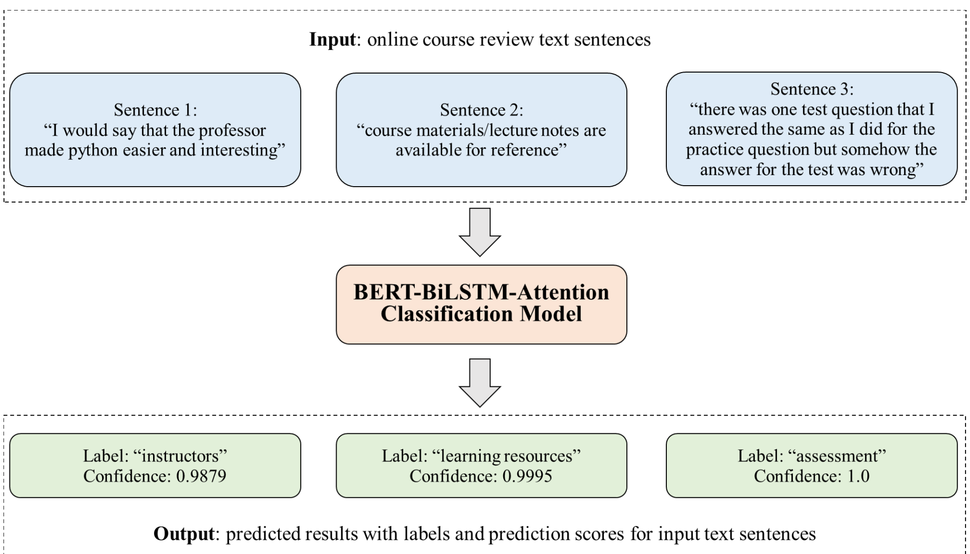


Notably, the instructor category presented the highest level of agreement between coders and classifier (0.932), followed by learning resources (0.913), overall evaluation (0.815), course quality (0.809), and assessment (0.791), all demonstrating a reasonable level of consistency. However, the agreement for categories like relationship, learner, and platforms and tools was lower, with these categories being frequently mispredicted as instructor, course quality, and overall evaluation. Specifically, for the relationship category, 13.3% of the records were incorrectly labelled as instructor. Similarly, 19.4% of the learner records were misclassified as course quality, and 12.4% were erroneously categorized as overall evaluation. Additionally, for the platforms and tools category, 18.2% of the records were mispredicted as overall evaluation.

After completing model training, the fine-tuned BERT-BiLSTM-Attention model was used to categorize 354,664 unlabelled course evaluation texts generated by MOOC learners. Figure 6 illustrates this process by displaying examples of the model's automated classifications. The trained model received three examples of learner-generated course evaluation texts as input to evaluate their semantic content based on prior learning from the training dataset. Subsequently, it generated predictions automatically, providing both the predicted category as well as its confidence level. When analysing the review sentence "I would say that the professor made Python easier and interesting", the model categorized it under the instructor category with the highest confidence value of 0.9879.

Figure 6

Examples of the Automatic Classification of Course Reviews by the Fine-Tuned BERT-BiLSTM-Attention Model

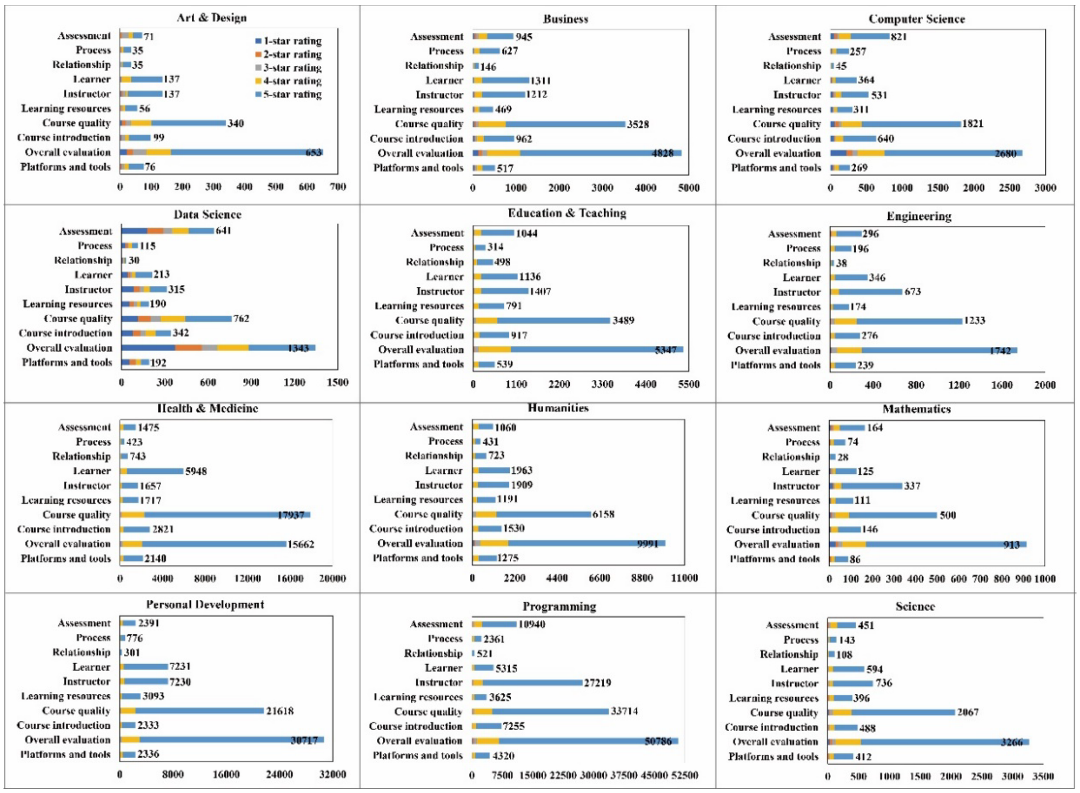


Topic Category Distributions Across Disciplines and Course Rating Groups (RQ3)

Using the fine-tuned BERT-BiLSTM-Attention model, this study automated the categorization of all review sentences provided by MOOC learners. The distribution of each topic category across 12 different discipline domains is presented in Figure 7. In 11 out of the 12 disciplines, excluding health and medicine MOOCs, the most frequently mentioned topic by learners in their reviews was overall evaluation, followed by course quality. In computer science, data science, and programming MOOCs, the category of assessment ranked as the topic mentioned third most often, with instances of 821, 641, and 10,940, respectively. Across all domains, the categories of process and relationship were seldom mentioned.

Figure 7

Number of Course Reviews for Different Topic Categories Across Discipline Domains



It was essential to investigate potential disparities in the occurrence of topic categories among MOOC courses rated as high and low to offer valuable insights into strategies for decreasing MOOC dropout rates. Therefore, a MANOVA analysis was performed to examine if the frequencies of topic categories differed depending on course star ratings. The findings of this analysis are detailed in Table 4.

The Box's M test ($\chi 2$ (55, n = 85718) = 7794.596, $p < 0.01$) revealed a significant result, indicating unequal covariance values across groups. Subsequently, Pillai's Trace statistic was employed, revealing a significant MANOVA effect (Pillai's Trace = 0.023545, F (1, 85718) = 206.66, $p < 0.01$). This suggested statistically significant differences among various course rating groups regarding dependent variables. Following this, univariate tests were conducted, showing significant differences among courses with different star ratings in all categories except relationship (F (1, 85,718) = 0.161, p = 0.688).

Table 4

Result of MANOVA Analysis

Category	High-rating		Low-rating		Univariate test		
	Mean	*SD*	Mean	*SD*	*F*	η^2	Sig.
Platforms and tools	0.113	0.001	0.329	0.023	342***	0.040	0.000
Overall evaluation	1.26	0.004	1.82	0.051	191***	0.020	0.000
Course introduction	0.173	0.001	0.389	0.024	237***	0.030	0.000
Course quality	0.936	0.003	0.754	0.031	39.7***	0.000	0.000
Learning resources	0.117	0.001	0.262	0.02	150***	0.002	0.000
Instructor	0.454	0.002	0.398	0.023	6.62**	0.000	0.01
Learner	0.254	0.002	0.204	0.017	8.03**	0.000	0.005
Relationship	0.032	0.001	0.029	0.005	0.161	0.000	0.688
Process	0.051	0.001	0.175	0.015	261***	0.003	0.000
Assessment	0.177	0.002	0.705	0.034	1,254***	0.014	0.000

Note. ***: $p < 0.001$; **: $p < 0.01$; *: $p < 0.05$.

Comparing mean values between high- and low-rating courses across nine topic categories revealed that high-rating courses exhibited higher frequency scores in course quality, instructor, and learner categories compared to low-rating ones. Low-rating courses showed higher frequency scores in platforms and tools, overall evaluation, course introduction, learning resources, process, and assessment categories compared to high-rating ones. However, the MANOVA analysis results also revealed no significant differences among various course rating groups regarding relationship ($p > 0.05$).

Discussion

Based on a manually annotated dataset comprising 9,996 course review sentences collected from Class Central, this study proposed and assessed the feasibility of classification models for automatically classifying reviews into 10 topic categories identified within the dataset.

Classification Performance of BERT Models (RQ1)

A BERT-BiLSTM-Attention model was proposed and fine-tuned for the automated classification of 10 topic categories. The outcomes revealed that the BERT-based models generally performed better than did traditional Word2vec-based models, consistent with previous studies on MOOC classification (e.g., El-Rashidy et al., 2023; Liu et al., 2023). For example, Liu et al. (2023) reported the outperformance of a MOOC-BERT model compared to machine learning and deep learning models like SVM and TextRNN in identifying learners' cognitive presence from large-scale MOOC discussion data. Similarly, El-Rashidy et al. (2023) reported that a higher accuracy value was achieved by combining BERT and multi-CNNs for MOOC post classification compared to BiGRU and BiLSTM. BERT-based models' superiority could be explained by their deep contextual understanding and ability to be fine-tuned on specific tasks, allowing them to capture the nuances of language effectively and adapt to various applications (Wulff et al., 2023).

In particular, this study highlighted the outperformance of the fine-tuned BERT-BiLSTM-Attention model that combined the strengths of each component, compared to other BERT- and Word2vec-based models in classifying review topics. Specifically, the proposed model exploited BERT's contextual embeddings and generalization ability across diverse texts to capture bidirectional context, while addressing its weakness in dealing with long-range dependencies. We used BiLSTM's sequential processing power to effectively manage sequential data and maintain context longer sentences, coupled with attention mechanism's capacity to prioritize important information. This led to richer and more nuanced feature representation and finally higher classification accuracy and scalability.

Classification Performance Across Topic Categories (RQ2)

The level of agreement between human annotators and the machine varied across different categories. Categories like overall evaluation, course quality, learning resources, and instructor exhibited high consistency (up to 0.80), whereas categories like learner and relationship showed lower levels of agreement (below 0.60). This discrepancy could be attributed to the data distribution, as categories showing better performance had significantly more instances compared to those with poorer performance. When it came to automatic classification, some categories were more straightforward for the fine-tuned BERT-BiLSTM-Attention model to identify and differentiate. For instance, the category instructor was relatively easy to identify due to the presence of distinct keywords (e.g., teacher, tutor), allowing the automatic model to assign reviews accordingly. For the review sentence "The teacher not only knows his materials but has a lot of experience working with first-time programming," the model could easily detect teacher and predict it as instructor accordingly.

Conversely, categories like learner and relationship were less discernible to the fine-tuned BERT-BiLSTM-Attention model and were prone to misclassification. For example, review sentences such as "I had only grabbed a basic feel of programming and patron using Codecademy right before enrolment of this class" and "The discussion groups were helpful and suppurative with the interaction between students and lecturer" belonged to categories learner and relationship, respectively. The model, however, mispredicted them as course quality and instructor. Such reviews often lack explicit keywords, requiring the model to consider multiple sentences or even entire passages in order to grasp their meanings. Additionally, the linguistic features and semantic expressions associated with these categories often overlap, posing challenges even for human annotators. Addressing these issues may require involving linguists to implement advanced linguistic analysis techniques like named entity recognition and part-of-speech tagging to more effectively parse the nuanced expressions and contextual meanings in order to improve model performance. Presently, we have involved domain experts to review and revaluate reviews exhibiting low $F1$-scores to make corrections.

Topic Distributions Across Disciplines and Course Rating Groups (RQ3)

The fine-tuned BERT-BiLSTM-Attention model was used to automatically code unlabelled data. This automatically coded data was then combined with previously coded data to identify the frequency distribution of review topic categories across disciplines. Corroborating with Chen et al. (2024), we found a large number of reviews related to overall evaluation, suggesting that instead of merely commenting on detailed aspects, learners tended to show overall perceptions within their comments. We also identified a high frequency of course quality while there were low frequencies of process and relationship, which could be explained by learners' low expectations and lack of willingness to interact with instructors due to unfamiliarity (Hew et al., 2020).

Variations were identified when topic distributions in different disciplines were compared. For example, learners engaged in technological courses, such as computer science, data science, and programming, exhibited high levels of engagement with assessment-related issues compared to learners in other disciplines, suggesting that these learners perceived evaluation as a critical component in the process of learning complex technical content (Qaddumi et al., 2021). Thus, instructors ought to tailor assessment design and feedback mechanisms to ensure their alignment with learning objectives and to support learners' skill development in technological disciplines (Conrad & Openo, 2018).

The significant differences in the frequencies of topic categories between high- and low-rating courses revealed by MANOVA analysis provided valuable insights into influential factors for learner satisfaction. Specifically, learners in high-rating courses more frequently mentioned issues related to course quality, instructor, and learner compared to those in low-rating courses, highlighting the importance of these factors in shaping learners' perceptions and satisfaction. According to Yousef and Sumner (2021), high-quality course content, effective instruction, and supportive learning communities contributed to positive learning experiences; thus, MOOC instructors and designers should enhance course quality, improve instructor support, and create positive atmospheres to effectively bolster online learning effectiveness and improve learning outcomes and satisfaction.

For low-rating courses, our analysis revealed significantly higher frequencies of platforms and tools, overall evaluation, course introduction, learning resources, process, and assessment than for high-rating courses. According to previous studies (e.g., Alario-Hoyos et al., 2017; Chen et al., 2024; Hew et al., 2020), (a) functional and usable platforms and tools, (b) clear and effective course introductions, (c) the availability and quality of learning resources and problem-solving support, and (d) transparent fair assessment contributed significantly to MOOC learners' overall satisfaction. Thus, MOOC instructors and designers should pay attention to improving platform functionality, instructional clarity, resource accessibility, and assessment fairness to promote learning outcomes and learner satisfaction.

Translating Evaluation Metrics Into Actionable Insights

The fine-tuned BERT-BiLSTM model demonstrated a slightly higher accuracy value of 0.8117 compared to the fine-tuned BERT-BiLSTM-Attention model, suggesting that fine-tuned BERT-BiLSTM had a marginally better ability to classify review topics correctly. Instructors who seek a trustworthy foundation for decision-making, could adopt the fine-tuned BERT-BiLSTM model, as the highest-accuracy model. Looking at the $F1$-score, the fine-tuned BERT-BiLSTM-Attention model outperformed baselines with a highest value of 0.762 in correctly identifying true positives while minimizing both false positives and false negatives. Thus, instructors who wish to capture all pertinent instances of relevant feedback without including irrelevant data would find the fine-tuned BERT-BiLSTM-Attention model, as the highest $F1$-score model, preferable.

Regarding classification across topic categories, the fine-tuned BERT-BiLSTM-Attention model showed high values for categories such as instructor" (0.9110) and assessment (0.8534), meaning that the model was highly effective in capturing nuanced feedback about these aspects, thus providing a reliable foundation for subsequent analysis. According to Chen et al. (2024), a model that classified the semantic content into appropriate categories was crucial for large-scale studies—such as rapidly exploring the relationship between categories and variables like sentiments to quickly reveal areas for improvement. Thus, for instructors who want to improve learner experience through instructor improvement and assessment design, the fine-tuned BERT-BiLSTM-Attention model, proficient in correctly categorizing relevant reviews, would be preferable.

Reflections, Limitations, and Future Work

Although the fine-tuned BERT-BiLSTM-Attention model outperformed baselines in classifying course review topics, implementing it is computationally intensive; future work may consider reducing model complexity and optimizing the training process through pruning and transfer learning. In determining hyperparameters, we referred to prior studies alongside initial experiments to balance performance and computational efficiency; however, improvements in model configuration could be considered in future work by evaluating different hyperparameters' effects on classification performance.

In measuring model performance and analysing topic distributions across disciplines and course rating groups, we used quantitative metrics and statistical approaches as they were capable of processing and analysing large-scale review data efficiently while reducing potential subjective bias. However, future work could incorporate qualitative analysis of sampled data to validate the results or complement with surveys or interviews to collect data on additional variables like course difficulty. This would provide a comprehensive understanding of MOOC learner satisfaction.

Regarding the dataset, the course reviews used in this study might contain learners' varying attitudes towards different topics and aspects; however, our analysis and results were independent of learners' sentiments. This is because our focus on identifying the semantic content within reviews relied mainly on the topic aspect-related terms (e.g., instructor, assessment) rather than words expressing sentiment. Furthermore, due to class imbalance (e.g., overall evaluation made up 35.54% while relationship just 0.90%), there were discrepancies in model performance across topic categories. Future work might augment the data to expand the training data for low-proportion categories to improve classification. Finally, we collected data from Class Central only; future work might include MOOC data from different platforms (e.g., Coursera) to validate our findings.

Conclusion and Implications

This study examined the efficacy of fine-tuned BERTs for classifying the semantic content of MOOC course reviews and investigated review topics' variations across disciplines and course rating groups. Results showed that fine-tuned BERTs generally outperformed Word2vec- and BERT-based models in predicting review categories, with the fine-tuned BERT-BiLSTM-Attention model demonstrating the highest $F1$-score and recall values of 0.7626 and 0.7578, especially for categories such as process, assessment, overall evaluation, and instructor (up to 0.80 accuracy). The distribution analysis highlighted differences in learners' concerns across disciplines; for example, learners in technical fields exhibited high engagement with assessment-related issues. The MANOVA results revealed significant differences in each topic category between courses in the high- and low-rating groups. Comparing the mean scores demonstrated better performance of high-rating courses in terms of course quality and instructor compared to low-rating courses.

The implications of this study were summarized in terms of five aspects. First, instructors can exploit the proposed methodologies that combine automatic classification and statistical modelling to monitor MOOC learners' needs and use data-driven insights for course improvements. Second, instructors should tailor course content and assessment methods to meet learners' needs in different disciplines. For example, for technical courses, robust assessment tools can be developed and updated to ensure fairness and clarity, and provide detailed feedback that addresses learners' queries. Third, given instructor performance's importance in high-rating courses, instructors should be provided with targeted training and resources to enhance learner engagement and achieve MOOC success. Furthermore, researchers should further improve the automatic models by involving education and AI experts familiar with both MOOC instruction and AI technologies to address underperforming categories like relationship and learner. Finally, as learners' needs may change over time, MOOC developers should consider designing tools for real-time analytics that combine automatic classification and statistical modelling with variables like time and learner characteristics. This approach would constantly trace learners' experiences and their perceptions of MOOCs.

Conflict of Interest

The authors declare that they have no conflicts of interest to report regarding the present study.

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Appendix

Coding Scheme for Topic Categories in MOOC Course Reviews

Table A1

Coding Scheme

Category	Description
Course introduction	Course information (e.g., syllabus, overview, schedule/calendar, requirement, certificate, credential, payment, language)
Course quality	Content and information quality, course difficulty, knowledge enhancement, beginner friendliness, practicality, usefulness, helpfulness
Learning resources	Availability of learning materials, textbooks, notes, handouts, slides
Instructor	Instructor knowledge, accessibility, enthusiasm for teaching, humour, presentation, pace of instruction
Learner	Learner background, leaner interest, educational needs (e.g., job or academic needs)
Relationship	Peer interaction, learner-instructor interaction
Assessment	Quizzes, assignments, projects, exercises, tests, experiments, lab activities, grading
Process	Giving and receiving feedback, participating in learning activities, problem-solving, availability of cases and examples during learning
Platforms and tools	Platform use, system quality, and video quality (e.g., captions, transcripts, speed, image, sound)
Others	Learner perception, overall evaluation, appreciation, recommendation

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Impact of Simulation-Based Learning on Learning Loss Among Nursing Students: A Quasi-Experimental Study

Alkadi Alshammari[1,*], Adnan Innab[2,*], Ahmed Nahari[3], Homoud Alanazi[4], Raeed Alanazi[5], and Ghada Almukhaini[6]
*[1]Assistant Professor, Community, Psychiatric and Mental Health Nursing Department, King Saud University; [2]Associate Professor, Nursing Administration and Education Department, Vice Dean of Student Affairs. King Saud University; [3]Assistant Professor, Medical Surgical Department, King Saud University; [4]Director of Nursing, Nursing Administration Department at Dental University Hospital, King Saud University; [5]Assistant Professor, Nursing Administration and Education Department, King Saud University; [6]Simulation Training Supervisor, Medical Surgical Department, College of Nursing; *Joint first authors*

Abstract

Nursing students faced learning losses during the COVID-19 pandemic due to the transition to virtual classes, inadequate communication, and reliance on virtual clinical training as a prerequisite for clinical practice. This study aimed to investigate the extent of learning loss experienced by nursing students and examine the impact of simulation-based learning (SBL) on mitigating this learning loss and on students' confidence, satisfaction, and performance before and after the SBL program. This quasi-experimental study used a within- and between-subjects design. Data were collected from January 2022 to May 2023 from 177 nursing students before and after the SBL program. The Learning Loss scale and Simulation Training Evaluation Questionnaire were used. Substantial learning losses were observed in nurses' knowledge, professional attitude, and skills before the intervention. The intervention group had significantly higher knowledge, professional attitude, and professional skills than the control group. The intervention significantly improved nursing students' confidence, expectations/satisfaction, and performance. The regression model revealed that age and weeks in internship were significant predictors of learning loss. Prior distance education experience did not show any significant association with learning loss. Thus, SBL is useful in crisis situations; it enhances nursing students' knowledge, professional attitudes, and professional skills. Course designers should consider integrating SBL into nursing curricula as an innovative teaching strategy to compensate for possible learning losses. This approach will help prepare graduates to enter the workforce with the ability to quickly adapt and practice confidently in clinical settings to ensure patient safety.

Keywords: learning loss, simulation-based learning, SBL, nursing student, competency, education

Introduction

Nursing education can be negatively affected during emergencies, disasters, and pandemics. During the coronavirus (COVID-19) pandemic, nursing instructors and students encountered challenges in meeting educational objectives (Kim et al., 2021). As universities shifted to virtual learning, clinical practices were disrupted in healthcare institutions (Al Shlowiy, 2021). Such changes led to reduced direct contact with instructors and hindered learning experiences (Ramos-Morcillo et al., 2020). Nurse instructors could not fully meet students' expectations, leading to practical concerns, reduced learning opportunities, and doubts about students' nursing career choices. These circumstances contributed to the deterioration of the learning process, ultimately leading to learning loss.

Learning loss, as a concept, refers to the decline in students' knowledge and skills compared to their expected academic growth trajectories, typically assessed by comparing current educational progress with historical data (Donnelly & Patrinos, 2022; Pier et al., 2021). This concept gains prominence during periods of educational disruption, such as prolonged school closures, when students may experience setbacks in achieving learning outcomes. Learning loss can have long-term consequences (Donnelly & Patrinos, 2022) on nursing graduates' competency and skills. Although several learning-loss prediction models have been developed (Azevedo et al., 2021), the actual impact of COVID-19 on students' learning progress has not been fully investigated. Before the onset of COVID-19, research highlighted the difficulties nursing students encounter due to insufficient skills and knowledge, emphasizing the need for targeted interventions to effectively address these challenges (Al Shlowiy, 2021; Kim et al., 2021; Suliman et al., 2021). The pandemic exacerbated these challenges, adversely affecting both theoretical and clinical learning, thereby intensifying learning loss (Angasu et al., 2021).

In such situations, integrating learning pedagogies such as simulation-based learning (SBL) is crucial (Stanley et al., 2018). The International Nursing Association for Clinical Simulation and Learning defines simulation as an educational method that replicates specific realistic scenarios to mimic real-life situations (INACSL Standards Committee, 2016), allowing students to practice and gain experience (Hung et al., 2021). Recently, SBL has become increasingly popular, offering opportunities for enhancing teaching, bridging the theory-practice gap, enhancing clinical practice and patient safety, and teaching clinical judgment skills (Lobão et al., 2023). Simulations offer a platform for learning and skill development in a safe and controlled environment, effectively improving knowledge, competency, confidence, satisfaction, self-efficacy, and self-esteem among nursing students (Hung et al., 2021; Koukourikos et al., 2021). Although immersive virtual reality (VR) technologies (including desktop, glasses, and head-mounted displays) enable students to experience the clinical environment remotely, even if they are physically elsewhere, mitigating the impact of geographic separation as experienced during the COVID-19 pandemic, these technologies also pose challenges including a lack of or limited access, inadequate training, and technical difficulties (Alshammari & Fayez Alanazi, 2023; Mariscal et al., 2020; Rushton et al., 2020).

It should be noted here the literature has revealed a scarcity of research specifically addressing learning loss post-COVID-19, particularly in countries such as the United States and Canada. Instead, studies have focused on broader impacts such as the shift to virtual learning. For example, research on nursing education in British Columbia found that nursing students perceived no significant decline in the quality of their clinical learning experiences during the pandemic, despite challenges such as technological disruptions

(Sferrazza et al., 2023). Similarly, studies on undergraduate nursing education highlighted various obstacles, including disrupted clinical experiences, potentially affecting students' career readiness (Head et al., 2022). While these studies did not quantify learning loss, they suggest it as a common concern in post-pandemic education.

Therefore, it is imperative to analyze empirical outcomes concerning student expectation/satisfaction, confidence, knowledge, attitude, and skills, particularly in light of potential learning loss exacerbated by the COVID-19 pandemic. Analyzing these outcomes will provide valuable insights into the impact of simulations on students' educational experiences. Furthermore, there is a gap in the existing research regarding the assessment of learning loss and the implications of SBL on nurse competency transfer to the clinical setting, and the assessment of learning loss during crises such as the COVID-19 pandemic, specifically in the context of Saudi Arabia. Thus, the aim of this study was to investigate the extent of learning loss experienced by nursing students and examine the impact of SBL on mitigating this learning loss, and on the levels of students' confidence, expectation/satisfaction, and performance before and after completing the SBL program.

Theoretical Framework

This study was guided by social cognitive theory (SCT), which was developed by Albert Bandura (1986) and posits that learning occurs when there is an interaction between the learner, environment, and behavior. Bandura (1986) also added the construct of self-efficacy to the SCT. This theory focuses on six main aspects: reciprocal determinism, behavioral capability, observational learning, reinforcements, expectations, and self-efficacy.

In this study, the concept of learning loss is explored through the lens of reciprocal determinism, which emphasizes the dynamic interplay between personal factors, environmental influences, and behavior. Simulation-based learning, on the other hand, is linked to behavioral capability, where students demonstrate the knowledge and skills acquired through the intervention. Students' expectations and satisfaction with the simulation align with the theory's constructs of expectations and reinforcements. This is particularly relevant as students recognize that the acquired skills help address the learning loss experienced during the COVID-19 pandemic. Furthermore, in this study, self-confidence is associated with self-efficacy, reflecting students' confidence in performing nursing skills under faculty supervision.

Method

Study Design

This quasi-experimental study utilized a within- and between-subjects design and was conducted from January 2022 to May 2023. A Convenience sampling was employed to recruit the participants.

Study Population and Sample

Nursing students in their fourth year of the bachelor's degree program and those in their fifth year (internship year) were invited to participate. This university is located in Saudi Arabia. Nursing students were informed about the study both in class and on the institution's digital learning platform. The inclusion criteria were being a fourth- or fifth- year student of the Bachelor of Science in Nursing program and being available for the simulation sessions.

G*Power (Version 3.1) (Faul et al., 2007) was used to determine the required sample size. Using a significance level of .05, power of .8, and effect size of .15, a minimum of 92 respondents was deemed necessary to run the regression analysis. The study sample comprised 177 participants, an adequate sample size. The survey was administered before and after the intervention. The intervention group comprised 102 students who participated in simulation-based scenarios, received a debriefing after each scenario, and completed a survey following the intervention. The control group comprised 75 participants.

Data Collection

Ethical approval for the study was granted by [KSU-HE22-390]. Permission to use the instruments was obtained from the authors. This study was conducted in accordance with the Declaration of Helsinki. The study objectives, risks and benefits, and the right to withdraw from the study were included in the recruitment statement. Participants were informed that their data would be used for research purposes and reported in an aggregated form. Written consents were obtained at enrollment.

A recruitment statement was distributed through social media (WhatsApp) and at the nursing college (King Saud University). Prospective participants were provided the contact information of the primary investigator (PI) to facilitate inquiries or further communication. The participants were administered a pretest online questionnaire to assess their baseline data one month prior to the intervention. The PI provided a schedule for weekly sessions, allowing students to select a suitable day. The intervention covered topics including medication preparation and administration, blood transfusions, and urinary catheterization. The posttest questionnaires were collected immediately after the intervention.

Intervention

The intervention design and its components were based on a pre-study survey that was distributed to nursing students and faculty members. The intervention design considered the key clinical competencies identified by nursing students and faculty members as being either "lost" or adversely affected in their learning experience during the COVID-19 pandemic. The intervention was delivered jointly by two nurses, a faculty member with a Doctor of Philosophy degree, and a clinical instructor with a Master of Science in Nursing degree. Table 1 outlines the components and durations of the intervention session, covering three nursing skills pertaining to patient safety: (a) medication preparation and administration, including medication errors, (b) blood transfusions, and (c) urinary catheterization and urinary tract infection. Each component included a review of essential knowledge and skills, simulation-based scenarios using the high-fidelity Laerdal SimMan® 3G Patient Simulator manikin, and debriefing. All were conducted within a single 150-minute session. The control group received the same content presented only as video-based education sessions on YouTube. Details about these three components of the intervention are shown in Table 1.

Table 1

Description and Duration of Intervention Components

Intervention component	Description	Duration, min
Medication preparation and administration	Pre-briefing of essential knowledge and skills needed for medication preparation and administration	30
	Participate in simulation-based scenarios	15
	Receive simulation debriefing	15
Blood transfusions	Pre-briefing of essential knowledge and skills needed for blood transfusions	15
	Participate in simulation-based scenarios	15
	Receive simulation debriefing	15
Urinary catheterization	Pre-briefing of essential knowledge and skills needed for urinary catheterization	15
	Participate in simulation-based scenarios	15
	Receive simulation debriefing	15

Measurements

All questionnaires were in English, including demographic characteristics (age, years of study, grade point average, and previous distance learning experience). Students' confidence, expectations, satisfaction, and performance in applying nursing procedures were measured using a simulation training evaluation questionnaire (STEQ), developed by (Aboushanab et al., 2018) (Aboushanab et al., 2018) This instrument was modified slightly to reflect simulation training in an academic setting. After modifying the questionnaire, three subject-matter experts assessed its face validity. The questionnaire included 15 items and three subscales that were measured on a 5-point Likert scale (from *strongly disagree* to *strongly agree*). Higher scores indicated greater confidence and satisfaction in performing lessons learned in the simulation training. In terms of internal consistency reliability, a Cronbach's alpha of .92 was reported by the original authors (Aboushanab et al., 2018). In this study, the Cronbach's alpha values of the subscales ranged from .83 to .86, while the reliability of the entire scale was .84.

Due to a lack of instruments that measure learning loss among university students, the researchers of this study developed a tool to measure learning loss, comprising three subscales: nursing knowledge, nursing professional skill competencies, and nursing professional attitude. The tool was evaluated by experts in the academic and clinical nursing fields to assess its content validity. Pilot testing was conducted among nursing students to ensure the clarity of the questions. Examples of items in the nursing knowledge subscale included: "I am aware of basic nursing principles and concepts related to patient safety," and "I believe basic nursing procedures were discussed adequately in my nursing program." In the nursing professional skill subscale, examples included: "I believe that my training has enabled me to be an effective team member," and "I believe that my training has made me more competent in performing patient health assessments."

Within the nursing professional attitude subscale, examples encompassed: "I feel I can take appropriate measures to prevent or minimize the risk of potential complications associated with basic nursing procedures," and "I feel optimistic about my future nursing career because I have received adequate education." These examples highlight various dimensions of nursing education and practice evaluated across the three subscales. In this study, the Cronbach's alpha values of the subscales ranged from .84 to .92, while the internal consistency reliability of the entire scale was .89, indicating that this instrument was reliable for measuring learning loss.

Data Analysis

Data analysis was performed using IBM SPSS Statistics for Windows (Version 29.0). The measures of central tendency (i.e., mean) and variability (range and standard deviation) for continuous data and frequencies and percentages for categorical data were calculated. Homogeneity between groups was tested using Levene's test. A paired-sample *t*-test was used to determine whether there was a significant difference between the pre- and post-intervention scores for the overall learning loss scale and its subscales. An independent sample *t*-test was used to determine the differences between the intervention and control groups in knowledge, professional attitude, professional skills, confidence, expectations/satisfaction, and performance with SBL in applying nursing skills. Pearson's product-moment correlation was used to determine the relationship between the learning loss and the STEQ subscales. Multiple linear regression was used to assess the influence of other factors (e.g., individual characteristics) on students' learning loss.

Results

Demographic Characteristics

Table 2 shows the characteristics of the 177 respondents in this study. The intervention and control groups consisted of 102 and 75 participants, respectively. The majority were aged between 20 and 22 years, had prior experience with distance education, and had been exposed to distance education for at least three semesters. More than one-third of participants had not yet started the internship year (41.8%), but the average number of weeks for those who had already started the internship was 4.44 (SD = 3.90).

An independent sample *t*-test was used to determine the differences between the groups according to the number of semesters in distance education and the internship period. In terms of semesters in distance education, there was no significant difference between the control and intervention group. In terms of the number of weeks in the internship, participants in the control group had an average of 3.9 weeks compared to those in the intervention group who had 4.7 weeks in the internship (p > .05).

Table 2

Participants' Demographic Characteristics

Characteristic	*n*	%
Age (years)		
20–22	144	81.4
23–26	33	18.6
Group		
Control	75	42.4
Intervention	102	57.6
Prior experience with distance education		
Yes	150	84.7
No	27	15.3
Semesters in distance education		
1	20	11.3
2	40	22.6
3	48	27.1
> 4	42	23.7
Started the internship		
Yes	67	37.9
No	74	41.8
Missing	36	20.3
Internship period		
< 1 month	42	23.7
> 1 month	21	11.9
Missing	4	2.3

Note. N = 177. For semesters in distance education, M = 3.01, SD = ±1.5. For internship period, M = 4.44, SD = ±3.9.

Nursing students faced some learning loss during the COVID-19 pandemic due to the transition to virtual classes, inadequate communication, and reliance on virtual clinical training as a prerequisite for clinical practice. Therefore, to investigate the learning loss among students, a paired-sample *t*-test was used to determine the differences between the pre- and post-intervention learning loss scores (Table 3). The higher the score, the lower the learning loss among nursing students. The learning loss scores after the intervention were higher than those before the intervention. There was also a significant increase in nursing knowledge (p < .001), nursing professional skills (p < .001), and nursing professional attitudes (p < .001) after the SBL, indicating that the intervention was effective in ameliorating learning loss.

The second aim was to assess the confidence and satisfaction levels of nursing students before and after completing the SBL program. The post-intervention STEQ score for the intervention group was significantly higher than the pre-intervention STEQ score for the same group. Furthermore, confidence, satisfaction with the simulation, and performance were significantly higher post-intervention ($p < .001$), indicating that the simulation training evaluation was effective. See Table 3.

Table 3

Paired Sample t*-Test Results for Learning Loss and Simulation Training Evaluation*

Variable	Pre-intervention	Post-intervention	*t*	95% CI	
	M (*SD*)	*M* (*SD*)		*LL*	*UL*
Learning loss scale	3.51 (0.64)	4.08 (0.60)	8.69	.240	.409
Nursing knowledge	3.58 (0.67)	4.09 (0.62)	7.80	.204	.388
Nursing professional skill	3.50 (0.77)	4.07 (0.66)	8.03	.237	.424
Nursing professional attitude	3.46 (0.69)	4.06 (0.65)	4.77	.250	.442
Simulation training evaluation	3.45 (0.80)	3.92 (0.82)	6.66	.177	.345
Confidence	3.40 (0.85)	3.92 (0.90)	6.12	.190	.393
Expectations/Satisfaction	3.70 (0.80)	4.01 (0.84)	6.69	.095	.258
Performance	3.31 (0.84)	3.86 (0.85)	6.66	.213	.416

Note. $N = 102$. $p < .001$, CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

An independent samples *t*-test was performed on the data with a 95% confidence interval (CI) for the mean difference between the intervention and control groups (see Table 4). The results revealed a statistically significant difference between the mean values of the two unpaired groups. Nursing knowledge in the intervention group ($M = 4.09$, $SD = 0.62$; $t = 3.676$, $p < .001$) was significantly higher than that in the control group ($M = 3.74$, $SD = 0.62$). This indicates that the SBL program helped nursing students improve their knowledge of patient safety and nursing procedures. Moreover, nursing professional skill competencies ($M = 4.07$, $SD = 0.66$) and professional attitudes ($M = 4.066$, $SD = 0.65$) were significantly higher in the intervention group than in the control group ($p < .001$). Students' confidence ($M = 3.93$, $SD = 0.90$), expectations/satisfaction ($M = 4.01$, $SD = 0.84$), and performance ($M = 3.86$, $SD = 0.84$) were significantly higher in the intervention group ($p < .001$) compared to the control group.

Table 4

Comparison of Differences in Learning Loss and Simulation Training Evaluation

Variable	Control		Intervention		*t*	*p*	95% CI	
	M	*SD*	*M*	*SD*			*LL*	*UL*
Learning loss	3.58	0.58	4.08	0.60	5.44	< .001	.670	.313
Nursing knowledge	3.74	0.62	4.09	0.62	3.67	< .001	.539	.162
Nursing professional skills	3.56	0.72	4.07	0.66	4.86	< .001	.714	.302
Nursing professional attitude	3.44	0.70	4.06	0.65	5.98	< .001	.821	.414
STEQ	3.47	0.67	3.94	0.82	4.06	< .001	.698	.241
Confidence	3.34	0.77	3.93	0.90	4.58	< .001	.854	.340
Expectations & satisfaction	3.80	0.68	4.01	0.84	1.837	< .05	.451	.016
Performance subscale	3.27	0.79	3.86	0.84	4.720	< .001	.844	.346

Note. Control group n = 75. Intervention group in the learning loss category n = 102; Intervention group in the STEQ category n = 101. CI = confidence interval; *LL* = lower limit; *UL* = upper limit; STEQ = simulation training evaluation questionnaire.

An independent samples t-test and one-way analysis of variance (ANOVA) were used to determine the association between learning loss and sociodemographic characteristics. The results revealed that neither learning loss ($p > .05$) nor its subscales (nursing knowledge, nursing professional skills, and nursing professional attitudes) were associated with any demographic factors. The results also revealed that the STEQ scores were not associated with sociodemographic factors ($p > .05$), indicating that participants' scores were not affected by covariates.

Pearson's correlation r was used to determine the relationship between the learning loss and simulation training evaluation subscales. Results are shown in Table 5. Nursing knowledge was significantly correlated with nursing professional skills ($r = .658$, $p < .01$), nursing professional attitude ($r = .737$, $p < .01$), confidence ($r = .432$, $p < .01$), satisfaction with the simulation ($r = .371$, $p < .01$), and performance ($r = .461$, $p < .01$). Further, nursing professional skills were significantly correlated with nursing professional attitudes ($r = .799$, $p < .01$), confidence ($r = .442$, $p < .01$), satisfaction with simulations ($r = .31$, $p < .01$), and performance in applying nursing procedures ($r = .503$, $p < .01$). Nursing professional attitudes were significantly correlated with confidence ($r = .482$, $p < .01$), satisfaction ($r = .291$, $p < .01$), and performance ($r = .498$, $p < .01$). In sum, all learning loss subscales were significantly correlated with the STEQ subscales ($p < .01$).

Table 5

Pearson Correlation Matrix for Learning Loss and Simulation Training Evaluation Subscales

Subscale	*n*	1	2	3	4	5	6
1. Nursing knowledge	177	–					
2. Nursing professional skills	177	.658*	–				
3. Nursing professional attitude	177	.737*	.799*	–			
4. Confidence	176	.432*	.442*	.482*	–		
5. Expectations/Satisfaction	176	.371*	.310*	.291*	.761*	–	
6. Performance	176	.461*	.503*	.498*	.845*	.761*	–

**$p \le .01$.

Multiple linear regression was used to examine the relationship between learning loss and demographic characteristics (i.e., weeks in internship, age, number of semesters in distance education). The regression model was significant: $F(3.50) = 4{,}865$, $p = .005$, $R^2 = .226$. Age and weeks in internship were found to be significant predictors of learning loss (Table 6). Number of semesters in distance education did not have any significant impact on learning loss ($\beta = .39$, $p > .05$).

Table 6

Multivariable Linear Regression for Learning Loss

Demographic characteristic	Unstandardized coefficients		Standardized coefficients	*t*	*p*
	B	*SE*	Beta		
Constant	10.543	.960		10.983	< .001
Age[a]	-1.356	.605	-.280	-2.243	.029*
Number of semesters with distance education	.390	.205	.241	1.909	.062
Number of weeks in internship program	.136	.061	.284	2.246	.029*

Note. [a] Age = 20–22 years vs. 23–26 years.

* $p < .05$

Discussion

The findings showed a substantial learning loss, considering the pre-intervention level of knowledge, skills, and attitude. These findings are consistent with previous studies that examined nursing students' perceptions of COVID-19's impact on their education and the challenges they faced during the pandemic (Angasu et al., 2021; Diab & Elgahsh, 2020; Smith et al., 2021). Evidence has shown that COVID-19 adversely affected theoretical and practical experiences among nursing students and prompted a transition to virtual education during the pandemic (Ilankoon et al., 2020; Kim et al., 2021).

The current study showed that the SBL intervention effectively mitigated learning loss and significantly improved student scores in knowledge, attitude, and performance skills. These results are similar to previous studies (Aqel & Ahmad, 2014; Gates et al., 2012; Haukedal et al., 2018). In Iran, a randomized clinical trial examining the impact of SBL on nursing students found substantial increased knowledge and performance in adult life support cardiopulmonary resuscitation, both immediately and 3 months after intervention (Habibli et al., 2020).

The findings of this study showed high levels of expectations/satisfaction and increased confidence and performance among nursing students who had access to SBL. These findings are consistent with those of previous research (Al Khasawneh et al., 2021; Alsalamah et al., 2022; Demirtas et al., 2021; Omer, 2016; Saied, 2017; Zapko et al., 2017). Moreover, Alharbi & Alharbi (2022) conducted a cross-sectional study in Saudi Arabia involving nursing students and found that they reported high levels of satisfaction and confidence after participating in human patient simulation experiences.

In the current study, the intervention group also demonstrated significantly higher nursing professional skill competencies and confidence than the control group. These results were consistent with previous studies (Arrogante et al., 2021; Azizi et al., 2022; Demirtas et al., 2021; Hsu et al., 2014; Mariani et al., 2017; Pol-Castañeda et al., 2022). Previous researchers reported that 85.6% of nursing students successfully acquired nursing competencies to effectively manage the reversible causes of cardiac arrest through clinical simulations (Arrogante et al., 2021). A mixed-method study involving 179 nursing students examined the impact of simulation on the six rights of medication administration, revealing that compliance with the six Rs improved, except for data documentation, which decreased from 54.8% to 45.8%. The students expressed their satisfaction with SBL, stating that it provided a realistic experience of healthcare practice (Pol-Castañeda et al., 2022).

Our study also highlighted the positive impact of SBL on nursing students' expectations. Significant differences were observed pre- and post-intervention, indicating a shift in the students' perceptions of learning through SBL and their anticipation of the learning environment. Our findings are consistent with those of earlier research involving medical students and anesthesia residents (Keskitalo & Ruokamo, 2016). Previous research revealed that actual experiences with SBL surpassed initial expectations, as revealed by significant differences in pre- and post-intervention questionnaire mean scores; students' expectations and experiences were positive.

Our results revealed a significant correlation between components of learning loss and simulation training. Mohsen et al., (2023) reported a significant positive correlation between nurses' total knowledge and practice scores immediately after the educational program and follow-up. However, a study assessing the impact of education programs on defibrillation cardioversion found no significant relationship between knowledge and practice (Ahmed et al., 2019).

Furthermore, we found a positive correlation between nurses' attitudes and their clinical performance. Our findings were consistent with those of other studies (Alias & Ludin, 2021; Nagy et al., 2022). For example, a cross-sectional study revealed a positive and strong association between participants' attitudes and practice (Alias & Ludin, 2021). Our study also revealed a significant positive correlation between nursing knowledge and confidence. Similarly, a descriptive correlational study conducted among 114 nurses revealed a positive relationship with nurses' attitudes (Mattar et al., 2015).

Our findings highlighted age and internship duration as significant predictors of learning loss. This finding is inconsistent with the evidence in the literature, which states that nursing students' competence is shaped by internship experience and age. Increasing age, along with additional training during internships, enhances confidence and self-directed learning readiness (Aboshaiqah et al., 2018; Alkorashy & Abuassi, 2016; Numminen et al., 2013). Similarly, Shinnick et al., 2012 ruled out age as a predictor of knowledge.

Implications, Strengths, and Limitations

This study is novel in that it examined learning loss among nursing students following a pandemic, while also exploring self-confidence, expectations/satisfaction, and students' performance with simulation training post-COVID-19. However, the study limitations include an incomparable sample of the intervention and control groups, absence of randomization, and lack of follow-up knowledge retention assessment. However, quasi-experimental studies offer valuable insights despite such limitations, and future research should consider measuring knowledge retention over an extended period.

The findings confirmed the effectiveness of integrating simulation as an educational strategy as it improved nursing students' confidence, expectations/satisfaction, and performance in the intervention group. These findings provide a basis for developing guidelines for implementing SBL in nursing education. Continuous evaluation and improvement of SBL programs are recommended to maximize the benefits of these pedagogical approaches and enhance the overall learning experience. To equip students for success in the clinical field and to bridge the gap between theory and practice, nursing schools must prioritize essential competencies that foster critical thinking and ensure students' competence as nurses.

Conclusion

This study highlighted the effectiveness of simulation interventions in enhancing various aspects of nursing students' development, including knowledge, professional attitudes, professional nursing skills, confidence, expectations/satisfaction, and performance. Our examination of these aspects has generated novel and significant findings that hold implications for nursing education not only in Saudi Arabia but also in international contexts. The integration of immersive simulation-based activities with traditional learning has proven to be an effective approach to address educational disruptions caused by crises, thereby preparing students for future crisis scenarios. This study has broader implications beyond Saudi Arabia, particularly in light of global uncertainties and crises such as pandemics. The insights gained from this study can guide nursing education practices worldwide.

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Self-, Peer, and Tutor Assessment in Online Microteaching Practice and Doctoral Students' Opinions

Emine Aruğaslan
Distance Education Vocational School, Isparta University of Applied Sciences, Turkey

Abstract

In online microteaching, pre-service teachers (PSTs) deliver lessons through online platforms, thus acquiring valuable experience in effective use of technological tools. In refining these experiences, it is crucial for the PSTs to undergo self-, peer, and tutor assessments. This study examined the concordance among self-, peer, and tutor assessments in online microteaching practices, along with students' views on their online microteaching experiences. A case study model was adopted, involving doctoral students enrolled in the *Planning and Evaluation in Instruction* course. The findings indicated alignment between students' self-assessment and peer assessment, albeit with lower scores compared to those provided by the course tutor. Overall, students expressed positive views regarding online microteaching. They highlighted the benefits of critical thinking, self-reflection, and peer feedback in refining their teaching strategies. However, challenges such as time management, communication, and planning were noted by the students.

Keywords: online microteaching, pre-service teachers, self-assessment, peer assessment, tutor assessment

Introduction

Technological advancements have been driving significant changes in educational processes, with traditional teaching methods evolving and being enhanced by various digital tools and platforms. With the advancement of technology, the concept of new generation education has undergone a transformation, becoming more diverse and dynamic. In this evolutionary process, online education methods in particular have emerged as a significant factor influencing the learning experiences of students. Therefore, it is crucial for institutions responsible for training future teachers to adopt and implement updated, contemporary educational methods (Otsupius, 2014). To enhance their pedagogical skills, effective strategies need to be used for pre-service teachers (PSTs). Herein, microteaching arises as one of the most crucial teaching techniques, adaptable to various stages of professional development. Microteaching is a methodology designed to enhance practical teaching experiences of PSTs (Meutia et al., 2018). Microteaching technique allows PSTs to simulate real classroom scenarios on a small scale, facilitating practical development of teaching skills such as lesson planning, presentation, classroom management, and student interaction (Kilic, 2010; Saban & Çoklar, 2013). Mahmud and Rawshon (2013) argued that microteaching can play an important role in teaching environments and provide opportunities to practice teaching activities under controlled and simulated conditions, while taking into account the complexity of real teaching situations.

