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Emotions Among Students Engaging in Connectivist Learning Experiences

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Abstract

Emotion has long been a question of great interest in a wide range of fields. As a general rule, emotions are categorized as positive, which we seek, and negative, from which we turn away. However, empirically-backed connectivists claim that even negative emotions produce positive effects on student performance. What is less clear is how this process happens. This study had two primary aims. First, to assess the prevalence and distribution of emotions in connectivist environments. Second, to provide in-depth and experiment-based analysis that shows how and when negative emotions have their positive effect. Data for this study were mainly collected using an aided think-aloud protocol with nine participants, each of whom received ten tasks. Findings of the current study confirmed the dominance of negative emotions in connectivist learning environments and presented a model that could explain the variation of empirical results. Implications for researchers and teachers in distance education are discussed.

Keywords: connectivism, emotion, control-value theory, online learning, higher education

Introduction

The work presented in this paper was grounded in connectivism literature (Aldahdouh, 2017; Aldahdouh, Osório, & Caires, 2015; Downes, 2007; Siemens, 2005). Siemens (2006) emphasized the importance of emotions in connectivism and contended that "cognition, emotion, perception, and beliefs are knowledge creation and knowledge navigation enablers" (p. 16). As well, connectivists recognized that online learning without explicit guidance from an instructor could be as frustrating as exploring unknown territories without a map (Siemens & Tittenberger, 2009), a conclusion which found supporting evidence in several empirical studies (Capdeferro & Romero, 2012; Kop, Fournier, & Mak, 2011; Mackness & Bell, 2015; Tschofen & Mackness, 2012). A common assumption among connectivists, however, is that these negative emotions will force learners "to search for answers, to ask help, to seek for patterns and, in other words, to form connections" (Aldahdouh et al., 2015, p. 16). Yet, an empirical-based understanding of how negative emotions contribute to positive outcomes is still lacking.

We referred to control-value theory in an attempt to gain a better understanding of the emotions effect (Pekrun, 2014; Pekrun & Perry, 2014). In control-value theory, negative emotions are further divided into activating (e.g., anger, anxiety, shame) and deactivating emotions (e.g., hopelessness, boredom). We focused our attention on the consequences of negative-activating emotions because it was this set of emotions that was hypothesized to have positive impact on students' performance in connectivism. However, we found that control-value theory did not reach a firm conclusion as to whether negative-activating emotions would lead specifically to positive or negative outcomes. As Pekrun and Perry (2014) wrote, "the motivational effects of positive deactivating and negative activating emotions are proposed to be more complex" (p. 132). On the one hand, negative-activating emotions are expected to undermine interest, and, on the other hand, they may induce more efforts to avoid failure. And as expected, the empirical results were mixed; frustration emotion, for example, (a) predicted negative performance in some studies (Pekrun et al., 2004; Valiente, Swanson, & Eisenberg, 2012); (b) predicted the use of favorable meta-cognition strategies in other studies (Artino, 2009; Artino & Jones, 2012); and (c) lacked the power to predict meaningful online learning strategies in Marchand and Gutierrez (2012). Other negative-activating emotions such as anger and anxiety showed the same pattern of hybrid results (Lane, Whyte, Terry, & Nevill, 2005; Marchand & Gutierrez, 2012; Pekrun, Elliot, & Maier, 2009; Pekrun et al., 2004). These mixed results have made researchers stumble in their interpretation (Artino, 2009) and the field lacks in-depth and experiment-based analysis that shows how and when negative emotions take their positive effect.

This study set out to attain two aims. One was to inspect the prevalence and distribution of emotions in connectivist environments by gathering the frequency and relative frequency of various emotions. There is a general supposition among researchers that negative emotions dominate the feelings of students in online learning environments (Artino, 2009; Capdeferro & Romero, 2012; Zembylas, 2008), to the extent that some have argued that there is one positive emotion occurrence for every three to four negative emotions (Valiente et al., 2012). However, this ratio dropped to only 1.7 in a context of test-related emotions (see the results of study 1 in Pekrun et al., 2004). The context is indeed influential in terms of the emotions experienced by the participants. In test-related context, for example (Pekrun et al., 2004), students reported different set of emotions than in a MOOC context (Zembylas, 2008). Therefore, the literature is still in need of a study addressing the emotions that occur in connectivist learning environments, beyond the framework of MOOCs. The second aim of the current study was to track the situations under which negative emotions produce their positive effect on a student's behavior. This study allowed learners' voices to emerge and brought out their own words.

Literature Review

Connectivism

Connectivists hold an alternative interpretation of how humans learn in a highly connected environment with abundant information (Downes, 2008; Siemens, 2005; Siemens & Conole, 2011; Wang, Chen, & Anderson, 2014). A central tenet of connectivism is that today, knowledge is dynamic and accelerating: "while there is a right answer now, it may be wrong tomorrow" (Siemens, 2005, p. 4). Although connectivists do not define knowledge, they propose that knowledge has a structure much like a network—because the network structure is powerful and inclusive (for more discussion about knowledge network, the reader is directed to Aldahdouh, 2019 and Downes, 2007).

To learn, in the connectivist view, is to form new connections or to recognize patterns of existing networks (Downes, 2016). Because the knowledge network is dynamic and chaotic, learning is viewed as a continuous process of adopting to newly formed patterns. A recent study by AlDahdouh (2018a) showed that learners form connections in three cyclic phases: planning, cognitive processing, and evaluating. The planning phase is a meta-cognitive process in which learners enumerate the surrounding nodes, order them, exclude some, and select one. Learners use three criteria in choosing nodes: (a) self-efficacy, (b) eligibility of the resource, and (c) feasibility of the resource. In the cognitive processing phase, learners interact with the selected nodes in hopes of finding the required information. The evolution phase refers to the process of questioning the value of the selected nodes.