In contexts that integrate online teaching techniques, microteaching helps PSTs refine their ability to use technology and effectively integrate digital tools. Online microteaching has emerged as essential for equipping PSTs with skills needed to conduct successful online lessons. This study aimed to analyze doctoral students' experiences and assessments of online microteaching practices, particularly within the scope of their pedagogical training in subject-specific teaching methods.

Microteaching

Microteaching is a comprehensive pedagogical approach that holds a significant position in the realms of teacher education, and professional development (Reddy, 2019). Microteaching is an effective teaching technique that has been used in PST education and other teaching and learning environments since the 1960s (Allen, 1967; Kilic, 2010; Otsupius, 2014). Microteaching enables PSTs to translate their theoretical knowledge into practice, refine their teaching abilities, and reveal various teaching styles by breaking down the teaching process into manageable segments (Allen, 1967; Altan, 2023; Karakaş et al., 2022). Microteaching aids PSTs in developing their skills and building self-confidence by conducting brief lessons for small groups within a controlled setting that simulates real classroom settings. It enables PSTs to closely observe and critically evaluate their own teaching methods by putting these under scrutiny (Kilic, 2010; Otsupius, 2014). Additionally, through microteaching practice, students have opportunities to observe a variety of teaching methods and strategies (Kokkinos, 2022). Consequently, these help PSTs focus more effectively on the processes of identifying and enhancing their strengths and addressing their weaknesses (Karataş & Cengiz, 2016).

Microteaching is a cyclical process of planning, teaching, feedback, replanning, and re-teaching (Reddy, 2019). Planning is a crucial element for effective teaching (Imaniah & Al Manar, 2022). During the planning phase of microteaching, PSTs develop a lesson plan by identifying the subject matter and selecting appropriate teaching strategies. Based on their lesson plan, PSTs conduct a brief teaching session, typically lasting 5 to 10 minutes (Allen, 1967). In this condensed course format, PSTs are observed by their peers and trainers, who then provide feedback on their teaching methods and performance. During microteaching sessions, PSTs' teaching performances are recorded on video, allowing them the opportunity to review and analyze their own performances afterwards (Allen, 1967; Altan, 2023).

The feedback stage, a crucial component of microteaching, encompasses self-assessment, peer assessment, and tutor assessment, each providing valuable insights into the teaching process. Self-assessment typically involves the PSTs reviewing video recording of their lesson and evaluating themselves based on predefined criteria. Peer assessment, on the other hand, entails PSTs assessing each other's teaching performances (Kokkinos, 2022). Since it can be difficult to evaluate one's own abilities, peer feedback becomes crucial in identifying areas for improvement (Otsupius, 2014). These assessments should include constructive criticism and encourage reflective actions to effectively evaluate PSTs' performance (Kusmawan, 2017; Otsupius, 2014; Remesh, 2013). Assessments are instrumental for PSTs to (a) identify both the strengths and areas for improvement in their teaching skills, (b) foster awareness about their pedagogical approaches (Karataş & Cengiz, 2016; Otsupius, 2014; Sarimanah et al., 2021), and (c) plan their teaching strategies more effectively (Imaniah & Al Manar, 2022; Kusmawan, 2017). Moreover, microteaching provides PSTs with the opportunity to collaborate with each other through peer feedback (Sun, 2014). Research on microteaching has indicated that engaging in microteaching practice significantly enhances PSTs' professional development and teaching skills (Arslan, 2021; Evangelou, 2022; Meutia et al., 2018; Reddy, 2019). Therefore, it can be stated that microteaching holds a significant place in PST education.

Online Microteaching

While online microteaching preserves the fundamental characteristics of traditional microteaching practices, it further incorporates the advantages offered by digital technologies. Although microteaching has been implemented in traditional face-to-face educational settings, the recent COVID-19 pandemic led to a more frequent implementation of microteaching in online environments. In online microteaching, PSTs deliver their lessons via online platforms, thereby gaining valuable experience in using technological tools effectively (Altan, 2023).

While online microteaching differs from traditional microteaching, these distinctions have primarily manifested in aspects such as teaching environment, nature of teacher-student interactions, and use of technological tools (Kusmawan, 2017). Whereas traditional microteaching is conducted in a setting where PSTs share the same environment, online microteaching involves conducting lessons remotely, typically using video conferencing tools. For online microteaching to be conducted effectively, it is essential that both PSTs and students have access to necessary technologies and possess skills to use them proficiently (Kusmawan, 2017).

Examination of studies on online microteaching practices have revealed that this technique is crucial for PSTs' professional development (Karakaş et al., 2022; Pham, 2022; Subekti et al, 2023). Online microteaching has been used to enhance the quality of teaching by practicing teachers (Kusmawan, 2017). Research has also demonstrated the effectiveness and feasibility of online microteaching in developing fundamental teaching skills during periods when face-to-face education is impossible, such as the COVID-19 pandemic (Altan, 2023; Kokkinos, 2022; Sarimanah et al., 2021).

Theoretical Framework

Fundamental theory framing this study was based on experiential learning theory (ELT). The concept of experiential learning can be traced back to the ideas of John Dewey in 1938 (Dewey, 1986). This study incorporated ELT as developed by Kolb (1984) who emphasized that experience and reflection play a central role in learning process. ELT describes learning as a process in which knowledge is created through the transformation of experience. Bower (2013) stated that experiential learning effectively closes the gap between theoretical knowledge and practical application, while also enhancing students' ability to communicate with each other. Kolb (1984) considered that this process was cyclical and comprised four stages: concrete experience, reflective observation, abstract conceptualization, and active experimentation. Based on Kolb's theory, Murrell and Claxton (1987) stated that learning had two dimensions: prehending and transforming. The prehending dimension is a span from concrete experience to abstract conceptualization, while transforming extends from reflective observation to active experimentation.

Microteaching is a cyclical process aimed at professional development of teacher candidates (Reddy, 2019). Kolb's (1984) cyclical process is in harmony with microteaching. PSTs gain concrete experience by planning and presenting lessons, and then they evaluate themselves through reflective observations. They develop theoretical models based on the information obtained from these evaluations and test these models in practice by applying them in subsequent courses. This cyclical process supports PSTs in both transforming their theoretical knowledge into practice and achieving continuous development. The stages of ELT strongly align with microteaching, facilitating PSTs in gaining and evaluating concrete experiences, developing theoretical models, and applying them in practice (Msimanga, 2021).

Research Questions

Studies on online microteaching, have not included comprehensive research considering self, peer, and instructor evaluations simultaneously, while also incorporating students' perspectives regarding online microteaching. Consequently, the primary aim of this research was to enable doctoral students engaged in pedagogical formation courses to (a) implement microteaching within an online setting; (b) conduct self-assessments, peer assessments, and tutor assessments thereafter; and (c) analyze the coherence and alignment of these assessments with each other. Based on the outcomes of these practices, this study also aimed to uncover students' perspectives and experiences. This study was framed by the following key research questions.

1. Is there a difference between self-, peer and tutor assessments in online microteaching practices?

2. What are students' views on the experience of online microteaching practice?

Method

Research Model

This study adopted the case study approach, a qualitative research method. The case study method is a significant model for analyzing complex situations within their respective contexts (Khan, 2019).

Context of Research

This study was conducted within the *Planning and Evaluation in Instruction (PEI)* course at the postgraduate level, delivered over 16 weeks through distance education using Adobe Connect. As part of this course, students were required to present a topic using the online microteaching technique and develop a lesson plan for the course they would be teaching. The students were instructed to record their online microteaching sessions for a maximum of 25 to 30 minutes and upload them to the learning management system. Each student developed their lessons within a self-determined timeframe in the system and presented them to their peers using distance education. In these sessions, the lecturing student assumed the role of a teacher (PST), while the listeners (peers) took on the role of students. (Throughout this article, the participants of this study are referred to as students.) Both the PST and the peers were asked to keep their cameras and microphones on during the online microteaching practices. After viewing their peer's lecture, each student completed the peer-assessment form and sent it to the evaluated peer and their tutor. Additionally, each student completed the self-assessment form after reviewing their own lecture and sent this to their tutor. The tutor watched all recorded lessons and completed the rubrics for each student, which were also used by the students for self- and peer assessments. Finally, interviews were conducted to collect student feedback on the online microteaching experience.

Participants

Participants were doctoral students enrolled in the *PEI* course during the spring semester of 2022–2023 academic year (Table 1). A total of eight students took this course, and the study was conducted with this small group. Imaniah and Al Manar (2022) and Remesh (2013) have emphasized the importance of implementing microteaching in small groups.

Table 1

Demographic Characteristics of Participants

Participant ID	Gender	Age	Engineering program
S1	Male	28	Forestry
S2	Female	32	Fisheries
S3	Male	27	Mechatronic
S4	Female	26	Horticultural
S5	Male	31	Electrical electronics
S6	Male	50	Mechatronic
S7	Female	34	Fisheries
S8	Male	42	Mechatronic

Data Collection Tools

The rubric for self-, peer, and tutor assessment used in this study was developed by the researcher through a review of the literature. The rubric was divided into three main sections: introduction to the course, implementation of the course, and completion of the course. In the rubric, both students and the tutor assigned scores ranging from one to five, covering 12 items corresponding to the main objectives and features of the *PEI* course.

After a thorough review of the literature, a semi-structured interview form was developed by the researcher to capture students' perspectives on online microteaching practice. To ensure content validity, the rubric and the semi-structured interview form were reviewed by two field experts and revised accordingly. Once the online microteaching sessions were concluded, the rubrics completed by students were collected via e-mail. The semi-structured interviews were applied online. Ethical approval for the research was secured from the university's Scientific Research and Publication Ethics Committee, in addition to obtaining requisite sanction from the Graduate School of Education.

Data Analysis

Analyses using the Shapiro-Wilk Test were conducted to determine if the data derived from the rubrics in online microteaching practice conformed to the assumption of normality. The analytical results indicated that the data for self-assessment did not follow a normal distribution (Shapiro-Wilk results for self-assessment = 0.803, $df = 8$, $p = .031$), while the data for peer and tutor assessments were found to be normally distributed (Shapiro-Wilk results for peer-assessment measurement = 0.870, $df = 8$, $p = .151$; results for tutor-assessment measurement = 0.969, $df = 8$, $p = .892$).

Due to these findings, non-parametric tests were employed for data analysis. The Friedman Test was used to examine the research question concerning the comparison of self-assessment, peer assessment, and tutor assessment scores, and to investigate whether there were statistically significant differences among them. This non-parametric statistical test was applied to determine whether there were statistically significant differences across two or more related groups. To identify the specific measurements for which differences occurred, pairwise comparisons were conducted using the Wilcoxon Signed-Ranks Test. Upon completion of online microteaching practices, interviews were conducted with students to ascertain their views on the process. The interview data were subjected to content analysis, and themes were established. To assess the study's reliability, the researcher and two field experts independently formulated themes, which were subsequently compared for consistency.

Findings

Findings Related to Self-, Peer, and Tutor Assessments

Students initially conducted self- and peer assessments of online microteaching sessions using the rubric. Subsequently, using the same rubric, the tutor evaluated each student's performance, by reviewing recorded course sessions. Table 2 presents mean scores and standard deviations for each dimension within the rubric and for the aggregate of all items in the rubric, pertaining to self-, peer, and tutor assessments.

Table 2

Descriptive Statistics

Dimension	Self-assessment		Peer assessment		Tutor assessment	
	$\bar{X}$	*SD*	$\bar{X}$	*SD*	$\bar{X}$	*SD*
Introduction	11.25	3.28	11.54	1.74	6.88	3.09
Implementation	17.125	4.49	11.54	3.46	12.5	1.31
Completion	13.5	4.59	13.08	3.66	10.13	2.64
Total	46.5	19.65	46.79	15.44	29.5	6.19

It was observed that the tutor's mean assessment scores across all dimensions and in total were lower than both self-assessment and peer-assessment means. The Friedman Test was used to assess whether the differences in these scores were statistically significant. The results of Friedman Test for all three assessments are presented in Table 3.

Table 3

Friedman Test Results

Assessment	Dimension	*n*	X^2	*df*	*p*
Self	Introduction	8	9.250	2	.010*
Peer	Implementation	8	6.750	2	.034*
Tutor	Completion	8	4.323	2	.115
Total		8	9.250	2	.010*

Note. * $p < 0.05$

Considering the results of the Friedman Test presented in Table 3, it was found that statistically significant differences existed in self-, peer-, and tutor-assessment scores in both the introduction ($X^2 = 9.250$, $p < .05$) and implementation ($X^2 = 6.750$, $p < .05$) dimensions, as well as in the overall general total ($X^2 = 9.250$, $p < .05$). However, no significant difference was observed in completion of the course dimension ($X^2 = 4.323$, $p > .05$). Mean ranks pertaining to these assessments are presented in Table 4.

Table 4

Mean Ranks for Assessments

Dimension	Self-assessment	Peer assessment	Tutor assessment
Introduction	2.50	2.38	1.13
Implementation	2.38	2.38	1.25
Completion	2.44	2.13	1.44
Total	2.50	2.38	1.13

Upon analyzing Table 4, it was noted that mean ranks of self-assessment are highest across all dimensions and in the total, though they were also notably close to mean ranks of peer assessment. Mean ranks of tutor assessment were found lower than those of self- and peer assessments. Wilcoxon Signed-Rank Test was employed to pinpoint the source of differences between the rank means of these assessments. Table 5 presents comparison results between students' self-assessments and peer assessments.

Table 5

Wilcoxon Signed-Rank Test Results: Comparing Self-Assessments and Peer Assessments

Dimension	Rank	*n*	Mean rank	Sum of ranks	*z*	*p*
Introduction	Negative	4	3.50	14.00	-.562	.574
	Positive	4	5.50	22.00		
	Ties	0				
	Total	8				
Implementation	Negative	4	3.63	14.50	-.491	.624
	Positive	4	5.38	21.50		
	Ties	0				
	Total	8				
Completion	Negative	5	4.70	23.50	-.771	.441
	Positive	3	4.17	12.50		
	Ties	0				

	Total	8				
Total	Negative	4	4.38	17.50	-.070	.944
	Positive	4	4.63	18.50		
	Ties	0				
	Total	8				

Note. * p <0.05

Based on Wilcoxon Signed-Rank Test results in Table 5, there was no significant difference between self- and peer assessments. These findings indicated that when evaluating their own performance, students' self-judgment aligned closely with that of their peers. Wilcoxon Signed-Rank Test results comparing students' self-assessment with tutor assessment are presented in Table 6.

Table 6

Wilcoxon Signed-Rank Test Results: Comparing Self-Assessments and Tutor Assessments

Dimension	Rank	*n*	Mean rank	Sum of ranks	*z*	*p*
Introduction	Negative	8	4.50	36.00	-2.533	.011*
	Positive	0	0.00	0.00		
	Ties	0				
	Total	8				
Implementation	Negative	7	4.93	34.50	-2.325	.020*
	Positive	1	1.50	1.50		
	Ties	0				
	Total	8				
Completion	Negative	6	4.17	25.00	-1.866	.062
	Positive	1	3.00	3.00		
	Ties	1				
	Total	8				
Total	Negative	8	4.500	36.00	-2.521	.012*
	Positive	0	0.00	0.00		
	Ties	0				
	Total	8				

Note. * p <0.05

According to the results in Table 6, a significant difference was observed between self-assessment and tutor assessment in the dimensions of introduction (z = -2.533, p < .05) and implementation (z = 2.325, p < .05), as well as in total score (z = -2.521, p < .05). The fact that the difference scores favoured negative ranks indicated that the tutor assessment was significantly lower than the self-assessment.

The comparison results of the Wilcoxon Signed-Rank Test for students' peer and tutor assessment are presented in Table 7.

Table 7

Wilcoxon Signed-Rank Test Results: Comparing Peer and Tutor Assessments

Dimension	Rank	*n*	Mean rank	Sum of ranks	*z*	*p*
Introduction	Negative	7	5.00	35.00	-2.383	.017*
	Positive	1	1.00	1.00		
	Ties	0				

	Total	8				
Implementation	Negative	7	5.00	35.00	-2.383	.017*
	Positive	1	1.00	1.00		
	Ties	0				
	Total	8				
Completion	Negative	6	5.17	31.00	-1.823	.068
	Positive	2	2.50	5.00		
	Ties	0				
	Total	8				
Total	Negative	7	5.00	35.00	-2.380	.017*
	Positive	1	1.00	1.00		
	Ties	0				
	Total	8				

Note. * p <0.05

According to results in Table 7, there was a significant difference between peer assessment and tutor assessment in the introduction (z = -2.383, p < .05) and implementation dimensions (z = -2.383, p < 0.05), as well as in the total score (z = -2.380, p < .05). The fact that the difference scores favoured negative ranks indicated that tutor assessment was significantly lower than peer assessments.

Findings Including Students' Opinions on Online Microteaching Practice

Following the completion of the self-, peer, and tutor assessments, students were interviewed regarding their experiences with online microteaching practice. These interviews were crucial for a thorough and detailed exploration of aspects that could not be captured through the rubric. The frequency and percentage values of the 11 themes emerged as a result of the interviews are given in Table 8.

Table 8

Themes and Frequency

Themes	*f*	%
Self- and peer assessment	14	18.92
Teaching methods and techniques	13	17.57
Teaching experience	9	12.16
Teaching principles	9	12.16
Communication	7	9.46
Time management	5	6.76
Planning	5	6.76
Instructional material	4	5.41
Technology	3	4.05
Field knowledge	3	4.05
Excitement	2	2.70
Total	74	100.00

The influence of self- and peer assessments on students' learning and development of their teaching practice is highly significant. In this context, the self- and peer assessment theme emerged as the topic most often emphasized in the interviews. This theme encompassed both positive and negative perspectives. The views of students who expressed that self- and peer assessment were beneficial and contributed to the improvement of their teaching skills are detailed below.

> When I conducted my own assessment and analyzed my friends' assessments, I realized that there were many points that I needed to take into account. (S4)

> The assessments made by my friends were very helpful. Especially at the end of the lesson, they found that I didn't give information about the next lesson. (S6)

Student views revealed that self- and peer assessments enabled students to evaluate and improve their teaching practices. These assessments provided valuable insights, helping students to identify and address weaknesses in their teaching approaches. Moreover, within the theme of self- and peer assessment, some students expressed concerns that knowing they would be evaluated by their peers negatively impacted their lectures, or they felt disappointed with the scores received. For example:

> In fact, although I should have been in charge of the class, I felt like a student making a presentation, not like a teacher, and the people in front of me felt as if they were only watching me to evaluate me. (S2)

Teaching methods and techniques emerged as the second prominent theme from the interview data analysis, accounting for 17.57% of the responses. Based on the reflections in their self-assessments during online microteaching practice, students recognized shortcomings in their teaching methods and techniques. Additionally, students expressed a preference for traditional face-to-face education over the online method.

> I wish I could apply what you have taught throughout the year, such as the way of addressing students, speaking effectively, actively participating in the lesson, and attracting students' attention, when the opportunity comes. (S1)

> I think communication is the biggest challenge in distance education. I couldn't even determine whether the students understood the subject or not. (S8)

When the assessments made from the students' perspective were analyzed, the results also revealed that they would manage the course process better and be more effective in using teaching methods and techniques if they would do online microteaching practice again.

> If I were to teach the same course again, I would manage time more effectively and engage students in lesson by asking questions or encouraging them to ask their own. (S3)

> If I had the opportunity to present my lesson once more, I would definitely include a practical activity. (S8)

The theme of teaching experience, in which students were acquainted with online microteaching technique, emerged as well (12.16%). This practice not only enabled students to apply the concepts learned in PEI course through microteaching but also provided them with first-hand experience in conducting an online course. Students' statements reflect how this process influenced their concepts and skills in teaching.

> I think microteaching really contributed to my skills in classroom management, student observation, and teaching. After my own classroom management experience, I realised that I should see my shortcomings and look at them from a different perspective. (S2)

> Having taught through distance education, I've realized it's more challenging than it appears and requires distinct methods. (S3)

> The fact that I decided on the content and time of the lesson gave me a good experience in understanding how to plan like an educator. (S5)

Another theme that emerged from students' responses to interview questions was that of teaching principles (12.16%), which included the basic principles for creating an effective learning environment. The sample sentences below exemplify the principles of (a) closeness to life, (b) openness, (c) moving from the known to the unknown, and (d) relevance to the student.

> I would incorporate aspects of daily life more into the lesson to make it more enjoyable and flowing. (S2)

> I feel I fall short in assessing the extent of students' prior knowledge about the topic and in engaging my peers during the lesson. (S3)

The general feedback from students following the online microteaching practice was that it had been highly beneficial in helping them recognize their own shortcomings.

In this study, students expressed challenges within the theme of communication (9.46%). While most students found teaching via distance education methods to be an exciting experience, it also posed challenges in effectively communicating with other students and monitoring the learning process. The following are sample sentences related to this theme.

> It was more difficult than I thought to keep the pulse of the students. (S4)

> Distance education was a more difficult teaching method in terms of establishing control over the classroom and communicating with students. But it was advantageous to have the computer at your disposal and the ability to join the course from any location. (S5)

Microteaching, which is crucial in enhancing the teaching skills of PSTs and in steering their learning processes, can present challenges in terms of time management and content planning. Time management (6.76%) emerged as another theme; the following sample statement was related to this theme.

> I think I didn't manage my time effectively. Although I rehearsed the lesson in advance, I somewhat exceeded the allotted time. (S3)

The importance of planning, whereby PSTs develop strategies for student needs and learning objectives by determining the course process in advance, was also revealed when student opinions were analyzed. Participants emphasized the importance of planning educational activities (6.76%).

> If I were to teach it again, I would prepare with better planning. (S1)

The selection and design of instructional materials used in online microteaching were seen as key factors that influence the effectiveness of the educational process. The following are participant expressions for the theme instructional material (5.41%).

> I made a new and different presentation by learning the Prezi application, I made a difference, but everyone prepared it from ordinary PowerPoint, I think I attracted attention with pictures and animations. (S1)

> In hindsight, supplementing the presentations with videos would have been better for capturing attention. (S5)

The use of technology in online microteaching activities had a significant impact on students' teaching. Difficulties encountered by students in using technology were categorized under the theme technology (4.05%).

> I forgot to record my first lesson, leading us to do a second recording next day. The lesson I recorded was actually my second time teaching it to my friends, so to avoid taking up more of their time, I couldn't elaborate much in the first lesson and missed covering several points I wanted to address. (S4)

Students' proficiency in their subject area was a crucial factor influencing their performance in online microteaching sessions. Insights regarding this aspect were categorized under the theme field knowledge (4.05%).

> This lack of mastery negatively impacted my presentation. (S1)

The expressions of excitement felt by students during their online microteaching experiences and how this affected their teaching process were categorized under the theme excitement (2.70%).

> I was very excited and worried about not being able to convey the subject. (S2)

The interview data shed light on students' experiences with online microteaching and how these experiences influenced their teaching abilities. Microteaching facilitated students' development of awareness in various aspects, including lecturing techniques, content preparation, and the use of technology. Self- and peer-assessment processes allowed students to evaluate and enhance their teaching methods. Although students perceived online education as less effective compared to face-to-face instruction, they acknowledged that experience of online teaching significantly contributed to their professional development.

Discussion and Conclusion

Findings from the self-assessments, peer assessments, and tutor assessments in this study revealed that there was no significant difference between students' self-assessments and peer assessments. However, tutor assessments differed significantly from the student assessments, both self- and peers. Therefore, while it can be concluded that students possess a self-judgment similar to their peers in evaluating their own performance, it appears that the tutor adopts a more critical and distinct perspective. This result aligned with findings from previous research, indicating that tutors tend to assign lower assessment scores compared to students (Papinczak et al., 2007). To mitigate the discrepancies between students' and the tutor's assessments, it is crucial to offer students more comprehensive and detailed training regarding assessment processes and academic expectations. For an effective assessment process, it is essential to educate students about evaluation criteria and enhance their skills in giving feedback.

Research on the impact of employing self- and peer assessment in educational settings has indicated that these types of assessments can enhance students' critical thinking skills, self-regulation strategies, and learning motivation (Duncan & Joyner, 2019). Self- and peer assessments helped students thoroughly analyze their teaching practices, pinpoint their strengths and weaknesses, and receive constructive feedback. On the other hand, some students reported that self- and peer assessments created pressure on their teaching, adversely impacting their performance, or that their expectations were not met regarding the scoring in peer assessments. These perspectives highlighted the delicate nature of assessing students' performance and the influence of individual perceptions on this process. In light of these findings, it can be concluded that incorporating self- and peer assessments in teacher education programs serves as a valuable tool for students to enhance their own abilities (Güneş & Kılıç, 2016), but the potential risks of stress and pressure associated with these processes should not be overlooked.

Online microteaching provided significant learning opportunities regarding the use of teaching methods and techniques, and enabled students to identify areas where their own teaching practices need improvement. While students highlighted the benefits of face-to-face education in fostering student engagement, capturing attention, and employing effective speaking techniques for teaching, they noted the absence of these elements in the online environment. However, some students reported that they adapted well to the online environment. While acknowledging the challenges faced in online microteaching, they also expressed their ability to make necessary adaptations and improvements to overcome these difficulties. Moore et al. (2011) emphasized that effective teaching in an online education context necessitates specific strategies and techniques going beyond those employed in traditional face-to-face education.

Microteaching helped students reinforce core topics of the course curriculum and offered a significant opportunity for them to acquire teaching experience within an online educational environment. Additionally, through the practice of online lecturing, students learned about the role of technology in education, challenges presented by this environment, and various alternative teaching methods. The academic literature has recognized that microteaching practices significantly contributes to professional development of PSTs (Evangelou, 2022; Reddy, 2019). Furthermore, it has been noted that microteaching helps PSTs transform their theoretical knowledge into practical skills, experiment with teaching strategies, and enhance their classroom interaction abilities. Küçükoğlu et al. (2012) observed that students with microteaching experience faced fewer challenges compared to those without experience.

Students' feedback following their online microteaching practice underscored the importance of the teaching principles theme. Fundamental teaching principles, such as (a) relevance to real-life, (b) openness, (c) progression from known to unknown concepts, and (d) student-centeredness are critical to establishing effective learning environments. These principles have been recognized as pedagogical strategies that enhance the effectiveness of a student-centered teaching approach, as well as the efficiency of both students and the overall teaching process (Sünbül, 2011). Pedagogical approaches, such as (a) using content resonating with daily life to heighten students' interest in course materials and enhance flow of the lesson (Dewey, 1986); (b) building upon students' existing knowledge to facilitate learning of new information (Ausubel, 1968); and (c) considering individual student differences to effectively meet each student's learning needs (Tomlinson, 2001) have been extensively covered in educational literature.

Through online microteaching practice, students gained experience in areas such as communication, time management, lesson planning, and the use of teaching materials. A notable issue generally experienced by students in online microteaching was the lack of effective communication, a finding supported by various studies. Karataş and Cengiz (2016) contended that communication issues in online microteaching arose from the absence of a traditional classroom setting, affecting how lessons were delivered to peers. Altan (2023) highlighted that the online environment presented certain limitations, such as inability to use body language, gestures, and eye contact effectively. He also noted that these limitations led to PSTs feeling isolated during online microteaching sessions. Regarding time management, it was observed that students struggled to use time effectively and efficiently in online microteaching practices. Time management is critically important in teaching. Findings of this study suggested that PSTs needed to work on improving their time management abilities during microteaching sessions. While Merc (2015) pointed out the issue of time constraints in microteaching practices, Karataş and Cengiz (2016) noted that these conditions provide a valuable opportunity for students to learn effective use of time. In general, PSTs need opportunities to improve their ability to (a) capture students' attention, (b) pose questions, (c) use and manage time effectively, and (d) conclude lessons efficiently (Kilic, 2010).

Strategic instructional planning focused on desired outcomes is crucial for effective teaching (Burleson & Thoron, 2014). Variations between planned and actual lessons during online microteaching sessions helped PSTs integrate theoretical knowledge and planning skills with real-time teaching experiences. It helped them develop their ability to comprehend the dynamics between planning and implementation, and to adapt educational strategies to real-time scenarios.

Analysis of students' statements indicated that teaching materials used in lectures should be engaging and distinctive. In online education, quality of these teaching materials is critical for the success of distance learning (Yildiz & Isman, 2016). In educational programs, equipping PSTs with skills to design and use instructional materials, as well as providing them with the necessary hardware and software, is considered essential for success in contemporary educational environments.

In this study, more specific themes, such as technology and content knowledge, also emerged. While the integration of technology in online education provides numerous opportunities, it simultaneously presents certain challenges. Such technological challenges represent practical issues that students encounter during microteaching practices, and their ability to overcome these challenges can influence their overall teaching performance. It is crucial for educational programs to more adequately prepare PSTs in the use of technology and to equip them with the necessary skills to be effective in online teaching environments. Altan (2023), noted that online microteaching practices enhanced PSTs' digital teaching skills, bolstered their commitment to teaching even in challenging circumstances, and strengthened their perceptual readiness for teaching in diverse educational settings.

Students' performance in online microteaching was closely tied to their subject knowledge, crucial for effectively presenting material and addressing student questions in depth. The impact of excitement on teaching should be regarded as a significant factor (Bunk et al., 2015). In the teaching process, excitement can serve as both a hindrance and a source of motivation. While it may be obvious that anxiety hampers students' performance, excitement can also drive them to be more meticulous and attentive. Therefore, educational programs should include instruction on managing such emotional responses and developing strategies to cope with them effectively. Additionally, several studies have highlighted that students experience anxiety due to being observed while presenting their lessons

(Donnelly & Fitzmaurice, 2011; Mahmud & Rawshon, 2013). These practice sessions typically represent PSTs' initial teaching experiences, and this anxiety can adversely affect their teaching activities (Karataş & Cengiz, 2016). However, Merc (2015) asserted that microteaching experience was an effective method for reducing PSTs' anxiety. In contrast, Altan (2023) highlighted the physical and emotional comfort experienced by PSTs during online microteaching.

This study, by examining the alignment among students' self-, peer, and tutor assessments, offers insights into the consistencies and discrepancies within assessment processes. Consequently, this study can serve as a significant step towards enhancing students' assessment skills and increasing their reliability. Additionally, this study offers a critical perspective on how students perceive and evaluate their experiences in online microteaching. It can contribute to identifying strategies that could be implemented to improve learning experiences and enhance student satisfaction in online microteaching environments.

The process of re-planning and re-implementation in microteaching is critical in terms of transforming the feedback given to students into practice and developing their teaching skills. Therefore, in future studies, PSTs can be encouraged to review their own performances after their first implementations, re-plan, and implement their lessons again in line with these plans. This study's limitation is its small sample size, comprising only doctoral students from various disciplines in a specific semester at the research institute. This restricts the findings' generalizability to a broader student population or different academic fields. The results of the study will contribute to the field about the applicability of online microteaching application in higher education or vocational training programs and evaluations by self, peers, and tutors.

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Peculiarities of the Development of Students' Musical Skills Under the Influence of Modern Software

Hui Yang
Conservatory of Music, Xinyang College, XinYang, China

Abstract

This study explored the impact of digital technologies on the development of musical skills among music students. A learning experiment was conducted with 66 students between the ages of 18 and 21 from China, France, Italy, and Spain. The study used the methods of a survey and online discussions. Participants verified that the present advancement of digital technologies allows artists to participate in a professional musical environment without formal schooling. Students in the experimental group had a more positive attitude toward learning and its significance for their personal and professional development. Most survey items were rated between 3 and 4 on a 4-point scale, indicating students' overall satisfaction with the training. The results of the online discussion also indicated a high level of support for the use of digital technologies in music education, as well as highlighting the innovative nature of the training course and the advantages of traditional music education. Three quarters of participants supported the use of digital technologies in education. Students in the experimental group were able to acquire more advanced professional musical skills, which facilitated the creation of melodies (including the composition of musical fragments on specified themes, musical arrangements of varying complexity, and the development of principles for processing musical works) compared to students in the control group (focused on the development of musical ear and sense of rhythm), who were initially trained under the traditional system. The study's findings support the effectiveness of an integrated strategy for nurturing musical creativity that involves collaboration between students, teachers, and cutting-edge technology.

Keywords: creative musical talents, digital music creativity, music creation technology, music education, music software

The Impact of Academic Music Education and Relevant Software on the Development of Musical Skills in the Contemporary World

Music is a universal medium that people use in their daily lives for both aesthetic pleasure and functional and social purposes (Valdivia et al., 2021). As a medium for evoking and expressing emotions, enhancing social experience, and establishing and strengthening cultural identity, music is an invaluable contributor to human development. In addition, music facilitates the exchange of personal attitudes, values, and beliefs as a means of self-reflection and activation (Bendel et al., 2022). Therefore, the reproduction of melodies requires a deliberate approach that facilitates the development of various methods of interpretation, ultimately resulting in distinctive sound qualities. The selection of interactive technologies represents a modern approach to the perception of educational materials, which is closely related to the choice of appropriate interactive potential.

The music industry and consumer habits have shifted dramatically over the last two decades. The realization of new technical capabilities has been a major force behind the gradual unfolding of these changes in a multi-stage transformation process (Dolata, 2021). The advent of the digital age has allowed for novel understandings of many aspects of today's professional music industry. It has shaken up the ways music and art are made, and professional performing practices have moved out of concert halls, theatres, and galleries into more diverse, interactive, digital, and democratic settings (Westerlund & Gaunt, 2021). Advanced digital technologies are widely adopted in the music education sector, modernizing the teaching process and the entire worldwide music industry (Wu & Tao, 2022). Digitalization in music education has increased access to high-quality educational options for a broader spectrum of people. Nevertheless, the digital revolution has not diminished the emphasis on individuality and hands-on experience that have always been hallmarks of music education (Pereverzeva et al., 2021).

Music education is a complex, skill-based learning process emphasizing improvisational performance and musical creativity (Liu et al., 2023). Recently, the focus of music education has changed from passing on traditional musical knowledge and experience from teacher to student to focusing on students' overall development and personal growth. Factors such as the development of personal and critical aesthetic taste, the enhancement of creative abilities, the acquisition of transferrable skills, and the empowerment of personal well-being have particular significance in the context of modern music education (Concina, 2023).

The expansion of new information technologies has brought about a revolution in music pedagogy. This has happened due to teachers having access to a setting where they can foster and advance online learning practices through increased connectivity, individualization, and collaboration. To enhance students' musical learning experiences, today's educators use a variety of technologies. A perfect fusion of music theory and practice is made possible by digital technologies, which offer numerous technical benefits and real-world applications (Liu et al., 2021). Modern technologies can enhance communication, effectiveness, and healthy practice in music learning through sophisticated and interactive behavioral analysis and feedback systems (Waddell & Williamon, 2019). Interactivity, integrity, didactic potential, a comfortable learning environment, and creativity are the benefits of using digital technologies for music-instrumental learning (Suvorov et al., 2022).

The music industry serves as an example of the inherent uniqueness and vulnerability of creative expression in light of the vast potential offered by today's multimedia technologies. These technologies, which include electronic musical instruments, specialized software, and sound equipment, are uniform and built to the musical instrument digital interface (MIDI) standard, which unites hardware, software, and hardware solutions to operate on a single digital communication protocol. Combining MIDI encoding and a sequencer is an alternative to digital music composition that can help musicians expand their creative toolkits (Malaschenko et al., 2020). Digital sound analysis and digital music control are the two main ways computer technology is used in music production (Wang & Zhou, 2022). Creative music students can switch from studio gear, including a multitrack recorder and an analog synthesizer, to a stand-alone computer environment that can offer a more accessible and liberating set of compositional tools thanks to computer-based music synthesis and sequencer software (Stevens, 2018). The three key elements of music education—sound analysis, creation, and processing—as well as the subsequent organization of that sound into musical material—are all made possible by digital technologies (Fornari, 2020).

Some authors claim that the global applicability of innovative technologies opens up new and, in fact, unlimited opportunities for self-realization. The use of innovations stimulates the rapid development of intelligence, raising learning to a new level. Additionally, compatibility with traditional music technologies allows for the continuity of musical eras and styles, as well as their interpenetration and synthesis, strengthening interest in musical culture in general (Gorbunova & Hiner, 2018). Gorbunova et al. (2018) addressed problems related to the process of teaching the art of performing on electronic musical instruments, emphasizing that the possibility of innovative training is possible in the presence of highly qualified teaching staff. Therefore, as in other industries, the development of students' knowledge and experience through the use of information technologies in music education should be a key principle of the modern educational system (Maba, 2020).

Creativity is a fundamental process involving imagination, exploration, discovery, experimentation, and curiosity. Digital art involves more than simply mastering new software. Educators use open technology to bridge the gap between art and a variety of other disciplines, including engineering, mathematics, computer science, statistics, physics, and telecommunications. Understanding how computers function is a prerequisite for learning digital art. Open technologies in the arts can therefore be a fantastic phenomenon for interdisciplinary dialogue (Junior & Schiavoni, 2019).

New digital media environments and applications enable students to demonstrate their talents, knowledge, and skills through creativity. Additionally, they can share their compositions via specific applications so that potential viewers can see them and give them a proper evaluation (Suvorov et al., 2022). Students can effectively express themselves through music using digital music technologies without even considering the fundamentals of music. Composing music with digital instruments can facilitate musical creativity and comprehension of musical phenomena and structures (Baek & Taylor, 2020). Visual programming languages appear to break new ground in music production (Bresson, 2022).

Modern music education is closely linked to the use of interactive systems for creating musical compositions. The use of the Lumanote application facilitates the training of piano students and enhances their motivation to create new melodies. This has led to higher performance outcomes for students using the Lumanote application compared to those who followed traditional learning methods. This can be attributed to the ability of interactive systems to overcome learning obstacles and focus on the development of specific musical functions (Zhao et al., 2022).

Augmented reality technologies have a significant impact on the implementation of educational practice, which can be achieved through applications such as Flowkey, Simply Piano, Skoove: Learn to Play Piano, and AR Pianist. Through the use of these applications, beginner students have been able to attain high levels of musical literacy, note reading, and working with musical material (Cui, 2022).

Creative thinking develops under the influence of multidisciplinary learning, allowing for the integration of multiple academic subjects and enabling a focus on various details. The MusiMath application facilitates the combination of music and mathematics, thereby enhancing the understanding of the principles of melody creation. Combined learning has positively influenced the expression of creativity across different academic domains, contributing to the development of creative thinking (Azaryahu et al., 2023).

The purpose of this research was to analyze the advantages of digital music applications (MadTracker, Virtual DJ, MU.Lab, and DarkWave Studio) for the development of musical skills among students. The hypothesis stated that the use of digital instruments contributes to the enhancement of the musical creative process and the development of musical skills. The following objectives were set:

1. Develop an experimental training course titled Music-Making: Innovative Technologies and Innovative Skills, with the goal of teaching music creation skills using computer software such as MadTracker, Virtual DJ, MU.Lab, and DarkWave Studio.

2. Administer a survey at the end of the training to determine students' attitudes towards the learning experience, its value in terms of personal and professional development, and its adequacy for carrying out the desired musical activity;

3. Hold an online discussion with experiment participants to ascertain students' attitudes towards traditional music education in light of modern technological opportunities.

Methods and Materials

Research Design

The performing arts, whether music, sculpture, painting, dance, or drama, can help people fulfill their innate desire for self-actualization. Self-expression through art is a key component of society's intellectual, emotional, and social development. Creativity is the basis of all art. Visual art expresses originality and creativity and combines the artist's innate drive, talent, and skill (Suguna, 2018). Using technological tools in the visual arts can help increase and deepen audiences' emotional connections to music (Oliveira et al., 2024).

Our study, conducted from September 2022 to December 2022, involved 66 students from China, France, Italy, and Spain. It examined students' attitudes towards traditional music education in the context of modern digital opportunities. We recruited participants through an awareness campaign on Facebook, WhatsApp, and WeChat that focused on an audience of music-related groups and sought to enlist people willing to participate in the 3-month training course. The open workshop presentation of the course Music-Making: Innovative Technologies and Innovative Skills drew 221 participants. We set the criteria for the two groups of participants in the experiment.

The control group, Beginner, included 32 students (Table 1). Students in the control group studied for 1 month using the traditional teaching method without the Innovation Program and then for another 2 months using the Innovation Program. They met the following requirements: interested in music art; aware of their musical talent; no musical education or skills; creative and interested in creativity; having basic computer skills and digital literacy; having the technological capability to work with music computer software and applications; being 18–21 years old; and, studying at a higher education institution (HEI). During the research process, these students relied on their knowledge, musical literacy, and instruments (most frequently the piano) to create musical compositions.

The experimental group, Intermediate, included 34 students (Table 2). They met the following requirements: interested in music art; aware of their musical talent; studying at a music education institution; having creativity and interest in creativity; having basic computer skills and digital literacy; having the technological capability to work with music computer software and applications; and being 18–21 years old. During the learning process, the students in the experimental group used digital technologies to facilitate their creation of musical compositions.

The Skillshare educational platform was used to deliver the 3-month educational programme. The moderators encouraged the students in the experimental group to use MadTracker, Virtual DJ, MU.Lab, and DarkWave Studio, four contemporary digital music creation tools, to create their musical pieces. The Innovation Program was the same for both groups. However, the control group received a condensed version of the training: the students did not study in as much detail as the experimental group. The control group was trained without the use of digital technologies, which necessitated a focus on theoretical and practical sessions instead of the incorporation of additional tools or mechanisms.

Table 1

Characteristics of the Beginner Group Participants

Country	*n*	Higher education institution
China	10	Beijing Normal University University (1 person) Beijing University of Posts and Telecommunications (3 people) Beijing University of Technology (2 people) Peking University (1 person) Tsinghua University (2 people) University of Science and Technology Beijing (1 person)
France	4	University of Bordeaux (1 person) University of Toulon (1 person) University of Tours (2 people)
Italy	8	University of Bologna (2 people) Humanitas University (4 people) University of Brescia (2 people)
Spain	10	Universidad Autónoma de Madrid (2 people) Universidad de Navarra (3 people)

		Universitat Politècnica de Catalunya (2 people)
		IE University (2 people)
		Universidad de Alcalá (1 person)
Total	32	

Table 2

Characteristics of the Intermediate Group Participants

Country	*n*	Higher Education Institution
China	12	Central Conservatory of Music (3 people)
		Fujian Normal University (2 people)
		China Conservatory of Music (1 person)
		Guangxi Arts Institute (4 people)
		Shenyang Conservatory of Music (1 person)
		Shanghai Conservatory of Music (1 person)
France	6	IMEP Paris College of Music (2 people)
		Institute for Research and Co-ordination in Acoustics/Music (2 people)
		Bordeaux Conservatory Jacques Thibaud (2 people)
Italy	7	Jul academy (3 people)
		SAE Institute Italy (3 people)
		International Academy of Modern Music Italy (1 person)
Spain	9	European University of Valencia (1 person)
		University of Granada (2 people)
		Complutense University of Madrid (2 people)
		Autonomous University of Barcelona (4 people)
Total	34	

A survey was held at the end of the training to determine students' attitudes towards the learning experience, its value in terms of personal and professional development, and its adequacy for carrying out the desired musical activity. The survey used 4-point Likert scale, with responses ranging from 1 = *completely disagree* to 4 = *completely agree*. The experts who conducted the survey were music teachers and experts in the field of music education. A total of 17 individuals were surveyed, all of whom were involved in teaching musical composition, both with and without the use of digital technologies. These individuals had experience in preparing students for music competitions, which involved applying various approaches to the creation of musical works. The questionnaire was evaluated by analyzing students' responses to questions regarding their attitude towards the learning experience and its value in terms of personal and professional growth, as well as its relevance to their desired musical activity. As the experts were professional educators, they were capable of evaluating the accuracy of the responses provided. However, this required students to give detailed answers to all questions, which would allow for the determination of their level of interest in learning and the assessment of their understanding of the mechanisms involved in creating musical compositions. During the evaluation, an analysis was conducted to distinguish between positive and negative responses. The responses to the questionnaire were analyzed using IBM SPSS Statistics (Version 25). The highest score, *very good*, was assigned a value of 1 (5/5 = 1), and *good* was given a value of 0.8 (4/5 = 0.8), with other scores assigned accordingly. Google Forms was used to administer the questionnaire. The use of Google Forms enabled immediate access to responses for all educators, thereby facilitating timely evaluation. The questionnaire had 10 questions:

1. Did the potential of the tested technologies help you implement your musical ideas?
2. Were you able to use the tested techniques to turn creative ideas into finished musical compositions?
3. Was your experience with technological music-making/using traditional approaches solutions simple, intuitive, and comfortable?
4. Did you require additional guidance from instructors in the process of creating musical technologies?
5. Did you require additional guidance from music instructors during the creative work phase?
6. Which of the tested music technologies'/traditional approaches benefits most impressed you during your music learning process?
7. Did you have the necessary skills to use music software/work with traditional learning mechanisms, given your knowledge of music composition and sound design?
8. Did you feel that you lacked basic musical knowledge and skills while creating music?
9. Do you believe that you need additional musical training to implement your creative ideas?
10. In your opinion, has participation in the training program affected your creative ability?

After the survey, we held a videoconference discussion with the students which we titled, Facilitating Academic Music Education for the Creative Self-Realisation of a Musician, and in which each participant had the opportunity to voice their opinion on whether taking part in formal educational programs is a good idea in order to realize their potential as talented musicians. The criteria for evaluating the effectiveness of the program were the following: overall satisfaction with the learning process; expectations for achieving musical goals and developing skills; and impressions of using digital technology/the traditional teaching approach in music training.

Students underwent a final examination over the course of one week. During the exam, students were required to create musical fragments and complete compositions based on specified criteria, while also considering their capabilities. To compose their works, students from both groups used interactive technologies that were employed by the experimental group during their training. This approach allowed for the assessment of the skills acquired by the students throughout the learning process. The skills initially selected were defined at the beginning of the study to enable melody creation. These skills were empirically derived through observation of senior students and the level of their performance on assignments related to musical composition. The skills acquired by the students were assessed by educators who participated in the earlier phase of the research. Accurate results were achieved through the application of a student's *t*-test (Barabash et al., 2021).

Limitation

The study's primary limitation was its small sample size and geographic scope (66 respondents from four countries). Additionally, we chose participants based on criteria. One reason was that the chosen age range (18–21 years old) made it difficult to understand how the target audience felt about digital music production. Finally, the number of digital tools included in the training course was another limitation, despite the Internet's vast supply of such tools.

Ethical Issues

The experiment was free to participants, and open-source developers provided the digital tools they used. We explained the study's purpose and objectives to the participants. They gave informed consent to participate in the experiment, which allowed us to ensure we were respecting the Declaration of Helsinki research protocols.

Results and Discussion

A survey was held at the end of the training to determine the students' attitudes towards the learning experience, its value in terms of personal and professional development, and its adequacy for carrying out the desired musical activity. The hypothesis suggests that the use of digital instruments contributes to the improvement of the musical creative process and the development of musical skills. The results showed (Table 3) that students in the experimental group had a more positive attitude toward learning and its significance for their personal and professional development.

Table 3

Students' Positive Attitudes Toward the Experimental Training, by Group

Group	*n*	*M*
Beginner	32	3.5
Intermediate	34	3.8

Note. The mean value is the average of the following scores: 1 = *completely disagree*, 2 = *slightly disagree*, 3 = *agree*, and 4 = *completely agree*.

Student participants conveyed mainly a positive attitude to the learning experience. Most responses had values ranging from 3 to 4 on a 4-point scale, indicating students' overall satisfaction with the training. The students believed that digital technologies allowed them to implement their musical ideas, create musical compositions, and develop the skills necessary to work with music software. Nevertheless, some students lacked the skills and level of music education to fully implement their creative ideas. Students in the beginner group also noted improvements in learning, which is connected with a more detailed elaboration of musical skills as a result of using the mechanisms of traditional training. However, they noted that the process of creating compositions using digital applications is more effective, as traditional learning mechanisms require a thorough development of each musical approach. Nevertheless, these improvements were less noticeable, which may have been due to the duration of the experimental intervention.

After the questionnaires were completed, we engaged the students in a video discussion on the topic Features of Talented Musicians' Development in the New Digital Age: The Mediating Function. Each participant was free to express their thoughts on the best methods and strategies for developing their musical talent. We summarised the participants' points of view and reached conclusions at the end of the video conference. The online discussion also confirmed the high level of support for the use of digital technologies in music education and highlighted the innovation of the training course and the advantages of traditional music education. The study yielded comprehensive results among students in both groups. See Table 4.

Table 4

Participants' Views on Traditional Music Education, Digital Technology, and the Experimental Course

Topic	*n*	Level of support (%)
Advantages of traditional music education	48	65
The use of digital technology in education	52	75
Innovation of the training course	58	80

Note. The level of support is the percentage of participants who agreed with a given statement about the topics listed in the table.

Participants confirmed that the current advancement of digital technology enables musicians to participate in a professional musical environment without formal education. Musical social networks and communities enable even newcomers to showcase their talents to a large audience. However, participants generally concluded that cultivating musical talent is a long process that requires both the student's effort and the skillful guidance of knowledgeable teachers. Intermediate group participants shared eight arguments in favour of traditional music education with a teacher:

1. The teacher provides the student with effective and proven practices and person-centered learning strategies.

2. The teacher maintains the student's intense motivation to learn. The basic motivators are students' personal and creative growth, success in lesson planning, and performance opportunities.

3. The teacher encourages students to become more culturally aware, broaden their horizons, and cultivate their musical imagination.

4. The teacher sets precise learning goals, emphasizes technological learning points, and offers timely feedback and encouragement.

5. The teacher fosters a student's dedication to the art of music and encourages long-term efforts by students to study music.

6. The teacher gives detailed instructions and feedback. The most effective method of teaching music is verbal because it incorporates teacher feedback.

7. The teacher-to-student dialogue facilitates the most effective methods of music education: transfer, collaboration, and induction.

8. The teacher encourages the student's musical abilities to advance.

The Beginner group participants confirmed that the learning experience they gained during the Music-Making: Innovative Technologies and Innovative Skills course significantly impacted their aspirations. It was also determined that their lack of musical skills, knowledge, and abilities limited their ability to put their creative ideas into action. Participants in the Beginner group agreed that digital music creation tools are excellent tools for novice musicians who want to experiment with music creation but lack the opportunity or desire to participate in formal training.

The Intermediate group participants discussed the appropriateness of using digital instruments in formal educational settings. They agreed that combining musical knowledge, skills, and abilities with the capabilities of digital instruments raises musical performance quality to a new level and opens a new future in musical art. The students concluded that modern professional musicians need to develop musical and digital literacy skills. Music educators should consider this as they modernize their curricula to reflect the trends of contemporary digital reality.

In the final stage of the research, an assessment of the acquired musical skills was conducted among students in both the control and experimental groups. Emphasis was placed on skills that facilitate the creation of musical compositions. Results are shown in Table 5.

Table 5

Musical Skills Acquired by Students During Training

Skill	Beginner group			Intermediate group			*t*	*p*
	%	*M*	*SD*	%	*M*	*SD*		
Development of musical ear	30	0.511	0.129	18	0.472	0.118	-1.993	.02
Development of sense of rhythm	23	0.471	0.124	17	0.468	0.116	-1.984	.03
Ability to create musical fragments based on a given theme	5	0.427	0.059	24	0.542	0.137	1.975	.05
Creation of musical arrangements	7	0.432	0.061	21	0.505	0.129	1.953	.04

Development of principles for processing musical works	17	0.454	0.103	20	0.493	0.126	1.938	.04
Skills not developed	18	0.463	0.115					

Based on the results, it was established that the students in the Beginner control group were able to develop basic skills in melody creation. However, these skills were insufficient for executing complex approaches in musical composition. To create musical compositions, control group students required additional analysis of similar compositions to facilitate the creation of their own works. During the creation of musical arrangements, control group students lacked the skills to eliminate extraneous noise, even when using digital technologies.

In contrast, the experimental group demonstrated more advanced results due to their use of interactive mechanisms during training, which led to a more nuanced perception of musical parameters. Enhanced musical ear contributed to a fuller perception of melodies, including the ability to recognize musical intervals and melodic embellishments. The development of a sense of rhythm allowed students to create musical compositions that effectively used strong and weak beats, thereby enhancing the expressiveness of the sound. This ability facilitated the creation of musical fragments and high-quality arrangements without additional preparation, resulting in improved sound quality, with a more balanced tone and reduced extraneous noise.

After analyzing recent scholarly publications, we informed the attendees of the following arguments in support of traditional teacher-led education:

1. According to Chinese researchers, teaching music not only serves as a means of imparting artistic knowledge but also helps students regulate their emotions, which positively affects their psychological health and academic and psychological performance (Sun, 2022).

2. According to Finnish researchers, music instruction enhances general cognitive abilities required for learning activities and positively affects students' nervous systems, auditory system reactivity, and neurocognitive development (Tervaniemi et al., 2018).

3. According to Colombian academics, learning music and an instrument improves a student's rhythmic accuracy, which influences their physical and motor development by enhancing their balance, laterality, and motor skills (Guzmán, 2021).

4. Malaysian scholars maintain that the abilities developed in the study of music can be applied to other fields, both social and cognitive. The learning theory can explain the ability of music education to positively influence students' academic performance. An education in music typically covers a wide range of topics and activities, such as how to play an instrument, sing in a choir, compose music, and read musical notes. These activities foster knowledge, skills, and attitudes that are transferable to other academic domains. The student creates a unique mental model of learning that can be applied to other subjects, such as science, mathematics, and languages by gaining knowledge and skills through independent study and group music practice (Haddad & Heong, 2020).

The recommendations of American, English, and Bolivian scholars to enhance the quality of music education are consistent with students' opinions on the significance of the technological modernization of curricula in music education institutions. Music education focuses on the interaction of people, music, and social contexts. The individual should be the primary focus of educational innovations because everyone has a distinct socio-musical ability resulting from their most intimate aesthetic experiences (Angel-Alvarado, 2020). For students to develop and maintain their musical identities, music education must be accessible and offer opportunities, skills, and support (Pitts, 2017). Modern music education necessitates the use of innovative teaching strategies that make students active participants in the teaching and learning process (Mamani Mamani & Quispe Chambi, 2021).

The participants concluded that musical talents should be developed in an environment that allows students to communicate and interact creatively. The open-source nature of some technology programmes, in the opinion of the Spanish researchers, improves collaborative musical practice by expanding the possibilities for people to produce musical works together. Encouraging collaborative music-making with participants outside the group/class allows the educator to design innovative learning tasks that engage students in more diligent learning (Cuervo et al., 2022). Costa Rican researchers believe that participating in collective musical activities makes a person feel safe, secure, important, needed, and accepted as a group member. Beyond its therapeutic purposes, music has the power to evoke a carefree and joyful mood solely to promote individual and social well-being (Lorenzo de Reizabal, 2022). According to Spanish academics, one benefit of using music technology in educational settings is that it encourages collaborative music-making even with individuals not in the group or class. This enables the development of novel tasks based on singing, choreography, staging, and musical interpretation (Cuervo et al., 2022).

Overall, the participants agreed that an integrated approach to developing creative musical talents is required, one that recognizes the interaction of the student, the teacher, and modern technology.

The way musicians now develop their musical practice has been revolutionized by music software. A study involving music students at the Universidad Nacional del Altiplano Puno found that using digital technology significantly impacted the teaching and learning process. Composing, arranging, and orchestrating music have all progressed as a result. Music computer software makes it easier to create audiovisual compositions. Most importantly, it allows for quick and easy management of notation and symbols (Valdivia et al., 2021). Peruvian researchers believe using artificial intelligence technologies to create music can accelerate the creative process. Systems with artificial intelligence are now among the technologies that are affordable to the general public. These platforms do not require prior technical expertise (such as programming knowledge) or formal musical training. Thus, to engage in creative activities, a user only needs a working knowledge of computers and some basic musical skills (Valdivia, 2022). Canadian researchers say digital technology in music education can help students unlock their creative potential. They contend that digital technology eliminates barriers that arise from a lack of musical knowledge or practices and impedes creativity. Consequently, students who cannot read or write music notation or play instruments can still create music using digital audio stations. Robichaud (2023) suggested using a digital-based explanatory model to understand better the creative process in music when using digital tools.

The ability to implement individual creative practice is the primary benefit of using digital technologies in music education (Mota, 2019). Making music is a creative act that relies on the creator's own ideas. Multimedia and processing technologies within computer technology are only used as aids to music creation, speeding up and streamlining the creative process. Using computer technology in music production can enhance a musical work's quality and give its creators new creative opportunities (Wang & Zhou, 2022).

Conclusion

This study confirmed the hypothesis about the positive impact of digital technology on the development of the musical creative process and musical skills of students. Participants in the experimental group showed a more positive attitude toward learning and its significance for personal and professional development because interactive technologies were used in training. Students in the control group exhibited lower levels of engagement in learning, as traditional approaches contributed to a more complex learning process. The research results indicated that the use of different instructional approaches affected the acquisition of varying levels of musical skills, which in turn influenced the professional creation of musical compositions.

The practical and scientific significance of the study lies in its ability to expand the understanding of digital technology and its impact on the process of musical learning and creativity. The information obtained from investigating traditional and innovative teaching methods can be useful for music teachers and educational institutions seeking to optimize their curricula and provide students with maximum opportunities to develop their musical potential. Thus, the results of this study can help modernize educational programs in music institutions and design new methods and tools for teaching music using digital technologies. In addition, they can serve as a basis for creating additional teaching materials and resources for self-study. Further research may focus on the impact of various types of digital technologies on specific musical skills, as well as on optimal strategies for using these technologies to enhance music learning and creativity. In addition, it is necessary to assess the effect of digital technologies on musical creativity in different age groups and cultural contexts.

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Implementation of an On-the-Job Training Method in a Distance Education Environment[i]

Şener Balat[1] and Selçuk Karaman[2]
[1]Bingöl University/Bingöl Vocational School of Technical Sciences, Bingöl, Türkiye; [2]Faculty of Economics and Administrative Sciences, Ankara Hacı Bayram Veli University, Ankara, Türkiye

Abstract

The aim of this study was to implement on-the-job training (OJT) in a distance learning environment. To achieve this, job analyses were conducted on spring semester beekeeping activities at a vocational school in the eastern Anatolia region of Türkiye, and content and activities were designed with an OJT environment prepared. Participants received a task video and checklist to be completed weekly during the relevant week of the season. They were required to record and send videos while performing tasks, with feedback provided, and they were encouraged to participate in expert/peer communication activities. Initially, participants completed tasks correctly at an 80% rate, which increased to 85% after feedback. Task completion levels were examined, showing higher levels for short, simple, and less risky tasks. The application showed a positive effect on academic achievement in favor of the final test.

Keywords: on-the-job training, distance education, skills teaching, distance vocational education, Türkiye

Introduction

Technological advancements have had a significant impact on job sectors and working conditions due to fast-paced changes. The changes occurring in various sectors necessitate the adoption of innovative technologies and the continuous self-improvement of employees using these technologies to maintain competitiveness. In recent years, global events have made use of technology in the workplace almost a necessity for developing the workforce, particularly in business life. The COVID-19 pandemic can be seen as one of the most prominent examples of the situation we are referring to, as it led to restrictions on face-to-face education and the worldwide inability to deliver certain types of teaching. This situation has affected the teaching of applied and skill-based behaviors to a significant extent and prompted teachers, instructors, and trainers in many fields to seek solutions regarding how to teach such learning tasks through distance education.

Many job fields provide education for their employees through on-the-job training (OJT) in face-to-face settings. This method can be conducted on a one-to-one basis or in small groups using the show-and-do technique, which is inherently suitable for teaching skills and practical job training. This study focuses on how this method can be adapted to distance learning and its tools, technical infrastructure, and methodology.

According to the literature, OJT refers to the activities performed by an individual in the workplace aimed at developing their knowledge, skills, and job-related attitudes (Pfau, 2005, as cited in Vasanthi & Basariya, 2019). There are two types of OJT, namely structured and unstructured (Basariya & Vasanthi, 2019). Although structured on-the-job training does not have a single and immutable method, it is stated that the following components should be present in this system (Levine, 1996, as cited in Ahadi & Jacobs, 2017):

- management support
- formal trainer support process
- checklists
- on-the-job training materials
- train-the-trainer program
- monitoring and reporting

Studies on distance OJT mostly focus on the unstructured OJT style and factors such as learning materials, tool effectiveness, attitude, satisfaction, and so forth. However, research on the structured OJT style, where skill-based learning is measured and a small sample group is selected for in-depth assessment performed using tools such as interviews and observations, is limited. OJT is used for acquiring performance-based learning, and therefore it is important to be able to support performance-based learning through distance training.

Unexpected situations such as the COVID-19 pandemic, increased workload, and different working conditions are crucial factors affecting problem-solving abilities. The pandemic has not only impacted our health but has also compelled society to adapt to new work environments. Industry workers have had to research online tools and techniques to adapt to these new conditions. This has created a need to transform experiential learning in vocational education into online and off-site learning. The transition from face-to-face education to online skills education creates significant challenges, especially for the teaching and learning of psychomotor skills (Seymour-Walsh et al., 2020). In this context, the purpose and research questions of this study are presented below.

OJT methods are preferred for achieving performance-based learning. In this context, it is crucial that distance training supports performance-based learning. Therefore, this study stands out for its focus on direct outcomes and skill development rather than the operational dynamics of distance training. Additionally, considering adult learning styles is another strength of this study.

The study has the potential to address gaps in the literature by examining the effectiveness of various approaches to teaching practical skills through distance learning. Designing a performance-focused framework for workplace e-learning and enhancing the supportive role of technology in distance education are also significant.

By facilitating performance-based learning through distance education and providing an alternative to experiential learning methods, the study has the potential to shape the design, implementation, and evaluation of future vocational and technical education processes. Furthermore, this study could play a crucial role in expanding workplace learning and continuous education opportunities, contributing to the development of adaptability skills and lifelong learning across various sectors.

The aim of this study was to design, implement, and evaluate a case of distance OJT in vocational education. In line with this objective, a distance OJT training environment was created to identify factors that affect participation, achievement, performance, and learning. In pursuit of this goal, the following research questions were posed:

1. What is the level of participation in distance OJT practices?
2. To what extent does distance OJT practice affect the academic achievements of employees?
3. To what extent is job performance improved through distance OJT practices?

Theoretical Framework and Related Research

On-the-job training has been described in various ways in academic literature. However, OJT is commonly defined as a training method in which employees develop the necessary knowledge and skills to perform a specific job by observing and participating in the activities of a person performing the job in the workplace (Na, 2021). OJT methods are typically categorized into two groups: structured and unstructured. S-OJT refers to the process wherein a skilled worker imparts competencies to a novice worker (Ahadi & Jacobs, 2017). S-OJT involves intentional learning tasks with a planned and systematic approach that includes specific steps in the learning process. On the other hand, unstructured OJT is a more informal type of learning wherein apprentices observe or perform tasks under the guidance of a mentor (Rothwell & Kazanas, 2011).

The literature presents various frameworks for structured S-OJT methodologies, with one of the most comprehensive being the model proposed by Ahadi and Jacobs (2017). This model offers a conceptual framework summarizing the findings from a review of existing research. It highlights how different components are interconnected. These components include:

1. characteristics of structured on-the-job training;
2. design, implementation, and delivery of training;
3. evaluation of structured on-the-job training;
4. performance, quality, and effectiveness outcomes;
5. financial aspects of structured on-the-job training; and
6. individual/organizational settings and geographical region.

The model emphasizes the critical importance of designing and structuring training specifically to ensure that it is systematic and effective. This framework stresses that the features of the training must align with organizational context and objectives, while also noting that the effectiveness of S-OJT depends on both the skills and commitment of the trainers as well as the readiness and engagement of the trainees.

The framework suggests that each stage design, implementation and evaluation is interconnected, with effective design leading to successful implementation and delivery, which in turn requires comprehensive evaluation to assess outcomes. The ultimate goals of S-OJT include improved performance, quality, effectiveness, and financial results.

In conclusion, the components of the S-OJT framework are interrelated, with each playing a crucial role in the overall effectiveness of the training process. Understanding these relationships enables organizations to better design and implement S-OJT programs that meet their specific needs and objectives.

There are different perspectives on how to measure business results. Kim and Lee (2001) focused on efficiency, effectiveness, and quality, while Borman and Motowidlo (1993) proposed two constructs: task and contextual performance. Matsuo (2014) also focused on teaching skills for OJT. Drawing on the literature of experiential learning and problem-solving, this study presents a framework for an OJT process consisting of seven steps under four main categories:

Plan

1. goal setting

2. action planning

   Do

3. implementing tasks
4. dealing with problems

   Check

5. assessing the results

   Act

6. extracting lessons
7. setting next goals

In this framework, quality improvement will be effective if improvements start with a good plan (plan), activities necessary to achieve the plan are implemented (do), results are checked (check) to understand the causes of the results and actions (act) are taken to improve the processes (Dahlgaard et al., 1995).

Changing working conditions require different formats for teaching methods. The skills and resources needed by workers during online education differ from those required for face-to-face education. Online learning requires students to regulate themselves, manage their time, and self-motivate. Additionally, it helps individuals enhance their self-regulation skills by providing structured feedback and monitoring tools in an effective online environment (Kaşıkçı & İzmirli, 2024).

The problems and challenges of distance learning in the workplace can be divided into two main groups. The first group of problems is related to learning occurring in the workplace and is associated with the nature of the work itself. The second group of problems is related to learning taking place in a virtual environment and is generally related to the presentation of learning materials. However, this situation conflicts with the purpose of workplace learning since the focus should be on creating and transferring knowledge rather than presenting materials.

OJT is an effective method for enabling employees to learn in the workplace. However, its effectiveness is directly related to the instructional materials and feedback methods. When used as the main instructional material in OJT, educational videos can help learners become more productive by increasing their practical knowledge in the workplace. The use of educational videos can make the learning process more effective by supporting it with visual and auditory elements. Sablić et al. (2021) have indicated that in this context, the method of teaching through videos enables students to observe their problem-solving processes and share their problem-solving methods, which, in turn, encourages them to develop and expand their ideas and establish clear connections between visuals and concepts.

Feedback is crucial in OJT. It is an important tool for monitoring, evaluating, and developing learners' performance. In the process of OJT, providing feedback helps learners identify their strengths and weaknesses and contributes to improving their performance. Learning conditions in which feedback is provided in a timely manner can result in higher learning performance (Jensen et al., 2021).

Various distance learning tools have been examined in different sectors and target audiences in distance learning studies. Skill-based studies were preferred in these investigations, and the effects of factors such as expert support, educational video designs, feedback, simulations, specially designed learning methods, and mobile devices were explored. However, there are no studies on direct distance OJT in the field of beekeeping. Current studies generally relate to distance colony monitoring, disease detection, and monitoring hive conditions such as temperature, humidity, weight, and safety by beekeepers. The focal points of the research are increasing beekeeping productivity, disease detection and reduction, colony protection, income increase, and distance colony monitoring.

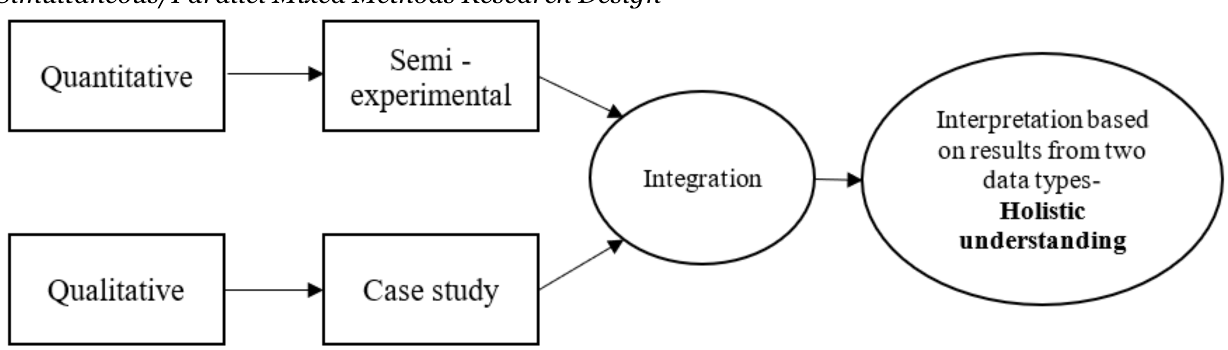
Another noteworthy aspect of this study is that more than half the studies were conducted in the past two years, which is believed to be due to the impact of the COVID-19 pandemic. The studies were generally conducted in various fields such as healthcare, construction, banking, agriculture, and maritime. It was observed that the distance OJT methods did not fully reflect the features found in S-OJT methods. In most studies, factors such as the effect of media used, material comparisons, applicability of a preferred technique in job training, and content analysis of previous studies in this area were examined.

Method

In this research, a concurrent design from mixed research methods was used. In concurrent design, qualitative and quantitative data are collected simultaneously. In the quantitative part, a quasi-experimental research method was employed and in the qualitative part, a case study method was used. As seen in Figure 1, quantitative and qualitative data are first collected and analyzed separately, and then these data are combined to interpret the results with a comprehensive understanding.

Figure 1

Simultaneous/Parallel Mixed Methods Research Design

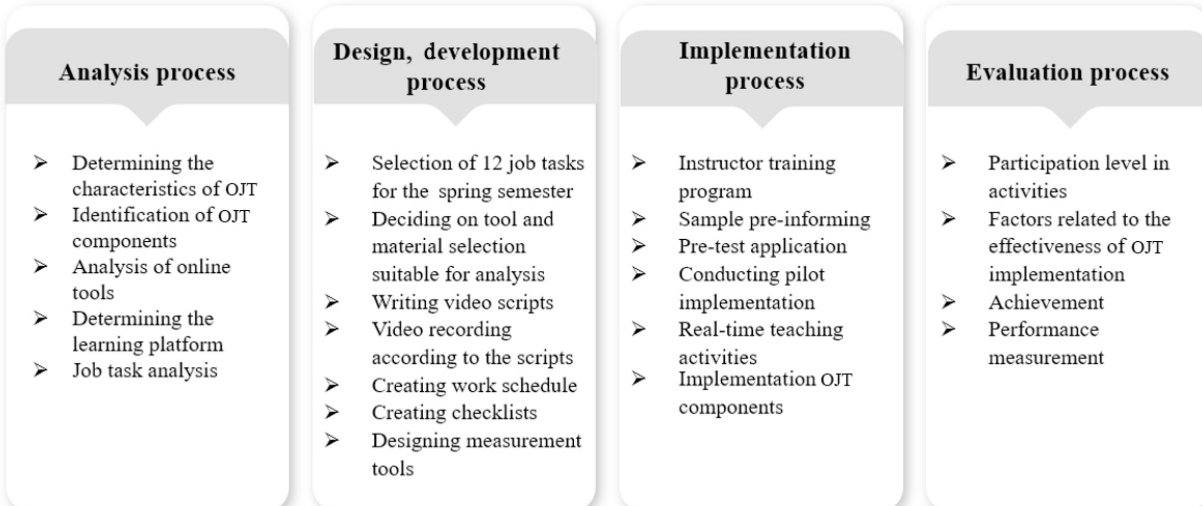


Design of Distance On-the-Job Training Process

The studies conducted on the application, analysis, design, and development stages of the distance OJT process have been elaborated in detail. Figure 2 explains the processes carried out in these stages.

Figure 2

Research Process



Determination of the Characteristics of the OJT Method and Distance OJT Management

In the OJT method applied in face-to-face instruction, various factors are necessary. It is important to identify these factors in the implementation process and determine the materials and tools that will be used in the distance learning environment. Table 1 shows the characteristics and matching status of the tools used in both environments.

Table 1

Determination of Characteristics of the OJT Method and Distance OJT Management

Feature of OJT	Characteristics of OJT in a distance learning environment
Apprentice-master relationship	Expert-beekeeper matching
Source of learning	Tutorial videos, expert support, feedback, peer training videos, and group interactions
Evaluation	1. Pretest and posttest 2. Checklists 3. Question-answer interaction and discussions 4. Performance evaluation (observation form) 5. Semi-structured interview 6. Event participation evaluation form
Instructor support	1. Ask the expert 2. Demonstrating with video and getting it done 3. Feedback 4. Checklists

Checklist	Creating a performance rubric that must be earned at the event
One-on-one or small group	Small sample selection
Work must be done in person	Providing material feedback that shows with training videos and pictures-videos

Beekeeping Job Tasks Needs Analysis, Creation of Educational Video Scenarios

The first author participated in an apiculture certification program in the eastern Anatolia region of Türkiye to analyze the job duties of the apiculture profession and actively engaged in beekeeping activities for two years. Focusing on spring season activities, 12 job duties were identified and a needs analysis was conducted to determine the appropriate materials and tools. The needs analysis involved the first author, an expert trainer and an apiculture course instructor. As a result of the needs analysis, educational video scenarios were prepared and converted into educational videos after expert review.

Creating Educational Videos

In the education video section, the sections related to how the job should be performed in terms of knowledge and skill instruction were prepared by the expert trainer. The reason for choosing an expert trainer was to have someone who personally carried out beekeeping activities and was a colleague of beekeepers. The expert provided the necessary equipment, controlling the scenario of each activity and shooting videos that used the demonstration and practice techniques under appropriate weather conditions during the relevant period of the activity. After the videos were reviewed by the expert and the research team and their suitability for educational purposes was determined, the same process was carried out for the next activity. Sample beekeeping task video footage is shown in Figure 3.

Figure 3

Sample Beekeeping Job Task Video Shots

Note. The visuals in Figure 3 illustrate examples of beekeeping tasks such as frame preparation and Insertion, hive cleaning and replacement, weak colony merging, and supplementation. In these visuals, an expert beekeeper demonstrates to novice or new beekeepers how to perform the 12 tasks outlined in the study step by step.

Creating a Job Calendar

In the field of apiculture, certain tasks that need to be performed in the spring season must be completed within specific time intervals. When creating the work assignments, the scheduled completion dates were taken into consideration. The purpose of this practice was to organize real-time OJT applications. Details of the work schedule are presented in the work schedule table below. If there were shared tasks to be performed during the same period, one or two tasks were planned together each week, depending on the level of difficulty of the job. Table 2 shows the beekeeping work program in detail.

Table 2

Beekeeping Work Schedule

Week	Time interval	Activity name	Job no.
1	April 26-May 2	Use of beekeeping equipment	1
2	May 3-9	Bellows burning and its use	2
		Hive cleaning and change	3
3	May 10-16	Frame preparation and delivery to the hive	4
		Spring feeding	5
4	May 17-23	Fighting the bee pest varroa	6
		Frame control	7
5	May 24-30	Reinforcement	8
		Merge weak colonies	9
6	May 31-June 6	Queen bee reception	10
7	May 7-June 15	Artificial swarm production	11
8	May 14-June 20	Adding honeycomb foundation and placing the queen excluder	12

Creation of Job Tasks Checklists

One of the important features of the OJT method we implemented is the use of job checklists. These checklists measure the level of learning of practical job skills. Job checklists control the number of tasks required to complete the job and provide feedback on employee performance. A total of 85 checklist tasks covering the 12 activities shown in Table 2 were created. These checklists were used to monitor participants' performance every week, to correct their mistakes and deficiencies. The checklists were prepared by taking into account the process steps included in each activity and were reviewed by experts. An example of the job checklists is presented in Figure 4.

Figure 4

Example Job Checklist Following Review by an Expert

Name and surname: xxx Activity: Placing the honey super and installing the queen excluder	P
1. Be careful to perform the process of adding the super in suitable weather conditions.	4
2. Open the hive cover and cover cloth calmly and give smoke with a smoker.	
3. Take 1-2 frames with closed brood from the brood chamber.	4
4. Perform compression of the frames surrounding the taken closed brood frames and give two foundation wax sheets to the 2nd and 9th frames in the hive.	4
5. Place the super properly on top of the brood chamber.	5
6. Put the swollen combs left over from the previous year to the right and left of the closed brood frames in the super.	3
7. Place the feeder in the super appropriately.	1
8. Cover the super with the cover cloth by wrapping it over the top of the four frames placed on top and hanging it down from the sides.	4
9. Properly close the cover cloth and hive cover of the super.	4
10. Place the queen excluder between the brood chamber and the super and cover the super with it.	5
11. Mention that there should be at least 20 frames in the hive when using the queen excluder.	

Note. The name and surname of the employee are masked to preserve anonymity. Here, P=1 means "very inadequate", P=2 means "inadequate", P=3 means "average", P=4 means "good", and P=5 means "very good". Green represents tasks correctly performed by the employee, black indicates corrections made by the employee after feedback, and red signifies incomplete task steps. The numbers in the colored boxes are scores based on a scale of 1 to 5.

Feedback given to the employee regarding which tasks were performed correctly and incorrectly was color coded. After receiving this feedback, the employee was expected to complete the tasks marked with a red box and resubmit the checklist.

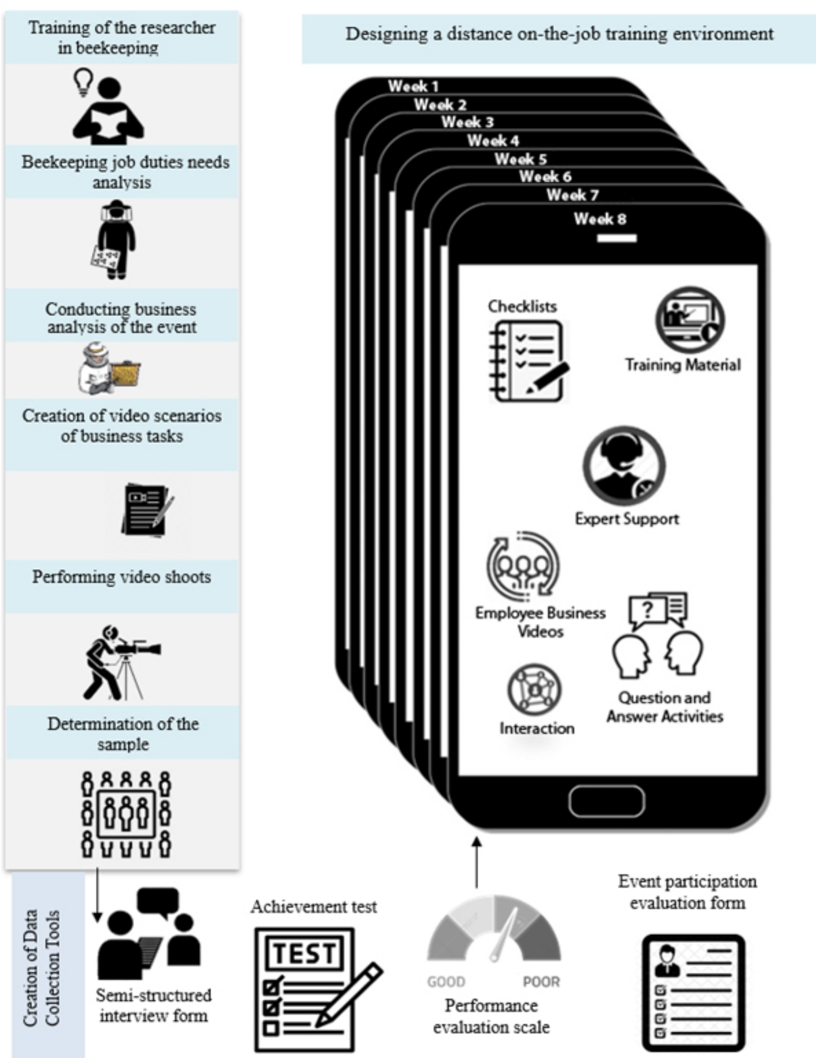
Implementation Process

In the implementation process, it was important for employees to have access to tools that would enable them to easily perform in a distance learning environment without face-to-face teaching methods, and for the implementation to take place in an environment that did not create communication or interaction problems. To this end, an instant messaging communication platform that allowed for smooth transfer of common content such as instant audio, visual, and document transmissions was used. The research covered an 8-week period that included the spring season in the beekeeping sector. Due to the nature of beekeeping, certain tasks must be performed during certain seasons; therefore, the implementation process was planned with an appropriate work schedule to perform real-time job skills. Detailed information about the processes carried out before and after the implementation process is presented in Figure 5.

The application process in Figure 5 can be summarized as follows: After completing vocational training in apiculture, the first researcher conducted an analysis of job duties in the profession and identified 12 job tasks that were carried out intensively during the spring season. Education scenarios were created for these tasks, and video recordings were made with the help of an expert. A sample of novice and new beekeepers who received face-to-face theoretical beekeeping education in an official institution was selected to conduct distance OJT, and data collection tools necessary for this process were identified. Finally, a mobile learning environment was created for the 8-week-long activities, where training materials were shared, expert support was provided, employees sent their job videos, question-answer interactions were enabled, and weekly checklists were sent and monitored through the interface of the environment.

Figure 5

Environment Design and Adaptation Process



To initiate the implementation process, a group named Distance Beekeeping Education was created. The interface of the group contained the factors mentioned in the design of the distance OJT environment, as depicted in Table 1. The group consisted of an expert beekeeper, 18 employees, and a researcher. The implementation process can be summarized as follows.

- Providing information about the process steps.
- Sharing the work calendar.
- Stating the weekly activities and explaining what employees need to do.
- Sharing the job task video every week.
- Sharing a blank checklist form that participants can use while performing their tasks.
- Instructing participants to watch the training video after completing their tasks, perform their tasks in accordance with the checklist, record it as a video or picture, and submit it to the group.
- Asking questions and getting answers from experts for any problems or questions that may arise during the activities.
- Weekly evaluation of the training videos by experts and sharing feedback checklist.
- Correcting missing or incorrectly performed job tasks and having the expert re-evaluate the corrections after feedback.
- This process was implemented for 8 weeks and aimed to encourage participants to correct errors and deficiencies in their job tasks and perform better in their work.

Study Group

This study examined a group consisting of 19 novice (1–3 years) and new (first-time) beekeepers who participated in a certificate training program organized by the Public Education Center and the Beekeepers Association in a city located in the eastern Anatolia region of Türkiye. From the selected 19 individuals, the study was conducted with 18 male students who actively continued the process. All participants in the study group were adults, with an average age of 32. The study group was selected using a purposive sampling method, which arises from the necessity of constructing a sample from a homogeneous subgroup. This sampling method is also known as selective or judgmental sampling and is combined with other sampling techniques to ensure sample diversity and representation of the studied population (Karačić Zanetti et al., 2023).

Data Collection Tools and Data Analysis

In this study, data were collected using a semi-structured interview form, a performance evaluation scale, an activity participation evaluation form, and an achievement test. The features and selection reasons for these instruments were explained in detail. Detailed information about which data collection tool was used for each research question and how the data were analyzed is presented in Table 3.

Table 3

Relationship Between Research Questions and Data Collection Instruments

Research question	Data collection tool	Analysis method
1. What is the level of participation in distance OJT practices?	• Evaluation form for activity participation • Semi-structured interview form	Descriptive statistics Content analysis
2. To what extent does distance OJT practice affect the academic achievements of employees?	• Achievement test	Descriptive statistics
3. To what extent is job performance improved through distance OJT practices?	• Evaluation form for activity participation • Performance evaluation scale	Descriptive statistics Content analysis

Achievement Test and Analysis of Data

The test designed to measure the academic achievement of employees was prepared by us with the help of an expert. The test was conducted using a time series design to measure the achievement level of employees. The test was administered before and after the implementation process and the data obtained were analyzed using a numerical data analysis program.

Semi-Structured Interview Form and Data Analysis

A semi-structured interview form was used to collect qualitative data. The aim of the interview was to evaluate the participants' satisfaction with the implementation process, the factors that were effective in learning, the problems encountered during the implementation process, and the factors that facilitated or hindered the work.

Performance Evaluation Scale and Analysis of Data

In the study, a performance evaluation scale was developed to measure skill-based learning. This scale, consisting of a total of 85 job tasks, including 12 job activities, encompasses the beekeeping profession's spring season activities. Each task was evaluated on a 5-point scale ranging from 1 (*very poor*) to 5 (*very good*). To increase data reliability, we performed separate observations from the expert trainers, and the average score was used.

We evaluated the job videos, and inter-observer agreement was calculated using the Cohen Kappa coefficient, with a reliability value of 0.69. Accordingly, it can be said that the inter-observer agreement was at a good level.

Evaluation Form for Activity Participation and Data Analysis

The study aimed to determine the level of task completion by creating an activity participation evaluation form that recorded data such as the number of tasks completed by each participant weekly, the number of tasks completed after job performance, the remaining tasks, and the number of tasks completed after feedback. The collected data was analyzed to determine the impact of feedback on a weekly and activity basis, as well as the level of material sharing and question-answer interaction between experts and participants. The data from the form was used to provide feedback to participants by experts every week, allowing them to correct their mistakes and deficiencies. The data was then analyzed and transformed into averages, percentages, frequencies, graphs, and tables.

Results

Level of Participation in Distance On-the-Job Training Applications

Quantitative data on the research questions were obtained from the activity participation evaluation form and analyzed using descriptive statistical analysis. Qualitative data, on the other hand, were analyzed using the content analysis method. The results of the analysis are presented in detail in Table 4.

Table 4

Application Process Activity Participation Level Data Analyses

Variable	*n*	Data per person (%)
Activities	1,530	100.0
Completed tasks/jobs	1,207	78.9
Remaining tasks/jobs	326	21.3
Tasks/jobs completed after feedback	87	5.7
Completed tasks/jobs	1,294	84.6
Remaining tasks/jobs after feedback	239	15.6

During an 8-week OJT activity, an 18-member employee group aimed to complete 1,530 work tasks. However, the employees completed only 1,207 activities during this period. Expert trainers evaluated the work videos/materials that the employees submitted to the learning platform at the end of each week and identified that the employees completed another 87 work tasks after feedback. At the end of the process, the employees had completed a total of 1,294 tasks and were unable to complete 239 tasks. Table 5 provides detailed information about the sharing of expert-student materials and question-answer interactions according to the weeks.

Table 5

Weekly Distribution of Expert-Employee Material Sharing and Question-Answer Interactions

Week	Activity	Interaction (n)	
		Expert initiated	Worker initiated
1	Beekeeping equipment and usage	19	90
2	How to use a smoker Hive cleaning and replacement	39	70.5

3	Frame preparation and installation Spring feeding	33	73
4	Fighting Varroa mite infestations Frame inspection	31	51
5	Supplemental feeding Combining weak colonies	35	45
6	Queen acceptance	34	50
7	Artificial swarm production	38	68
8	Placing a honeybee layer and placing a queen bee grid	51	72

Note. Expert initiated M = 35; Worker initiated M = 64.9.

According to the data presented in Table 5, the number of interactions and material sharing between experts and employees varies significantly across weeks. Expert trainers conducted an average of 35 material or question-answer interactions throughout the implementation period, while employees, in response, engaged in an average of 64.9 material sharing or question-answer activities. These findings indicate that the level of interaction between experts and employees differs based on the nature of activities and the weeks, with employees participating more intensively in material sharing and question-answer interactions.

Now, several sample opinions obtained from interviews with employees participating in the distance OJT are presented. These show some of the reactions to elements of the OJT.

- Participant 9: "The feedback given while doing the job was definitely helpful. Because I could see my mistakes and have the opportunity to correct them. This way, I was approaching the work more systematically and accurately."

- Participant 7: "I did not have difficulty in performing tasks that required practical skills. The hardest task in the work was giving consistency to the syrup. It was a challenging task as it was a bit risky. Also, there were more details in giving consistency to the syrup, and it was a long process, so it was challenging for me."

- Participant 2: "The question-answer discussions during the trainings contributed to my learning of new things related to work. I think I learned new things in many questions."

- Participant 16: "I was motivated by watching the videos of other participants. I thought I was doing my job better. I usually randomly selected and watched videos."

Impact on Employees' Academic Achievements

To determine the variation in the academic achievement of the employees, a pretest and posttest were administered. A dependent samples t-test was conducted to identify the differences in vocational knowledge of the participants, and the results are presented in Table 6.

Table 6

Comparison of Participants' Achievements Before and After the Distance Learning Application

Variable	*n*	$\bar{X}$	*SS*	*t*	*SD*	*p*
Pretest score	18	36	12.50	-9.392	17	.00
Posttest score	18	67.78	18.58			

As shown in Table 6, there was a statistically significant difference in favor of the posttest scores ($\bar{X}$ = 67.78) compared to the pretest scores ($\bar{X}$ = 36) [$t(18) = -9.392$, $p < .05$]. A dependent sample *t*-test to determine the difference in professional knowledge of the participants before and after the program was also conducted.

Level of Job Performance Achieved With Distance OJT Application

To evaluate the performance, an observation form was used to analyze all video content sent by participants to the learning platform, and data were obtained by evaluating each task on a scale of 5. A total of 85 job tasks covering 12 activities were defined during the application period, and the average values of these tasks were then grouped by activity. Table 7 shows the 12 activities and the mean scores of participants.

Table 7

Performance Evaluation Data by Activity

Activity	Score ($\bar{X}$)
Beekeeping supplies and usage	3.8
Bellows combustion and use	4.3
Hive cleaning and change	4.0
Frame preparation and delivery to the hive	3.4
Spring feed	3.9
Fighting the bee pest Varroa	4.1
Frame control	3.7
Reinforcement	4.0
Merge weak colonies	3.9
Queen bee acceptance	3.8
Artificial son production	3.4
Placing the honeybee layer and placing the queen bee grid	3.2

Note. $M = 3.78$.

In Table 7, it is seen that, based on video observations, the activities with the highest performance level on average were lighting and using the smoker ($\bar{X}$ = 4.3), combatting the honeybee pest Varroa ($\bar{X}$ = 4.1), and cleaning and changing the hive ($\bar{X}$ = 4.0). On the other hand, the activities with the lowest performance level on average were giving the honeycomb foundation and placing the queen excluder ($\bar{X}$ = 3.2), producing an artificial swarm ($\bar{X}$=3.4), and preparing and giving the frame to the hive ($\bar{X}$ = 3.4).

We found that the performance level of tasks in beekeeping such as lighting and using the smoker, combatting the Varroa mite, and cleaning and changing the hive, which are simpler, shorter, and less complex, was higher. On the other hand, the performance level of longer, more complex, and risky tasks, such as giving honeycomb foundation and placing a queen excluder, artificial swarming, and preparing and giving the frames to the hive, was lower.

Discussion

On-the-job training is carried out through the master-apprentice relationship and by focusing on the demonstration of the worker's behavior. If the OJT method applied in this study is imitated exactly, it can be assumed that learning behavior is achieved. In the distance OJT application used in this study, 78.9% of the 85 job tasks were completed, and this value corresponds to approximately 85% of the total number of tasks. This high level is attributed to factors such as participants both receiving regular feedback and being adults able to observe their own job performance and encourage each other while performing the same job on the same learning platform. Weng et al. (2015) emphasized the significant relationship between the support received from peers and experts and employees' learning performance and participation in e-learning programs. Similarly, Warr et al. (1999) argued that external factors such as teaching strategies, learning motivation, support, and trust influence the learning process. Morrison and Brantner (1992) highlighted factors such as time spent on task, task complexity, self-efficacy, and organizational climate as influencing learning and job participation. Sangeeta and Tandon's (2021) study indicated that facilitative conditions have a positive impact on performance expectations and online learning, whereas effort expectations and social activity may yield more uncertain results. Furthermore, Martins et al. (2019) suggested that environmental factors perceived as facilitative by employees during training programs can provide opportunities that motivate and support learners. In light of these studies, the importance of support, teaching strategies, and environmental factors in the learning process for employees becomes evident.

On the other hand, we observed that 15.6% of tasks were not completed. Klein et al. (2006) noted that environmental conditions or events can be perceived by employees as facilitators or barriers. Due to participants' personal characteristics, job suitability, or the nature of the job, it may not be possible to perform all learning tasks, especially for novice or new employees, as the profession may involve risky, challenging, or varied working conditions. Interview data with employees discussing the impact of this situation were obtained. More than half stated that their work environment included factors that made the job more difficult, for example, temperature, job-specific clothing, and so on.

According to the results of achievement tests conducted before and after the application, distance learning can increase academic achievement. The fact that the activities were directly related to practical application also had a positive effect on paper-based exams. It has been noted that learning is more permanent and effective if people learn when they most need it, and that instant application reinforces knowledge acquisition and makes future use of information more permanent (Harun, 2001). Therefore, it is important for employees to have access to the necessary knowledge and material at the exact moment they need them.

There are many factors that contribute to the success of employees during distance OJT. These factors include experiencing the work while doing it, being part of a social group, receiving interactive support from an expert trainer, receiving continuous monitoring and feedback, and having the opportunity to correct mistakes. Dyson et al. (2009) have pointed out that there are still things that need to be done to improve learning and have emphasized the need to prioritize the design of teaching strategies for active, experiential learning.

In this distance OJT program, a total of 85 work tasks were identified. The components of distance OJT were effective in establishing the foundation of the implementation process. The literature has stated that OJT is mainly used for skill development. The work of Van Zolingen et al. (2000) argued that a strong connection is formed between education and application through OJT, resulting in more effective learning of skills acquired on the job.

In addition, high satisfaction levels of employees are related to the high average values of learning tasks. In this regard, Sun et al. (2008) found that students who perceive e-learning as useful performed better. Another data obtained in this study indicates that learners performed less well in skilled tasks compared to simpler, shorter, and less detailed tasks. The reason for the difference in performance in work tasks is due to the structure of the work environment inherently containing various risks (e.g., due to the discomfort of bees resulting from prolonged work and the resulting increase in aggression in bees, the worker may panic and perform the job incompletely, etc.). Additionally, the inherent complexity of some work tasks can result in a difference in performance. For example, the low average values in certain work tasks and the high average values in others may be due to the participants' preference for risk-free, simple, easy, and less complex tasks.

According to the literature, the challenges encountered in distance learning include student's attitude towards the content, nature, and complexity of the course, as well as factors such as lack of interest, inadequate study programs, and activities (Hicks et al., 2007). Abbad et al. (2010) emphasized that these difficulties can lead to discontinuation of education or incomplete course activities, while Klein et al. (2006) focused on how environmental conditions or events can be perceived by students as facilitators or barriers depending on individual characteristics and instructions. Martins et al. (2019) suggested that if these factors are perceived as facilitators, they can motivate learning and present good opportunities, thus helping employees acquire new knowledge and skills.

Conclusion and Suggestions

Achieving high levels of participation in distance OJT applications requires receiving regular feedback, focusing on job outcomes, and providing a supportive learning environment. The effective design of training strategies, increasing learning motivation, and the perception of environmental factors as facilitative by employees influence the success of distance OJT programs. Particularly, it can be said that support between peers and experts influences learning performance and participation. Additionally, distance OJT enhances academic achievement and positively impacts job performance. However, challenges such as incomplete tasks were encountered in this study. Therefore, in the design of training programs, careful selection and organization of learning materials and activities according to the nature of job tasks are necessary. Furthermore, continuous feedback during the learning process and opportunities for correcting errors are important.

Based on the findings of this study, there are some practical applications that businesses and educational institutions should consider when developing distance OJT programs. For example, effective teaching strategies should be designed and implemented in OJT programs. Especially, interactive learning methods associated with practical applications should be preferred. Furthermore, since the conditions of the work environment can affect employees' participation and success, it should be ensured that the work environment is positive and supportive. In addition, training materials and activities should be closely related to the nature of the work. Practical applications should be designed to allow immediate application of theoretical knowledge. Diversification of materials considering individual employee characteristics is also important. Various efforts should be made, such as customizing training videos for more complex, longer-term, and riskier job tasks, designing profession-specific learning platforms, and integrating widely used mobile applications.

In this study, there were various limitations in the implementation of the distance on-the-job training method, such as the nature of the existing beekeeping sector in terms of working conditions, the structure of job tasks, and the educational level of the workforce engaged in the sector and their technological proficiency. Adapting this method to different businesses or sectors may pose additional limitations.

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Evaluating AI-Personalized Learning Interventions in Distance Education

Selvaraj Vijayakumar and Sajida Bhanu Panwale
B.S. Abdurrahman Crescent Institute of Science and Technology, India

Abstract

This study aimed to evaluate the utility of artificial intelligence (AI) in improving the persuasive communication skills of online Master of Business Administration (MBA) students. In particular, this study investigated the influence of personalization through AI using the Google Gemini platform on conventional and online instructional approaches. This quasi-experimental study used a pretest and posttest design to compare two groups of MBA students pursuing persuasive online communication. The experimental group (n = 32) interacted with the AI-based personalized learning materials, whereas the control group (n = 32) used standard instructor-designed online modules. During the 12-week intervention period, the experimental group was provided with customized practice activities. Conversely, the control group was offered conventional online learning material. The effectiveness of both approaches was evaluated using pretests and posttests. The results of Tukey's Honestly Significant Difference (HSD) test provided insight into the areas where AI-based personalized learning had a statistically significant impact. These results support the conclusions derived from an analysis of variance and further validate the study's research hypotheses. This study demonstrates the advantages of incorporating AI into language development for remote learners and offers valuable insights for integrating AI-driven technologies into distance education.

Keywords: learner agency, adaptive technology, micro-learning, disruptive innovation, distributed learning

Introduction

The increasing complexity of online learning platforms necessitates customized language development for part-time Master of Business Administration (MBA) students, who must juggle professional, personal, and academic responsibilities. Effective communication is essential for their academic success and professional growth (Randolph, 2008). MBA students need to develop several key communication skills, including clear articulation of ideas, coherent organization of arguments, persuasive engagement of the audience, and effective leadership communication. These skills are crucial for delivering impactful presentations, negotiating successfully, and writing compelling professional documents (DiBenedetto & Bembenutty, 2011).

The target learners often face challenges such as organizing and presenting arguments coherently, engaging and maintaining the interest of their audience, and effectively leading teams and managing projects (McGraw & Tidwell, 2001). Inadequate communication skills can lead to lower academic performance, reduced participation, and hindered career progression (Randolph, 2008). Additionally, poor communication can exacerbate stress and anxiety, negatively impacting overall well-being and academic outcomes (Francis, 2012).

Effective communication skills are critical for success in both academic and professional settings, especially in MBA programs where students must demonstrate leadership, project management, and stakeholder engagement. Deficiencies in these skills can create obstacles in managing responsibilities effectively, thereby contributing to increased stress and potentially impacting overall performance and career development (Ongus et al., 2017). Therefore, addressing these communication challenges through tailored language development programs is vital. Such programs can enhance students' ability to balance their diverse responsibilities and succeed in both academic and professional endeavours.

This study's theoretical framework is based on the principles of individualized learning and adaptive education. Customized educational settings that adjust to the specific requirements of each student can significantly improve the results of the learning process (Wang & Mendori, 2012). This study uses these ideas in the context of language acquisition, harnessing the power of artificial intelligence (AI) to offer tailored feedback and flexible learning trajectories. Through this study, we intend to facilitate learners in achieving their communication objectives and succeeding in their academic pursuits by providing customizable elements that create a personalized and engaging language-learning experience.

This study examines how AI can improve the persuasive communication abilities of MBA students in online environments. AI technologies can assist students in overcoming communication hurdles by providing tailored feedback and adaptive learning routes to address specific issues. The use of AI in this particular context is intended to provide MBA students with the essential abilities to express ideas with clarity, logically organize arguments, and effectively interact with their audience. These skills are directly pertinent and vital to the MBA curriculum and future professional endeavours.

In distance learning, instructor-led materials frequently fall short of students' varied needs, particularly in terms of language development. These materials typically adopt a one-size-fits-all approach that hinders effective language acquisition and student progress (Shevchenko et al., 2021). This one-size-fits-all approach fails to consider learners' learning styles, prior knowledge, and language proficiency levels, resulting in a gap between the educational content and specific needs. The lack of flexibility in conventional materials, which strictly adhere to a predetermined syllabus and pace, often clashes with a learner's unique educational journey, potentially leading to feelings of frustration and disengagement, especially for those who require additional support or progress at a different pace (Tomasik et al., 2020). Traditional approaches lack personalized feedback on language output and skill development, which helps learners identify areas for growth and improve their language skills.

One of the limitations of traditional learning materials is that they frequently adhere to teacher-centric models that do not provide personalized feedback mechanisms. This lack of feedback can make it difficult for learners to identify and rectify their linguistic weaknesses, which may ultimately impede their language development (Paterson et al., 2020). This model limits learner autonomy, reduces motivation, and restricts collaborative learning opportunities, which are crucial for language development (Palincsar & Herrenkohl, 2002). These challenges, including the absence of tailored instruction, limited adaptability, insufficient personalized feedback, restricted learner agency, and limited collaborative learning opportunities, result in a mismatch between the educational content and learner requirements.

AI has shown remarkable potential in overcoming these limitations and personalizing language learning (Huang et al., 2023). AI-powered tools offer customized, engaging learning experiences and enhance language acquisition. These cutting-edge technologies, adept at analysing learner data, create tailored pathways that are in harmony with the learner's distinct objectives and requirements. In doing so, they refute the traditional educational approach and foster effective language development. Moreover, AI-powered systems offer immediate feedback on language construction and skill progression (Liang et al., 2021). AI-driven technologies offering personalized feedback, simulations, and interactive games have the potential to revolutionize language learning and motivate and engage students (Crompton & Burke, 2023). Using AI capabilities, language learning can be reimagined as a dynamic and interactive experience.

Moreover, AI can facilitate collaborative learning by connecting learners from diverse backgrounds, thereby promoting social interaction and knowledge exchange (Wang et al., 2023). Therefore, this study aimed to compare AI-based personalized language learning with traditional instructor-designed courses, focusing on enhancing persuasive communication abilities in online MBA students using a quasi-experimental methodology. This study sought to assess whether AI-based customized language learning improves persuasive communication abilities more efficiently than traditional techniques.

Hypotheses

Given the experimental nature of this study, the following hypotheses were formulated for examination:

1. The use of AI in personalized language learning will lead to greater improvement in persuasive communication skills compared with traditional instructor-designed courses among online MBA students.

2. The application of AI in personalized language learning will positively impact specific student learning outcomes more than in traditional instructor-designed courses.

Review of Literature

Efficacy of Personalized Learning in AI-Facilitated Environments

Wang and Mendori (2012) examined a customizable online language-learning support system. This system is especially good at making concepts easier to understand and showing how AI can be used to accommodate each student's individual learning preferences and knowledge levels. Another study addressed the issue of personalizing online courses by proposing a methodology through the application of natural language processing technologies (Lund et al., 2023). The shift to remote digital learning underscores the importance of personalized feedback in student-centred learning (Istenič, 2021). This study indicated that tailored feedback is necessary for remote students to learn effectively. Understanding how AI can deliver personalized feedback and enhance persuasive communication skills in online MBA programs is essential.

Artificial neural networks, intelligent tutoring systems, and natural language processing have been widely applied in personalized language learning (PLL), according to a comprehensive study by Chen et al. (2021). These tools have been shown to improve language learning and learner satisfaction, suggesting that they may help online MBA students improve their persuasive communication skills. Similarly, Sánchez-Villalon and Ortega (2007) investigated the potential of web-based learning, particularly in the context of personal learning environments (PLE). They proposed an alternative solution using online learning environments (OLE) and a writing e-learning appliance (AWLA) that integrated various language and communication tools. This approach promotes learner-created pathways, breaking down the barriers to traditional learning and potentially enhancing the persuasive communication skills of MBA students through technology-supported, personalized learning.

Obari et al. (2020) investigated the possibility of using AI tools, such as smart speakers and smartphone apps, to improve Japanese undergraduates' command of English. According to their data, learners exposed to AI materials performed better than those exposed to conventional online resources. In summary, several studies have shown that AI-driven personalized language instruction can enhance language proficiency and student satisfaction, surpassing the effectiveness of conventional instructor-led language classes. The issues of addressing the effects of peer pressure, preserving student motivation, and incorporating diversity continue to require further attention and development.

Learning Outcomes in Personalized Technological Environments

Maghsudi et al. (2021) found that it is crucial to devise a personalized learning plan that considers learners' strengths and weaknesses to facilitate knowledge acquisition. This method, which educational institutions are increasingly adopting, uses AI and big data analysis to identify and cater to individual student characteristics. Although these methods can suggest optimal content and curricula, some challenges need to be addressed, such as the absence of peer interaction and maintaining learner motivation. According to Chiu, Moorhouse, et al. (2023), automated data-driven personalized feedback within intelligent tutoring systems (ITS) improved student performance significantly by 22.95%. This study demonstrated the superiority of ITS in promoting learning compared with other computer-based instructional methods.

AI-powered personalized learning resources have garnered considerable traction because of their competence in meeting the varied requirements of learners and complementing classroom teaching (Zhao, 2022). Research has found that adaptive learning can personalize instruction based on students' backgrounds and interests, resulting in improved problem-solving efficiency. Personalized interventions have been shown to benefit struggling students and positively impact learning outcomes.

Despite advancements in online education, real-time interaction remains challenging. ITS offer a promising solution by providing real-time personalized learning guidance and resource recommendations. Previous research has highlighted several challenges in the development of ITS, including learner modelling and human-computer interaction. (Chiu, Xia, et al., 2023). In summary, these studies collectively indicate that AI-based personalized language learning can significantly improve student learning outcomes and educational competencies, resulting in higher course completion rates than traditional instructor-designed courses. In essence, the data suggest that AI has the potential to transform personalized learning experiences by addressing the distinct needs of students.

Methodology

Research Design

The impacts of AI-based personalized learning and standard instructor-designed modules in an online MBA course were compared using a quasi-experimental pretest–posttest methodology. A quasi-experimental design, ideal for educational research, allows the examination of educational interventions in a natural setting (Shadish, Cook, & Campbell, 2002). The experimental and control groups were established through two complete classes, allowing for a comparison of the two teaching approaches while controlling for outside factors. The experimental design was deemed appropriate for assessing the impact of AI-based tools on students' final grades, as it simulates the practical application of these technologies (Chen et al., 2021; Wang & Mendori, 2012).

Ethical considerations played a significant role in the present study. To ensure that the study adhered to ethical norms for research involving human participants, particularly in an educational context, the university's Institutional Review Board (IRB) provided ethical approval prior to the study. With assurances of privacy and security in data processing, all participants provided their informed consent. The intervention was designed to avoid disrupting participants' regular learning processes or academic performance. The study strictly followed the intervention research protocol by protecting participants' integrity and upholding the institution's academic standards. The university granted ethical approval, ensuring that the research complied with ethical standards for studies involving human participants in an academic setting (Istenič, 2021; Lund et al., 2023). The study was conducted over 12 weeks.

Participants

This study involved 64 part-time MBA students enrolled in an online course during the 2023 academic year at B. S. Abdur Rahman Crescent University, Chennai, India. All participants were non-native English speakers with diverse educational backgrounds and work experiences. Course requirements and practical considerations necessitated a non-random assignment of participants to experimental or control groups using purposive sampling. The groups were formed based on enrolment order and received either AI-based personalized learning materials (experimental group) or traditional instructor-designed online modules (control group).

Instruments

Communication skills were assessed using a comprehensive rubric focusing on fluency, accuracy, organization, and overall effectiveness. These criteria are widely used in language proficiency studies, as evidenced by Chen et al. (2021), among others. Andrade (2000) and Moskal (2000) discussed the use of rubrics in promoting thinking and learning, thus supporting the assessment approach of the current study.

This rubric was designed to be used for both pre- and post-assessments. Each element was assessed on a scale of 0 to 2.5, resulting in a potential overall score of 10 for each sales pitch presentation. See Table 1.

Table 1

Assessment Tool—Standardised Rubric for Evaluating Sales Pitches

Attribute	Assessment criteria				
	Excellent (2.1–2.5)	Good (1.6–2.0)	Satisfactory (1.1–1.5)	Needs improvement (0.6–1.0)	Poor (0–0.5)
Fluency	Speech flows smoothly and naturally	There are minor hesitations, but it still flows well	Some hesitations affect flow	Frequent hesitations disrupt the flow	Extremely choppy and disjointed speech
Accuracy	Error-free grammatical usage	Minor grammatical errors are present	Noticeable grammatical errors	Frequent grammatical mistakes	Speech is heavily laden with errors
Organization	Highly logical and well-structured	Mostly clear structure and logic	Some disorganization is evident	Lacks clear structure and logic	Completely disorganized
Overall effectiveness	Highly persuasive and engaging	Generally engaging and persuasive	Moderately engaging and persuasive	Limited in engagement and persuasion	Not engaging or persuasive

To guarantee content validity of the rubric, a panel of three educators in business communication and online learning scrutinized the initial draft. Their input aided in enhancing the rubric to capture the crucial aspects of an effective sales pitch with greater precision. The rubric then underwent pilot testing with a selection of sales pitches from a prior course. This process enabled the refinement of the scoring criteria to ensure clarity and measurability. To assess the inter-rater reliability, two independent raters evaluated the sample presentations using the rubric. A high correlation between their scores (Cohen's kappa > 0.8) confirmed the dependability of the rubric. During implementation, two independent raters scored each presentation, and any discrepancies in scoring were addressed through discussion to ensure consistency and fairness in the evaluation.

Procedure

The research project lasted over 12 weeks, during which the experimental and control groups were subjected to diverse educational resources. These resources are compared in Table 2 and discussed in the next sections.

Table 2

Pedagogical Framework—A Comparison

Aspect	Participant groups	
	AI-based personalized learning (experimental)	Instructor-designed online modules (control)
Platform	Google Gemini AI platform	Moodle LMS
Content development	Customized based on individual pretest performance and learning preferences	Standardized video lectures, readings, and discussion forums
Learning path	Interactive lessons, practice activities, personalized feedback	Fixed curriculum without personalization
Delivery mode	Adaptive LMS allows personalized access and progress tracking	The same LMS used for delivering standardized content
Interaction monitoring	Analytics tools in LMS tracking engagement, plus AI platform insights	Analytics tools in LMS tracking engagement and participation
Additional features	Customized learning paths and progress tracking specific to each learner	The standard learning experience for all students

Note. AI = artificial intelligence; LMS = learning management system.

AI-Based Personalized Learning Materials (Experimental Group)

The experimental group had a distinctive learning experience facilitated by the Google Gemini AI platform. This platform uses sophisticated machine learning algorithms to analyse the pretest results of each student, along with their individual learning preferences and engagement patterns. Based on this comprehensive analysis, the AI platform generated personalized learning paths for each participant of the experimental group. These paths comprised interactive lessons, practice activities, and targeted feedback, all of which were tailored to each student's specific needs and progression. These materials were delivered through an adaptive learning management system (LMS), which not only enabled students to access the content at their convenience but also allowed them to monitor their progress. This approach was designed to offer a highly individualized learning experience, potentially enhancing the efficiency and effectiveness of skill acquisition.

Instructor-Designed Online Modules (Control Group)

In contrast, the control group received a more conventional form of online education. The learning materials for this group were developed by the course instructor and consisted of a series of standardized video lectures, readings, and discussion forums. These modules were hosted on the same LMS as the AI-based materials but lacked the adaptive and personalized features of the experimental group's materials. Instead, they followed a fixed curriculum designed to cover the same educational content and objectives as the AI-based program, albeit without a personalized element. Thus, this group's learning experience adhered to traditional online learning methodologies and served as a benchmark against which the efficacy of the AI-based approach could be evaluated.

The LMS was equipped with analytics designed to track various metrics to assess participants' engagement with their respective learning materials. These metrics included the amount of time spent on each module, the degree of interaction with interactive elements, completion rates of lessons and activities, and participation levels in discussion forums. For the experimental group, an AI platform provided additional analytics that offered deeper insights into each student's interaction with personalized learning elements, such as usage patterns and progression along custom learning paths. The objective of learning analytics was to provide a comprehensive comparison between the two educational approaches, assessing not only the effectiveness of AI-based personalized learning in an online setting but also the dynamics of student interaction and engagement with innovative educational technologies.

AI-Based Personalized Learning Materials

The personalized learning materials for the experimental group were developed using a machine learning algorithm integrated into the Google Gemini AI platform. This algorithm analyses a range of data points to create highly individualized learning paths for each student. Key data points included the initial assessment scores from the pretest, which provided a baseline for each student's persuasive communication skills. Moreover, the algorithm considered variables such as students' engagement patterns (time spent on various tasks and frequency of logins), interactions with different types of content (videos, readings, and interactive exercises), and responses to formative assessments embedded within the course. As the students progressed through the course, the algorithm continuously assessed their performance on ongoing assessments and activities in real time. Based on this data, the learning paths were adjusted to accommodate each student's evolving requirements. If a student demonstrated improvements in specific areas, the algorithm would introduce more advanced concepts or challenging tasks to those areas. Conversely, if a student struggled with certain topics, the algorithm provided additional resources and exercises to reinforce learning in these areas. This adaptive approach enabled the learning experience to remain aligned with each student's pace and learning style, aiming to maximize their engagement and educational outcomes.

Instructor-Designed Online Modules

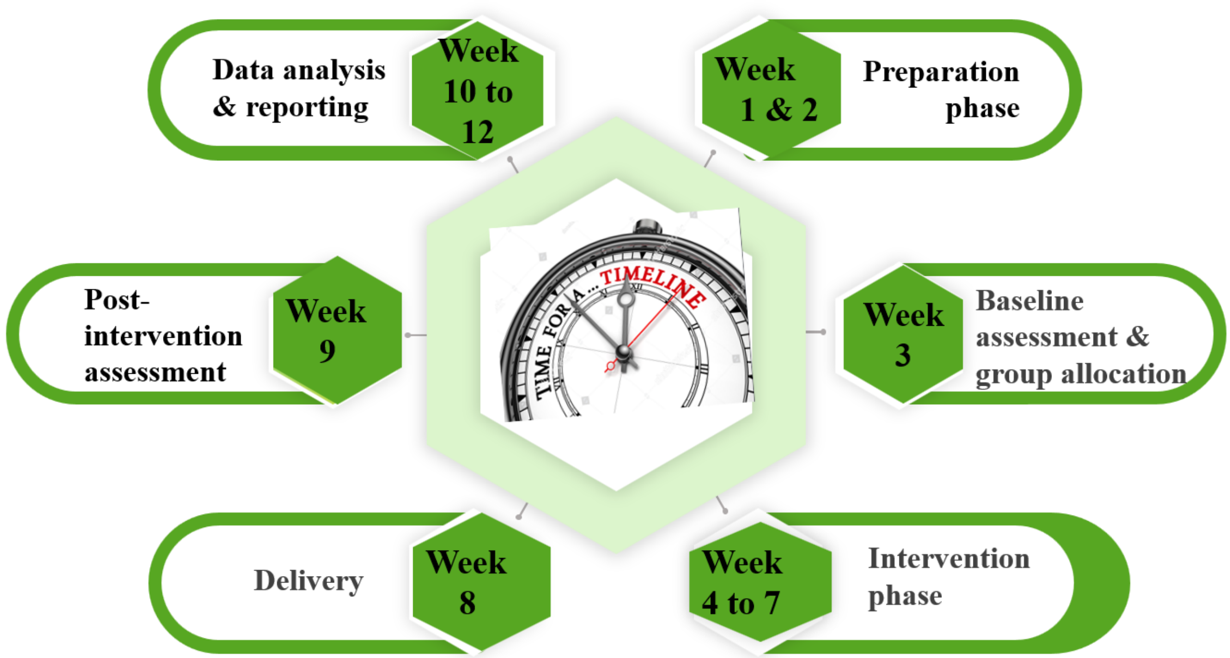
The control group received instructor-designed online modules that were created to be comparable in educational value to the AI-based materials used by the experimental group. These modules were designed by an expert in persuasive communication and covered the same topics and learning objectives as in the AI-based curriculum. The content included well-structured video lectures, relevant readings, and case studies organized around specific themes or skills in persuasive communication. Interactive elements such as discussion forums were also incorporated to provide students with opportunities to engage with peers and instructors. Formative assessments, such as quizzes and short writing assignments, were included at regular intervals to gauge the student's understanding and retention of the material. While these modules lacked the adaptive and personalized features of AI-based materials, they were designed to be engaging and pedagogically sound, ensuring that all students had access to high-quality educational resources.

Study Timeline

The study followed the procedure detailed in the previous section and ran for 12 weeks, according to the timeline shown in Figure 1. The steps are discussed in the sections that follow.

Figure 1

Timeline for Study



Preparation Phase (Weeks 1-2)

The planning and creation of the study were accomplished during the initial week, which entailed the development and refinement of the research materials and protocols to guarantee their suitability for the goals of the study. Following all required ethical standards, the researchers secured approval from the appropriate institutional review boards and ensured that participants provided informed consent. The following week was dedicated to conducting initial training sessions for the raters, emphasizing the employment of a standardized rubric to guarantee impartiality in the evaluations. The AI-driven learning platform and LMS were thoroughly evaluated and prepared to guarantee their full operational capacity and ability to meet the requirements of the study.

Baseline Assessment and Group Allocation (Week 3)

During the 3rd week, participants underwent a pretest fluency assessment, which served as a means of establishing a baseline measurement of their initial abilities. The information gathered from these assessments was then carefully analyzed to create a baseline reference point for evaluating the results of the study. At the completion of the 3rd week, the subjects were assigned to the control or experimental groups based on purposive sampling, following the established criteria. This allocation was undertaken to ensure both groups accurately reflected the broader participant pool, thereby enhancing the validity of the findings.

Intervention Phase (Weeks 4-7)

At the beginning of weeks 4 to 7, the experimental group initiated the use of personalized AI-based learning materials. The control group was provided with instructor-created online modules. The interactions of participants with both types of learning materials were observed and recorded, supplying information on their levels of engagement and usage patterns.

Delivery (Week 8)

The distribution of educational resources was determined during the 8th week. Subsequently, participants were asked to share during feedback sessions their thoughts and feelings regarding the resources they had used. Data gathered from the feedback sessions aimed to complement the quantitative data gathered in this study.

Post-Intervention Assessment (Week 9)

At the beginning of the 9th week, assessments of posttest fluency were conducted with all participants. These assessments were designed to replicate the pretests, thereby ensuring data compatibility. After the assessments were completed, all data were stored safely for subsequent analysis.

Data Analysis and Reporting (Weeks 10–12)

During weeks 10 and 11, the researchers conducted an inferential statistical analysis of the pre- and posttest data. This analysis was critical for determining any statistically significant changes in the participants' fluency resulting from the intervention. Moreover, the researchers analysed qualitative feedback to interpret the participants' subjective experiences and the perceived impact of the intervention. The study was completed and finalized. This report integrates the results of both quantitative and qualitative analyses and provides a comprehensive overview of the study's outcomes. Additionally, the research team prepared for the dissemination of these findings by selecting appropriate platforms and formats for sharing results with the academic community and other relevant stakeholders.

Data Analysis

The analysis focused on the measures of overall effectiveness, correctness, and fluency and organization. Furthermore, the analysis aimed to determine any differences in learning outcomes, particularly in the area of organization, between the experimental and control group. The quantitative methodology employed in this study was essential for achieving primary research objectives and gaining a comprehensive understanding of the effectiveness of AI-enhanced learning approaches in a distributed educational context. Significant insights were obtained regarding the unique contributions of personalized learning tools to the development of key communication competencies through the use of inferential statistical methods.

A two-way analysis of variance (ANOVA) with repeated measures was deemed suitable because it allowed for the analysis of changes in the same subjects over two points in time, providing insights into both intra- and inter-group effects. To identify which sets of means differed significantly from one another, a post hoc analysis technique known as Tukey's Honestly Significant Difference (HSD) test was employed. This post hoc analysis was crucial for providing a more detailed understanding of the impact of educational interventions on various parameters of persuasive communication skills. The use of Tukey's HSD test in conjunction with other statistical methods resulted in a more comprehensive analysis. Table 3 presents the results of the inferential statistics. A discussion of each parameter follows.

Table 3

Descriptive Statistics and Effect Sizes for Key Study Variables

Parameter	Group	Pretest *M* (*SD*)	Posttest *M* (*SD*)	*p*	η^2
Fluency	Control	5.2 (0.8)	5.6 (0.9)	< .05	0.08
	Experimental	5.3 (0.9)	6.4 (0.7)	< .05	0.08
Accuracy	Control	4.9 (1.0)	5.2 (1.1)	< .05	0.07
	Experimental	5.0 (0.9)	6.2 (0.8)	< .05	0.07
Overall effectiveness	Control	6.1 (1.1)	6.5 (1.2)	< .05	0.09
	Experimental	6.2 (1.2)	7.5 (1.0)	< .05	0.09
Organization	Control	5.8 (0.7)	6.0 (0.8)	> .05	0.02
	Experimental	5.9 (0.6)	6.1 (0.7)	> .05	0.02

Fluency

The experimental group demonstrated considerable improvement in fluency, showing a statistically significant rise from pre-test to post-test, while the control group exhibited a smaller yet significant improvement. Thus, the experimental group, which was exposed to the AI-based learning approach, exhibited greater enhancement in fluency than the control group.

Accuracy

The accuracy parameter exhibited a similar trend. The average posttest score of the experimental group was 6.2 (*SD* = 0.8), which was a notable improvement from the pretest score of 5.0 (*SD* = 0.9). This improvement was statistically significant ($p < .05$) with an effect size of 0.07. The control group achieved a score of 5.2 (*SD* = 1.1) in the posttest, increasing from 4.9 (*SD* = 1.0) in the pretest. However, this improvement was less significant. These findings suggest that AI-based personalized learning materials are more effective than traditional methods in enhancing the accuracy of persuasive communication skills.

Overall Effectiveness

In terms of overall effectiveness, the experimental group achieved considerable improvement, with scores increasing from 6.2 (*SD* = 1.2) in the pretest to 7.5 (*SD* = 1.0) in the posttest. A modest effect size of 0.09 was associated with this improvement, which was statistically significant ($p < .05$). With scores rising from 6.1 (*SD* = 1.1) to 6.5 (*SD* = 1.2), the control group likewise showed improvement, but to a lesser degree. These results provide evidence that the AI-based learning method is more successful in improving overall persuasive communication abilities. When compared to the control group, the experimental group performed far better in terms of fluency, accuracy, and overall efficacy. Small effect sizes and *p* values below .05 support these enhancements.

Organization

In terms of the organization parameter, there were no clear variations between the two datasets. Both groups demonstrated marginal enhancement, with the experimental group improving from a mean score of 5.9 to 6.1 and the control group from 5.8 to 6.0. The *p* values were higher than .05, and there was a small effect size. This lack of disparity between the two groups may be attributed to several factors. First, the nature of the content and instructional methods in both learning approaches may have been sufficiently similar to address the organizational aspects of communication, leaving little scope for AI-based personalization to exhibit a distinct advantage. Second, the inherent limitations of the study design, such as the duration of the intervention or the scope of the curriculum, may have affected the potential to observe significant differences in this particular area.

After a two-way ANOVA showed significant interactions, Tukey's HSD test was used for post hoc comparisons to determine which group means were different. When comparing the pre- and posttest scores of the experimental group, it was clear they had made considerable gains in fluency, accuracy, and overall effectiveness. According to Tukey's HSD test, the control group had a posttest mean score of 5.6, whereas the experimental group had a considerably higher mean score of 6.4. The mean difference between the two groups was 0.8, and the *p*-value was $< .05$. Similarly, the results showed a significant difference of 1.0 in mean accuracy between the experimental ($M = 6.2$) and control ($M = 5.2$) groups, with a *p*-value less than 0.05.. In terms of organization, however, Tukey's HSD did not show any significant changes between the groups when comparing the pre- and posttest scores; both groups had similar results (6.1 for the experimental group and 6.0 for the control group; $p > .05$).

The study results related to the first research hypothesis revealed that incorporating AI into personalized language learning significantly enhanced the persuasive communication skills of online MBA students. This was demonstrated through posttest improvements, wherein the experimental group exhibited a substantial improvement in fluency, accuracy, and overall effectiveness in their communication skills compared to the control group. These findings align with the current literature, which suggests that AI-based personalized learning environments can address learners' individual needs more effectively, leading to improved language proficiency outcomes.

Regarding the second research hypothesis, the majority of the assessed parameters showed that AI-driven personalized learning had a beneficial impact on specific student learning outcomes. However, it failed to produce a significant effect on the organization aspect of persuasive communication skills. Both the control group and experimental group's posttest mean increased only slightly. These findings suggest that while AI personalization may significantly enhance certain aspects of language learning, its influence on organizational skills is negligible, and it may require additional instructional strategies or support. Future research could benefit from a hybrid approach that integrates AI personalization with conventional methodologies to improve all aspects of persuasive communication more comprehensively.

Discussion

Interpretation of Results

In this study, the results were interpreted within the context of existing literature and theoretical frameworks on AI in education and language learning. The improvements in fluency, accuracy, and overall effectiveness among participants in the experimental group corroborate prior research, which has posited that AI-based personalized learning significantly enhanced language acquisition (Liu et al., 2021). These findings align with the theoretical framework, suggesting that AI-driven personalization effectively caters to individual learning styles and needs.

Alignment With Previous Studies

Consistent with earlier studies showing that AI could improve certain language skills, we found that both fluency and accuracy improved during our investigation (Crawford et al., 2023). This consistency suggests that AI tools are particularly adept at identifying and addressing language problems. However, the lack of a significant difference found in the organization parameter contrasts with some literature indicating that AI-based tools could also improve structural aspects of language learning (Long & McLaren, 2024). This discrepancy may have been the result of the specific AI tools used or the duration of the intervention.

Practical Implications

The findings of this study have significant implications for online MBA programs. The integration of AI-based personalized learning tools can significantly enhance students' communication skills. Adaptive algorithms capable of effectively targeting specific language skills are crucial for achieving this goal. However, it also points to the need for further research to develop tools that can enhance the organization aspects of language learning. While AI-based tools significantly enhance learning outcomes, they should be integrated as part of a comprehensive educational strategy that includes traditional methods, especially in aspects where AI tools might not have a distinct advantage. This study adds to the expanding literature on the use of AI in classrooms and offers empirical evidence that personalized learning powered by AI is effective.

Limitations and Future Research

Several constraints that may have influenced the results of this study were identified. First, the small sample size of 64 participants was a limitation that could restrict the generalizability of the conclusions. Future studies with larger sample sizes may yield more robust data with broader applicability. Additionally, the AI algorithm used in the learning materials of the experimental group was designed specifically for this study, which raises questions regarding its replicability in different educational settings or subject areas. Furthermore, the homogeneity of the student population, comprising part-time MBA students from a private university in India, who were all non-native English speakers, might limit the generalizability of the findings.

To further understand the possibilities and constraints of AI in education, future studies should investigate a range of AI-based tools and algorithms in different educational contexts and subject types. Research could also be expanded to examine other aspects of communication, such as emotional intelligence, critical thinking, and argumentation. The results of this study highlight how personalized learning materials powered by AI can improve persuasive communication; however, these constraints underscore the necessity for additional studies to enhance and expand our comprehension of AI's function in educational settings.

Conclusion

The findings from this study contribute to the expanding body of research on the use of AI in education, particularly in online MBA programs and language acquisition. Participants in the experimental group who interacted with personalized AI-based learning materials showed significant improvements in fluency, accuracy, and overall effectiveness. These results indicate that AI-driven tools can enhance communication skills, supporting the findings of Jadhav et al. (2023) regarding the effectiveness of AI in tailored education.

The implications of this study for distance education theory are significant as they demonstrate how AI can personalize learning experiences to effectively meet individual needs. This study highlights the necessity for further investigation into AI's capabilities and limitations in various educational contexts and with different student populations. In practice, integrating AI-based tools into distance education can enhance learning outcomes; however, it is essential to complement these tools with traditional methods to address language learning comprehensively. Future research should explore the limitations of this study, including the sample size and specificity of the AI system. Expanding research to include diverse student populations and educational settings, as proposed by Suen et al. (2020), and investigating a broader spectrum of AI tools will provide deeper insights into the diverse applications of AI in education.

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The Impact of a Learning Analytics Based Feedback System on Students' Academic Achievement and Self-Regulated Learning in a Flipped Classroom

Emine Cabı[1] and Hacer Türkoğlu[2]

[1]Department of Computer and Instructional Technologies Education, Faculty of Education, Başkent University, Ankara, Türkiye; [2]Department of Mathematics and Science Education, Faculty of Education, Başkent University, Ankara, Türkiye

Abstract

Recent advancements in educational technology have enabled teachers to use learning analytics (LA) and flipped classrooms. The present study investigated the impact of a LA-based feedback system on students' academic achievement and self-regulated learning (SRL) in a flipped learning (FL) environment. The study used a pretest-posttest control group quasi-experimental design with 71 pre-service teachers in the experimental group and 56 pre-service teachers in the control group, both enrolled in an information technology course. The experimental group received LA-based feedback during a 4-week training program in the FL classroom, while the control group did not receive this feedback. Data were collected using an achievement test, an online SRL questionnaire, and a student opinion form. The study found that the students' SRL and academic achievement were not significantly affected by the LA-based feedback system in FL classrooms. In contrast, according to the qualitative research findings, students claimed the LA-based feedback helped them learn because it allowed them to monitor their learning processes.

Keywords: learning analytics, flipped learning, academic achievement, experimental design, self-regulation

Introduction

Learning Analytics and Personalised Feedback

In online learning environments, students' interactions are typically recorded and stored, generating digital traces known as log data. This data can be mined and analyzed to uncover learning behavior patterns, offering valuable insights into educational practices. This approach is referred to as learning analytics (LA). According to Siemens and Gašević (2012), learning analytics involves the measurement, collection, analysis, and reporting of data about learners and their contexts, aimed at understanding and optimizing both learning and the environments where it takes place. Due to its potential to enhance teaching and learning outcomes, LA has drawn a lot of interest from academics and practitioners (Kovanovic et al., 2021; Šereš et al., 2022). To better understand and support the learning process, there has been an increasing emphasis on analysing students' online learning data (Kew & Tasir, 2021; Wong et al., 2022). Since it is still in its early stages of development, LA offers a promising method for comprehending, optimising, and enhancing the learning process (Klašnja-Milićević et al., 2020).

Using data gathered by educational tools and platforms, LA is used to make possible data-driven decisions to enhance student learning (Kovanovic et al., 2021). One of the main objectives of LA practice is to create learning experiences, such as offering personalised feedback, giving advice, and providing learning resources to meet students' needs (Wong et al., 2022). Various features are offered by these systems, including learning suggestions, visualisations, reminders, grading, and self-assessment options (Klašnja-Milićević et al., 2020). LA empowers educators to monitor each student's learning obstacles and the development of their success, while offering customised feedback based on individual progress (Karaoglan Yilmaz & Yilmaz, 2020). As a result, LA has become increasingly prevalent in the production of proactive feedback in online or blended learning environments (Lu et al., 2017; Pardo et al., 2019; Sedrakyan et al., 2020; Uzir et al., 2020).

Personalised digital learning systems enable teachers to tailor their instruction to students' individual needs and learner characteristics (Hwang et al., 2020). Feedback plays a critical role in personalised learning scenarios. Scholars argue that adaptive and personalised feedback has the potential to raise student academic achievement (Ustun et al., 2022), reflect students' developmental and motivational needs (Koenka & Anderman, 2019), and empower them for self-regulated learning (SRL; Ouyang & Jiao, 2021; Ustun et al., 2022).

LA in Flipped Learning

Flipped learning (FL) is a student-centered approach where teachers' lectures are moved to pre-class time, allowing for more in-class practice and discussion to enhance students' deep learning and address their learning challenges (Bergmann & Sams, 2012). The most comprehensive definition comes from the Flipped Learning Network (2014):

> Flipped learning is a pedagogical approach in which direct instruction moves from the group learning space to the individual learning space, and the resulting group space is transformed into a dynamic, interactive learning environment where the educator guides students as they apply concepts and engage creatively in the subject matter ("What is flipped learning?" section).

In FL environments, learners are accountable for their own learning and are able to customise it to fit their needs in terms of time, level, and pace (O'Flaherty & Phillips, 2015; Staker & Horn, 2012). Because the FL model requires learners to prepare for class by studying particular topics outside of the classroom, success can be explained in part by frequent and regular access to course materials and outside content and how students navigate between materials or content of the classroom (Davies et al., 2021; Montgomery et al., 2019). Identification of the factors influencing students' academic achievement is one of the ways LA is used in the FL model (Algayres & Triantafyllou, 2020; Lin & Hwang, 2018). However, LA makes it simpler to identify students at risk (Bayazit et al., 2022). Design of FL environments frequently incorporates LA to reveal students' learning styles (Dooley & Makasis, 2020; Jovanović et al., 2017; Lin & Hwang, 2018; Rubio-Fernández et al., 2019; Silva, et al., 2018).

SRL, LA, and FL

According to Pintrich (2000), SRL is a proactive and beneficial process in which students actively set their learning objectives, make an effort to manage, regulate, and check on their cognition, motivation, and behaviour, and are constrained by their objectives and the contextual elements of their environment.

The link between SRL, improved performance, and desirable learning outcomes has been established (Schunk & Greene, 2017). It has been hypothesised that guiding students (Zimmermann, 2002) who acquire their metacognitive, motivational, and behavioural attitudes independently to plan, oversee, and assess their own learning procedures can promote the use of SRL strategies and thereby enhance learning outcomes (Guo, 2022).

SRL is particularly important in the FL because students need to be actively prepared before coming to class in order to benefit from face-to-face activities (Omarchevska et al., 2024). Learners can develop strategies to improve their SRL and academic achievement in FL (Silva et al., 2018; Ustun et al., 2022). LA is also critical to measuring SRL skills by tracking and archiving students' strategies (You, 2015). It enables instructors to understand how students interact with learning tasks, tools, and materials in their academic endeavours (Tempelaar et al., 2024). More specifically, as Gašević et al. (2016) pointed out, LA enables instructors to identify the topics students struggle with and provide personalized instructions or process-oriented feedback accordingly. Therefore, LA has great potential to directly impact students' SRL and academic achievement.

Participating in out-of-class activities to prepare for in-class activities in flipped classrooms is a challenging aspect of this model and is associated with students' low self-regulation (Akçayır & Akçayır, 2018). Additionally, students complain about not receiving enough feedback out-of-class in the FL model (Birgili & Demir, 2022). Given the difficulty of participating in out-of-class activities in FL, students' interaction behaviors can be assessed through LA obtained from the learning management system (LMS; Yang et al., 2021). Learning analytics dashboards (LAD) are successful in giving students feedback, but sometimes the complexity of LAD designs may be overwhelming for students (Ramaswami et al., 2023). Therefore, LA-based personalized feedback can be provided out-of-class in FL, and these factors constitute the rationale for this study.

Studies on the impact of LA on student achievement and SRL in the online learning environment have been conducted in this context (Çebi & Güyer, 2020; Kim et al., 2018; Li & Tsai, 2017; Lim et al., 2023). However, very few empirical studies (Silva et al., 2018) as well as subsequent evaluations of student achievement (Ustun et al., 2022) have investigated the impact of LA on students' SRL. On the other hand, there is little proof that the claimed potential for improving learning practices has been successfully transferred to higher education practice, despite the fact that many studies on LA highlight this potential (Šereš et al., 2022).

Based on the limited literature, we decided to investigate the impact of a flipped learning based learning analytics (FLLA) feedback system on students' SRL and academic achievement.

There were three research questions:

1. Are there significant differences between students in a traditional FL environment and those supported with FLLA-based feedback in terms of their academic achievement?

2. Are there significant differences between students in a traditional FL environment and those supported with FLLA-based feedback in terms of their SRL?

3. What are the pre-service teachers' perspectives on the FLLA-based feedback?

Methodology

Design of the Study

The research followed a quasi-experimental design. With quasi-experimental designs, a popular approach to quasi-experiments, an experimental group and a control group are selected without random assignment. Both groups take a pretest, the experimental group receives a treatment, and then both groups take a posttest (Creswell, 2009).

In our study, it was examined whether there was a difference between the experimental and control groups determined by selection without random assignment. While the students in the control group received traditional FL training, the students in the experimental group received FLLA-based feedback. Before and after the 4-week training, pretests and posttests were administered to measure the academic achievement and SRL of the students. The academic achievement test was developed for this specific study, and the Online Self-Regulated Learning Questionnaire (OSLQ) was used to measure students' SRL. The OLSQ was developed by Lan et al (2004), then shortened by Barnard et al (2008) and adapted into Turkish by Kilis and Yıldırım (2018). The validity and reliability of these data collection tools were tested, and both tools were accepted as valid and reliable. Table 1 shows the study design.

Table 1

Design of the Research Model

Group	Assignment	Pretest	Treatment	Posttest
Experimental	R	Achievement test OSLQ	FLLA-based feedback	Achievement test OSLQ Student opinion form
Control	R	Achievement test	FL	Achievement test

OSLQ	OSLQ

Note. R = unbiased assignment; OSLQ = Online Self-Regulated Learning Questionnaire; FLLA = flipped learning-based learning analytics; FL = flipped learning.

Content and the Procedure

The necessary learning environments for the experimental and control groups were created to conduct the training. A total of 3 hours of instruction were given in the FL environment to both groups, including 1 hour of face-to-face instruction and 2 hours of online instruction. Before the experimental process began, students in both groups received training on how to use the LMS (Moodle) and the FL model, and guidance on the roles and responsibilities in this model. Table 2 provides a general description of the activities in this FL environment.

Table 2

Weekly Activities in the FL Environment

Week	Topic	Activities	
		At home	In class
1	Introduction Pretest		Readiness training OSLQ Achievement test
2	What is Microsoft Excel? Table data entry—Formatting	Weeks 2–5: Documents (pdf) Microsoft Excel Videos	Weeks 2–5: Quizzes Kahoot games In-class applications
3	Data formatting Adding a chart		
4	Formula usage Functions		
5	Formulas functions Grade calculation		
6	Posttest		OSLQ Achievement test Student opinion form

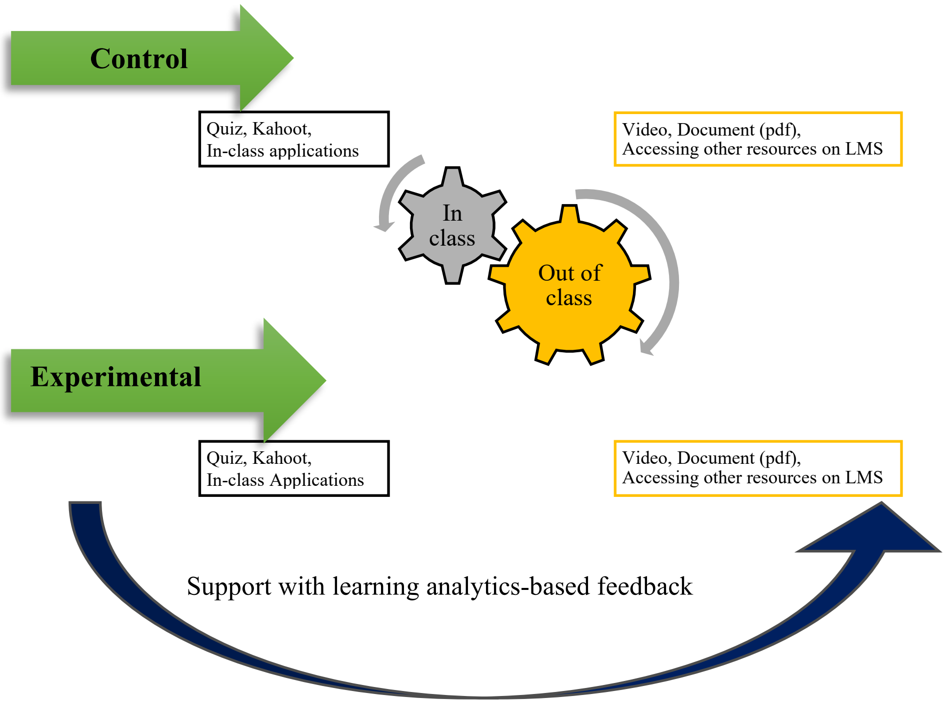
Note. OSLQ = Online Self-Regulated Learning Questionnaire.

The various learning activities shown in Table 2 (resource document, video, quiz, classroom practice) were created within the parameters of the study.

For the experimental group trained with FL, an instructional design based on LA was created. Learners were supported with LA feedback. Figure 1 shows an overview of the learning activities of the experimental and control groups.

Figure 1

Features of the Learning Environments for the Experimental and Control Groups

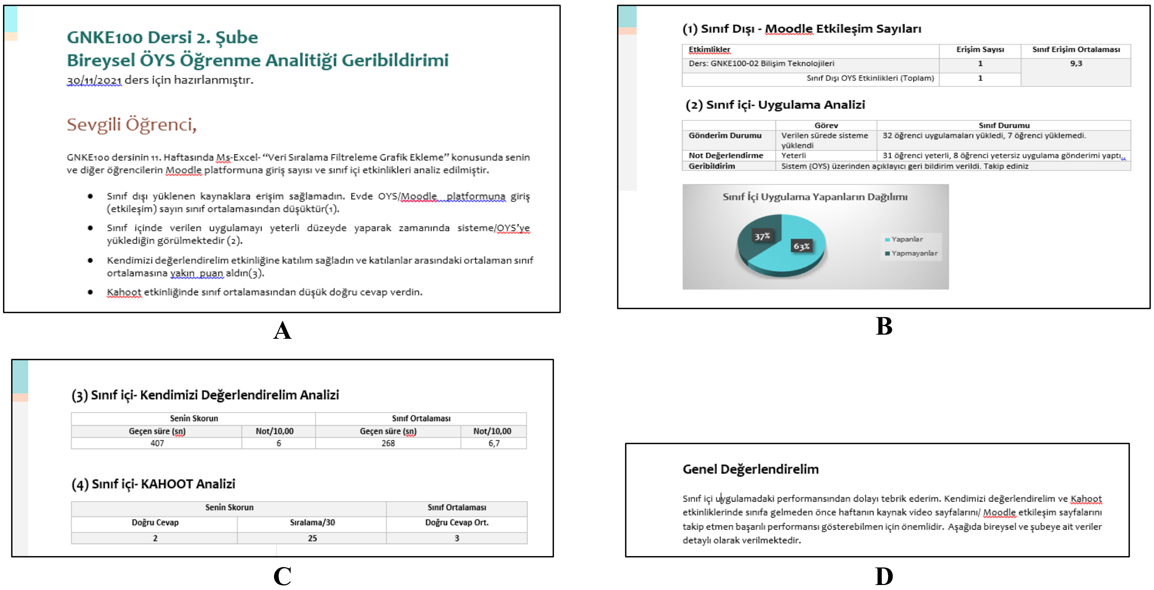


Support/Intervention Strategies With LA Feedback

Providing one-to-one advice in LA practice (in areas such as learning paths, resources, feedback, and workspaces) gives learners control of their learning processes and progress (Wong et al., 2022). The necessity of including individualised feedback in LA is consistently suggested and used in research (Guo, 2022; Ustun et al., 2022). In this study, the instructors monitored the participation status of each student in the experimental group and sent an Individual Learning Analytics Feedback Report by e-mail at the end of each week. They also directed students to look at their e-mail messages in class time to review the reports. Examples from some of the feedback reports, in the original Turkish language, are shown in Figure 2.

Figure 2

Samples of the Individual Learning Analytics Feedback Report



Note. Panel A: Analysis of the students' individual data of general performance and engagement. Panel B: Analysis of LMS/Moodle interaction and in-class applications (Microsoft Excel). Panel C: Analysis of in-class activities (Quiz and Kahoot). Panel D: Personalised textual feedback based on recent performance and engagement. All feedback was given in Turkish. Data shown in the panels is anonymous.

The Individual Learning Analytics Feedback Reports featured analysis of student performance and engagement with Kahoot, in-class practice, quizzes, Moodle interaction numbers and times, and general evaluation. There were three types of feedback:

1. Statistical feedback from an analysis of the student's individual data of performance and engagement.

2. Feedback based on descriptive statistics and graphs from analysis of individual and class data to facilitate students' understanding and help them compare their online activities with those of their classmates.

3. Textual feedback including sending each student a personalised message to assess their recent performance.

Both the individual student performance and the class averages were included in the weekly report. Individual and class averages were shown in the report to encourage students at risk of failure or dropping out to work harder and perform better.

Participants

The 127 participants of the study were undergraduate students who took the Information Technologies course in the fall semester of the 2021–2022 academic year at a foundation university in Ankara, Turkey. All students participating in the research were pre-service teachers—first-year students in the

Faculty of Education. Initially, there were 130 participants, but three were excluded because they did not participate in the survey and process evaluation. There were 56 participants (52 females and four males) in the control group and 71 students (61 females and 10 males) in the experimental group.

Data Collection Tools

LMS Interaction Analytics

Students in the experimental group received the Individual Learning Analytics Feedback Report for 4 weeks. Data were obtained from the LMS (Moodle) and analysed. Each student's frequency of course access, course sources, and activities (videos, documents, and Microsoft Excel worksheets) for out-of-class interaction behaviours were examined. As for interaction behaviours during face-to-face instruction, in-class applications (score and completion status), a mini-exam (score and completion time), and a Kahoot activity score were examined. Class averages of these interaction behaviours were also calculated.

Achievement Test

A suitable number of questions was chosen for the achievement test items based on the time allocated for each topic during the course, and 35 multiple-choice questions were also created. A measurement and evaluation expert as well as three subject-matter specialists evaluated these questions to ensure content validity (Sireci & Faulkner-Bond, 2014). According to the experts, some changes and revisions were necessary. Three items were rephrased, and five items were eliminated. Additionally, in accordance with the feedback offered by the measurement and evaluation expert, items testing the same subject were grouped together and listed in a linear fashion.

In the end, separate from the study groups, an achievement test consisting of 30 multiple-choice questions was administered to 83 students enrolled in the Information Technologies course, and item analysis was performed. The student scores were ranked from high to low for the item analysis. Two student groups were identified: the 27% lower group and the 27% upper group, based on score rankings. The necessary formulas were used to determine the item difficulty and discrimination indices of the questions according to these lower and upper groups. The analysis led to the creation of a test with 30 items and a difficulty index ranging from 0.34 to 0.98. The discrimination index of the items varied between 0.29 and 0.84. One item, which had the lowest discrimination index (0.29), was added to the test after correction. The Kuder-Richardson Formula 20 (*KR20*) was applied to measure the internal reliability of the test, and the reliability coefficient was found to be 0.76. As this was within the acceptable ranges (Kline, 2013), the test was deemed to have sufficient internal reliability. The test was administered to the students as a pretest before the intervention and as a posttest after the intervention.

Online Self-Regulated Learning Questionnaire (OSLQ)

The OSLQ was used to gather data on learners' perceptions of SRL in the online learning environment. Lan et al. (2004) originally created the OLSQ, which Barnard et al. (2008) later condensed to 24 Likert-type items. The questionnaire was adapted into Turkish by Kilis and Yıldırım (2018) and validated with data from 321 students. Internal consistency coefficients calculated for the scale's reliability, as shown by Cronbach's alpha coefficients, ranged from .67 to .87, and .95 for the entire scale. Goal-setting, environment structuring, task strategies, time management, help-seeking, and self-evaluation are the six subdimensions of the 5-point Likert-type scale.

In this study, the OSLQ factor structure was tested with confirmatory factor analysis (CFA) by administering it to 130 students. Fit indices were computed for the construct validity factor analysis and the six-factor model, which are the same as the original scale. The chi-square value, which is accepted as the initial fit index, was examined first and found to be significant (χ^2 = 448.31, *SD* = 237, *p* = .00). The χ^2/*SD* ratio was 1.89, normed fit index (NFI) = 0.92, non-normed fit index (NNFI) = 0.95, comparative fit index (CFI) = 0.78, goodness-of-fit index (GFI) = 0.78, adjusted goodness-of-fit-index (AGFI) = 0.72, standardised root mean square residual index (SRMS) = 0.07, root mean square error of approximation (RMSEA) = 0.05. Based on the fit indices, it was determined that the observed values were mostly within acceptable value ranges (Schermelleh-Engel et al., 2003). The GFI ranges from zero to one and is affected by sample size, with larger samples yielding more appropriate values (Schumacker & Lomax, 2004). The factor loadings of the items were investigated using the scale's path diagram. The factor weights of the items were found to range from 0.35 (item 20) to 0.83 (item 18).

Student Opinion Form

After the experimental research process, student opinions were collected from the experimental group. Depending on the nature of the response, a semi-structured interview form was employed to gather additional data. Regarding the effectiveness of the weekly feedback reports, opinions and suggestions were solicited via the interview form. Sample questions asked were: How did the FLLA-based feedback contribute to your learning? Were there any disadvantages? A total of 56 pre-service teachers in the experimental group answered these questions.

Data Analysis

In this study, cluster sampling was used within the scope of probability sampling. First of all, the population was divided into clusters. The clusters were selected randomly using simple random sampling techniques to form experimental and control groups as per Alvi (2016). To ascertain whether there was a significant difference between the groups in terms of academic achievement and the SRL subdimensions pretest scores, an independent sample *t*-test was conducted.

Table 3

Independent Samples t*-Test Results of Achievement and SRL PreTest Scores of Experimental and Control Groups*

Scale	Group	$\bar{x}$	*s*	*SD*	*t*	*p*
Academic achievement	Experimental	14.22	3.81	125	-1.21	.23
	Control	13.21	4.99			
Goal setting	Experimental	3.84	0.59	125	0.50	.62
	Control	3.89	0.54			
Environment structuring	Experimental	4.30	0.55	125	0.73	.46
	Control	4.37	0.54			
Task strategies	Experimental	3.51	0.72	125	-0.56	.57
	Control	3.44	0.65			

Time management	Experimental	3.44	0.80	125	0.25	.80
	Control	3.47	0.69			
Help-seeking	Experimental	3.86	0.60	125	-0.73	.47
	Control	3.78	0.73			
Self-evaluation	Experimental	3.75	0.65	125	-0.13	.90
	Control	3.73	0.60			

Note. Experimental group n = 71. Control group n = 56.

Table 3 shows that the differences in the achievement and attitude scale pretest mean scores of the experimental and control groups were not significant at the level of .05. This result indicates that both groups could take part in the experiment.

A descriptive analysis of the distribution of the pretest and posttest results of the research's dependent variable, according to group, was carried out prior to choosing the analyses that would be carried out. In this study, the normality of the data was assessed using skewness and kurtosis coefficients as well as graphical evaluations. According to George and Mallery (2019), a normal distribution is defined as having kurtosis and skewness values between -2 and +2. The covariance analysis (ANCOVA) was used to assess the significance of the difference in posttest scores between the groups. Experimental studies frequently employ a one-way analysis of covariance, in which pretest results are controlled as a covariate (Büyüköztürk, 2021). Before performing the ANCOVA, it was verified that the variance of the dependent variable across all groups was equal, that the covariate had a linear relationship with the dependent variable across all groups, and that the slopes of the regression curves across all groups were equal in terms of the dependent variable's prediction based on the covariance.

The academic achievement variables' pretest and posttest skewness values ranged between -0.69 and -0.33 (SE= 0.21), respectively, and their kurtosis values ranged between 0.38 and 1.10 (SE = 0.42). Examining the ANCOVA assumptions revealed that the variances of the posttest scores from Levene's Test were equal (F = 0.529, p = .468), and the scatter plot displayed linear relationships. Additionally, there was no difference in the slopes of the regression curves used to predict academic achievement posttest results based on academic achievement pretest results according to group (F = 0.218, p = .641).

Skewness and kurtosis were visually evaluated for the OSLQ subdimensions of goal setting, environment structuring, task strategies, time management, help-seeking, and self-evaluation. Data from three participants that fell into the extreme ranges, based on the z-score results, were deleted. The skewness values of subdimensions in the pretest and posttest varied between -0.79 and 0.15 (SE = 0.21), respectively, and their kurtosis values ranged from between 0.26 and 2.00 (SE = 0.42). All scale subdimensions' presumptions were tested prior to ANCOVA. The posttest scores of the six subdimensions of the OSLQ produced equal variances from Levene's Test. Respectively, these values were: F = 1.074, p = .302; F = 0.945, p = .333; F = 0.921, p = .339; F = 1.075, p = .302; F = 2.866, p = .093; and F = 0.556, p = .457. The scatter plot revealed linear relationships. In addition, the slopes of the regression curves used to predict posttest academic achievement results based on pretest academic achievement scores according to group were equal. For each subdimension respectively, the values were: F = 0.439, p = .509; F = 2.133, p = .147; F = 0.973, p = .326; F = 0.073, p = .787; F = 0.737, p =

.392; and F = 0.023, p = .879. These analyses revealed that the subdimensions of the academic achievement test and the online SRL scale met the ANCOVA assumptions.

Results

Findings Related to Academic Achievement

When determining whether there was a difference between the academic achievement posttest scores of the groups to which various teaching strategies were applied, an ANCOVA was carried out. The academic achievement pretest scores, which have an impact on the posttests, were used as a covariate, and so, first, the corrected means of the posttest scores were calculated. The academic achievement posttest scores of the experimental group were found to be slightly higher than those of the control group. Results are shown in Table 4.

Table 4

Corrected Means of Academic Achievement Posttest Scores

Group	n	$\bar{x}$	Corrected $\bar{x}$
Experimental	71	22.96	22.90
Control	56	22.04	22.11

Table 5 provides the findings of the ANCOVA of the posttest scores. The academic achievement posttest scores of the students in the experimental and control groups did not differ significantly when the effect of the academic achievement pretest scores was controlled (F = 2.229, p = .138).

Table 5

Results of ANCOVA on Academic Achievement Posttest Scores

Source	*SS*	*df*	*MS*	*F*	*p*
Pretest	50.47	1	50.47	5.90	.017
Group	19.06	1	19.06	2.23	.138
Error	1,060.34	124	8.55		
Total	65,724.00	127			

Note. ANCOVA = analysis of covariance.

Findings Related to SRL

To control the effect of the pretest scores of the subdimensions of SRL, the corrected means of the posttest scores were calculated, and these are given in Table 6. The posttest scores for the experimental group's self-regulation subdimensions, with the exception of time management, were similar to those of the control group when the corrected means were taken into consideration. The corrected mean scores of the experimental group for time management ($\bar{x}$ = 3.75) and help seeking ($\bar{x}$ = 4.02) were higher than the control group scores for the same variables ($\bar{x}$ = 3.65; $\bar{x}$ = 3.91, respectively).

Table 6

Corrected Means of SRL Posttest Scores

Factor	Group	$\bar{x}$	Corrected $\bar{x}$
Goal setting	Experimental	4.00	4.01
	Control	4.04	4.03
Environment structuring	Experimental	4.21	4.23
	Control	4.30	4.28
Task strategies	Experimental	3.69	3.68
	Control	3.67	3.69
Time management	Experimental	3.74	3.75
	Control	3.66	3.65
Help-seeking	Experimental	4.04	4.02
	Control	3.89	3.91
Self-evaluation	Experimental	3.94	3.94
	Control	3.99	3.99

Note. Experimental group n = 71. Control group n = 56.

The SRL subdimensions of the corrected posttest mean scores for the experimental and control groups were compared using ANCOVA to determine whether there was a statistically significant difference. The analysis showed that there was no statistically significant difference between the experimental and control groups. Table 7 presents these findings.

Table 7

Results of ANCOVA on SRL Posttest Scores

Source	*SS*	*df*	*MS*	*F*	*p*
Goal setting					
Pretest	45236.00	1	45236.00	22947.00	.000
Group	0.01	1	0.01	0.03	.863
Error	33018.00	124	0.27		
Total	2087.2	127			
Environment structuring					
Pretest	9988.00	1	9988.00	32438.00	.000
Group	0.01	1	0.09	0.31	.579
Error	38182.00	124	0.31		
Total	2344.50	127			

Task strategies					
Pretest	10542.00	1	10542	24.26	.000
Group	0.06	1	0.06	0.01	.911
Error	53881.00	124	0.44		
Total	1787188.00	127			
Time management					
Pretest	8495.00	1	8495.00	17667.00	.000
Group	0.27	1	0.27	0.56	.454
Error	59623.00	124	0.48		
Total	1812954.00	127			
Help-seeking					
Pretest	8554.00	1	8554.00	23014.00	.000
Group	0.365	1	0.37	0.98	.324
Error	46.09	124	0.37		
Total	2059375.00	127			
Self-evaluation					
Pretest	4784.00	1	4784.00	12934.00	.000
Group	0.08	1	0.08	0.23	.634
Error	45861.00	124	0.37		
Total	2046875.00	127			

Student Perception of FLLA-Based Interventions

The opinions of the students in the experimental group were collected following the implementation of FLLA, and the opinions were then divided by content analysis into two themes: positive and negative. Table 8 lists the categories, some sample statements, and their frequency for students' positive perceptions.

Table 8

Frequency of Positive Views on the Impact of Weekly Feedback Reports

Category	Sample statement	*f*
Positive effects on learning	"It aided in identifying my knowledge gaps."	10
	"By identifying my knowledge gaps and creating a study plan, it assisted me in resolving this shortcoming."	8
	"It helped me learn better."	6
Contentedness	Satisfied (general expression: "good," "positive")	20
Providing motivation	Motivated (general expression: "motivated," "encouraged")	9
	"It encouraged me to study for the upcoming week."	4
	"I was motivated by realising my success and how well I performed compared to the rest of the class."	2

	"It inspired me to work harder and conduct more research."	1
	"It helped me to love the lesson. I began to like the lesson."	1
Raising awareness about improvement	"It gave me the opportunity to monitor my progress."	3
	"It made me aware of my improvement."	2

The FLLA-based feedback was generally deemed satisfactory by the students. Nevertheless, there were also negative remarks, though they were few in comparison to the positive ones. While two participants said, "I am upset to receive negative comments in the feedback," another said, "It doesn't have any disadvantages, but it is frustrating to see my performance decline week by week. However, the instructor knows that this should motivate us rather than annoy us." Only one student admitted, "I initially had trouble following the reports, but eventually I got used to it."

Discussion

The purpose of this study was to investigate how students' academic achievement and SRL are affected by a feedback system based on FLLA. Although the mean scores of the students in the experimental group were higher than those of the students in the control group, it was found that there was no statistically significant difference between them as has been the case in other studies (Kim et al, 2016; Park & Jo, 2015). However, contrary to these findings, some studies (Aguilar et al., 2021; Roberts et al., 2017; Ustun et al., 2021) have shown that students who have access to a LAD perform better academically than students who do not.

The mean scores of goal setting, environment structuring, task strategies, help-seeking, and self-evaluation on the SRL scale were approximately equal in the experimental and control groups. However, the experimental group's mean time management and help seeking scores were higher than the control group. . When the corrected posttest scores of the groups from the sub-dimensions of the SRL scale were examined, no significant difference was identified in the mean scores of the experimental group compared to the control group. This result demonstrates that a LA-based feedback system has no influence on students' SRL. In a related study Kim et al. (2016) stated that a LAD is interesting and impressive at first glance, but it is insufficient to motivate students to revisit it. However, Lu et al. (2017), Silva et al. (2018), and Lim et al. (2023) contended that using LA in FL can foster SRL by assisting students in identifying techniques that will boost their academic achievement.

The findings revealed that the students who did not receive FLLA-based feedback engaged in learning activity patterns similar to those of students who did, which may help to explain why the students in all groups achieved similar learning outcomes. There are some possible reasons why this should be the case.

For one, LA is directly related to student engagement in online courses and engagement is the most significant predictor of achievement in the FL (Polat et al., 2022). The fact that the frequency of students' access to course elements was close between the groups may explain the lack of a significant difference in their achievement. However, Doo and Park (2024) showed that one of the factors affecting success in the FL was time and space among the students' resource management strategies, and that resource access was not related to success.

Another reason could be that the experimental period of 4 weeks may not have been sufficient for the experimental process. Perhaps more significant results could be achieved if the training were provided for a longer period of time—for example, between 10 and 16 weeks (Fidan, 2023; Shen & Chang, 2023; Ustun et al., 2021). In fact, in similar studies, Pardo et al. (2019) conducted their experimental periods for 3 years. However, in the design of the FL, there is no clear distinction in how long a course should be in order for the FL structure to be effective. As a matter of fact, there are studies in which the effect on academic achievement in FL environments as short as 4 or 6 weeks has been shown to be positive (Karaca et al., 2024; Polat & Taslibeyaz, 2023).

Another factor that may have affected the results is student characteristics (Gašević et. al., 2016). According to Kim et al. (2016), instead of providing the same feedback to all students, grouping students in clusters based on their learning characteristics before the training and intervening afterwards would be more effective. As in other studies (Karaoglan Yilmaz, 2022; Ustun et al., 2021), while FLLA appears to increase learner motivation because it allows students to control their own learning processes, it may also raise students' stress levels by making them realise their failures (Ustun et al., 2021). Therefore, the frequency and timing of LA-based reports, along with guiding advice and suggestions, should be designed according to student preferences, as this positively affects student motivation and participation in the course (Sedrakyan et al., 2020; Wang & Han, 2021).

Conclusion

This study was conducted to determine the effect of FLLA-based feedback on academic performance and SRL. Within the scope of the study, the in-class and out-of-class participation of the students in the experimental group was monitored and weekly individual feedback reports with the LA statistics obtained from the LMS were sent to students. Although the average scores of the students in the experimental group were higher than the students in the control group, no significant difference was found in terms of academic achievement and SRL. This shows that the FLLA-based feedback system had no effect on students' achievement and SRL. In contrast, according to the qualitative research findings, students claimed the feedback helped them because it allowed them to monitor their own learning progress.

This study presents several limitations. First of all, the data only included information from one particular course at one university. Future research should be done to confirm that student subpopulations and learning patterns are valid in other contexts.

Many facets of LA may be represented by the interaction behaviours looked at in the individualised feedback report examined in this study. However, additional interaction behaviours could also be investigated, such as submitting homework, taking part in a live lesson, participating in a discussion, and answering questions.

Four weeks may not have been sufficient for the experimental process. Instead, if more training were provided, perhaps more accurate results could be attained. In future studies, the effect of variables related to both student-system interaction and where and when students access pre-class activities on achievement could be taken into consideration.

Finally, there were probably other variables to consider. The homogeneous assignment of students from various programmes to the experimental and control groups, the use of the same course materials and instructor, and the students' perspectives on the information technology course as controlling factors could all result in different interpretations. Importantly, in this study, the lecturers developed the personalised feedback reports manually via the LMS and in-class activities. Using software that could be integrated into the LMS or other learning platform that reports LA indicators and sends these automatically to students on a regular basis could allow for a more systematic process and the elimination of potential flaws that could be created in manually prepared reports.

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Analyzing Learning Sentiments on a MOOC Discussion Forum Through Epistemic Network Analysis

Jianhui Yu
School of Education, Zhejiang International Studies University, Xihu District, Hangzhou, 310023, China

Abstract

Sentiments expressed on massive open online course (MOOC) discussion forums significantly influence learning effectiveness and academic performance. The evolution of learning sentiments on MOOC discussion forums is a dynamic process; however, a gap exists in the current understanding of the interplay between evolving sentiments and their impact on MOOC efficacy. Consequently, to enhance MOOC effectiveness further empirical research is needed to uncover the underlying patterns and temporal dynamics of learning sentiments. This study collected online discussions from 158 MOOC participants and examined the discussions using epistemic network analysis to identify how learning sentiment patterns differed according to performance level and learning topics. The results showed that learning sentiment patterns were affected by both performance level and learning topics, with participants in the high-score group exhibiting stronger associations between engagement-neutral and neutral-frustration, and fewer connections between frustration-delight and frustration-boredom when compared to those in the low-score group. In addition, this study found that engagement was strongly linked to all learning topics in the high-score group, whereas for the low-score group, only engagement and experience showed strong connections. Based on these findings, we discuss the implications for learners and instructors in paving the way for the development of targeted interventions and instructional strategies tailored to optimize MOOC effectiveness.

Keywords: learning sentiments, epistemic network analysis, MOOC discussion forum, learning topics, MOOC effectiveness

Introduction

In recent years, Massive Open Online Courses (MOOCs) have gained popularity as an effective online learning model due to their customized services, real-time feedback and flexible learning. Notably, discussion forums in MOOCs can provide an interactive environment for students (Wei et al., 2024). Several studies have shown that MOOC forums generate a significant volume of discussion data containing comprehensive records of behaviors during the MOOC learning process, which provides an opportunity to explore more deeply the sentiment patterns on MOOC forums (Ye & Zhou, 2022).

There has been increased emphasis on exploring learning sentiments in online learning. Positive sentiments (e.g., flow, delight) may be modulators of high-quality interactions and knowledge construction, whereas negative sentiments (e.g., boredom, frustration) could detrimentally impact interactions during the learning process (Shao et al., 2023). Furthermore, current research has shown that learning sentiments differ based on the occasion (Harley et al., 2015) and topic (Tan & Jung, 2024). Several studies have also emphasized that sentiments undergo dynamic changes during the learning process, particularly when learners encounter cognitive disequilibrium and equilibrium (D'Mello & Graesser, 2012). In the online learning context, learning sentiments become more complex because the non-face-to-face learning environment affects the emotional atmosphere (Huang et al., 2021; Shao et al., 2023). Therefore, it is important to further understand the developmental trajectory of learning sentiments in MOOC discussion forums.

Previous research has demonstrated that sentiments significantly influence learners' academic performance in MOOC discussion forums and are therefore critical for assessing the effectiveness of MOOCs (Ye & Zhou, 2022). Some researchers have investigated the relationship between academic performance and sentiments (Parker et al., 2021; Shao et al., 2023). Specifically, King et al. (2015) focused on the sentiments of boredom, anxiety, and enjoyment, as these can significantly influence learners' academic performance. High-performing learners who experienced higher levels of positive sentiments were more engaged and exhibited lower levels of disaffection. In contrast, low-performing learners typically experienced more negative sentiments (King et al., 2015). Overall, it is widely recognized that different academic performance groups exhibit varying learning sentiments. However, specific differences in learning sentiment patterns between these groups within the context of MOOC discussion forums remain largely unexplored. Therefore, this study applied epistemic network analysis (ENA; Lund et al., 2017) to identify how learning sentiment patterns differed between high- and low-score groups in MOOC discussion forums.

Literature Review

Sentiment Analysis in Online Discussions

Recently, research interest in exploring learning sentiments within online learning discussions has displayed a notable surge (Ye & Zhou, 2022; Huang et al., 2019). The terms sentiment and emotion are frequently employed interchangeably. This primarily stems from the fact that both emotions and sentiments are influenced by a range of components that encompass cognitive, motivational, affective, physiological, and expressive elements (Pekrun & Marsh, 2022). However, in the learning context, sentiments diverge from emotions in terms of the duration that learners experience them. Sentiments arise and persist, whereas emotions typically endure for relatively short periods, generally ranging from a few seconds to a few minutes (Huang et al., 2019). In online learning context, learning sentiments reflect the attitude or perspectives on things when interacting with others (Ye & Zhou, 2022). This study specifically focused on feelings directly related to learning tasks in MOOCs, encompassing learners' feelings about comprehending course content, perception of challenges in exercises, and feelings of collaboration with peers. Flow theory was chosen to support the analysis of learning sentiments in this study (Kiuru et al., 2022).

Specific studies have examined the sentiment categories prevalent in online learning contexts, leading to the observation that various sentiments may manifest during online learning discussions (Tan & Jung, 2024). In the field of positive sentiment research, D'Mello and Graesser (2012) have described engagement as a cognitive state characterized by intense focus, concentration, and full immersion in a given task. Avry et al. (2020) determined that the attainment of one's goals and the successful resolution of problems can lead to feelings of delight. A substantial literature has consistently indicated a positive correlation between feelings of delight and academic performance (Liu et al., 2022). Surprise might be elicited by cognitive incongruity caused by the disconnect between incoming information and prior knowledge (Yang et al., 2024). Lehman et al. (2012) found that confusion arose when learners encountered information that conflicted with their existing knowledge, leaving them uncertain about the way forward. Similarly, D'Mello et al. (2014) posited that confusion was likely to manifest when newly acquired information resisted integration into pre-existing mental models, and revealed a positive correlation between confusion and academic performance. Conversely, another study reported a negative association between confusion and academic performance (Richey et al., 2019). Frustration was a common sentiment among learners participating in collaborative online learning environments (Yang et al., 2021). Peterson and Zengilowski (2024) found that when learners failed to resolve the uncertainty associated with confusion, they may feel frustrated. Boredom ensues when an individual perceives an inherent lack of meaning within an activity (Beymer & Schmidt, 2023). Previous research has provided evidence of associations between suboptimal learning outcomes and both boredom and frustration (Baker et al., 2010). Gasper and Danube (2016) posited that neutral states often manifested in the absence or minimal presence of both positive and negative sentiments. Arguel et al. (2019) highlighted the possibility of neutral sentiment during the knowledge construction process. Hence, this study focused on seven distinct sentiment states: engagement, delight, surprise, boredom, confusion, frustration, and neutral. These sentiments have been recognized as among the most common learning-centered sentiments and have the potential to predict academic performance (Zheng & Huang, 2016).

A growing research stream has recently explored the evolving nature of learning sentiments (Huang et al., 2021; Rebolledo-Mendez et al., 2021). Lehman et al. (2012) introduced a conceptual framework to elucidate the dynamics of sentiment states, including engagement, frustration, boredom, and confusion. This model affirmed that learners in a state of engagement may encounter cognitive disequilibrium and confusion when faced with obstacles to their goals or other challenges. Rebolledo-Mendez et al. (2021) investigated the temporal dynamics of sentiments, including confusion, boredom, neutral, frustration, and engagement, and found that learners with limited sentiment regulation abilities frequently transitioned from boredom to frustration and from engagement to neutral. Overall, these findings indicated that sentiments undergo temporal changes concurrent with the evolution of cognitive processes during learning. Hence, this study aimed to uncover the underlying patterns and temporal dynamics of learning sentiments in MOOC discussion forums.

Group Differences in Learning Sentiments

Numerous previous studies have objectively noted differences in sentiments among various groups (Ye & Zhou, 2022). For example, Ye and Zhou (2022) indicated that the most significant difference between higher- and lower- performing groups was positive sentiments, suggesting that positive sentiments can promote learners' behavioral interactions. The higher- performing group had stronger associations around positive and confused sentiments; lower-performing groups had stronger associations around off-topic discussion. Han et al. (2021) proposed patterns of sentiments for four categories of learners, divided by social interactions type (i.e., posts, views, replies, votes) in MOOC forums. Learners with persistent interactions with various sentiments showed significantly higher frequencies of sentiments than did other learners. Huang et al. (2024) investigated emotion sequence patterns in the posts of MOOC discussion forums and revealed that learners in the low-level interaction group experienced more emotion transition from boredom to frustration than did the average- and high- level interaction group. Huang et al. (2021) examined the evolution of sentiments across three interaction levels in blended learning, namely surface, deep, and social-emotional. Their results indicated that during deep interactions, learning sentiments could evolve from negative to insightful. In contrast, the sentiment network derived from social-emotional interactions showed stronger connections in joking-positive and joking-negative sentiments compared to the other two interaction levels. Overall, previous studies have provided evidence of group differences in learning sentiment. However, existing research has typically focused on one or only a few aspects. The type and inner structure of learning sentiment differences in regard to performance remain unclear and warrant further investigation.

Epistemic Network Analysis

ENA combines traditional qualitative and quantitative methodologies with contemporary computational techniques and data analytics. This integration enables researchers to extract deep insights from their datasets (Andrist et al., 2018). ENA is a data analysis approach that focuses on reducing dimensionality and modeling connections among concepts within coded data. ENA leverages cognition, communication, action, and other pertinent aspects of group interaction and systematically characterizes them using suitable coding schemes, aligning with established practices in content analysis (Alonso-Nuez et al., 2020). An epistemic network is constructed by assigning codes to different elements present in online discussions, in which each node in the network represents these codes. The connections between nodes are determined by the occurrence of the codes within a pertinent unit of analysis, such as an individual discussion message or message sequence. Thus, each concept or significant feature within a dataset is depicted as a distinct node within the network. When a specific feature is identified within a data segment, the corresponding data are coded accordingly. ENA uses coded data to construct ENA networks by examining the co-occurrence of codes within a dataset. This process involves quantifying the co-occurrences to formulate weighted network models. In these models, the thickness of the edges (representing connections between nodes), size of nodes corresponding to specific codes, and spatial arrangement of nodes relative to one another collectively provide valuable insights into the dataset. This is understood through a systematic examination of codes within defined time windows, followed by the assignment of weights to their co-occurrences (Lund et al., 2017). Weight-based structuring, accomplished through dimensionality reduction, leads to a visualization focused on the selected variables of interest, enabling insightful comparisons.

Research Questions

Our aim was to expand the coding frameworks for learning sentiments established by previous researchers and provide additional evidence of the effectiveness of ENA in the analysis of MOOC discussion forums. In this study, learning sentiments expressed on MOOC discussion forums were conceptualized as a network comprising seven distinct dimensions. ENA was used to investigate the interrelationships among these dimensions and compare the salient properties of the epistemic networks generated by different participant groups. The primary research questions addressed in this study were as follows:

> RQ1: What is the frequency distribution of participants' sentiments on MOOC discussion forums?
>
> RQ2: What are the time-series characteristics of participants' sentiments on MOOC discussion forums?
>
> RQ3: What distinctions exist in the epistemic network characteristics of sentiments between participants in high- and low-score groups?
>
> RQ4: What distinctions exist in the epistemic network characteristics of sentiments between high- and low-score groups concerning different learning topics?

Methodology

Research Design and Participants

The study sample consisted of 158 learners who had registered for an online course titled *Applications of Mind Maps in Teaching*, offered on the Chinese MOOC University platform, one of the largest online learning communities in China. The course's primary objective was to enhance learners' proficiency in using mind maps as a pedagogical strategy. The course was accessible to the public and was not affiliated with any college or university curriculum.

During each week of the course, participants typically spent approximately three to six hours engaging with course materials. These activities included reading course materials, viewing instructional videos, participating in discussion forums, and completing unit quizzes. Notably, the MOOC did not operate entirely on a self-paced basis; each unit was made available at the start of the scheduled week. The course covered six learning topics related to mind maps, as shown in Table 1.

Table 1

Learning Topics in MOOC Online Discussions

Learning topic	Description
Theory	Try to use mind mapping to discuss the theories that guide mind mapping
Experience	Share experiences using mind mapping in teaching
Application	Discuss the application of mind mapping in teaching activities
Strategy	Discuss teaching mind-mapping strategies in inquiry learning
Evaluation	How to use mind mapping for teaching evaluation
Condition	Discuss the condition of mind mapping in teaching

Data Collection

We collected data from three distinct categories: demographic characteristics, performance data, and online discussions. The demographic data encompassed information such as the participants' IDs, names, genders, majors, and regions. Participant performance was based on scores on tests, assignments, online discussions, and the final examination (worth 35%, 20%, 15% and 30% of the final grade, respectively). Subsequently, based on their final performance scores, learners who scored above the average were placed in the high-score group, while those who scored below the average were placed in the low-score group.

Participants' online discussions served as reflections of their learning sentiments. The online discussion messages were organized chronologically and stored in Excel to facilitate subsequent coding and analysis processes and to reveal the underlying learning sentiment patterns.

Learning Sentiment Coding Scheme

Before conducting ENA, it was necessary to convert participants' qualitative discussion message data from the MOOC forums into quantitative data. Drawing on an extensive literature review, we aimed to investigate variations in learning sentiments in online discussions. To accomplish this, seven sentiment categories closely linked to the learning process were identified: engagement, delight, confusion, frustration, boredom, surprise, and neutral. The coding scheme is presented in Table 2. Previous research has indicated that these categories are sufficient for distinguishing learning sentiments in online discussions (Zheng & Huang, 2016). In general, each message was assigned a single label. In cases where a message exhibited multiple sentiments, multiple labels were appended accordingly.

Table 2

Coding Scheme for Learning Sentiments in Online Discussions

Sentiment	Code	Description	Example
Engagement	EN	A state of being fully engaged in a task	Mind mapping enhances my ability to establish intricate relationships among knowledge domains, facilitating a comprehensive exploration of knowledge emergence and progression.
Delight	DE	A high degree of satisfaction	I am content with the efficacy of the mind maps I have created in aiding my retention of the learned material.
Confusion	CO	A sense of uncertainty or bewilderment	I am uncertain about the effective construction of lucid mind maps within the confines of a mobile learning environment.
Boredom	BO	Experiencing tiredness or restlessness stemming from a lack of interest	This chapter predominantly delves into abstract concepts and theories concerning mind mapping, which I find very boring.
Frustration	FR	Discontentment or irritation arising from encountering cognitive stagnation or impasse	This issue has persisted for multiple days without a satisfactory resolution. It is really frustrating.
Surprise	SU	A state of wonder and astonishment, often triggered by unexpected occurrences	The circular structure employed in mind mapping is truly remarkable. Its novelty has left me pleasantly surprised.
Neutral	NE	A state of ambiguity or ambivalence	Mind maps can be used to design teaching objectives and set content arrangements.

By employing these coding schemes for learning sentiments, 1,316 online discussion messages encompassing six learning topics were systematically coded by two proficient raters. The coders possessed expertise in both sentiment framework and content analysis for encoding data from online discussions. First, a test set comprising 400 messages, representing approximately 30% of the complete dataset, was drawn from the MOOC discussion forum. This test set was employed to assess coding consistency between the two raters. The inter-coder reliability coefficient was computed, yielding a value of 0.85 (Cohen's kappa), signifying a robust level of reliability. The two raters subsequently negotiated to reconcile discrepancies and enhance their understanding of the coding scheme. The remaining messages were then evenly distributed and independently coded by both raters. Ultimately, this process yielded 1,349 codes representing learning sentiments.

Data Analysis Methods

We conducted a comprehensive three-stage analysis of the three types of data, namely demographics, performance, and online discussion. The initial stage aimed to investigate the categories and frequency distributions of the learning sentiments by statistical analysis. In the second stage, time series analysis was carried out to examine the time-series characteristics of learning sentiments by using the ggplot data visualization package in R software. Based on the results of qualitative content analysis, the third and fourth stages compared learning sentiments across varying performance levels and topics using the ENA Web Tool (https://www.epistemicnetwork.org/).

To address the third and fourth research questions, seven learning sentiments from the coding scheme were designated as codes and the stanza size was fixed at four. To compare the differences between two groups, we analyzed the locations of projected points in the ENA. Normality checks suggested that the distributions of projected points were nonnormal. Then, a two-sample Mann–Whitney *U* test was used to compare differences in X- and Y-axis values between groups. We interpreted the meaning of any variance by computing the mean networks, which involved averaging the connection weights across the networks within each group. Additionally, we compared the means and individual networks using network difference graphs. These graphs were derived by subtracting the weight of each connection in one network from the corresponding connections in another network.

Results

Frequency Distribution of Participants' Sentiments on MOOC Discussion Forums

Table 3 shows the frequency distribution of the participants' learning sentiments. All seven learning sentiments appeared in the participants' online discussions, albeit with different proportions. Engagement occurred most frequently (EN: 508, 37.7%), followed by frustration (FR: 284, 21.1%). Boredom (BO: 11, 0.8%) and surprise (SU: 5, 0.4%) had the lowest values.

Table 3

Descriptive Statistics for Learning Sentiments

Category	Number	Percentage
Engagement	508	37.7%
Confusion	103	7.6%

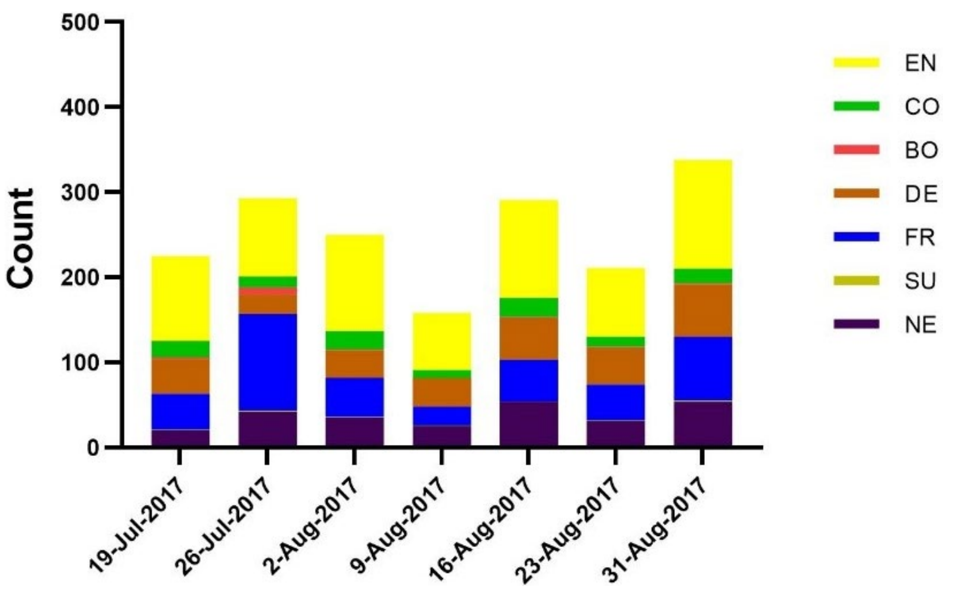
Boredom	11	0.8%
Delight	230	17.0%
Frustration	284	21.1%
Surprise	5	0.4%
Neutral	208	15.4%

Time-Series Characteristics of Participants' Sentiments on MOOC Discussion Forums

We employed time as the horizontal axis and the number of learning sentiments as the vertical axis to construct a time-series diagram, as illustrated in Figure 1. Figure 1 shows the evolving dynamics of sentiments throughout the learning process over time. Notably, the density of learning sentiments varied at different time points. The seven types of learning sentiments alternated in appearance; however, their distributions exhibited variations. Engagement and delight consistently emerged as the most prevalent sentiments, which persisted throughout the learning process. In contrast, boredom and surprise were infrequently observed throughout the duration of the course.

Figure 1

Time-Series Characteristics of Learning Sentiments

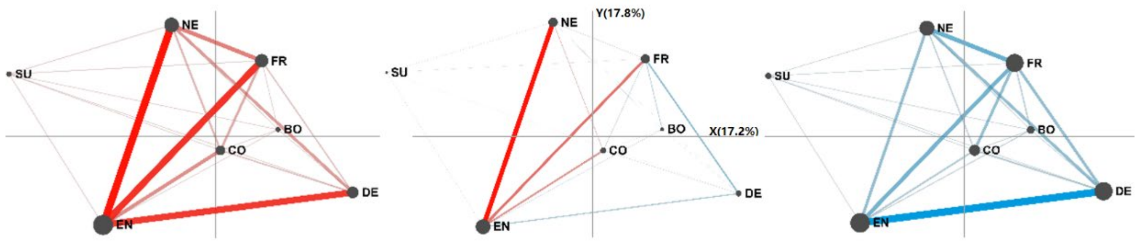


Distinctions in the Epistemic Network Characteristics of Sentiments Between Participants in the High- and Low-Score Groups

We then performed ENA to identify the learning sentiment patterns within the high- and low-score groups. Figure 2 shows the epistemic networks of participants in the high-score group (left, marked in red) and the low-score group (right, marked in blue) in an online discussion; a difference network graph (center) indicates how the learning sentiments of each group differed. In this comparison plot, the connection weights were compared between the two groups. The thicker lines indicate stronger connections. Regarding the differences in epistemic connections, participants in the high-score group exhibited stronger connections between EN and NE, as well as between EN and FR. Conversely, the low-score group displayed stronger connections between FR and DE.

Figure 2

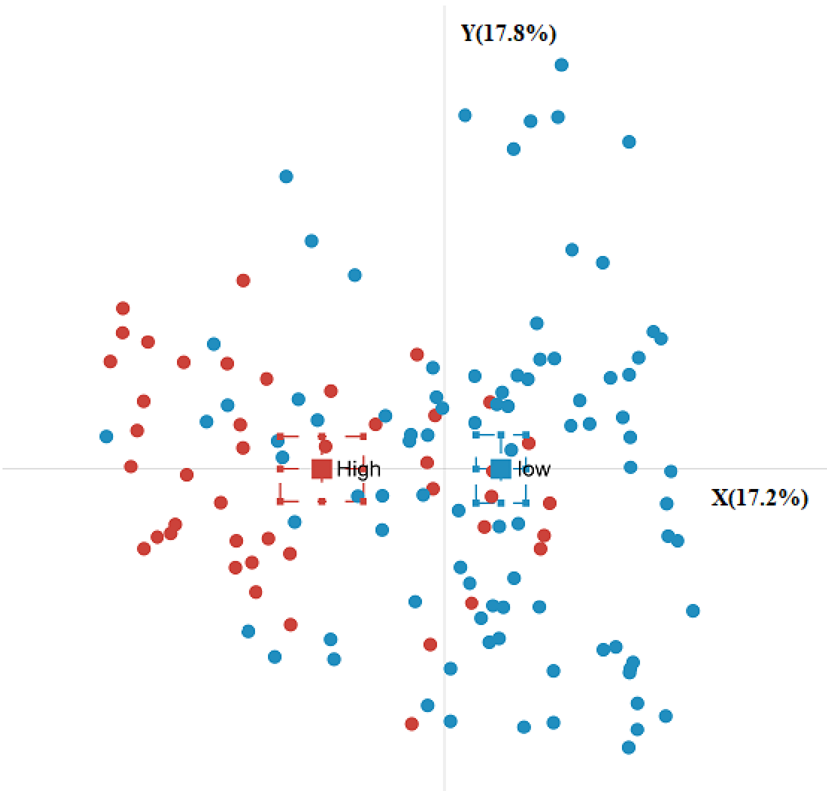
Mean Discourse Networks of Learning Sentiments on MOOC Discussion Forums



The mean value for the high-score group was positioned towards the left side of the ENA space, as illustrated in Figure 3. Conversely, the low-score group was located on the right side of the ENA space. Based on the distribution of learning sentiments within the ENA space, the high-score group expressed EN and NE more frequently, while the low-score group expressed DE and FR more frequently.

Figure 3

Comparison of High-Score (Red) and Low-Score (Blue) Groups



We also conducted two-sample Mann–Whitney *U* test to assess the potential differences in ENA characteristics between the high- and low-score groups. Table 4 presents the results. In terms of the first dimension (X-axis), the test assuming unequal variances revealed a statistically significant difference between the high- and low-score groups at alpha = 0.05 level. However, along the second dimension (Y-axis), the test assuming unequal variances indicated that the high-score group was not significantly different from the low-score group at an alpha level of 0.05.

Table 4

Results of the T-test for ENA Characteristics Between High- and Low-Score Groups

Dimension	Group	*n*	Mean	*SD*	*t*	*d*
First dimension (X-axis)	Low-score	90	0.30	0.68	7.41^{*}	1.31
	High-score	68	-0.64	0.77		
Second dimension (Y-axis)	Low-score	90	0.00	0.94	0	0
	High-score	68	0.00	0.60		

Note. $^{*}p < 0.05$.

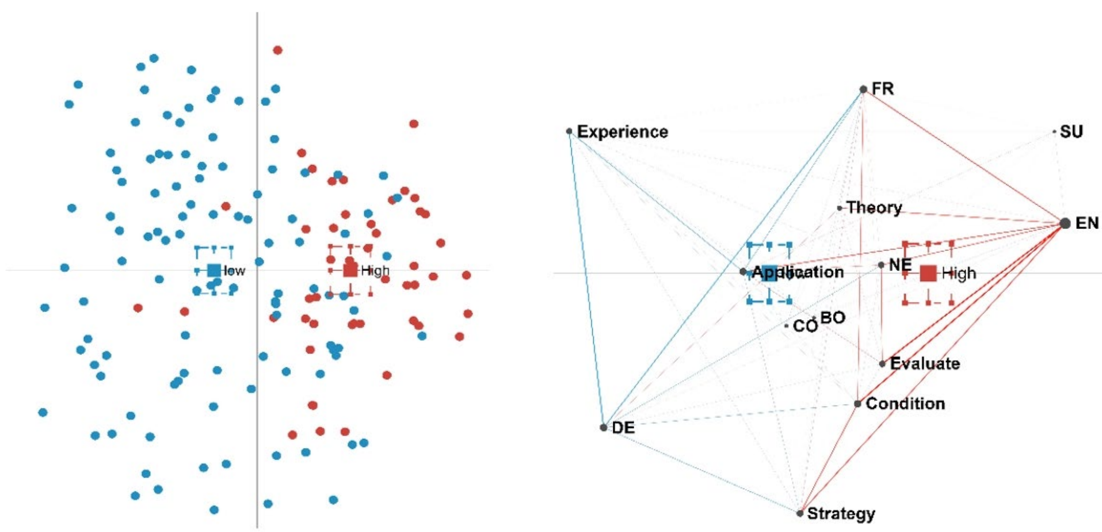
Distinctions in the Epistemic Network Characteristics of Sentiments Between High- and Low-Score Groups Concerning Different Learning Topics

Figure 4(a) displays the group averages for both the high-score (red) and low-score (blue) groups, illustrating the relationship between learning sentiments and learning topics. The visualization employed X and Y, which collectively accounted for 8.6% and 10.6% of the variability in the epistemic networks established by the participants, respectively. The circles represent the high-score group in red and the low-score group in blue. Rectangles denote group-averaged networks, with each encircled by lines indicating 95% confidence intervals.

Figure 4(b) reveals a significant difference between the groups along the X-axis (t = -8.32; p = 0.00; r = 0.95), where the effect size (r = 0.95) is notably high. The results indicated that the learning topics were predominantly situated at the center of the network, except for the learning topics of experience and strategy, which appeared to hold singular importance in the course and were primarily captured along the Y-axis. Furthermore, Figure 4(b) indicates that the high-score group displayed more connections with EN, whereas the low-score group tended to contribute more online discussions linked to DE.

Figure 4

Comparison of High-Score (Red) and Low-Score (Blue) Groups Regarding Learning Topics



(a) (b)

Table 5 shows the connection coefficients of the epistemic networks within both the high- and low-score groups. The values in Table 5 represent the frequency-weighted occurrence of each connection in the online discussion. The results revealed several significant connections between learning sentiments, such as the link between FR and EN. In addition, the conditions and strategies of the learning topics had significant connections. However, focusing on the relationship between the learning topic and sentiments, EN showed strong links to all learning topics, in which the values were greater than 0.15 in the high-score group, whereas for the low-score group, only EN and experience showed strong connections, with values greater than 0.15. In addition, FR and experience showed significant connections for the high- and low-score groups, with values reaching 0.17.

Table 5

ENA Network Weights for Learning Sentiments

Connection	High-score group	Low-score group
EN–Experience	0.18	0.17
EN–Theory	0.15	0.09
EN–Application	0.17	0.10
FR–Experience	0.17	0.17
EN–Condition	0.19	0.09
EN–Evaluation	0.16	0.06
EN–Strategy	0.18	0.10

Discussion

On MOOC discussion forums, EN (508 discourses, 37.7%) and DE (230 discourses, 17.0%) were the most common positive sentiments, while BO (11 discourses, 0.8%) was the least common negative sentiment. Numerous studies have shown that positive sentimental states such as engagement and delight manifest when a learner's existing knowledge aligns with new information being acquired or when learning tasks have been accomplished (Tan & Jung, 2024). In contrast, negative sentiments such as boredom and frustration were likely to arise when individuals encountered impediments to their learning objectives (Camacho-Morles et al., 2021). In this study, frustration significantly outweighed boredom. This underscored the importance of instructors meticulously tracing the underlying causes of emerging frustration. Lehman et al. (2012) demonstrated that as frustration escalates, learners may encounter increasing challenges in devising new strategies to achieve their goals. Frustration could happen if a subject one studies is highly complex even though one has studied or prepared for it. These findings are consistent with flow theory, which suggests that highly challenging situations that surpass an individual's current skill level can evoke feelings of anxiety and frustration (Wei et al., 2024). Moreover, confusion emerged as the most prevalent sentiment, which aligned with the findings of D'Mello et al. (2014), who suggested that confusion may be conducive to complex learning and deep cognitive processing. Although positive sentiments were common in this study, it is crucial to address it promptly once it is detected. Failure to do so may lead to negative learning outcomes, potentially culminating in frustration for learners.

In addition, we found that the seven types of learning sentiments appeared alternately in the online discourse, and the density of learning sentiments varied at different times. This finding was consistent with prior research that argued learning sentiments displayed periodic and dynamic features during the online learning process (Huang et al., 2019). Such research offered evidence that, when engaging in intricate MOOC learning tasks or assignments, learners' sentiments were subject to dynamic fluctuations influenced by their goals and knowledge levels (Ye & Zhou, 2022). This highlighted the importance of instructors tracing the underlying causes of learning sentiment dynamics. For example, D'Mello and Graesser (2012) developed a model to elucidate the dynamics of affective states that arose during deep learning activities to address pedagogical and motivational strategies.

Moreover, the results indicated that the high-score group engaged in more discourse characterized by engagement and neutral sentiment while displaying fewer instances of delight and frustration compared to the low-score group. These findings aligned with Yang et al. (2024), who highlighted the notable correlation between learners' academic performance and the occurrence of positive sentiments. Learning sentiment has also been identified as a significant predictor of academic performance (Xing et al., 2019). Regarding the learning sentiment patterns, we found that the high-score group exhibited stronger connections between engagement and neutral, as well as between engagement and frustration. However, the low-score group experienced more frustration, followed by delight, than did the high-score group. If a learner experiences chronic frustration, they may be operating at the limits of their current abilities, often associated with learning within the zone of proximal development. Consequently, endeavoring to identify and address such frustrations, with a special focus on offering additional guidance to learners, is imperative. This intervention aimed to break the cycle in which learners became bored and remained bored for prolonged periods. However, frustrations are not always negative; they can direct learners to be grittier when faced with frustrations in learning.

As an additional significant contribution, our results offered insights into the association between learning topics and sentiments for the high- and low-score groups. These results indicated a difference between the learning topics and learning sentiments for distinct groups. Our research confirmed that participants in the high-score group had more links between all other learning topics and evaluations than did their peers in the low-score group. This finding aligned with the conclusion of Alonso-Nuez et al. (2020) who showed that learners who engaged in more evaluation activities exhibited stronger academic performance. Additionally, our findings suggested that engagement was strongly linked to all learning topics (i.e., theory, condition, experience, strategy, application, and evaluation). This was consistent with the conclusions of Huang et al. (2019), who discovered that a learning task or topic could evoke several diverse positive sentiments (engagement) at the beginning of the learning process. In addition, frustration and experience had significant connections in the high- and low-score groups. We posit this phenomenon resulted from the features of the learning topic of experience. Most participants always experienced problems that could not be solved in time when operating the mind-mapping software, which often led to frustration.

This study has significantly advanced our understanding of learning sentiments in educational contexts, clarifying the dynamic nature of sentimental changes across various groups and tasks during MOOC learning. By incorporating both learning sentiments and topics into our analysis, we enhanced our ability to decipher the evolving connections among shifting sentiments. This research provided valuable insights for instructional designers and educators, providing them with effective pedagogical strategies to facilitate positive sentimental transitions and effective sentimental regulation in MOOCs. For example, instructional designers and educators can design teaching strategies and evaluate the complexity of learning tasks carefully to motivate learners to invest effort and achieve success. This finding aligned with the conclusion of (Peterson & Zengilowski, 2024); pedagogical strategies such as providing learners with challenges can support optimal positive sentimental when the challenge is appropriate or may result in sentiments like frustration when the challenge is too great or lacks support.

Conclusion and Limitations

Contemporary education researchers have increasingly highlighted the essential role of learning sentiments in online learning communities. However, further research is needed in the educational field regarding learning sentiments. Compared with traditional conceptualizations, learning analytics, particularly ENA, have the potential to explore learning sentiment dimensions through unconventional approaches. This study gathered online discussions from 158 participants and analyzed them using ENA to determine how individual learning sentiment patterns varied based on performance level and learning topics. Our research has marked a transition from the static paradigm of conceptualizing sentiments to analyzing dynamic sentimental processes. This novel approach can reveal underlying patterns and temporal dynamics of learning sentiments, thereby enhancing MOOC effectiveness.

This study had several limitations that merit acknowledgment. First, the assessment of online discussions should be automated to enable differentiation between distinct categories within learning sentiment dimensions. Guidelines for automated analysis of online discourse offer valuable insights. Second, it is conceivable that employing different coding schemes or analyzing a separate dataset to code learning sentiments may yield contrasting results. Future research should investigate learning sentiment coding patterns across various contexts and participant groups. Third, dichotomization of the final scores may have introduced statistical errors that could affect the rigor of the conclusions. One avenue for future research would involve exploring more effective methods for group differentiation. Finally, the study relied on forum discussions data only to detect the sentimental states, which could have potentially led to inaccuracies in the results. Future research should employ mixed methods to collect data and explore sentimental patterns.

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A Categorical Confirmatory Factor Analysis for Validating the Turkish Version of the Self-Directed Online Learning Scale (SDOLS-T)

Hongwei Yang, PhD[1], Müslim Alanoğlu, PhD[2], Songül Karabatak, PhD[2], Jian Su, PhD[3], and Kelly Bradley, PhD[4]
[1]University of West Florida; [2]Fırat University; [3]University of Tennessee; [4]University of Kentucky

Abstract

This study developed and validated the Turkish version of the Self-Directed Online Learning Scale (SDOLS-T) for assessing students' perceptions of their self-directed learning (SDL) ability in an online environment. Specifically, this study conducted in two stages multiple categorical confirmatory factor analyses factoring in the ordered categorical structure of the SDOLS-T data. The data in this study came from a parent study which utilized the SDOLS-T and other instruments for data collection. From among the three competing models the literature recommends examining to explain the shared variance of items in a survey, the results at stage 1 showed that the correlated, two-factor structure, originally proposed for the SDOLS, was also the best-fit model for the SDOLS-T. At stage 2, using the best-fit model from stage 1, measurement invariance analyses were conducted to examine the extent to which SDL under the SDOLS-T was understood and measured equivalently across the groups specified by four dichotomous demographic variables: gender, network connection, online learning experience, and grade. The stage 2 results indicate the SDOLS-T reached scalar invariance at least for gender and network connection, thus allowing the comparison of latent or manifest means, or any other scores (e.g., total scores, Rasch scores), across the groups by these two demographic variables. In the end, the findings support the SDOLS-T for use in facilitating educational practice (e.g., improving instructional design), advancing scholarly literature (e.g., investigating SDL measurement and content area issues), and informing policy/decision-making (e.g., increasing retention rates and reducing dropout) in online education in Turkey.

Keywords: self-directed learning, online teaching and learning, confirmatory factor analysis, ordered categorical data, measurement invariance

Introduction

The literature of online education has identified fundamental characteristics of a successful online learning environment (Hone & Said, 2016). Among them is students' self-directed learning (SDL) or self-management of learning, a consistent and essential characteristic recognized in online learning readiness and effectiveness (Prior et al., 2016). The literature indicates SDL supports students' abilities to manage their overall learning activities, think critically, and cognitively monitor their learning performance when they navigate through the increasingly complex learning process. SDL contributes to the interaction and collaboration of students with their peers and instructors for feedback and support (Garrison, 1997; Kim et al., 2014).

As a core theoretical construct in adult education, SDL has been referred to as both a personal attribute and a process (Song & Hill, 2007). In a book published nearly 50 years ago, Knowles (1975) described SDL as an adult students' ability to self-manage their learning; his guide was a go-to book for adult students developing competencies in self-directed learning (Long, 1977). Caffarella (1993) outlined three principles underlying SDL: (a) self-initiated learning, (b) more learner autonomy, and (c) greater learner control. Hiemstra (1994) interpreted SDL as a process in which adult students could plan, navigate, and evaluate their learning on the path to their personal learning goals. In contrast, Garrison (1997) established a more comprehensive theoretical model of SDL which focused on the learning process containing both motivational and cognitive aspects of learning. This model integrated three overlapping learning dimensions: (a) motivation, (b) internal monitoring, and (c) external management. Regarding lifelong learning, SDL is a preferred learning process to help students stay current (Kidane et al., 2020). Some researchers further concluded that SDL and lifelong learning are related to such an extent that they each serve as the basis of the other (Tekkol & Demirel, 2018). Finally, students' SDL ability may be influenced by their culture (Ahmad & Majid, 2010; Demircioğlu et al., 2018; Suh et al., 2015). Therefore, the measurement of SDL in a collectivist culture (e.g., Turkey) may be different from that in an individualistic culture (e.g., USA).

Research has been conducted on SDL in online education, a learning delivery modality becoming increasingly popular around the world largely due to the recent COVID-19 pandemic and rapid development of instructional technologies. Noting that SDL may function differently by learning context (e.g., online context), Song and Hill (2007) investigated and compared various contexts where self-direction in learning occurred. They concluded a better understanding of SDL characteristics unique to the online context supports better online education experiences. On the other hand, research supports online education as the right place for students to self-manage their learning, and students' SDL capability is significantly associated with their online readiness, disposition, engagement, and eventually academic achievement (Balcı et al., 2021; Kara, 2022; Karatas & Arpaci, 2021; Ozer & Yukselir, 2021). It is widely believed that online education will continue to thrive globally (Abuhammad, 2020; Xie et al., 2020). Accordingly, self-directed online learning is anticipated to continue to generate interest among researchers worldwide.

Instruments Measuring SDL

Many instruments measuring SDL are based on Knowles's andragogic theory (Cadorin et al., 2017) and have evolved into various contexts that include cultures and languages, fields of study, and student populations (Cadorin et al., 2013; Cheng et al., 2010; Jung et al., 2012). Comprehensive reviews of studies validating SDL instruments are available in Cadorin et al. (2017) and Sawatsky (2017).

Focusing on the online environment, the Self-Directed Online Learning Scale (SDOLS) was developed in English in the USA, validated by Su (2016), and subsequently re-validated by Yang et al. (2020). The 17-item instrument consists of two dimensions: *autonomous learning* (AUL; eight items) and *asynchronous online learning* (ASL; nine items). Respondents rate the items on a 5-point Likert scale that ranges from 1 = *strongly disagree* to 5 = *strongly agree*. All 17 items are positively worded, and a higher score on an item represents a higher level of the aspect of SDL measured by that item.

Adaptation of SDOLS to the Turkish Language

In Turkey, as in other countries, there has been a transition to online teaching and learning over the past few years due to the COVID-19 pandemic and the advancement of instructional technologies. In turn, it may be reasonable to anticipate more SDL-related research in Turkish because the online environment is an ideal place for students to self-manage their learning. Therefore, survey instruments with solid psychometric properties for measuring students' SDL ability are expected to be in even greater need.

Presented in Table 1 are a few instruments used to measure SDL. These instruments have been identified from an extensive literature review, and it is noteworthy that many SDL-related studies in Turkish, including several which took place prior to the pandemic, have used these instruments. Table 1 shows: (a) the full name of the instrument, (b) its original developer, (c) the researchers who subsequently adapted the instruments to Turkish, if any, and (d) in which studies in Turkish the instruments were administered. These studies demonstrate the importance of SDL measurement to scholarly literature, including that of online education, in Turkish.

Although properly measuring SDL is critical in online education, there are problems with the existing SDL instruments. First, many such instruments are not designed specifically for the online teaching and learning context. In Table 1, for example, among the six instruments measuring SDL, only two serve the exclusive needs of online education: the Readiness for Online Learning Scale developed in Turkish by Yurdugül and Demir (2017) and the Online Learning Readiness Scale adapted to Turkish by İlhan and Çetin (2013) and Yurdugül and Alsancak Sırakaya (2013). Second, many existing studies validating SDL instruments (e.g., the three studies just cited) have inadequacies in their methodology. They have treated the almost always ordered categorical response data from these surveys as if they were continuous when examining the instruments' psychometric properties. Such a practice, though still common, is known to result in unsatisfactory consequences, including the underestimation of the standard error and an inflated χ^2 statistic, among others (Byrne, 2010; Kline, 2016). At the same time, very few of these studies investigated whether their instruments provided equivalent measures, for example, measurement invariance, per Millsap (2011), Putnick and Bornstein (2016), and Svetina et al. (2020), of SDL across groups created by demographic variables such as gender. Meaningful comparisons of statistical measures, such as scale or subscale means, from across different groups should not be made until an appropriate level of measurement invariance is achieved.

Table 1

Self-Directed Learning Instruments Used in Turkish Studies

Instrument	Developer(s)	Adaptation to Turkish	Administered in Turkish studies
Readiness for Online Learning Scale	Yurdugül & Demir (2017)	NA	Karatas & Arpaci (2021)
Self-Directed Learning Skills Scale	Askin Tekkol & Demirel (2018) Askin (2015)	NA	Karagülle & Berkant (2022) Peker Ünal (2022) Karatas & Arpaci (2021) Tekkol & Demirel (2018)
Self-Directed Learning Inventory	Suh et al. (2015)	Çelik & Arslan (2016)	Demircioğlu et al. (2018)
Online Learning Readiness Scale	Hung et al. (2010)	İlhan & Çetin (2013) Yurdugül & Alsancak Sırakaya (2013)	Kara (2022) Ates Cobanoglu & Cobanoglu (2021) Balcı et al. (2021)
Self-Directed Learning Scale	Lounsbury et al. (2009) Lounsbury & Gibson (2006)	Demircioğlu et al. (2018)	Ozer & Yukselir (2021) Durnali (2020) Saritepeci & Orak (2019)
Self-Directed Learning Readiness Scale	Fisher et al. (2001) Guglielmino (1977)	Kocaman et al. (2006)	Ahmad et al. (2019) Ertuğ & Faydali (2018) Ünsal Avdal (2013)

Because online education is expected to continue to thrive in Turkey (Daily Sabah, 2021; Polat et al., 2022; Republic of Turkey Ministry of National Education, n.d.), this study is significant in that, by adapting the SDOLS to the Turkish language, it provides another tool for measuring SDL dedicated to online education that may be useful to the work of researchers, instructional designers, and policy- and decision-makers in Turkey. Ideally, the SDOLS-T is properly validated with regard to its psychometric properties based on the appropriate methodology capable of addressing the inadequacies outlined earlier in this section.

Research Questions

The study validated the SDOLS-T for its psychometric properties including measurement invariance describing the extent to which SDL under the SDOLS-T is understood and measured equivalently across the groups specified by demographic variables (Svetina et al., 2020). Specifically, the study addressed two research questions:

RQ1. What is the best-fit factor structure of the SDOLS-T: that of the original SDOLS or common alternative structures from the literature?

RQ2. To what extent does the best-fit factor structure underlying the SDOLS-T measure the same construct across the groups created by several demographic variables measured in the study: (a) gender, (b) network connection, (c) previous online learning experience, and (d) grade level?

When addressing these questions, the study provided insights into Turkish university students' SDL.

Method

As part of a parent study reviewed and approved by the university research ethics committee, the study investigated the psychometric properties of the SDOLS-T. To adapt the SDOLS to the SDOLS-T, permission was first secured from the developer of the SDOLS for its adaptation using the back-translation method (Brislin, 1970). Next, all 17 items were translated into Turkish to derive the initial draft of the SDOLS-T which was reviewed by the university's faculty members in education. With the feedback from the education faculty, the initial SDOLS-T instrument was revised and next translated back into English (SDOLS-T-E). The SDOLS-T-E instrument was reviewed by the SDOLS developer for consistency in meaning with the SDOLS instrument. Further revisions were made to the SDOLS-T based on the feedback on the SDOLS-T-E, which led to the final SDOLS-T instrument. Similar to the SDOLS, the SDOLS-T has 17 positively-worded items in two dimensions: autonomous learning (AUL: eight items) and asynchronous online learning (ASL: nine items), and each item has five Likert response options ranging from 1 = *strongly disagree* to 5 = *strongly agree*.

Participants

The participants were 1,989 undergraduate students enrolled in the Faculty of Education of a Turkish university in the 2020–2021 academic year and were recruited into the larger-scale parent study. The data used here were collected from these undergraduate students during February and April 2021 as part of the parent study. The data contain 332 completed responses to all 17 SDOLS-T items plus four dichotomous demographic items. The data were used to run several confirmatory factor analyses (CFAs) to assess the underlying factor structure of the SDOLS-T and identify certain psychometric evidence for the instrument.

Table 2 presents descriptive statistics of the student respondents focusing on the demographic variables outlined in RQ2. About two thirds of the student participants were female and an even higher proportion had had no online learning experience. The percentage of students accessing the course using a smart device was slightly higher than that of students using a PC. Finally, the split was about even between higher (third- and fourth-year undergraduates) and lower (first- and second-year undergraduates) grade students.

Table 2

Demographic Characteristics of Participants

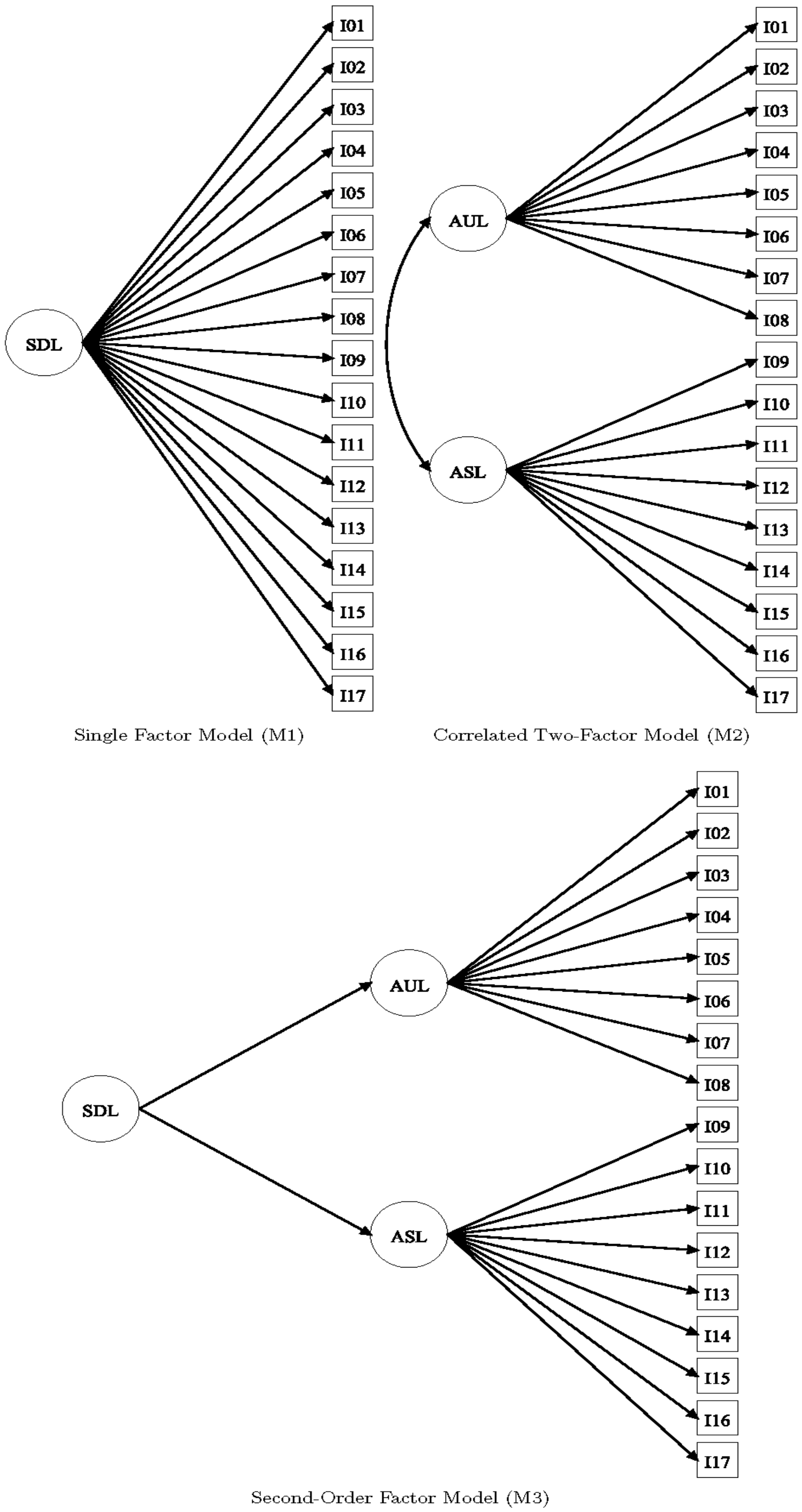
Demographic variable	Category	*n*	%
Gender	Female	224	67.5
	Male	108	32.5
Network connection	PC	150	45.2
	Smart device	182	54.8
Online learning experience	No	243	73.2
	Yes	89	26.8
Grade	Higher	159	47.9
	Lower	173	52.1

Data Analysis Techniques

The SDOLS-T was validated in two stages, and CFA served as the analytical framework in both instances. Stage 1 for RQ1 used CFA to assess three competing model structures (Figure 1) which the methodological literature recommends should be examined because all are designed to explain the shared variance between items in a survey instrument (Gignac & Kretzschmar, 2017). These three models were: (a) the single factor model (M1); (b) the correlated two-factor model [M2, original structure from Su (2016)]; and (c) the second-order factor model (M3). With the best-fit model from stage 1, stage 2 for RQ2 further assessed the structure for levels of measurement invariance across the groups specified by each of the four demographic variables: (a) gender, (b) network connection, (c) online learning experience, and (d) grade.

Figure 1

Three Competing Factor Structures for the SDOLS-T in Stage 1



Note. SDL = self-directed learning; AUL = autonomous learning; ASL = asynchronous online learning; I = Item.

At stage 1 for RQ1, commonly used model fit statistics were examined to assess the three competing structures: χ^2 test and alternative fit indices (AFIs) including the comparative fit index (CFI), the root mean square error of approximation (RMSEA), the standardized root mean square residual (SRMR), and the Tucker–Lewis index (TLI). At stage 2 for RQ2, the changes in these fit statistics (i.e., χ^2 difference test and changes in the AFIs) were assessed to compare a hierarchy of two models, with one being nested within the other through model structure or parameter (equality) constraints at a certain level of measurement invariance.

In particular, regarding stage 2, given different levels of measurement invariance (Sass, 2011), this study investigated whether the SDOLS-T could reach scalar invariance, that is, strong (factorial) invariance, under each demographic variable. Scalar invariance requires three levels of invariance be retained simultaneously across the groups: (a) identical model structure or configural invariance, though all model parameters are still allowed to differ across groups, (b) equal thresholds for ordered categorical item response data or equal intercepts for continuous item response data, and (c) equal factor loadings. Only when scalar invariance holds can the comparison of groups be conducted regarding the latent factor or manifest means, or any other scores (e.g., total scores, Rasch scores; Putnick & Bornstein, 2016; Sass, 2011; Svetina et al., 2020; Thompson & Green, 2013). As for the ordering of testing invariance hypotheses, Wu and Estabrook (2016) argued that, for ordered categorical data, model identification would be more complex due to the presence of threshold parameters and recommended that, when the data contains more than two categories, threshold invariance be assessed ahead of the invariance of other parameters. This recommendation was implemented in previous studies (e.g., Svetina et al., 2020). When analyzing the SDOLS-T data, the study took the same recommended approach and, after establishing configural invariance, proceeded to test threshold invariance before assessing loading invariance.

Finally, regarding the software for CFA, the study used the lavaan and the semTools packages in R; the former is capable of handling ordered categorical data through a weighted least squares (WLS) estimator (Jorgensen et al., 2022; Rosseel, 2012). Stage 1 used the lavaan package only. In stage 2, when conducting a sequence of hierarchical tests to impose increasingly more restrictive equality constraints on CFA parameters across each pair of groups, the semTools::measEq.syntax() function served to automatically generate the lavaan model syntax and implement the model identification and invariance constraints by Wu and Estabrook (2016) under the δ-parameterization (Svetina et al., 2020). The models were next estimated by the lavaan package. In the end, to compare two nested models when testing an invariance hypothesis, the lavaan::lavTestLRT() function was used.

Results

The results from the two stages of analyses are outlined next. Notably, the cutoff values used here for assessing model fit at both stages were traditionally designed for the normal-theory maximum likelihood estimation with continuous data. By contrast, this study implemented a WLS estimator with ordered categorical data. Although there exist known methodological issues regarding applying these traditional cutoffs in a research context such as this, the practice has been widely accepted in the literature and will continue until better alternatives are proposed and established (Xia & Yang, 2019).

Results of Stage 1

The model fit statistics of M1 through M3 are presented in Table 3 (AFIs only). All three models demonstrated an adequate fit on CFI and TLI because they were close to the upper limit of 1.00 for a perfect fit. M2 performed the best on both criteria. Regarding SRMR, only M2 and M1 were lower than the cutoff of .080 for a good fit with M2 being the lowest. Finally, regarding RMSEA, M2 had the lowest value of .0533, also lower than the cutoff of .08 for an adequate fit (Byrne, 2010; MacCallum et al., 1996; West et al., 2012). Evidently, out of the three models, the correlated two-factor structure (M2) demonstrated the best fit as assessed by the highest values of CFI and TLI and the lowest values of RMSEA and SRMR.

Table 3

Results of Confirmatory Factor Analyses of Competing SDOLS-T Model Structures

Model	χ^2	df	RMSEA	CFI	SRMR	TLI
Single Factor Model (M1)	488.11**	187	.0697	.9772	.0743	.9834
Two-Factor Model (M2)	360.96**	186	.0533	.9867	.0647	.9903
Second-Order Factor Model (M3)	925.14**	187	.1092	.9441	.1078	.9593

Note. SDOLS-T = Turkish Version of the Self-Directed Online Learning Scale; RMSEA = root mean square error of approximation; CFI = comparative fit index; SRMR = standardized root mean square residual; TLI = Tucker–Lewis index.

$^{**}p < .01$.

Results of Stage 2

The results of the measurement invariance analyses of the four demographic variables are presented in Table 4. Each measurement invariance analysis for one demographic variable was based on the sequence of three models (configural invariance/identical structure, equal threshold, and equal loading) proposed in Wu and Estabrook (2016) and implemented in, for example, Svetina et al. (2020). Referring to Table 4, at the configural invariance level, the four models from the four demographic variables all demonstrated an adequate fit as measured by RMSEA, CFI, SRMR, and TLI, even though they all had a statistically significant χ^2 test. Next, at the equal threshold level, all four χ^2 difference tests were statistically nonsignificant (Δp ranged from .0879–.4858), indicating that the equal threshold constraints did not significantly decrease the fit of each model. The changes in all AFIs were minimal at the third decimal place, suggesting no significantly worse fit from the equal threshold constraints (Chen, 2007; Cheung & Rensvold, 2002). Finally, at the equal loading level, two of the four χ^2 difference tests were statistically nonsignificant (gender and network connection), while the others were significant (online learning experience and grade), even though none of the changes in the AFIs indicated any significant decrease in model fit. In summary, scalar invariance was achieved for gender and network connection. For online learning experience and grade, their scalar invariance was supported by all AFIs, but not by the χ^2 difference test.

Table 4

Model Fit Statistics for Measurement Invariance Assessment Under Each of the Four Demographic Variables

Demographic variable	Equality constraints	χ^2	df	$\Delta\chi^2$	Δdf	RMSEA	ΔRMSEA	CFI	ΔCFI	SRMR	ΔSRMR	TLI	ΔTLI
Gender	Configural	572.68**	236			.0930		.9776		.0811		.9742	
	Threshold	595.90**	270	42.629	34	.0855	-.0075	.9783	.0007	.0811	.0000	.9781	.0039
	Loading	635.78**	285	22.001	15	.0864	.0009	.9766	-.0017	.0820	.0009	.9777	-.0004
Network connection	Configural	565.78**	236			.0920		.9777		.0803		.9743	
	Threshold	590.19**	270	45.626	34	.0848	-.0072	.9783	.0006	.0803	.0000	.9782	.0039
	Loading	632.15**	285	24.229	15	.0859	.0011	.9765	-.0018	.0812	.0009	.9776	-.0006
Online learning experience	Configural	580.54**	236			.0941		.9770		.0792		.9735	
	Threshold	604.48**	270	44.321	34	.0866	-.0075	.9776	.0006	.0792	.0000	.9775	.0040
	Loading	677.84**	285	36.952**	15	.0914	.0048	.9737	-.0039	.0803	.0011	.9749	-.0026
Grade	Configural	574.55**	236			.0932		.9781		.0796		.9747	
	Threshold	590.91**	270	33.627	34	.0849	-.0083	.9792	.0011	.0796	.0000	.9791	.0044
	Loading	663.61**	285	38.965**	15	.0897	.0048	.9755	-.0037	.0819	.0023	.9766	-.0025

Note. RMSEA = root mean square error of approximation; CFI = comparative fit index; SRMR = standardized root mean square residual; TLI = Tucker–Lewis index.
$^{**}p < .01$.

Discussion

The study validated the SDOLS-T instrument, a Turkish version of the original SDOLS instrument developed to measure students' ability to take charge of their online learning. From WLS-based confirmatory factor analyses using the ordered categorical data from a sample of 332 undergraduate students majoring in education in a Turkish university, the study found psychometric evidence for the new instrument and assessed the extent to which the SDOLS-T functioned equivalently for four demographic groups: gender, network connection, online learning experience, and grade.

Addressing RQ1

Regarding the first research question on the fit of each competing model to the data, the study examined three competing model structures for the SDOLS-T suggested from the methodological literature based on commonly used model fit indices. All three models were statistically significant on the χ^2 test. Regarding the four AFI statistics, the correlated two-factor model (M2) was unanimously the best model; the other two were less satisfactory on either one (RMSERA in the case of M1) or two (SRMR and RMSEA in the case of M3) of the four AFIs. In summary, the findings from stage 1 confirm that the same factor structure proposed by Su (2016) for the SDOLS also applies to the SDOLS-T.

Addressing RQ2

Regarding the second research question on the extent to which the SDOLS-T measures the same construct across the groups created by the four demographic variables, a measurement invariance approach was taken, where both the χ^2 difference test and the changes in AFIs were used to compare pairs of nested models. The four AFIs supported up to the scalar invariance of the SDOLS-T across the four demographic group pairs. Additionally, for gender and network connection only, scalar invariance was also supported by the χ^2 difference test. In summary, the measurement invariance analyses support the comparison of the SDOLS-T latent factor, manifest means, or other scores across groups specified by gender and network connection. As for groups defined by online learning experience and grade, any such comparison should proceed with caution. To compare the latent factor means when an appropriate level of measurement invariance is not satisfied, one recommended approach from the literature is to compare the groups on relevant statistics with and without imposing the equality constraints which have been tested to be invalid. If the discrepancies in model parameter estimates are small, comparing groups may be justified (Chen, 2008; Schmitt & Kuljanin, 2008).

Conclusion

The study examined the psychometric properties of the SDOLS-T for measuring Turkish university students' ability to take charge of their learning in an online environment. First, through a comparison of three competing model structures which were all designed to explain the shared variance between the items of a survey instrument, the study concluded that the SDOLS-T has the same underlying structure as the original SDOLS instrument in English, with eight items measuring autonomous learning and the other nine measuring asynchronous online learning. Next, through measurement invariance analyses, the study concluded that the SDOLS-T allows the comparison of latent or manifest means, or any other scores (e.g., total scores, Rasch scores), across groups defined by gender and network connection where scalar invariance is unanimously supported by all fit statistics used in the study. The study briefly describes an approach from the literature for comparing those scores of groups defined by online learning experience and grade where scalar invariance is supported by AFIs only.

Implications of This Study

The study has implications for educational practice, research, and policy and decision-making in higher education in Turkey. First, for educational practice, instructional designers in Turkish colleges and universities may use the SDOLS-T as a diagnostic tool to measure and assess online students' readiness and identify those whose SDL ability is relatively low before adjusting course designs to improve students' self-directed skills and subsequently the chance of their success in online learning (Edmondson et al., 2012; Khiat, 2015; Tekkol & Demirel, 2018). Second, for research, the study offers a new instrument in Turkish for assessing students' SDL ability in online learning. The instrument may be further validated for more research contexts in Turkey (e.g., Turkish students in secondary education), or serve as an outside criterion with which other instruments measuring theoretically-related constructs are correlated for evidence of construct validity (Demircioğlu et al., 2018). The instrument may also be used in SDL-related content area research in online education to characterize environments which are effective in helping students acquire and advance their SDL skills and/or to explore how students' SDL skills are related to their academic success, desire for further academic pursuits and lifelong learning, and prospects of employability (Ahmad et al., 2019; Tekkol & Demirel, 2018). Third, for policy- and decision-making, the data collected using the SDOLS-T may help higher education administrators in Turkey better understand how their students' SDL ability is related to their engagement and success in online courses, to the completion of online programs under the university-provided online learning management systems, and to students' readiness for the job market. Accordingly, administrators may become better informed when making policies to more effectively reduce dropout and increase retention rates and designing strategies and tasks to better prepare students to become more SDL-capable for their prospective employers (Ahmad et al., 2019; Schulze, 2014; Sun et al., 2022).

Finally, the successful adaptation of the SDOLS instrument into the SDOLS-T in the Turkish setting may serve as evidence of the SDOLS having a high level of cultural sensitivity which may easily enable its use in multicultural settings. Thus, it is reasonable to anticipate the successful adaptation here may inspire similar SDOLS-related, scale validation studies in other languages. Further, in large-scale, cross-cultural research, the availability of the instrument in multiple languages would allow the survey to be filled out by participants from around the world in their native languages. With the collected survey data analyzed using the measurement invariance method, it would be possible to investigate the cultural universality of the (components/aspects, as measured by various survey (e.g., the SDOLS-T) items, of the) SDL construct.

Limitations and Future Extensions

This study is not without limitations, which could serve as future research directions. First, even though the original SDOLS was validated through Rasch modeling (Bond & Fox, 2015; Yang et al., 2020), the study here took a CFA approach under the structural equation modeling framework instead. Therefore, a possible extension of the study is to apply Rasch modeling to the SDOLS-T for additional psychometric evidence. Under Rasch modeling, differential item functioning may be used to assess the lack of measurement invariance (i.e., noninvariance) of SDOLS-T items, if any (Kim & Yoon, 2011; Meade et al., 2007). Second, the study did not assess the longitudinal invariance of the SDOLS-T. If students' level of SDL ability evolves substantially over time (e.g., over years), ceiling or floor effects may occur later in life. Accordingly, SDOLS-T items may need to be updated to adjust for students' behavioral changes.

Besides, if the underlying meaning of SDL also evolves (e.g., the way students self-manage their learning changes over time as the field of online education is rapidly developing), the SDOLS-T instrument may need revisions as well to ensure it is still the construct of SDL that is measured (Chen, 2008; Widaman et al., 2010). Therefore, another possible extension of the study is to examine the longitudinal invariance of the SDOLS-T to assess its continued validity over time (Millsap & Cham, 2013). Finally, because any sign of item noninvariance contributing to model misfit is concerning in terms of item quality (Sass, 2011), identifying individual noninvariant items by conducting item level analyses could be a future extension of the existing study. Such analyses are usually guided by the modification indices suggesting which items could be freed to improve model fit, thus leading to partial measurement invariance at a certain level (Schmitt & Kuljanin, 2008).

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Comparative Effectiveness of Approaches to Students' Labour Education in Universities in the New Era With the Use of Information Technologies

Ting Xu
School of Marxism, Changchun Normal University, Changchun, China

Abstract

This study aimed to identify and compare the efficiency of different theoretical (competence-oriented) and practical (system-activity) approaches to labour education of college students in China using the Open edX online learning platform. The study was conducted at the Shengda College of Economics and Business Management. It involved 150 first-year college students and two full-time teacher-employees from the Labour Protection Department who had responsibility to ensure the quality of labour education and supervise the process of its introduction. The practical approach was 75% more effective when college students were allowed to choose work according to their preferences. The study showed that the practical approach decreased students' motivation to work by 3%, while the average motivation with a theoretical approach was 45% higher than with a practical one, due to lack of physical work and exhaustion at work.

Keywords: approaches to teaching, labour education, labour market, labour skills, physical labour

Introduction

Currently, the majority of college students in China are not fond of and therefore neglect labour education, which causes poor labour education (Zou et al., 2020). The change in the status of labour education and increasing its role in the education system are associated with the historical burden of training specialists in China's new era (Chen & Xie, 2020). Quality-oriented education is an inevitable outcome of synchronous educational and social development and an important sign of the comprehensive implementation of modern educational ideas (Meng et al., 2020). Several important discussions were held in China on strengthening labour education, where participants stressed that every person's work, creativity, knowledge, and talent should be respected (Xi, 2017). At the National Education Conference, emphasis was placed on the importance of fostering a work ethic among students, teaching them to respect labour and helping them understand the benefits of work (Yang, 2020).

In the modern world, where technological advancements occur rapidly and continuously, proficiency in working with information technologies has emerged as a crucial competency for attaining a successful career (Wen, 2021). Information technologies not only streamline and expedite work processes but also open new avenues for labour creativity, innovation, and collaboration (Lv, 2022). Incorporating information technologies into labour education helps students cultivate digital literacy skills, proficiency with diverse software applications and tools, and knowledge of ethical and secure information usage practices (Lv, 2022; Wen, 2021). Information technologies are also opening up new possibilities for organizing work activities, such as remote work, telecommunications, and global collaboration (Mansurjonovich, 2022).

Labour education is a process that helps shape a person's need for work, describes the benefits of professional specialization, and develops practical, creative, and labour culture skills (Liu, 2019). The labour education of students involves all types of student activities, namely educational and research work, educational activities, industrial practice, and social and domestic work (Damianakis et al., 2020).

Another crucial task of college students' labour education is the psychological preparation for work in their chosen specialty, the education of freedom, patience, perseverance in overcoming difficulties, neatness at a workplace, explanation of the public property value, and so forth (Li, 2019). Some researchers also noted that student labour education's major goal is forming conscious residents by developing labour skills, active citizenship, high moral qualities, and spirituality among the young generation (Du & Gao, 2020). Through the joint efforts of the whole society, labour education is an independent part of most university curriculums, which, however, may result in certain problems (Chen, 2020). Thus, for example, if a school defines a labour course as compulsory and credit-related, some students demonstrate a perfunctory attitude to it. Certain measures may be required to change public attitudes to labour education and convince each worker of the uniqueness of their labour and skill. First, the structure of labour education should be reformed (Zhejin, 2019).

Meantime, each higher education institution requires an adjusted system for collecting and analyzing information about its graduates' activities. This could enable prompt solving of the problems related to improving the labour training of students. It would also be required to provide conditions for the formation of a professional labour culture among future specialists (Antonelli et al., 2020).

Consequently, it is necessary to provide training for teachers, which involves teaching the educational methodology of organizing and stimulating work (Stevens et al., 2019).

Students' labour education is, on the one hand, future-oriented (i.e., the education of a student as a future specialist with inherent positive professional traits and labour skills and abilities), while on the other hand, it is the very process of training specialists within the framework of learning, social work, and so forth (Zhang, 2020). Nowadays, college students urgently need strengthened labour education, integrating labour thinking into the entire education and training process and establishing a comprehensive system for developing talents and labour training (Haijiao, 2018). It is possible to enrich the content of students' practical experience, standardize their behavioural habits and provide for their self-cultivation, train college students' will, and encourage them to form a proactive mindset and respect for others (Zhang et al., 2019). The correct understanding of labour values is of great importance for students' personal development and social progress, including the comprehensive development of useful skills, morality, mind, body, beauty, and labour (Ying & Zheng, 2018).

The relevance of the topic is confirmed by the fact that labour education at universities is critical for the development of not only professional skills but also work values, which are the basis for career success in the modern world. With the rapid development of information technology, the ability to effectively use this technology is becoming essential for successful professional growth. Labour education is an integral part of preparing students for professional life, and modern information technologies can contribute to the effectiveness of labour education. This study aimed to make an original contribution to the literature on open and distributed learning through a unique combination of theoretical and practical approaches using information technology. The specific context of the study in China allows for a better understanding of local characteristics and needs in labour education, and the in-depth comparative analysis of the effectiveness of different approaches to labour education based on strong empirical evidence adds new insights to the field. The findings of this research show that better information on labour market outcomes and the development of more effective approaches to student labour education can serve as a goal for local colleges to improve the prospects of their students in the labour market.

Literature Review

Labour education constitutes an indispensable component of the education system, as its successful implementation and ongoing advocacy foster the development of appropriate values within students and enhance their comprehension of fundamental socialist ideals (Lianzhao, 2017). In the past, higher education reform deeply focused only on practical values, neglecting upbringing and human nature, inevitably leading to the loss of proper character and cultural integrity (Xu, 2018).

Researchers note that labour education forms the correct labour ideas and consciousness in students in special labour courses to master certain labour skills (Xinhua, 2018). However, labour as the main means of human survival has not disappeared or declined but has been constantly transformed (Meng et al., 2020). It is crucial to bear in mind that information technologies do not replace other aspects of labour education, such as the development of professional skills, leadership qualities, and communication abilities (Wen, 2021).

The concept of quality education is not isolated. It is the inheritance and development of ancient and modern Chinese and foreign educational ideas. This particularly entails the systematic consolidation of the favourable and unfavourable outcomes of educational reform and the findings derived from theoretical sublimation (Xu, 2018). Nowadays, college students face numerous temptations, namely the Internet, entertaining star talent shows, and all types of bad habits, which affect their thinking and distort values (Xia & Liu, 2019). General Secretary Xi Jinping at the National Education Conference emphasized that education's main aim is to encourage the self-cultivation of college students and to teach socialist core values. This implies implementing labour education on college campuses, paying attention to the labour process, and introducing innovative labour methods. These measures promote the spirit of work and cherish labour achievements that can convey the values of diligence, simplicity, solidarity, and friendship (Xi, 2017).

Each person from a certain age begins independent labour activity, which requires a developed habit of working, the desire to realize potential, and the proper moral and psychological readiness. The development of such attitudes is one of the main duties of the family, the school, and higher educational institutions (Kirkeboen et al., 2016). In addition, the sooner these characteristics begin to develop, the faster and more productive the result (Nabiullina et al., 2020).

One core aspect of young people's psychological preparation for work is the formation of a sense of responsibility and the ability to take care of themselves (Scott-Clayton, 2015). In turn, the feeling of self-responsibility contributes to the development of such vital personality traits as initiative, enterprise, and creativity (Phillippe & González Sullivan, 2017). Labour education effectiveness suggests that a student needs work and feels joy from the labour process through the realization of their knowledge and skills since these factors are inherent in the human essence (Baker, 2018).

Regarding labour education, Xi Jinping explained it as education that enables people to form correct labour attitudes and relations to develop labour habits (Xi, 2017). It is emphasized that labour education facilitates the formation of correct labour views, attitudes, and work habits among students, which allows them to acquire various knowledge and skills. Guangya Wang noted that life is an education that creates hardworking citizens able to work with nature's forces and build a highly harmonious society. In turn, Tao Xingzhi proved that "hands and brains work together" and considered labour education as a kind of "creative education" (Wang, 2017). Wang and Wang (2020) deeply understood labour education's universality and uniqueness based on the inheritance and development of its excellent traditions among college students, while actively exploring effective approaches to strengthen such education in the new era. Both students and schools need to be aware of and respond to expected economic outcomes, and it is thus that community colleges will be able to successfully fulfil their mission to improve students' labour market performance (Krupskaya, 2015).

Labour Education and Information Technologies

Several information technologies can be applied in the field of labour education (Lv, 2022; Mansurjonovich, 2022; Wen, 2021):

1. Virtual reality (VR): VR technologies enable the creation of immersive simulations of work environments and situations, allowing students to practice and develop their skills in a safe virtual setting.

2. Augmented reality (AR): AR technologies permit the incorporation of virtual elements into the real environment, offering new opportunities for learning and training.

3. Simulations and virtual laboratories: The use of simulations and virtual laboratories empowers students to engage in practice and skill development within specific work domains.

4. Cloud technologies and online platforms: Cloud technologies and online platforms enable students to access educational resources and materials anytime and anywhere. This may encompass online courses, digital libraries, webinars, and other forms of online learning that support the enhancement of professional skills and knowledge.

5. Mobile applications and devices: Mobile applications and devices allow students to access educational materials and complete tasks at any time and place.

These are merely a few examples of information technologies that can be used in labour education. The specific selection of technologies depends on particular objectives and the student's needs within a field or profession.

Problem Statement

The analysis of scientific works has shown that the issue of labour education for college students is an urgent problem in the new era.

This study aimed to identify and compare the efficiency of different theoretical (competence-oriented) and practical (system-activity) approaches to labour education of university students, using the Open edX online learning platform.

We had two research objectives:

- Study the level of influence on students' motivation to work comparing theoretical and practical approaches.

- Determine whether there was a significant difference between competence-oriented or system-activity approaches on the efficiency of teaching students to work.

Methods and Materials

Participants

The study was carried out at the Shengda College of Economics and Business Management in China. Appendix A describes the theoretical and practical approaches to labour education used at the college. In total, 150 first-year students participated in the research, which also involved two full-time teacher-employees from the Department of Labour Protection who were tasked with providing for the quality of labour education and supervision of the program. The number of females and males was equal since the research was not aiming to study the influence of gender on attitudes to labour education. Initially, there were more than 150 first-year students interested in taking part in the experiment, however, some later refused for unknown reasons. According to statistics, first-year students are more attentive to each step of learning than senior students are; thus, this sample was chosen in order to collect as many opinions as possible to identify areas for development in labour education.

Procedure

The participants were evenly distributed into two distinct groups: experimental and control, each comprising 75 students. In the experimental group, the training involved the competence-oriented method using the Open edX platform, while in the control group, the system-activity method using the Open edX platform was applied. The advantages of using the online learning platform Open edX included the opportunities it allowed students to: personally create an individual study schedule; record and view video tutorials; upload course assignments; and do homework within selected time limits.

Labour education training took one academic semester with distance classes. The Labour Protection Department proposed the theoretical (competence-oriented) and practical (system-activity) labour education approaches.

The competence-oriented approach to teaching involves various theoretical knowledge and skills that may be applied in specific practical situations to solve life problems. The primary objectives of this approach are to provide a clear understanding of the history and meaning of college-specific labour education and to underscore its importance and necessity. In the theoretical part of the training, students are taught about the concept of labour, its significance in modern times, labour ideology, and related topics. Labour department employees engage in labour propaganda before each labour practice, encourage active participation in the education practice, and teach safety.

The system-activity approach to teaching involves a result-oriented activity that provides feedback. This approach takes into account the psychological aspects, age-related factors, and individual characteristics influencing the development of a student's personality. The process requires a student's active, versatile, independent, and cognitive presence. A compulsory course for first-year students, this approach involves an hour of work a day for each student during one academic semester. A quantitative evaluation of the working conditions for every student was conducted and published regularly as a basis for evaluating a particular student's performance in the semester. Moreover, labour courses were incorporated into the college curriculum during internships.

The study was performed in stages:

1. Development of a student survey tool to study the effectiveness of approaches to labour education.

2. Administration of the questionnaires.

3. Checking the validity of the content, design, and reliability of the tool.

4. Data analysis.

The efficiency of approaches to college students' labour education was determined using the work motivation indicator, as it influences the duration and result of work. To measure work motivation, the McClelland test, which asks the central question "What drives you?" (Nabiullina et al., 2020), was used. The test identified the leading need of each student to find an incentive and made it possible to choose an effective way to increase motivation. Dedicated employees are the ones whose motivation coincides with their needs. Through motivation, it is possible to explore each student's attitude to professional activity and evaluate the internal and external factors of labour motivation (including students' personal needs), incentives to work, and peculiarities of working conditions.

Study Design

This study used a quantitative descriptive approach with a questionnaire that required written responses and a scoring method for those responses.

Data Collection

The experiment involved the survey method to collect data. Two questionnaires were provided to students: one following the theoretical course and one following the practical course. The questionnaires are shown in Appendix B. The questionnaires aimed to ascertain the following indicators: the concentration of students on labour education theory; students' understanding of educational materials (both practical and theoretical); the motivation of students to practice labour education; and, students' learning results. For each completed practical lesson, the student responses were scored, receiving a predetermined number of points, which were totaled at the end of the academic semester.

We also tested the content validity, design validity, and reliability of the questionnaires. These indicators were estimated using the inter-rating method by two experts. The content validity test resulted in a score of 1, meaning that the study questionnaire had high content validity. In the validity assessment, all questionnaire items achieved an estimated R-value surpassing 0.444, using an r table with N = 20 at a 5% significance level. Cronbach's alpha was 0.897, and thus the factor was > 0.8, indicating excellent reliability.

Data Analysis

To describe the data, the questionnaire and its content were preliminarily analyzed, and the reliability of the selected information was checked using IBM SPSS Statistics (Version 26). In addition, t-tests were used to compare the differences between the two labour education approaches.

Ethical Principles

All ethical principles were discussed before conducting the study. Consequently, the head of the college approved the research, and all participating students and teachers signed an agreement to participate in the experiment. The principles of reliability and competence in collecting information were observed.

Limitations

Since the subject of the research is extensive, the results of the study could have been affected by the student sample size. Additionally, the limited study duration posed a challenge, as the span of one semester proved inadequate for thoroughly evaluating the long-term efficacy of various approaches to student labour education. Furthermore, the age of students may have influenced the result since young people are more active in work than those in the older generation; the younger generation needs to earn a living, while the older one retires. We did not examine the effect of gender.

Results

Table 1 presents the results of the analysis of covariance (ANCOVA) of the student's motivation levels. The adjusted mean and standard error were 6.7 and 0.11 for the control group, and 8.4 and 0.12 for the experimental group. According to the results, there was a significant difference in scores between the two groups after testing (F = 9.84, $p < .05$).

Table 1

Results of Analysis of Covariance of Student Motivation

Group	*n*	Value	*SD*	*M* (adjusted)	*SE*	*F*	η^2
Experimental	75	6.6	0.74	6.7	0.11		
Control	75	8.5	0.71	8.4	0.12	9.84*	0.15

*$p < .01$

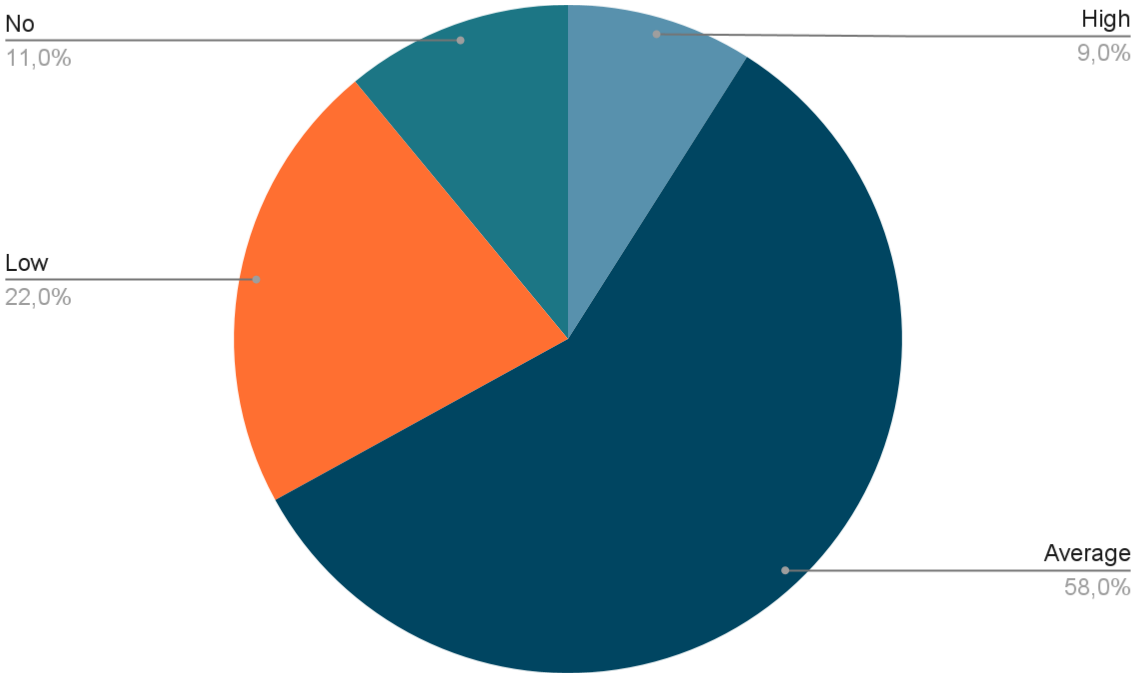
The data obtained indicate that when using the Open edX online platform to teach labour education, the system-activity method is more effective in increasing students' academic motivation. There was a significant difference in the motivation level of the experimental and control groups, with the second showing higher results. This suggests much more clearly that the system-activity approach is more effective when compared to the competence-oriented approach.

The Effectiveness of the Theoretical, Competence-Based Approach

The influence of the theoretical approach on students' motivation to work was determined after lectures were delivered to first-year college students. The lectures conveyed information about what work is, why it is so important in modern times, and the expanded ideology of work. According to the results of the questionnaire and the motivation test, college students expressed their readiness to participate in work: 9% were extremely motivated, 58% showed a desire to work actively, 22% experienced negative emotions during physical labour with low motivation, and 11% were generally not motivated to work. Figure 1 shows that the majority of college students were positive about physical work and wanted to acquire more life skills.

Figure 1

Experimental Group's Attitude to Work (Theoretical Approach)



The Effectiveness of the Practical, System-Activity Approach

Based on the analysis of results from students who were part of the group that received their labour education through the system-activity approach, i.e., practical work (practical classes), it emerged that if college students can choose their favourite type of activity, their motivation increases to 75%. If students are assigned a task that does not interest them, their motivation drops to 35%. However, 15% of students simply do the work assigned.

When students are allowed to choose tasks that interest them, their motivation increases, emphasizing the importance of integrating personal interests into the learning process to increase motivation and productivity. Restriction in the choice of tasks can negatively affect performance, so this aspect should be taken into account when planning learning tasks. A neutral attitude to the choice of physical work for some students may mean that the physical aspect of tasks is not a determining factor for their effectiveness. These results are shown in Table 2.

Table 2

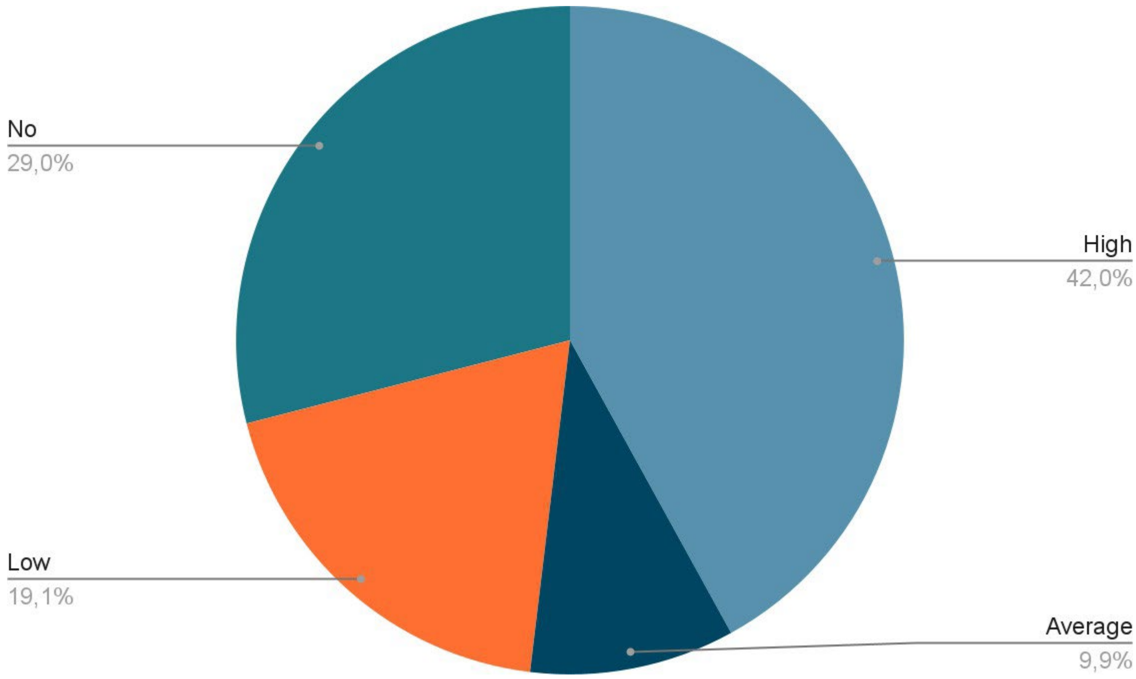
Influence of Different Indicators on Students' Motivation

Indicator	Efficiency, %
Students choose an interesting job for themselves.	75
Students are unable to choose work according to their preference.	35
Neutral attitude towards the choice of physical work.	15

Students' motivation to work under the system-activity approach, i.e., practical, is presented in Figure 2. Analysis revealed that 55% of students were motivated to work, 25% showed low motivation for physical labour, 13% demonstrated average motivation, and 7% were not motivated and refused to be engaged in practice.

Figure 2

Control Group's Attitude to Work (Practical Approach)



Further analysis of the practical approach showed that the work of college students extended beyond mechanical labour, such as sweeping floors and washing tables, to complex work requiring the interaction of mental and physical force. Hence, the guidance offered by educators served the dual purpose of enhancing college students' learning efficiency and promoting active involvement in practical work experiences.

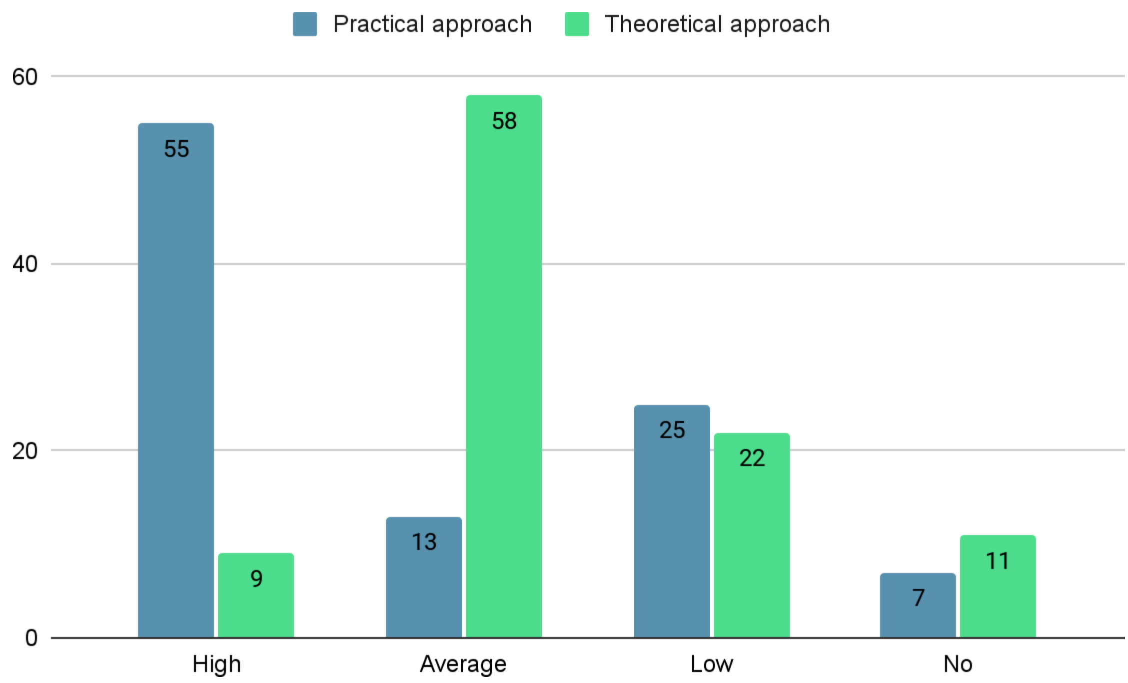
Comparative Effectiveness of the Two Approaches to Labour Education

The curriculum and the theoretical approach to training are the basic forms of labour education in China. However, our results suggest that improving the structure of the labour education curriculum in terms of adding practice is a measure that could enhance student motivation.

Figure 3 presents the comparative effectiveness of approaches to labour education for college students.

Figure 3

Comparative Effectiveness of Labour Education Approaches



The practical approach increased motivation to work by 3%. Meanwhile, when assessing the students with average motivation, the theoretical approach was 45% higher than the practical one. This may be due to the fact that those students had not had an experience of physical work; they had not felt tired or suffered pain while working. Furthermore, 55% of students taught under the practical approach were highly motivated to work, but only 9% with the theoretical approach. One reason may be that students in practice communicate, gain new knowledge, and receive advice, feedback, and help from others. Hence, the student's interest in work significantly increases. The percentage of students without motivation was 4% higher with a theoretical approach since the theory fails to reveal all the advantages of work in the same way that the practical activity would.

Table 3 presents the differences in the effectiveness of approaches to the labour education of college students in this study.

Table 3

Results of the t*-Test of College Students' Motivation Comparing Two Approaches to Labour Education*

Teaching approach	Students, *n*	Value	*SD*	*t*
Theoretical	75	1.365	0.392	0.820
Practical	75	1.452	0.216	

The data did not show a level of significance ($t = 0.820$, $p > .05$). Thus, the comparative effectiveness of the two approaches was more or less equal. This suggests that labour education is comprised of both practice and theory.

Discussion

Labour education has always been substantive content and a method of education and training in China. Labour training allows college students to realize the core socialist values in the new era, improve the quality of life in college, and develop the ability to innovate and be creative (Krupskaya, 2015). Colleges' key aim is to prepare students for the labour market. In light of this, work culture and the adoption of innovative teaching methods represent a crucial source for the cultivation of labour values.

Research has shown that less than 40% of a sample of community college students in California accurately ranked broad categories of specialties in terms of labour market outcomes (Baker et al., 2018). Students believed that average salaries were 13% higher than they were. They also underestimated the possibility of their employment by almost 25%. The article found that the main efficiency determinants of student labour education approaches were beliefs about course enjoyment and grades.

A similar survey was conducted within the framework of Yang's research (2020), regarding practical content and practical significance. Students of vocational educational institutions answered the question: What do you think is the main importance of participating in practical activities in college? The students surveyed believed they could accumulate work experience (74.51%), enrich extracurricular life (68.14%), and gain additional life experience (62.75%).

While the results of other studies are diverse, there are some similarities with this research. For instance, 74.51% of the students surveyed believed that labour education in college facilitates the accumulation of work experience (Yang, 2020). In turn, in our study, 55% of Shengda College students were motivated to work through in-depth communication with people and society since it was easier for them to obtain more knowledge and help from others in a practical way. Moreover, college students realized the organizers' regularity and professionalism and believed that labour activity was appropriate for their development (Li, 2021). On the other hand, some studies showed that social skills and performance indicators tend to increase after occupational therapy training. Moreover, it was found that two groups of data did not reach the level of significance (t = 0.820, p > .05). Thus, the two approaches to college students' labour education did not have a significant difference in terms of effectiveness.

Conclusions

This study of the approaches to labour education demonstrated that the practical approach increased motivation to work by 3%. At the same time, among those with average motivation, the theoretical approach was 45% more motivating compared to the practical one due to the lack of exhausting physical work. Besides, 55% of students taught with the practical approach showed a high motivation to work while only 9% of those taught with a theoretical approach reported the same level of motivation. When engaged in practical work, students communicate, receive advice and feedback, and obtain new knowledge. The share of students with a lack of motivation was 4% higher with the theoretical approach. The t-test data in this study showed that the two sets of descriptive test data did not reach the level of significance (t = 0.820, p > .05), and thus, the two approaches to students' labour education in terms of efficiency do not differ considerably.

In terms of the practical application of this research, the findings promote the idea of improving the effectiveness of approaches to students' labour education as a goal for colleges to advance the prospects of their students in the labour market. The improvement of labour education and upgrading its form and content have an important practical value for modern students and personnel training. Further development will require expanding research on labour education efficiency and investigating new approaches to educate professionals, which will be beneficial for both employees and the state.

Funding

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Appendix A

Shengda College Work Education Program

A person can benefit from developing good life habits. Shengda College labour education is an educational and realization method of forming positive daily habits. The single-semester program is designed for first-year students. On a compulsory basis, each student is required to work an hour a day for the academic semester.

Theoretical Approach

The theoretical program on labour education teaches the following topics in the form of lectures:

1. The concept and ideology of labour
2. Fostering a positive attitude towards work and desire to assist students
3. Formation of work skills and their continuous improvement
4. Cultivating the habit of labour efforts with readiness to take an active part in work
5. Creating a positive interaction in the labour process and the education of collectivism, mutual assistance, and the ability to bring the work started to an end
6. Safety precautions

The lectures are given face-to-face with the use of presentations by teachers of labour education. Additionally, a board, computer, and projector were used to conduct lectures.

Practical Approach

Labour education is provided by a reliable organization, mechanism, and system. This involves the establishment of a special managing organization, namely the Labour Protection Department. There are regular classes on the following issues: measures for the implementation of labour education; measures for the competition of cleanliness among students; self-service; household work; collective labour; manual labour; labour in nature; and regulations on the management of labour protection. The classes are aimed at standardization of labour education management, improvement of various mechanisms, and quantitative assessments of labour education, which are mainly reflected in the secondary colleges' daily work.

These are the components of the practical training program:

1. Labour in Nature and Manual Work. In particular, this refers to one-minute environmental protection, the activities that encourage all students to use the time between lessons to set up desks and chairs, collect garbage, and develop the habit of cleaning up and caring for the environment. The Clean and Tidy Dining Environment activities teach students to take responsibility for cleaning up leftovers on tables after meals, consciously returning dishes, classifying and recycling waste, and forming good dining and living habits. The activities also include cleaning college areas and the garden, planting flowers, and watering trees.

2. Measures for the Competition of Cleanliness Among Students and Self-Service. This component means integration of labour education into campus culture. Shengda College's motto is "The realization of self-reliance mainly depends on the development of labour education and the implementation of work and study programs." In the school environment, students are required to participate and achieve cleanliness through work practice. In addition, the spirit of work and labour requirements are reflected in Shengda's motto, which includes guidance such as "get up early in the morning and sweep the yard," "dress and be neat," "work harder, strengthen muscles and bones," and so forth. Shengda College cultivates students' work awareness and improves their labour abilities via campus cultural slogans and specific study and life requirements. Work diversity provides more opportunities than burdens. At the same time, an individual should use labour to move from self-help to helping others.

3. "Household Work" and "Collective Labour" imply the combination of main labour and collective work with study. The main labour refers to the educational method of the daily half-hour compulsory labour training course at Shengda College. Collective work mainly indicates various group works in college (for instance, cleaning the dining room and toilets). To accept an idea of glorious work, a change of thinking is required to associate work with positive emotions, such as praise and encouragement, and understand that physical labour aims to adjust to the changing times.

Practical classes are conducted by teachers of labour education. They also use the college garden, dining room, toilets, and other facilities. During the training period, students were required to choose cleaning the campus, caring for plants, or another task once a week. For each completed practical lesson, students received a certain score (ranging from 1 to 5), depending on performance (1 = poor, 5 = excellent).

Appendix B

Questionnaire 1

1. What is labour? What is it for?
2. Give the definition of labour ideology.
3. What is your attitude towards physical labour?
4. List the rules of collectivist education.
5. How do you bring the work started to an end?
6. What skills have you been able to learn through physical labour (work skills, health promotion, respect for comrades, the ability to overcome difficulties, etc.)?
7. What are the internal and external reasons for labour motivation?
8. After completing the theoretical course, did your motivation for work increase? Why?
9. What emotions do you experience when you think about work or physical labour?
10. Identify 5 basic safety rules for physical labour.

Questionnaire 2

1. Where would you like to work most (in the field, at an enterprise, in the service sector, etc.)?
2. Which kind of work is preferable for you: permanent or seasonal?
3. Do you do housework?
4. What aspects of physical labour are you most interested in (physical training, results of labour, the opportunity to gain skills in a particular profession, etc.)?
5. Do you have the opportunity to expand and deepen your knowledge of various subjects (physics, mathematics, chemistry, biology, history, etc.) during physical labour?
6. What motives induce you to work?
7. What do you dislike about physical labour (bad organization, low pay, the unfriendly attitude of production workers, etc.)?
8. What tasks did you carry out for your team? Why? What exactly did you like and dislike about that work?
9. What have you done for your team and individual comrades on your own initiative?

10. What keeps you from doing good public errands? How do you overcome these difficulties?

11. What qualities have you been able to form, develop or strengthen through physical labour (work skills, health promotion, respect for comrades, the ability to overcome difficulties, etc.)?

12. Is mutual assistance important in practice?

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Manuscript Selection in a Literature Review: "Free-Full-Text-or-Next" as a New Criterion

Fabio Galli, M.Sc MedEd
University of South Wales (Alumnus, not affiliated), United Kingdom

Abstract

Literature inclusion and exclusion (E/I) criteria are a fundamental selection methodology in different applications. Mainly, the E/I criteria are identified and chosen with respect to the question for which the manuscript itself is produced, thus allowing the selection of the literature. This procedure is not always related to the economic availability of independent subjects (e.g., researchers, authors, students) or even institutions in low-income areas or with little willingness to cover the use of paid materials. The proposed criterion (free-full-text-or-next) aims to support independent subjects (without affiliations) or subjects belonging to economically disadvantaged areas.

Keywords: medical education, faculty development, peer support, literature review, research

Free-Full-Text-or-Next: A Proposed Literature Review Criterion

Literature reviews are tools for collecting, observing, and analysing literature relating to a specific and focused topic. The literature review, particularly if using systematic methods, involves a manuscript search protocol and involves the use of inclusion and exclusion criteria (E/I criteria; Snyder, 2019; van Wee & Banister, 2023). The free-full-text-or-next (FFTN) is proposed as a criterion applicable in the literature search phase or in the selection phase using E/I. FFTN aims to represent a support criterion for researchers of every discipline unable to use access to databases through an institutional profile, unable to purchase manuscripts, and free from the request to third parties for access to the manuscripts of interest.

The characteristics of FFTN include the exclusive use of literature granted completely free of charge, without the need for institutional profiles or the obligation to request a free copy from the authors. The FFTN criterion is proposed as inclusive and fair, accessible by every researcher anywhere in the world, regardless of personal or institutional economic possibilities, regardless of rankings, and regardless of institutional affiliations. FFTN is proposed as a useful criterion for independent researchers and authors, and/or those with a lack of funds. The lack of personal or institutional funds, or the location in low-income areas, can limit the use of paid manuscript types, limiting or impeding the development of activities of researchers, students, institutions. The FFTN criterion thus allows us to make the choice or need to use exclusively free material visible, and to make this choice a criterion like others already in use.

The proposal contained in the FFTN criterion is to be considered an additional opportunity compared to the criteria already present, as well as being an incentive to offer more and more literature that is not only open access but without formal mandatory requirements. The proposal of the FFTN criterion does not have the objective of excluding or boycotting paid material, but rather of being a choice criterion to be declared within the literature review development process, which is also an incentive and visibility for the works proposed by subjects (e.g., individual authors/researchers, universities, institutes) with low spending capacity or opportunities. Even if there is the indisputable possibility of generating selection bias, the use of the FFTN criterion declared in the procedure would have the same loss as any other E/I criteria used (e.g., period/range, publication date, publication language) already used in literature reviews. The advantages of applying the FFTN criterion can be aimed mainly at stakeholders without funding, stakeholders with reduced spending, and students. The product of using the criterion will not be of lower quality compared to the use of the other criteria; furthermore, the publication cost, in the form of article processing costs (APC), does not influence the impact of the proposed article (Maddi & Sapinho, 2022).

To conclude, the free-full-text-or-next (FFTN) can be considered an advantageous criterion from a financial point of view, which allows the use of quality literature, and which allows the generation of a quality product. FFTN allows a methodology for which literature is also selected due to the absence of payments, absence of institutional/academic profiles, thus generating a factor of inclusiveness and equity, with the strict need to declare its use within the procedures and paying attention to possible bias.

Conflict of Interest: There is no conflict of interest.

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Facilitating Students' Emotional Engagement in Synchronous Online Learning: A Systematic Literature Review

Yaxin Tu[1], Qiyun Wang[2, 3,*], and Changqin Huang[1]
*[1]Key Laboratory of Intelligent Education Technology and Application of Zhejiang Province, Zhejiang Normal University, Jinhua, Zhejiang, China; [2]Department of Learning Sciences and Assessment, National Institute of Education, Nanyang Technological University, Singapore; [3]Center for Research and Development in Learning, Nanyang Technological University, Singapore; *Corresponding author*

Abstract

Learners' emotional engagement in synchronous online learning (SOL) is critical for improving learning persistence and performance. Nevertheless, there is currently a lack of comprehensive and systematic reviews of emotional engagement in SOL. This review synthesizes the strategies to promote emotional engagement in SOL found in published empirical studies. A total of 32 articles were systematically analyzed by following the grounded theory approach. The primary themes were grouped into four categories: (a) instructor actions (e.g., interacting informally before and after class, encouraging the expression of ideas), (b) learner behaviors (e.g., building rapport with peers, recognizing individual accountability), (c) environment characteristics (e.g., creating a supportive atmosphere, selecting communication modes), and (d) activity design (e.g., using breakout rooms, embedding diverse elements). These findings offer comprehensive understanding and guidance for promoting emotional engagement in SOL for instructors, researchers, and course developers.

Keywords: synchronous learning, emotional engagement, online learning, strategies, technology

Introduction

During the COVID-19 pandemic, numerous educational institutions experienced a swift transition in their approaches to learning and teaching. Specifically, online learning replaced a substantial portion of face-to-face instruction, employing online technologies to facilitate instructor-student interaction (Dahlstrom-Hakki et al., 2020). Synchronous and asynchronous online learning are two representative communication modes, characterized by the level of interactivity and immediacy of communication (Vlachopoulos & Makri, 2019). Compared to asynchronous learning, synchronous learning offers multiple ways of interacting, sharing, and collaborating in real-time through videoconferences, webcasts, and interactive learning models (Bailey et al., 2021). Synchronous online learning was swiftly adopted by course instructors during the COVID-19 pandemic. While technology bridges timing gaps in interactions, the sense of transactional distance associated with the student facing a screen could result in a less immersive learning atmosphere and lower emotional attachment (Chiu et al., 2023). Consequently, there could be low emotional engagement of students in synchronous online learning (SOL).

Piaget's theory of affective development in constructivism states emotional development runs parallel to cognitive development, influencing cognitive growth. This theory provides a foundational basis for enhancing students' emotional engagement. The increasing importance of emotional engagement to student persistence and performance in the online learning environment has been emphasized by several studies. For example, Özhan and Kocadere (2020) underscored the influence of emotional engagement on learning motivation. In another SOL course, Zhou et al. (2022) found that emotional engagement was the most essential type of engagement in predicting students' behavioral intentions. Furthermore, a growing body of evidence indicates that learners who lack emotional engagement are prone to disengagement both behaviorally and cognitively (Dubovi, 2022). The emotional engagement level of students has been regarded as a benchmark for the quality of SOL (Daher et al., 2021). However, enhancing emotional engagement is challenging in SOL environments, given their intricate spatial and temporal dynamics. In prior research, Murphy et al. (2020) found that students usually expressed negative emotional engagement like uncertainty, anxiety, and nervousness when transitioning to virtual classes. Similarly, Salta et al. (2022) found a lower level of emotional engagement among students in both synchronous and asynchronous online environments compared to the traditional learning setting.

The low emotional engagement of students in SOL was influenced by various factors, such as apathetic learning atmosphere, low personal pride, feelings of isolation (Apridayani & Waluyo, 2022), unfamiliarity with learning, and poor expectation management (Brown et al., 2023). Some empirical studies on SOL have endeavored to improve emotional engagement using diverse strategies. Furthermore, several scholars have conducted systematic literature reviews on the strategies to enhance student engagement in various contexts including massive open online courses (Wei et al., 2021), blended synchronous learning (Wang & Huang, 2023), and flipped learning in schools (Bond, 2020). Most of the reviews focus on the cognitive and behavioral engagement dimensions. This review differs from prior studies in that it focuses on the studies that specifically apply emotional engagement interventions. The purpose of this study was hence to identify the strategies applied in the empirical studies to promote students' emotional engagement in SOL environments.

Emotional Engagement

Engagement generally comprises behavioral, cognitive, and emotional dimensions (Fredricks et al., 2016). Specifically, emotional engagement, the focus of our study, refers to students' affective reactions such as their positive and negative responses to learning environments and activities (Martin & Borup, 2022). In traditional physical learning environments, behavioral, cognitive, and emotional engagement have been recognized as crucial factors influencing students' self-efficacy, academic achievement, and overall success (Bowden et al., 2021; Chen et al., 2020). In online learning environments, the absence of visual and body language cues and classroom atmosphere makes emotional engagement more critical (Aladsani, 2022).

Emotional engagement is commonly divided into two categories: positive emotional engagement such as enjoyment and pride, and negative emotional engagement such as boredom and anxiety (Lu et al., 2023), all of which have been demonstrated to have noteworthy associations with academic and psychological outcomes (Wang et al., 2015). Viewed from an internal process perspective, emotional engagement encompasses both the sense of emotional connectedness and emotional expression (Lim et al., 2020). Emotional connectedness is a psychological state in which learners experience a sense of emotional connection or belonging, reflecting a common personal experience in the community (Lacoste & Dekker, 2016). Besides, emotional engagement is established through individual's emotional expression via texts, picture, facial expressions, and gestures, through which people communicate their internal state to others (Caspi & Etgar, 2023).

To promote students' positive emotional connectedness and expression in SOL, researchers have investigated the influencing factors of emotional engagement and implemented experimental interventions. Specifically, strategies such as using various learning interactions, instant feedback, and interactive storytelling trailers, are proven to be effective in promoting emotional engagement in SOL (Daher et al., 2021; Hisey et al., 2022; Zainuddin et al., 2022). Besides, some scholars have explored the use of various strategies to increase student emotional engagement (Heilporn & Lakhal, 2021). Thus, it is imperative to systematically synthesize and summarize useful strategies for improving emotional engagement in SOL.

Methods

This review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, which were designed to enhance the reporting quality of systematic reviews (Moher et al., 2009). This version of the PRISMA statement, which includes a 27-item checklist for reporting in systematic reviews, was chosen because its recommendations have been widely endorsed and adopted by researchers (Page & Moher, 2017).

Literature Search

The literature search was conducted systematically from the following online databases: Scopus, Web of Science, Science Direct, EBSCOhost, Taylor and Francis, and Wiley Online Library in October 2023. The selection of these databases considered the multidisciplinary nature of the research topic. The words used in the title, abstract, and keywords included ("synchronous" OR "simultaneous" OR "web conferenc*" OR "video conferenc*" OR "virtual classroom" OR "econferenc*" OR "virtual conferenc*" OR "webinar") AND ("emotional engagement" OR "affective engagement"). It is possible that other relevant articles, which may have used different terms or were included in alternative databases, were inadvertently overlooked. To address this issue, we further employed a snowball approach that screened the reference lists of the identified articles at the end of the search phase. The inclusion criteria were: (a) original research from peer-reviewed journals; (b) written in English; and (c) available in full text. We did not impose any restrictions on the publication timeframe. In total, the search produced 312 articles, which were included for further selection.

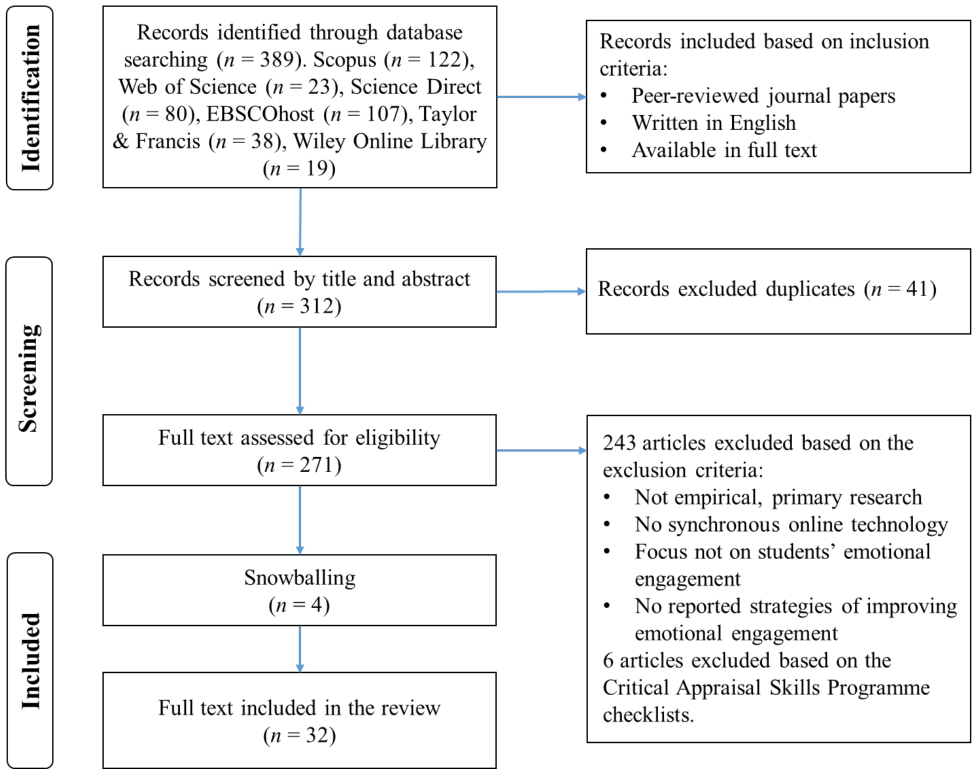
Selection

For each article, the title, abstract, and full text were reviewed. Upon initial examination, it was discovered that SOL could be categorized into three distinct subtypes based on communication modes: text-SOL supported by instant message service, voice-SOL supported by audio-conferencing systems, and video-SOL supported by videoconferencing systems. In this study, all three online learning modalities were included in the review to investigate strategies for enhancing emotional engagement in diverse SOL contexts.

Figure 1 depicts the literature selection process. By checking the titles, abstracts, and full texts, 41 articles were removed due to being duplicates; thus, 271 articles remained for further selection. In further reading of the remaining literature, 243 articles were filtered out due to the various reasons. For one, the studies that did not focus on students' emotional engagement were excluded. For another, the articles exploring students' emotional engagement but not reporting on strategies for improving emotional engagement were filtered out. After further assessing the quality of articles by following the Critical Appraisal Skills Programme (2018) checklist, six articles were excluded due to their poor quality. Finally, the selection resulted in 32 eligible articles for the systematic review.

Figure 1

Literature Selection Process



Data Collection and Coding

In this systematic review, the following data were extracted from each full paper: authorship, year of publication, participants, subjects, research methods, study length, synchronous techniques used, and proposed strategies. The proposed strategies were typically distributed across sentences or paragraphs. The basic unit of analysis was phrases that contained keywords such as *emotion*, *engagement*, and *strategies*. This process started with creating a table in Microsoft Excel. Each article was added as a new row in the table, with key data items included. For ease of management, the articles were sorted alphabetically by author name, and each article was assigned a unique code for identification (see Appendix). Then, each article was analyzed through thematic coding by the first author to discover effective strategies for improving students' emotional engagement in SOL and frequently discussed with the second author when uncertainty arose. The second author specialized in learning engagement in SOL, which enhanced the accuracy and validity of the coding. In the present study, the coding process followed the underlying paradigm of grounded theory and went through open, axial, and selective coding stages. The grounded theory employs a systematic procedure to summarize data features through hierarchical coding and systematically explores conceptual connections within codes, enabling the development of a theoretical framework that comprehensively explains the phenomenon as a whole.

During the open coding stage, the first author initially read all the articles to gain an overall understanding. Subsequently, codes were generated for the data items related to strategies, and data with similar codes were organized into themes. To ensure reliability and reduce personal biases in coding, the second author randomly selected 25% of the articles and independently coded them. Following this, the two authors discussed the items and assigned provisional codes to the strategies aimed at enhancing emotional engagement. During the axial coding stage, the two authors frequently discussed and analyzed the above strategies and coded them in a higher level of categories. After discussions, the authors decided to classify the strategies into four main themes (i.e., instructor actions, student behaviors, environment characteristics, and activity design). The selective coding stage centered on the refining subthemes related to strategies and entailed a thorough review of the literature to uncover additional evidence.

Results

Overview of the Studies

Table 1 illustrates the educational contexts of the studies on emotional engagement in SOL. Most of the studies (*n* = 27, 84%) were conducted in higher education, primarily with undergraduate learners (*n* = 19) and graduate learners (*n* = 2). In contrast, a limited number of studies focused on K–12 learners (*n* = 5). Regarding research methods, a mixed-method approach incorporating both qualitative and quantitative findings was frequently employed (*n* = 23, 72%). Five studies focused solely on qualitative research, providing reports on how synchronous techniques were designed and implemented in online learning, as well as capturing the perception of learners or instructors through observations, interviews, and written reflections. Four studies were quantitative in nature, investigating learners' performance and perceptions in face-to-face and synchronous video-based learning contexts, that is, article E3, E9(learners' emotions), E21(group awareness), and E28 (learners' aggressive responses). The three most frequently cited articles were E29, E11, and E9. In 2024, the number of citations for each one according to Google Scholar was as follows: E29 (Yang, 2011) had 203; E11 (Gregory & Masters, 2012) had 142; and E9 (D'Errico et al., 2016) had 134. Among them, Yang (2011) developed a system that supported learners and teachers to communicate synchronously in e-meetings, and documented intensive and reciprocal engagement among students.

Table 1

Educational Context and Research Methods of the Eligible Studies

Category	Studies, *n*	Citations
Educational context		
Higher education		
Graduate	2	E7, E13
Undergraduate	19	E2, E3, E9, E10, E11, E12, E15, E17, E18, E19, E20, E21, E22, E24, E25, E27, E29, E30, E31
Not identified	6	E1, E4, E5, E8, F14, E16

K–12	5	E6, E22, E26, E28, E32
Research method		
Qualitative	5	E1, E4, E5, E6, E22
Mixed method	23	E2, E7, E8, E10, E11, E12, E13, E14, E15, E16, E17, E18, E19, E20, E23, E24, E25, E26, E27, E29, E30, E31, E32
Quantitative	4	E3, E9, E21, E28

Note. See Appendix for definition of citations and References for full citations.

Strategies

After a thematic coding process based on the grounded theory, we categorized the eligible articles into four common themes according to the type of strategies presented in each one: instructor actions, learner behaviors, environment characteristics, and learning activity designs. As shown in Table 2, the four common themes were further divided into 18 subthemes.

Table 2

Frequency of Common Themes in Strategies

Theme and subtheme	Frequency, *n* (%)	Citations
Instructor actions		
Interacting informally before and after class	7 (22)	E1, E3, E4, E8, E15, E17, E19
Encouraging the expression of ideas	7 (22)	E1, E2, E3, E4, E15, E25, E29
Giving immediate feedback	6 (19)	E2, E15, E18, E19, E23, E26
Providing learning scaffolding	4 (13)	E24, E25, E26, E29
Learner behaviors		
Building rapport with peers	6 (19)	E2, E3, E10, E12, E27, E30
Recognizing individual accountability	6 (19)	E12, E15, E16, E21, E26, E32
Developing self-regulation	5 (16)	E15, E17, E22, E24, E30
Stimulating positive feelings	3 (9)	E2, E9, E12
Environment characteristics		
Creating supportive atmosphere	8 (25)	E1, E2, E4, E15, E16, E18, E20, E23
Selecting communication modes	7 (22)	E2, E8, E17, E18, E22, E25, E30
Providing technical support	5 (16)	E10, E17, E20, E21, E25

Activity design		
Interaction enhancement		
Using breakout rooms	8 (25)	E7, E13, E16, E17, E18, E19, E25, E27
Creating interaction opportunities	7 (22)	E1, E12, E13, E17, E19, E20, E26
Content enhancement		
Embedding diverse elements	6 (19)	E5, E6, E11, E14, E28, E31
Designing inquiry-based tasks	2 (6)	E7, E29
Linking with real-life situations	2 (6)	E13, E32
Process support		
Using cognitively assistive tools	4 (13)	E6, E11, E15, E21
Personalizing learning process	3 (9)	E4, E15, E20

Strategies Related to Instructors

For promoting learners' emotional engagement in SOL from the perspective of instructor actions, the common strategies identified in the reviewed literature included: interacting informally before and after class (n = 7, 22%), encouraging the expression of ideas (n = 7, 22%), giving immediate feedback (n = 6, 19%), and providing learning scaffolding (n = 4, 13%).

Interacting informally before and after class contributes to fostering a closer instructor-student relationship and strengthening students' sense of belonging in online learning. It was found that instructors spending time to greet and engage in non-academic conversations before class helped to build emotional engagement (E1, E19). In two studies, the instructors reminding learners to check their devices and Internet connectivity, and establishing clear protocols and ground rules for the learning process also helped to emotionally engage students (E1, E17). To set a positive emotional tone, it seems that warm-up activities at the beginning of each class played an important role (E4, E8, E15). Furthermore, two additional studies also emphasized the significant role of informal interaction after class in promoting students' emotional engagement (E3, E19).

Encouraging the expression of ideas refers to instructors motivating learners to voice their thoughts and feelings, share personal experiences, and articulate their expectations. Allowing learners to express emotions in text chat and responses such as using emojis was helpful for keeping them emotionally engaged (E3, E29). To elicit learners' positive emotional responses, three studies employed the strategy of assisting students in connecting content, providing them with the opportunity to share their thoughts (E2, E15, E25). In addition, instructors sharing their own experiences with the students and encouraging the learners to share their feelings helped to alleviate negative experiences (E1). In the study of Brown et al. (2023), the implementation of weekly news bulletins, coupled with reminding students of expectations, proved conducive to fostering emotional engagement (E4).

Giving immediate feedback to learners could meet learners' psychological needs and foster their emotional engagement (E26). In three studies where formative, immediate, and high-quality feedback from instructors was provided to individual learners, the students were generally emotionally engaged (E2, E15, E23). In two other studies, instructors checking in with each group during the group discussions to provide guidance and feedback proved instrumental in elevating learners' sense of connectedness (E18, E19). In addition, providing learning scaffolding was about setting learning plans and offering materials based on learners' experiences and background knowledge (E24). Two studies suggested that teachers' actions in epistemic scaffolding design were the most determining factor in promoting student engagement (E25, E26). Furthermore, questions such as "What do you think would bring you confidence?" were included in the scaffolding provided by instructors to enhance learners' emotional engagement (E29).

Strategies Related to Learners

Learners are also responsible for their own emotional engagement in SOL. The common strategies applied in the reviewed literature included: building rapport with peers (n = 6, 19%), recognizing individual accountability (n = 6, 19%), developing self-regulation (n = 5, 16%), and stimulating positive feelings (n = 3, 9%).

Building rapport with peers is the exchange process of emotional and information support among online learners. Giving appropriate peer comments on learning tasks or assignments, and addressing learners' mistakes in a proper manner helped reduce negative emotional responses (E12). Furthermore, five studies suggested that students actively involving themselves in Q&A activities (E30), exchanging opinions and sharing experiences (E3, E12, E27), and providing assistance when peers were unable to answer teachers' inquiries (E2) helped learners to be more emotionally engaged. To build a deeper emotional connection with peers, displaying empathy through body language was shown to be an effective strategy (E10). In addition, the reviewed literature underscored the significance of enabling learners to recognize their accountability (E16). For instance, learners being given more ownership and autonomy also helped to increase their level of reciprocal emotional relationships (E15, E26, E32). Furthermore, two studies suggested learners' accountability and awareness in group activities were related to their own and group members' emotional experiences (E12, E21).

Developing self-regulation includes learners' external regulation in aspects such as learning goals, study plans, learning spaces, and help seeking. In the study E24, learners' goal-setting helped to increase positive emotions. Three studies suggested that students developing routines to spend time wisely on learning tasks helps to maintain emotional engagement (E15, E22, E30). Besides, arranging learning spaces, including selecting a desk position by a window and clearing learners' workspace, were considered an external strategy to engage students emotionally (E22). Finally, learners searching for additional materials and finding ways to make them relevant and interesting were highly helpful (E17, E22). Stimulating positive feelings is about promoting learners' personal experiences and internal regulation of personal feelings. Two studies suggested that learners' satisfaction and personal pride, coupled with positive emotions, played a crucial role in significantly enhancing their emotional engagement (E2, E9). Learners' positive feelings can be stimulated indirectly through some manipulable behaviors such as moderating learners' sensitivity. In another study (E12), learners who are sensitive to peer criticism usually experienced less emotional engagement.

Strategies Related to Learning Environments

The common strategies related to the learning environment included creating a supportive atmosphere (*n* = 8, 25%), selecting communication modes (*n* = 7, 22%), and providing technical support (*n* = 5, 16%).

Creating a supportive atmosphere entails establishing an environment that fosters stress reduction, facilitates the exchange of ideas, and encourages seeking help in SOL. The reviewed studies showed that creating a warmer and more familiar learning environment helped alleviate learners' stress (E4, E20). It was reported that the environments that fostered a sense of safety and openness empowered learners to feel comfortable asking questions and sharing their thoughts and ideas (E1, E15, E16, E18, E23). In addition, two studies have highlighted the significance of cultivating a friendly online class environment, wherein instructors and peers demonstrate a willingness to assist and genuinely care about meeting learners' needs (E2, E15).

Selecting communication modes determines the characteristics of SOL, including interactivity and visibility. For example, Dao et al. (2021) discovered that the video chat via Facebook Messenger enabled learners to see each other and talk quickly, and hence facilitated greater emotional engagement compared to the text chat (E8). Besides, to promote the visibility of synchronous interaction, webcams were employed and further discussed in six studies (E2, E17, E18, E22, E25, E30). They all indicated that turning on the webcam helped students see each other's facial expressions and body language, maximizing their positive emotional experiences. Nevertheless, the research of E22 also suggested that the camera-induced self-awareness and negative feelings of discomfort contributed to learners' emotional disengagement. Thus, the influence of the camera on learning engagement is worth further exploration based on the characteristics of learners and contexts (Händel et al., 2022).

Providing technical support aims at addressing technical issues such as platform use and network connectivity. The reviewed literature suggested that technical issues about Internet connection, browser compatibility, and microphones made learners feel frustrated and caused unpleasant emotional experiences. To address these issues, four studies (E10, E17, E21, E25) emphasized that checking devices and Internet before class, and establishing an accessibility task force to provide students with prompt solutions were highly helpful. Besides, using the library and other resources available during the class helped to alleviate learners' concern arising from technical issues (E20).

Strategies Related to Learning Activities

To enhance learner emotional engagement, strategies related to the learning activity were categorized into three groups: interaction enhancement, content enhancement, and process support.

Interaction Enhancement. The activities in this strategy are designed to foster both learner-learner and learner-instructor interactions, thereby promoting emotional engagement among learners. This involves using breakout rooms (*n* = 8, 25%) and creating interaction opportunities (*n* = 7, 22%). Five studies suggested that organizing online small group activities and using breakout rooms helped to build a sense of social connectedness, and increase positive emotions (E16, E17, E18, E25, E27). Another study suggested that breakout sessions facilitated learners' content understanding and further contributed to emotional engagement (E7). Besides, two studies emphasized that randomly assigning students to groups and maintaining the same team for the whole semester could contribute to positive emotional engagement (E13, E19). It was also suggested that creating opportunities for the effective design of lecture time (E20), collaborative assignments (E13, E19) and online discussion activities (E1, E12, E17, E26) helped to break the social isolation of lockdown.

Content Enhancement. The activities within this strategy are tailored to facilitate learner-content interaction, thereby stimulating positive emotional experiences. This encompasses embedding diverse elements (n = 6, 19%), designing inquiry-based tasks (n = 2, 6%), and linking with real-life situations (n = 2, 6%). In the reviewed literature, games (E6, E31), role-play activities (E5, E11), storytelling trailers (E14), and interactive VR (E28) were used to extend emotional engagement. Two reviewed studies reported that designing inquiry-based tasks stimulating students' inquiry and exploration enabled students to engage emotionally in learning activities (E7, E29). Linking with real-life situations requires learners to be provided with content that encompasses authentic tasks and reflects real-world situations (E13, E32), and helps learners to relate to the course on an emotional level.

Process Support. The strategies include using cognitively assistive tools (n = 4, 13%) and personalizing the learning process (n = 3, 9%). Thinking tools were used in two studies, which included using the Six Thinking Hats framework to assist learners in considering multiple perspectives (E11) and employing a think-aloud strategy fostering critical thinking during the planning and execution of tasks (E15). Furthermore, a visualization tool demonstrating the engagement level of each group member motivated learners to work on the group task and enabled them to express positive emotions (E21). Additional supportive tools, such as Google translator, were introduced in E6, aiding in promoting affective engagement associated with the development of students' self-efficacy in learning. The personalization was emphasized as a crucial aspect of promoting emotional engagement in two studies (E4, E20). For example, in E4, a module map was created that allowed students to track their personalized progress.

Discussion

Findings and Trends for Promoting Emotional Engagement in SOL

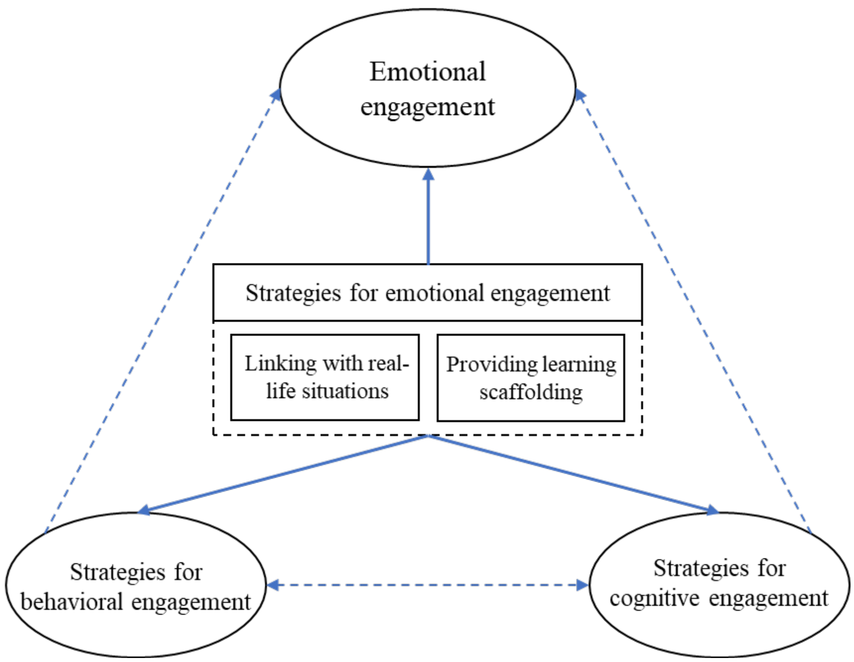
This review discovered that instructors, learners, learning environments, and course activities could offer robust support for facilitating emotional engagement of learners in SOL. This finding is consistent with the result of another study conducted by Wang et al. (2023), who identified the factors and strategies for engaging learners in SOL but targeting engagement in general.

Among the strategies identified, we posit that certain strategies were more specifically tailored to enhance emotional engagement. For example, instructors encouraging students to express their ideas helped students engage emotionally, breaking the silence on emotion between students (Beatty, 2002). Another strategy of learners, recognizing individual accountability, is helpful for building emotional connectedness, as students who are emotionally connected to peers and instructors often adopt prosocial values (Jdaitawi, 2015). In addition, a supportive atmosphere should be created, as learners will feel safe and become loving and engaged emotionally in their environments (Keville et al., 2013).

Some strategies that are useful for emotional engagement could also be used to support other dimensions of engagement. For example, linking with practice was also reported to enhance learners' cognitive engagement in the study by Heilporn and Lakhal (2021). Providing learning scaffolding was helpful for engaging students behaviorally as well (Yang, 2011). This finding supports the notion that the three dimensions of engagement are interconnected rather than isolated (Martin & Borup, 2022). Figure 2 shows how some strategies useful for promoting emotional engagement, such as linking with real-life situations and providing learning scaffolding, may also work for behavioral or cognitive engagement.

Figure 2

The Relationships Between Behavioral, Cognitive, and Emotional Engagement Strategies



Note. The solid lines represent relationships confirmed in this study, while dashed lines indicate those that require further exploration.

Implications

The findings of this review have implications for instructors, course developers, and researchers. Instructors must realize the importance of promoting emotional engagement in SOL and employ strategies to enable learners to engage in learning emotionally. Before and after a synchronous online session, instructors should spend time interacting with learners informally and set warm-up activities to build emotional connections. During the session, instructors should provide proper learning scaffolding and give immediate feedback to support effective learning, further meeting learners' emotional needs. Moreover, instructors should actively encourage learners to express their thoughts, ideas, and feelings, facilitating community-building and learners' emotional expression (Berry, 2019).

The establishment of safe, open, and warm environments and the design of multi-oriented learning activities are crucial for promoting students' emotional engagement, which need joint efforts from instructors, learners, and course developers. More specifically, video-based synchronous techniques can be widely implemented to promote emotional engagement. Instructors should build an environment that supports learners to comfortably exchange ideas and seek help. Learners also need to understand their dominant roles in the SOL process. The strategies they can use include exchanging emotional feelings and offering support to peers by giving comments kindly, generating empathy, and sharing their experiences. In addition, establishing an accessibility task force to promptly provide students with helpful solutions for technical issues will alleviate learners' psychological stress.

For course developers, they need to consider the diversity in learning activities design orientation, aiming to increase the opportunities for interactions between learners and instructors, peers, content, and tools. Especially in terms of the design of course content, learning activities can embed inquiry-based tasks and interesting elements, and be relevant to real-life situations. In addition, there is a need for increased focus on the design and development of emotional engagement analysis and intervention systems that facilitate the implementation of various strategies.

The results of this study have implications for researchers as well. First, researchers should pay particular attention to the inconsistent findings concerning emotional engagement enhancement. For example, there is a need to further explore the varying effect of using webcams in SOL as some studies show students were comfortable with webcams (e.g., Jia et al., 2022) while other studies do not (e.g., Oittinen et al., 2022). Second, the way certain strategies affect the emotional, cognitive, and behavioral dimensions of engagement needs to be further explored. Third, learners' individual factors, such as self-regulation and individual accountability, are deemed significant and are highlighted, but they prove challenging to influence through external sources (Hofer et al., 2021). Therefore, the internal mechanisms of promoting emotional engagement from positive psychological perspectives should be further investigated.

Conclusion

This study presents a systematic review of the strategies for promoting emotional engagement in SOL and aims to develop a comprehensive and systematic understanding of this topic. This review not only outlined the current research characteristics and trends in the literature but also classified the strategies for promoting emotional engagement in SOL. Based on the results of the analysis, this review provides implications for instructors, learners, course developers, and researchers. We hope that the findings of this review provide guidance for practitioners and researchers looking to adopt the SOL approach to better engage online learners emotionally.

Nevertheless, this study has a few limitations. Firstly, there is limited availability of empirical articles on emotional engagement in SOL within peer-reviewed journals, posing challenges in drawing definitive conclusions regarding the effectiveness of the applied strategies. Another limitation is the lack of in-depth exploration into how to provide support to educational stakeholders, such as instructors and institutions, to help promote students' emotional engagement. The review also identified some other areas that warrant further exploration in future research. First, greater attention should be given to the creation of supportive and warm learning environments leveraging intelligent technology. Specifically, immersive technologies such as VR/AR and metaverse could be incorporated into SOL to enhance learners' emotional experiences and engagement (Lee & Hwang, 2022). Besides, the measurement of emotional engagement in the reviewed literature mainly relies on questionnaires and individual interviews. In future research, using multimodal data, such as facial expressions and body movements, could offer a more comprehensive understanding of learners' emotional engagement.

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Appendix

Table A1

Articles Included in the Systematic Review

Eligibility no.	Citation
E1	Andrew et al., 2021
E2	Apridayani & Waluyo, 2022
E3	Aubrey & Philpott, 2023
E4	Brown et al., 2023
E5	Cornelius et al., 2011
E6	Daher et al., 2022
E7	Daher et al., 2021
E8	Dao et al., 2021
E9	D'Errico et al., 2016
E10	Garcia & Jung, 2021
E11	Gregory & Masters, 2012
E12	Hafour & Alwaleedi, 2022
E13	Heilporn & Lakhal, 2021
E14	Hisey et al., 2022
E15	Jaber Rafidi & Wagner, 2023
E16	James et al., 2022
E17	Ji et al., 2022
E18	Jia et al., 2022
E19	Jia et al., 2023
E20	Limniou et al., 2022
E21	Liu et al., 2018
E22	Oittinen et al., 2022
E23	Ole & Gallos, 2023
E24	Qiu & Bui, 2022
E25	Raes, 2022
E26	Shi et al., 2023
E27	Thacker et al., 2022
E28	Verhoef et al., 2022
E29	Yang, 2011

E30	Yuyun, 2023
E31	Zainuddin et al., 2022
E32	Zhou et al., 2022

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Bibliometric Insights Into the Open Education Landscape

Rong Zou[1], Leilei Jiang[2,3], and Walton Wider[4,5,*]
*[1]School of Foreign Languages, Jiangsu Open University, Nanjing, China; [2]Faculty of Education and Liberal Arts, INTI International University, Nilai, Malaysia; [3]School of Architecture, Jinken College of Technology, Nanjing, China; [4]Faculty of Business and Communications, INTI International University, Nilai, Malaysia; [5]Department of Applied Economic Sciences, Wekerle Sandor Uzleti Foiskola, Budapest, Hungary; *Corresponding author*

Abstract

This bibliometric analysis explores the rapidly growing field of open education, offering insight into its nature and the wide range of academic topics it covers. This study applies co-citation and co-word analyses approach to critically review 402 publications from the Web of Science database. The aim is to identify emerging topics, seminal works, and dominant trends in the literature on open education. The co-citation analysis identifies key publications and thematic clusters that define the field, including discussions on pedagogical innovations, equity and accessibility, quality assurance, and the global impact of open educational practices (OEP). Co-word analysis, on the other hand, highlights the recurrent and emerging keywords within the literature, revealing focal points such as digital transformation in education, the role of massive open online courses (MOOCs), and the significance of open educational resources (OER) in fostering inclusive and equitable learning environments. This study stands out for its quantitative approach in mapping the current academic conditions of open education, offering insights into the dynamic interplay between technology, policy, and pedagogy. It emphasizes the need for a collaborative, inclusive approach to education, employing open educational resources and methods to fulfill the different needs of learners globally. Through this analysis, the study contributes to a deeper understanding of the current state and future directions of open education, advocating for policies and practices that support sustainable, accessible, and high-quality educational experiences.

Keywords: open education, bibliometric analysis, Web of Science, education policy

Introduction

Open education, as defined by Cunha et al. (2020), is a revolutionary trend in modern education, altering traditional learning frameworks and providing superior access to knowledge resources. This approach to learning includes a range of practices, including open educational resources (OER), massive open online courses (MOOCs), open textbooks, and open-access journals, all of which aim to democratize education by making it more accessible and affordable (Mishra et al., 2022; Stracke et al., 2019; Weller, 2020). The current state of open education is marked by its rapid expansion and increasing adoption across the world, propelled by the digital revolution. The principles of inclusivity, affordability, and collaboration are at its core, facilitating the provision of high-quality educational materials to a global audience, irrespective of their geographical location or socioeconomic status (Croft & Brown, 2020; Gunawardena, 2020). This movement has not only altered how educational content is created and shared but also prompted the rebuilding of pedagogical methods, assessment techniques, and the nature of knowledge itself, fostering a more connected and interactive global learning community (Zhang et al., 2019).

However, despite the widespread recognition of open education's importance, limited comprehensive research addresses its full scope. While numerous studies have examined specific aspects, such as OER and MOOCs, there remains a need for work that critically engages with the broader framework of open education. Recent studies have pointed to this gap. For instance, Clinton-Lisell et al. (2023) proposed the SCOPE framework for organizing research on open education, emphasizing social justice, cost, outcomes, perceptions, and engagement. This framework underscores the need for a more structured research inquiry to cover the broad aspects of open education. Zawacki-Richter et al. (2020) also highlighted the importance of examining specific elements like MOOCs and OER and the macro, meso, and micro levels of open educational practices (OEP). Similarly, Shareefa et al. (2023) found in a comprehensive metasynthesis that the limited scope of prior reviews inhibits the full understanding of the concept, further emphasizing the need for more inclusive research efforts. Iniesto et al. (2021) focused on inclusivity and sustainability in open education, pointing to challenges like insufficient accessibility standards and the need for frameworks like Universal Design for Learning. These papers underscore the pressing need for broader research beyond isolated elements to consider the entire ecosystem of open education.

This study aims to address two critical questions:

1. What are the key trends and emerging areas in open education?
2. How can these findings inform policy and practice to promote more equitable access to educational resources?

These questions are essential as the literature often presents fragmented views, lacking a holistic perspective on how different elements of open education interact to shape learning outcomes and accessibility. By engaging with the existing body of research, this paper critiques and builds upon previous findings to offer a more integrated understanding of the field.

However, despite substantial progress in the field of open education, some gaps and obstacles remain. One of the main issues is the uneven adoption and implementation of OEP across different regions and institutions, leading to disparities in access and quality (Gangathulasi et al., 2023). According to UNESCO (2023), only about 10% of schools in sub-Saharan Africa have access to the internet, compared to nearly 90% in western Europe and North America. This digital divide directly impacts the accessibility of OER, leading to disparities in the quality of education. Moreover, a lack of awareness and understanding about OER among educators in less developed regions further exacerbates this issue, preventing the full realization of open education's potential to democratize learning (Farrow et al., 2023). Meanwhile, in the past 5 years, there have been investigations into the theme of open education, with some scholars using bibliometric methods for their research. For instance, Irwanto et al. (2023) explored the expansion of MOOCs in higher education, while Tlili et al. (2022) focused on the challenges and opportunities of OER in Africa, highlighting regional disparities. Mishra et al. (2022) offered a bibliometric examination of OER trends and patterns. However, the majority of these studies focus only on specific aspects. Our research fills this gap by providing a more comprehensive analysis of the open education landscape, assessing multiple dimensions, and offering critical insights into the trends and challenges within the field.

This study seeks to identify significant publications, thematic patterns, and pedagogy developments within the entire field of open education. Therefore, there is a pressing need for comprehensive research that extends beyond the analysis of OER and MOOCs to include other crucial elements of open education, like open-access journals and open textbooks, as well as the ongoing discussions surrounding pedagogy, assessment, and knowledge creation. These discussions highlight the necessity for a deeper understanding of OEP, emphasizing how they can be customized and implemented to address the varied needs and contexts of learners effectively.

To fill these gaps, this research employs bibliometric analysis as an effective instrument to uncover a wider insight that can guide the future direction of open education. This paper proposes to use co-citation and co-word analyses to filter through the vast literature on open education, to find key publications, determine theme trends, and trace recent developments in the field. By mapping the academic context of open education, this study aims to bring insight into the primary contributors, intellectual clusters, and developing concerns, providing a thorough assessment of current and future developments. Such an analysis is critical in providing policymakers and educational stakeholders with the data they need to make informed decisions. Through this approach, the paper hopes to contribute to the democratization of education, ensuring that learning materials and experiences are accessible to all, thus fostering a more inclusive, equitable, and collaborative educational environment.

Literature Review

The exploration of open education in recent years has taken place across multiple topics, each adding distinctively to our collective understanding and defining the course of this educational trend. As we delve further into these topics, the demand for a bibliometric study becomes evident to map the field and critically address the gaps left by previous research. While existing studies provide fragmented insights, they often need a comprehensive critique or synthesis that would allow for a more unified understanding of the complex interactions within the field of open education. This study aims to address this gap by offering a more cohesive and critical evaluation of the literature.

Pedagogical Innovations and Learning Design

At the heart of open education lies the quest for innovative pedagogical strategies and learning designs that meet the needs of the digital age. Kim et al. (2020) focus on user engagement within OER platforms, linking active participation to lower attrition rates, suggesting that pedagogical designs must prioritize keeping learners engaged. However, merely focusing on engagement overlooks the complexities of sustaining that engagement over time and across diverse learner groups. Ramirez-Montoya (2020) expands the discourse to the broader challenges of integrating educational innovations in open education. This implies that engagement alone is insufficient; pedagogical models' adaptability and flexibility are crucial for long-term success. Yet, while these studies highlight innovative strategies, they often need to address how such innovations can be universally applied or sustained, leaving critical questions about scalability and inclusivity unanswered. Zawacki-Richter et al. (2020) call for further research into open education's pedagogical aspects, hinting at innovative educational practices' complexity and unexplored potential. This lack of comprehensive critique leaves a gap in understanding how to balance innovation with practicality in educational design effectively. These studies form a learner-centric narrative that highlights the importance of engagement and innovative pedagogy in reducing dropout rates and stresses the need for these pedagogical strategies to be sustainable and adaptable in OEP.

Quality Assurance and Sustainability

Ensuring the quality and sustainability of open educational resources and practices is important. Luo and Ye (2021) explore the quality of language MOOCs through learners' perspectives, identifying key criteria that contribute to their effectiveness. While this study emphasizes the importance of meeting learners' needs and expectations, it falls short of critiquing how these criteria can be universally applied across different contexts or languages, limiting its broader application. Poce et al. (2020) assess MOOC users' experiences within a virtual mobility project, aiming to enhance quality through preliminary feedback. Their focus on user experience as a quality indicator suggests that continuous improvement and adaptability are essential for sustaining MOOC quality. However, such frameworks often neglect the challenges of maintaining consistent quality across diverse platforms and regions, especially in underresourced areas. Shah et al. (2023) introduce a framework for the formative evaluation of MOOC pedagogy, highlighting the need for MOOCs to be designed and evaluated with the learner in mind for educational efficacy. Although valuable, many of these studies do not fully explore the complexities of maintaining sustainability in resource-constrained environments, leaving the long-term quality assurance issue insufficiently addressed. These studies reveal a shared emphasis on the learner's experience as a crucial quality measure in MOOCs but underscore the necessity of deeper investigation into how these learner-centric strategies can be adapted globally and sustainably.

Global Perspectives: Diverse Challenges and Unified Solutions

The worldwide breadth of open education presents an assortment of challenges and opportunities. Bali et al. (2020) advocate for framing OEP within a social justice perspective, emphasizing the potential of OEP to address inequalities in education globally. While this perspective is commendable, it often lacks practical strategies for addressing the deep-seated systemic barriers that prevent equitable access, particularly in regions with severe infrastructural challenges. Wolfenden and Adinolfi (2019) investigate the localization of OER for teacher development, emphasizing the importance of enabling educators to adapt resources to their contexts, thus boosting agency. While localization is essential, there is limited discussion on how these localized practices can be scaled or integrated into broader, global frameworks of open education. As a result, solving global educational difficulties through OEP involves a two-pronged approach: pushing for social justice to ensure fair access and empowering local educators to personalize educational resources to their specific teaching and learning settings. However, the literature often lacks a critical exploration of how these dual objectives—global equity and local agency—can be harmonized to produce scalable, long-term solutions.

In summary, the diverse nature of open education research, from pedagogical innovations to policy implications, forms the bedrock of our bibliometric analysis. However, a critical gap remains in the literature's ability to link these distinct areas to offer universal solutions cohesively. While existing studies provide valuable insights, they often need to address the interconnectedness of pedagogical, technological, and policy-oriented solutions, leading to fragmented knowledge. Therefore, our research synthesizes these findings and proposes cohesive models of digital pedagogy and effective strategies for bridging the digital divide, ensuring the sustainability of resources and identifying universal solutions to global challenges in open education. Through this approach, we aim to contribute to a more comprehensive and practical understanding of open education, equipping policymakers and educators with the tools they need to foster inclusivity, adaptability, and long-term sustainability.

Present Study

The primary goal of this study is to conduct a comprehensive exploration of the scholarly literature within the open education domain. Using a two-pronged bibliometric analysis, this study thoroughly assesses the entire literature on open education. It seeks to fill knowledge gaps by clarifying current and future research directions in open education. This study aims to

- examine the past and current trends in open education through co-citation analysis, and
- spot future trends in the field of open education through co-word analysis.

Methods

Bibliometric Approach

Bibliometric research analyzes and measures the influence of academic publications using a quantitative examination of scientific literature (Wider et al., 2024a), analyzing many aspects of research output using statistical approaches, such as the number of publications, citations, and patterns of collaboration, among other things (Zhang et al., 2024). Bibliometric analysis can locate developing themes, key texts, and trends in particular academic fields (Yang et al., 2024). Bibliometric research, including co-citation and co-word analyses, is a useful tool for evaluating and understanding the development of research fields and spotting possible growth areas or future directions within a specific subject (Wider et al., 2024b).

The foundation of co-citation analysis is that if two publications are often referenced together, their contents are probably connected (Bronk et al., 2023). With the help of this method, one may discover the structure of the body of scientific literature in a certain field of study as well as the most significant publications and authors in a given field of study (Ali et al., 2022). Co-word analysis, on the other hand, is concerned with the co-occurrence of keywords in scientific publications. It can highlight the prevalent themes and links within a specific research subject by detecting commonly occurring phrases (Chandrakumar et al., 2024). Additionally, it can forecast a study area's future course, giving a glance into its development (Mejia et al., 2021). Therefore, co-word analysis can be used to assess a topic's future tendencies (Zhao et al., 2024).

Data Screening and Data Collection

This study used a rigorous search method in the Web of Science (WoS) database to thoroughly evaluate the vast academic literature on open education. The WoS database is esteemed for its extensive scope and high quality, rendering it suitable for bibliometric analyses (Yan & Zhiping, 2023). It comprehensively represents important global research (Martín-Martín et al., 2021). The search was conducted in September 2023 and was carefully designed to cover all academic literature on open education, ensuring that all relevant research up to that point was included. The keyword "Open Education" was exclusively employed in the "TOPIC" search field, a deliberate decision to hone the process on publications directly relevant to this field. The "TOPIC" field was selected for its comprehensive inclusion criteria, ensuring the capture of instances where "Open Education" appeared in the publication title, abstract, or keywords. This approach cast a broad net to include all relevant research outputs. The study also included all research areas to capture the diverse character of open education research. Notably, the study did not limit the document type, including various forms of scholarly outputs such as articles, reviews, conference proceedings, and book chapters. Adopting this inclusive strategy aims to enhance the bibliometric evaluation by thoroughly studying original research contributions, reviews, and other academic discussions.

The inclusion criteria were established to ensure a comprehensive yet focused selection of literature. We included articles that (a) specifically addressed topics related to open education, (b) were peer-reviewed or underwent a formal editorial review process, and (c) were published in the English language. We considered various document types, including articles, reviews, conference proceedings, and book chapters, to provide a comprehensive view of empirical studies and theoretical discussions. This inclusivity aimed to capture the diverse nature of open education research. However, we excluded publications that (a) were outside the scope of open education, such as general discussions on educational policy without a clear focus on openness, and (b) were non-English due to accessibility constraints. To ensure the reliability of the analysis, several measures were taken: (a) a team of researchers independently screened the initial set of articles retrieved from the search, ensuring consistency and agreement in applying the inclusion and exclusion criteria; (b) in cases where disagreements occurred during the screening process, a third reviewer was consulted to resolve discrepancies, ensuring unbiased selection; and (c) a pilot analysis of the selected studies was conducted to confirm the relevance and consistency of the data before proceeding with the full bibliometric analysis.

This exhaustive search strategy retained a final set of 402 articles, which formed the basis of our bibliometric analysis. By integrating a thorough and structured inclusion and exclusion process and employing reliability measures, we ensured that the analysis provided a robust and accurate mapping of the academic landscape of open education research. We utilized version 1.6.18 of the VOSviewer software to conduct our data analysis.

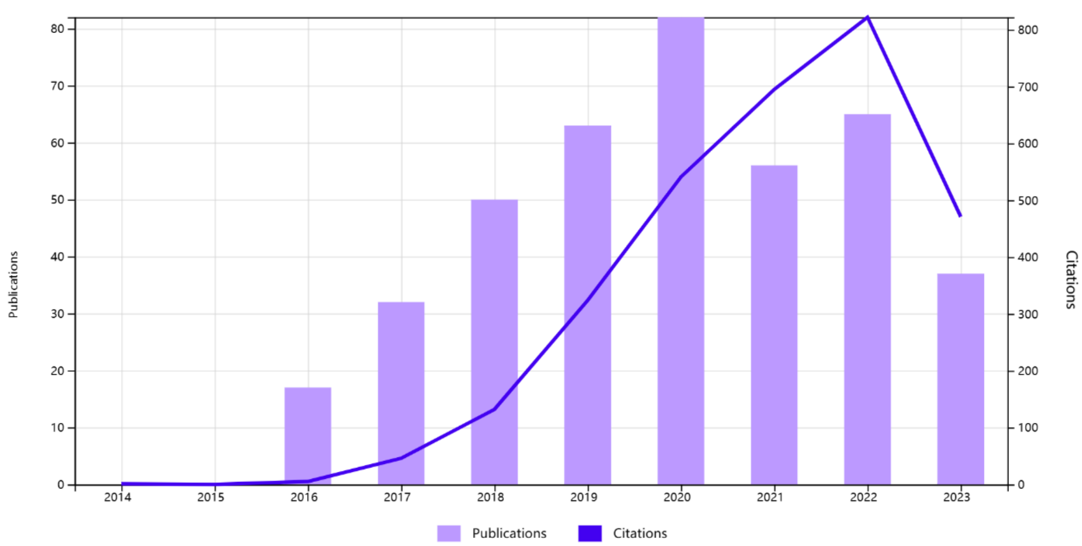
Result and Discussion

Trends in Publication and Descriptive Analysis

For the selected articles (N = 402), the WoS database produced 3,041 citations, of which 329 were self-citations. The average number of citations per article was 7.56, and the H-index was 27. The 402 articles show that open education research is gaining popularity. There were no publications prior to 2015, but significant contributions started to appear in 2016. Since then, publications have grown steadily in number. There were 82 publications in 2020, meaning there were more publications in 2020 than there were in 2016. The number of articles, however, quickly fell to 56 in 2021, indicating specific changes that occurred over this time. Up to 2022, more academic studies about open education were cited. The number of publications published and the number of citations received from 2014 to 2023 are shown in Figure 1.

Figure 1

Number of Publications and Citations Between 2014 and September 2023



Co-Citation Analysis

The citation threshold was set at 9 for the co-citation analysis, yielding 57 cited references. Figure 2 shows a network analysis resulting from the sources provided. Table 1 lists the top 10 co-cited references with the highest overall link strength.

Figure 2

Co-Citation Analysis (VOSviewer Visualization)

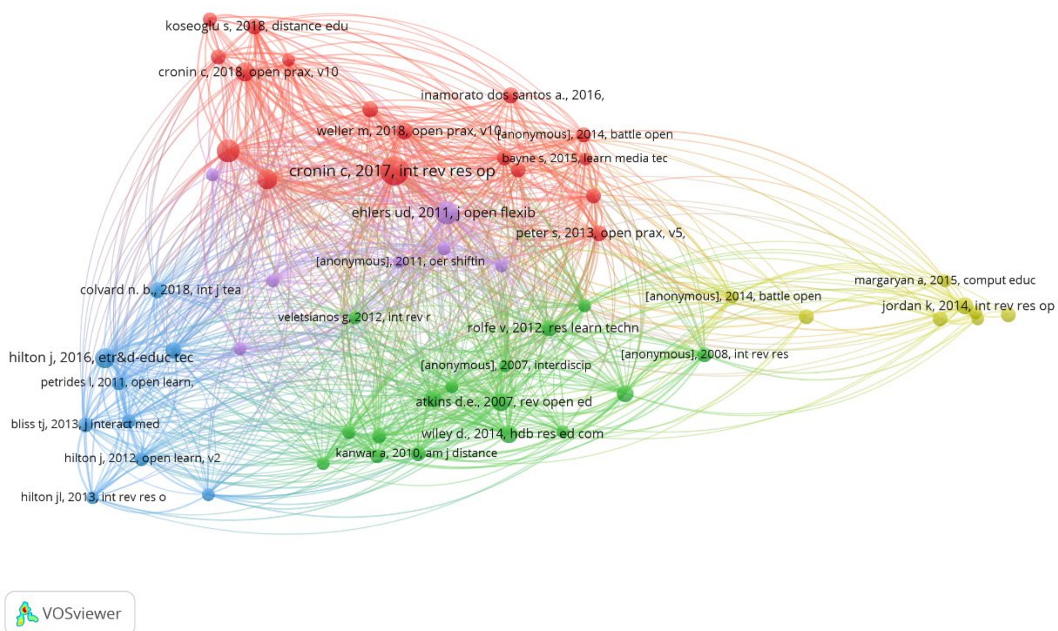


Table 1

Top 10 Documents in Terms of Co-Citation and Total Link Strength

No.	Documents	Citation	Total link strength
1	Cronin, C. (2017). Openness and praxis: Exploring the use of open educational practices in higher education. *International Review of Research in Open and Distributed Learning*, *18*(5), 15–34.	46	228
2	Ehlers, U. D. (2011). Extending the territory: From open educational resources to open educational practices. *Journal of Open, Flexible and Distance Learning*, *15*(2), 1–10.	28	165
3	Wiley, D., & Hilton, J. L., III. (2018). Defining OER-enabled pedagogy. *The International Review of Research in Open and Distributed Learning*, *19*(4).	28	122
4	Hilton, J. (2016). Open educational resources and college textbook choices: A review of research on	23	86

No.	Documents	Citation	Total link strength
	efficacy and perceptions. *Educational Technology Research and Development*, *64*, 573–590.		
5	Hegarty, B. (2015). Attributes of open pedagogy: A model for using open educational resources. *Educational Technology*, 3–13.	22	121
6	Cronin, C., & MacLaren, I. (2018). Conceptualising OEP: A review of theoretical and empirical literature in open educational practices. *Open Praxis*, *10*(2), 127–143.	20	109
7	Atkins, D. E., Brown, J. S., & Hammond, A. L. (2007). *A review of the open educational resources (OER) movement: Achievements, challenges, and new opportunities* (Vol. 164). Mountain View: Creative Common.	19	110
8	Wiley, D., Bliss, T. J., & McEwen, M. (2014). Open educational resources: A review of the literature. *Handbook of Research on Educational Communications and Technology*, 781–789.	18	79
9	Jordan, K. (2014). Initial trends in enrolment and completion of massive open online courses. *International Review of Research in Open and Distributed Learning*, *15*(1), 133–160.	16	26
10	Weller, M., Jordan, K., DeVries, I., & Rolfe, V. (2018). Mapping the open education landscape: Citation network analysis of historical open and distance education research. *Open Praxis*, *10*(2), 109–126.	16	87

The co-citation analysis identified five distinct clusters, each representing a unique topic within the field of open education. These clusters provide a thematic structure for understanding the key research areas and offer insights into open education's evolution and current state. Below is a detailed description of each cluster and a critical discussion of its contributions and limitations.

Cluster 1 (Red): Evolving Open Education (17 Publications)

This cluster forms a comprehensive exploration of the "Evolving Open Education" theme, with a focus on the transition from OER to OEP. The literature underscores a pivotal shift in the field, moving from access to resources to a more nuanced understanding of pedagogy, technology, and social justice within education. While Wiley and Hilton III (2018) lay a firm foundation with the concept of OER-enabled pedagogy, many of the subsequent studies (Peter & Deimann, 2013; Weller et al., 2018) offer historical and conceptual analyses without fully addressing the challenges of practical implementation. Lambert (2018) and Bali et al. (2020) align open education with social justice, emphasizing equity and access. However, despite the promising discourse on social justice, there is a lack of empirical research that explores how these frameworks are applied in diverse educational contexts, particularly in underresourced regions. This body of work reflects a transition in open education, but the focus remains largely theoretical, with limited practical exploration of how to operationalize openness in real-world educational settings. Therefore, while this cluster provides a rich conceptual foundation, it calls for further empirical investigation to bridge the gap between theory and practice.

Cluster 2 (Green): OER's Role in Education (16 Publications)

The second cluster delves into the role of OER in education, tracing its evolution from initial enthusiasm about access to a more critical debate on its broader implications. Early works, such as Atkins et al. (2007), celebrated the democratizing potential of OER. Still, the narrative has since shifted toward questioning OER's sustainability and practical integration within institutional cultures. Studies like those by Wiley (2014) and Cox and Trotter (2016) critique the gap between OER's theoretical potential and its real-world implementation, particularly regarding institutional support and faculty engagement. Kanwar et al. (2010) and Rolfe (2012) explore the economic and pedagogical barriers to OER adoption, particularly in the Global South, where infrastructural limitations often impede its success. While these studies provide valuable insights, they stop short of offering actionable solutions for overcoming these barriers, leaving a gap in the literature regarding practical strategies for scaling OER in diverse contexts. This cluster emphasizes the need for a more strategic and thoughtful integration of OER into pedagogical practices, moving beyond theoretical discussions to address the real-world challenges of sustainability and scalability.

Cluster 3 (Blue): Adoption of Open Education (9 Publications)

The third cluster focuses on the adoption and impact of open education across various educational levels. Research in this cluster highlights the cost-saving benefits and positive effects on student success metrics, particularly in terms of textbook affordability and improved learning outcomes (Bliss et al., 2013; Colvard et al., 2018; Petrides et al., 2011). However, while the literature provides ample evidence of the financial benefits of open education, it often needs a critical analysis of how these benefits translate into long-term educational outcomes. Faculty and student perceptions of open education are generally positive. Still, there needs to be more exploration of the challenges and resistance to adoption, particularly from faculty who may be hesitant to change established teaching practices (Hilton, 2016). This body of research makes a compelling case for the broader adoption of open education, but it would benefit from a more critical examination of the institutional and cultural factors that influence adoption, particularly in regions with less established open education frameworks.

Cluster 4 (Yellow): Educational Paradigms of MOOCs (8 Publications)

Cluster 4 focuses on MOOCs and the educational paradigms that underpin them. The literature draws on foundational theories of learning, such as Vygotsky's (1978) social construction of knowledge, to analyze the effectiveness of MOOCs in fostering learning. While Vygotsky's theories provide a solid theoretical framework, the practical challenges of applying these paradigms in massive, often impersonal online environments remain underexplored. Margaryan et al. (2015), Liyanagunawardena et al. (2013), and Jordan (2014) examine the instructional quality and enrollment patterns of MOOCs, but there is a recurring critique that MOOCs often fail to live up to their democratizing potential, with high dropout rates and limited engagement from learners. MacDonald (2015) raises important questions about the paradox of "openness" in MOOCs, highlighting the tension between the promise of accessible education and the reality of low completion rates and limited interaction. This cluster suggests that while MOOCs offer innovative educational opportunities, their success is hindered by challenges related to learner engagement and the scalability of pedagogical approaches.

Cluster 5 (Purple): Implementation of OEP (7 Publications)

The final cluster addresses the implementation of OEP, emphasizing a shift from using open resources to fostering participatory, collaborative learning environments. Early works by Ehlers (2011) and Lane and McAndrew (2010) pioneered the change toward open practices. However, more studies highlight the practical challenges of embedding these practices into everyday teaching (Jhangiani et al., 2016; Paskevicius, 2017). Research in this cluster reveals a growing interest in how open pedagogy can transform educational experiences, but it also identifies significant barriers, such as faculty resistance, lack of institutional support, and insufficient training in open practices (Andrade et al., 2011; Kaatrakoski et al., 2017). While the literature provides valuable frameworks for understanding OEP, there is a need for more empirical research that evaluates the long-term impact of these practices on teaching and learning outcomes. This cluster emphasizes moving beyond resource-oriented approaches to foster deeper engagement with open educational philosophies. However, more research is needed to overcome the practical barriers to OEP implementation.

Table 2 summarizes the co-citation analysis conducted on open education research. The table provides information on cluster labels, publication counts, and representative articles.

Table 2

Co-Citation Clusters on Open Education

Cluster	Cluster label	Number of publications	Representative publications
1 (Red)	Evolving open education	17	Wiley and Hilton (2018); Peter and Deimann (2013); Hegarty (2015); Knox (2013); Bayne (2015); Nascimbeni and Burgos (2016); Lambert (2018); dos Santos et al. (2016)
2 (Green)	OER's role in education	16	Tuomi (2013); Rolfe (2012); Mishra (2017); Kanwar et al. (2010); D'Antoni (2009); Cox and Trotter (2016); Atkins et al. (2007)
3 (Blue)	Adoption of open education	9	Bliss et al. (2013); Fischer et al. (2015); Hilton (2016); Petrides et al. (2011)
4 (Yellow)	Educational paradigms of MOOCs	8	Jordan (2014); Margaryan et al. (2015); Liyanagunawardena et al. (2013); Vygotsky and Cole (1978); Braun and Clarke (2006); Daniel (2012)
5 (Purple)	Implementation of OEP	7	Ehlers (2011); Andrade et al. (2011); Beetham et al. (2012); Kaatrakoski et al.

Cluster	Cluster label	Number of publications	Representative publications
			(2017); Jhangiani et al. (2016); Lane and McAndrew (2010); Paskevicius (2017)

Note. Author's interpretation derived from VOSviewer analysis. OER = Open Educational Resources; MOOCs = Massive Open Online Courses; OEP = Open Educational Practices.

Co-Occurrence of Keyword

There were at least seven occurrences of each of the 49 keywords discovered. According to the co-word analysis, the most frequently used keyword was "Open education" (182 occurrences), followed by "Open educational resources" (63 occurrences) and "OER" (46 occurrences). Table 3 displays the top 15 co-occurring keywords within this study domain.

Table 3

The 15 Most Frequent Keywords in the Keyword Co-Occurrence Analysis

Rank	Keyword	Occurrences	Total link strength
1	Open education	182	369
2	Open educational resources	63	156
3	OER	46	144
4	Higher education	48	133
5	MOOCs	41	96
6	Open educational practices	23	70
7	Open pedagogy	18	68
8	Education	31	62
9	Students	21	59
10	Online learning	21	58
11	Quality	13	56
12	Impact	14	52
13	Teachers	13	50
14	Technology	17	49
15	Distance education	22	48

Note. OER = Open Educational Resources; MOOCs = Massive Open Online Courses.

The co-word analysis identified five interconnected clusters, each offering insights into emerging trends and future directions for research in open education. These clusters point to key areas where more in-depth exploration is needed to address unresolved challenges and leverage the full potential of OEP.

Cluster 1 (Red): Blended Learning in Open Education

This cluster, consisting of 12 keywords, focuses on "Blended Learning in Open Education," which integrates digital technology into traditional pedagogical models. While blended learning has been widely acknowledged for its potential to cater to diverse learning needs, a critical gap in the literature lies in understanding the scalability and quality assurance mechanisms needed to ensure consistent educational outcomes across varied contexts (Ngoasong, 2022). Future research will likely explore these challenges, particularly in underresourced regions, where infrastructure limitations may hinder implementing blended models effectively. Additionally, there is a need to examine how blended learning can be adapted to ensure equity, as Chohan and Hu (2022) suggest that digital inclusion remains a significant barrier. The anticipated research will also focus on enhancing the design of MOOCs to address persistently high dropout rates and improve engagement, ensuring that learners benefit from personalized and flexible approaches (Bettiol et al., 2022). The findings in this cluster suggest that blended learning offers great promise for democratizing education. However, without a deeper understanding of how to maintain engagement and quality in diverse educational environments, the full potential of blended models may remain unrealized.

Cluster 2 (Green): Openness in the COVID-19 Era

This cluster, comprising 11 keywords, addresses "Openness in the COVID-19 Era," with the pandemic serving as a catalyst for the rapid adoption of OEP. The global shift to remote learning during the pandemic exposed opportunities and challenges for open education, highlighting the urgent need for research into how these innovations can be sustained post-crisis (Assaf & Gan, 2021). While OER proved to be vital in ensuring continuity of learning, especially in underserved regions, future studies will likely investigate the sustainability of this shift and the infrastructural gaps that need to be addressed (Sangster et al., 2020). The pandemic also elevated the role of open science in addressing global challenges. However, there is a need to explore how the open science model can continue to foster collaboration beyond crisis contexts (Calder et al., 2022). This cluster suggests that while the pandemic created an immediate need for open resources, the long-term challenge will be ensuring that these resources remain integrated into educational systems in ways that promote resilience and adaptability. Future research may focus on strategies to institutionalize these open practices to build a more accessible and flexible education system that can withstand future disruptions (Farsawang & Songkram, 2023).

Cluster 3 (Blue): Challenges of OER Adoption

The "Challenges of OER Adoption" cluster, with 11 keywords, underscores the barriers to effectively integrating OER into educational frameworks. While much of the literature celebrates the potential cost-saving and accessibility benefits of OER, there remains a critical gap in understanding how institutional and cultural factors influence adoption, particularly regarding faculty resistance and institutional support (Kauffman, 2021). Predictions for future research suggest a growing focus on developing models that address these barriers, with attention to creating incentives for faculty adoption and aligning OER initiatives with institutional priorities. Furthermore, the need for sustainable funding and long-term planning for OER initiatives remains underexplored, especially in regions with limited educational budgets (Gong, 2024; McGowan, 2020). Future research will aim to uncover practical strategies for scaling OER adoption and developing open textbooks and other resources that can be maintained over time (Tlili et al., 2023). The cluster suggests that addressing these adoption challenges will be crucial for OER to fulfill its promise of improving educational access and equity.

Cluster 4 (Yellow): Inclusive Digital Pedagogy

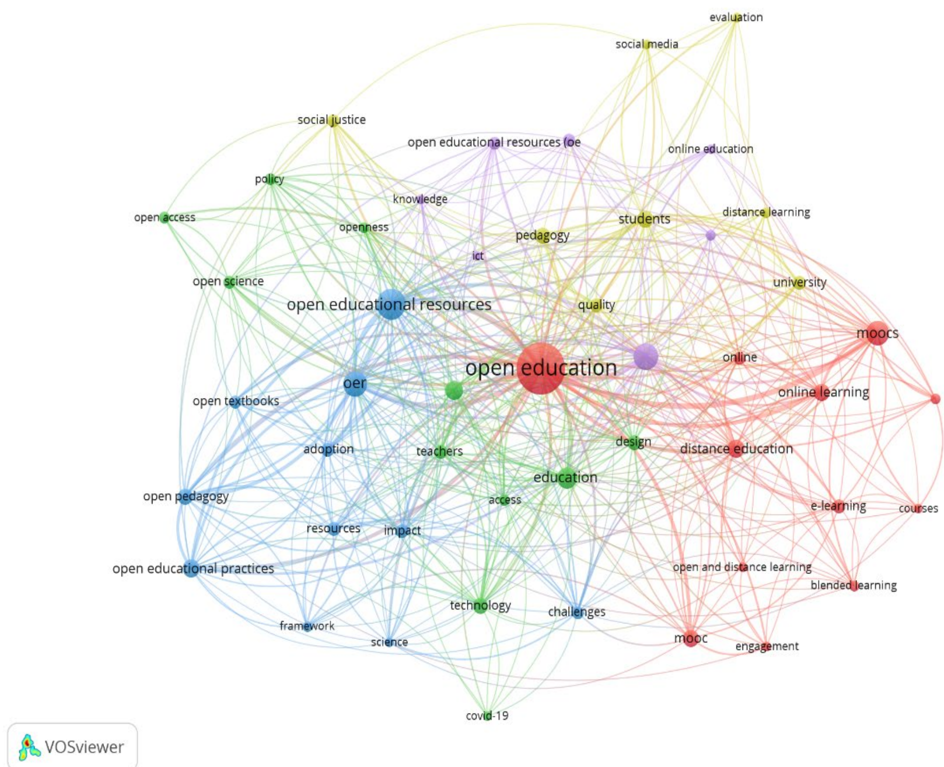
The eight keywords in this cluster emphasize "Inclusive Digital Pedagogy," a theme that reflects the shift toward digital learning models in higher education. While digital pedagogy can potentially increase inclusivity, especially for marginalized students, more empirical research is still needed on how these tools are implemented to reduce inequalities (Laufer et al., 2021). Future research will likely evaluate digital platforms' effectiveness in creating equitable learning environments and minimizing the digital divide. The role of social media and other digital platforms in supporting interaction and collaboration within inclusive pedagogical frameworks will likely be a focus of future studies (O'Dwyer et al., 2023). The findings suggest that digital pedagogy can support more equitable learning opportunities but only if the design and implementation of these platforms actively work to reduce disparities rather than exacerbate them. This area of research will need to examine how digital tools can be adapted to different socioeconomic contexts to ensure that all learners benefit from high-quality education.

Cluster 5 (Purple): Collaborative Online Academia

The "Collaborative Online Academia" cluster, comprising seven keywords, points to the growing role of collaboration in online learning environments facilitated by OER and Information and Communication Technology (ICT). While collaborative learning has the potential to enhance educational quality by breaking down geographic and institutional barriers, future research will need to explore how such collaboration can be sustained across diverse contexts (Huang et al., 2020). The integration of ICT into higher education is poised to become a focal point of future studies, particularly in terms of how universities can apply these tools to promote meaningful knowledge exchange and interdisciplinary collaboration (Bilan et al., 2023). Additionally, researchers will likely examine how to overcome the infrastructural and technical challenges that can limit the success of collaborative online academia, especially in regions where access to reliable technology is limited (Cui et al., 2020). The findings suggest that while the potential for collaboration through OER and ICT is clear, its realization depends on overcoming these barriers to ensure widespread participation and engagement. Figure 3 shows a network analysis resulting from the co-word analysis.

Figure 3

Co-Word Analysis of Open Education Research (Vosviewer Visualization)



The co-word analysis reveals several key areas for future research in open education. Table 4 summarizes the co-word analysis conducted on open education.

Table 4

Co-Word Analysis on Open Education

Cluster no. and color	Cluster label	Number of keywords	Representative keywords
1 (Red)	Blended learning in open education	12	"blended learning," "courses," "distance education," "e-learning," "engagement," "massive open online courses," "MOOCs," "online," "online learning," "open and distance learning," "open education"
2 (Green)	Openness in the COVID-19 era	11	"access," "COVID-19," "design," "education," "open access," "open education resources," "open science,"

Cluster no. and color	Cluster label	Number of keywords	Representative keywords
			“openness,” “policy,” “teachers,” “technology”
3 (Blue)	Challenges of OER adoption	11	“adoption,” “challenges,” “framework,” “impact,” “OER,” “open educational practices,” “open educational resources,” “open pedagogy,” “open textbooks,” “resources,” “science”
4 (Yellow)	Inclusive digital pedagogy	8	“distance learning,” “evaluation,” “pedagogy,” “quality,” “social justice,” “social media,” “students,” “university”
5 (Purple)	Collaborative online academia	7	“higher education,” “open educational resources (OER),” “higher-education,” “collaboration,” “knowledge,” “ICT,” “online education”

Note. Author’s interpretation derived from VOSviewer analysis. OER = Open Educational Resources.

Implications

The theoretical implications of this bibliometric analysis highlight the fluid and evolving nature of open education, as evidenced in the co-citation analysis. Open education is not a static concept but a dynamic entity, constantly adapting to emerging educational needs, technological advancements, and societal challenges. This aligns with Bozkurt et al. (2019) and Cronin (2017), who emphasized that open education frameworks are characterized by their responsiveness to the shifting landscape of global education. The continuous evolution of open education carries profound implications for educational theory, prompting a reevaluation of how knowledge is disseminated, acquired, and shared across borders and contexts. Our findings support Wiley and Hilton III (2018), who argued for a shift from merely providing access to educational resources to focusing on how these resources can be integrated into pedagogical frameworks that emphasize equity and inclusion. This intersection of pedagogy, technology, and social justice has emerged as a critical component in advancing the open education movement, demonstrating that open education can serve as a vehicle for addressing broader societal inequalities.

Our findings also shows that the OEP field’s evolution aligns with current educational demands, especially in equity, accessibility, and pedagogical innovation. Previous studies have similarly highlighted the importance of this intersection. For example, Lambert (2018) and Bali et al. (2020) connected open education with social justice, emphasizing that OEP can be a powerful tool for promoting equity and democratizing knowledge. Our analysis reinforces these conclusions, suggesting that the future of open education lies in its ability to continuously adapt to changing educational demands while remaining anchored in accessibility, inclusivity, and empowerment. Thus, this study not only expands the theoretical framework around open education but also supports our aim to offer a cohesive understanding of how OEP develop and their broader implications for educators and policymakers. The study emphasizes that educators and policymakers must continuously redefine and innovate OEP, ensuring they remain relevant in diverse global contexts.

On the practical side, this research underscores the importance of implementing and advocating for open educational resources and practices within higher education, particularly to reduce financial barriers and increase access to diverse learning resources. The co-occurrence analysis findings strongly align with prior studies' results (Bliss et al., 2013; Hilton, 2016), which similarly highlighted the financial and accessibility benefits of integrating OER into educational curricula. OER significantly reduces financial burdens on students, facilitating greater participation from underrepresented groups and democratizing access to higher education. This supports our goal of highlighting how OER can contribute to bridging the digital divide and promoting inclusivity.

Beyond financial savings, the flexibility offered by OER allows students to access learning materials at their convenience, promoting personalized learning paths that cater to individual schedules and learning styles. This flexibility, as noted by Wiley (2014), is one of the critical advantages of OER, enabling students to tailor their learning experience to their specific needs, thus fostering greater engagement and retention. The adaptability of OER enhances learning outcomes and empowers students by providing them with the autonomy to control their learning process. However, as our research and earlier studies (Cox & Trotter, 2016; Rolfe, 2012) suggest, the successful implementation of OER is not without challenges. Faculty acceptance and institutional support play pivotal roles in effectively adopting open resources. Faculty reluctance to adopt OER is a significant challenge, often stemming from concerns about quality, lack of familiarity, and the absence of institutional incentives. Our findings echo these concerns, suggesting that without comprehensive faculty development programs and institutional policies that incentivize OER adoption, the potential of open education to transform learning environments may be limited. This aligns with the work of Paskevicius (2017), who emphasized that faculty development and support are essential to overcoming barriers to OER adoption, particularly regarding pedagogical innovation and integration into existing curricula.

Institutions must actively foster a culture of openness by providing educators with the necessary tools, training, and incentives to adopt OER. This point is also supported by Jhangiani et al. (2016), who argued that institutional policy changes are critical for ensuring that OER becomes a mainstream component of educational delivery. Our analysis suggests that such institutional efforts are crucial for OER initiatives' long-term success and sustainability, particularly as the demand for flexible and accessible educational resources continues to grow.

Overall, the findings from this bibliometric analysis validate the insights from previous research and provide new directions for theoretical exploration and practical implementation. By comparing the current study's results with established literature, it is evident that while the advantages of OER and OEP are well-documented, significant gaps in faculty engagement and institutional support still need to be addressed. Addressing these gaps aligns with our study's aim to provide educators and policymakers with actionable insights on enhancing the effectiveness of open education initiatives.

Conclusion, Limitations, and Future Avenue

The bibliometric analysis provided a broader understanding of the diverse nature of open education, emphasizing its evolution and responsiveness to educational demands. Open education emerges from research as a dynamic and ever-evolving field (Bozkurt et al., 2023), shaped by the collaborative efforts of educators, researchers, and institutions. The practical significance of embracing OER is clear, offering substantial benefits such as cost savings, greater accessibility, and enhanced learning outcomes. OER serve as a powerful means to alleviate the financial strain on students and democratize access to quality education. Their flexibility and potential for personalization lead to richer educational experiences, aligning with modern learners' needs.

Although this review provides insightful information, it is constrained. In this review, several limitations are addressed. First, the analysis only includes sources listed in the WoS database. Other databases, such as Dimension and Scopus, may produce different outputs. Despite using only one database, WoS is thought to be the world's most dependable and robust database, ensuring that all the articles are of high caliber (Pranckute, 2021). Second, bias issues could have resulted from the qualitative interpretation of the clusters. Based on previous research in the clusters of co-citation analysis and the relationships between the keywords in the co-word analysis, the authors' examination of the clusters led to the development of this inductive approach. The science's subjective threshold value determination is still another drawback. Another drawback is the subjective selection of the threshold value in the science mapping study. The authors' interpretation was used to finalize the clusters, which could have caused bias. The cluster labels and threshold values were cross-checked among the authors to confirm their resilience and accurate representation of the knowledge structure to address both problems. Lastly, the findings may not fully account for regional or institutional variations in adopting open educational practices and resources.

Future research should take into account several options to address these limitations and improve our knowledge of open education. First, by capturing quantitative trends and qualitative views from academics, educators, and students, bibliometric analysis combined with qualitative research techniques may offer a more complete picture of the topic. To guarantee that educational practices and policies remain responsive to the shifting demands of students and educators in the digital era, it is crucial to examine how open education is continuously developing. Second, while considering regional and institutional differences, research should examine the contextual elements that affect adopting open educational practices and materials. Finally, a more delicate examination of open education's potential challenges and drawbacks would contribute to a more balanced and holistic understanding of the field. By addressing these future avenues, we can continue to promote openness, accessibility, and innovation in education.

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