Few studies have investigated the individual learning experience in connectivist environments (Mackness & Bell, 2015; Tschofen & Mackness, 2012). Participant emotions were considered in those studies, but only on the margins. For example, Kop et al. (2011) tracked what the participants of two MOOCs thought and felt, and found that MOOC newcomers felt confused and overwhelmed. As a result of a high level of autonomy, some participants felt included, accepted, and empowered, while others felt threatened and lost. Quite similar results were found by Mackness and Bell (2015), but additionally they spotted one interesting result—some participants recognized the fact that the organizers of MOOC in which they were participating were actually testing a new learning environment, with learners playing in a role similar to lab rats. Once again, the participants took two stances; some felt proud to be among the few who were building new knowledge, while others felt upset about the whole experiment. The issues of self-direction and self-motivation in the face of setbacks have now been fully recognized in connectivism literature (Aldahdouh & Osório, 2016; Downes, 2019).

Connectivism has been subjected to considerable criticism (Clarà & Barberà, 2013; Kop & Hill, 2008; Verhagen, 2006). Downes (2019) contended that most of the arguments against connectivism sprang from theoretical papers. Yet, the arousal of negative emotions in connectivist environments have led some researchers to adopt a skeptical view of connectivism and its ability to guide the teaching practices in online learning (Ament & Edwards, 2018; Cabrero & Román, 2018; Pando, 2018). For example, Ament and Edwards (2018) urged teachers to ignore recent trends in mobile learning, especially those calling for marginalizing the role of teacher (such as in connectivism and personalized learning) because this will lead only to a deterioration of learner performance, both academically and emotionally. For connectivists, the negative emotions are just part of a normal learning process. How can learning ever happen, unless a learner experiences some sorts of confusion, anger, and frustration? Even more, AlDahdouh et al. (2015) argued that negative emotions do have a positive impact on learners' performance in that they push learners out of their comfort zone.

Control-Value Theory

The basic proposition in control-value theory emphasizes the role of control and value appraisals (Pekrun, Goetz, Frenzel, Barchfeld, & Perry, 2011; Pekrun et al., 2004; Pekrun & Perry, 2014). The theory acknowledged the various types of factors that can explain the arousal of emotions, all of which are proposed to take effect through two proximal antecedents—the perceived control of one's actions and outcomes, and the perceived value of the task's activities and outcomes. To put it simply, triggering students' emotions is thought to be preceded by changing in their self-concept of power over the task and their assessment of the task's value. It has been proposed that anxiety, for instance, is triggered when a student is uncertain about exam results (low outcomes-control), while anxiety becomes hopelessness when the uncertainty of exam results dips to a complete lack of hope. Anger is experienced when the results are highly appreciated (high outcome-value), while the teacher's activities are perceived as useless (low activity-value). Other emotions follow similar patterns and are aroused by a preceding combination of control and value appraisals (for more details, see Pekrun & Perry, 2014).

In a series of qualitative and quantitative studies, Pekrun and colleagues (Pekrun et al., 2011; Pekrun & Perry, 2014) tested the above-mentioned model and its applicability in examination contexts at schools and universities. The results identified two crossing dimensions that classify nine emotions into four sets of interrelated emotion profiles, as shown in Figure 1. According to Pekrun and colleagues' qualitative studies, almost all human emotions were reported by the participants, but the nine emotions represented in Figure 1 were the most often reported, and the most influential on the students' motivation and academic performance.

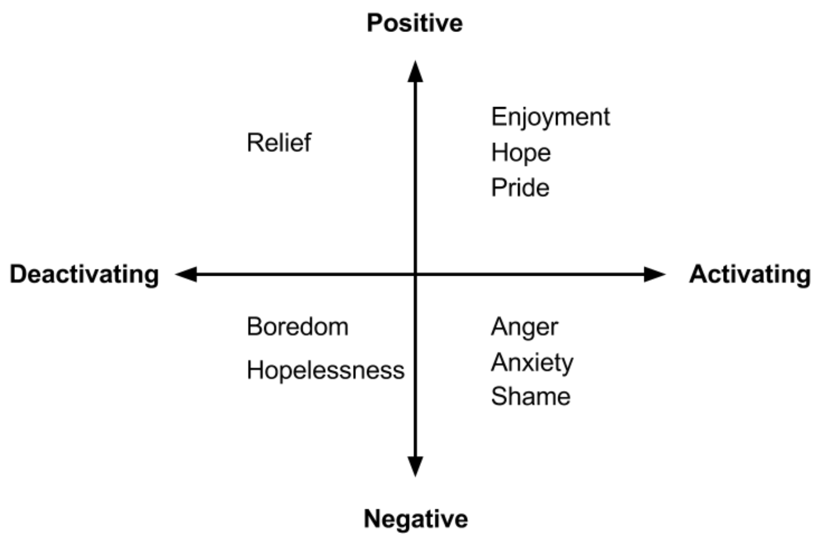

Figure 1. Taxonomy of achievement emotions into four categories.

Each emotion profile has different effects on student goals, motivations, and academic performance (Pekrun et al., 2011; Pekrun & Perry, 2014). Consistent findings across different studies showed that positive-activating emotions are associated with adaptive consequences, such as (a) elaboration and meta-cognition (Artino & Jones, 2012); (b) learning strategies (Marchand & Gutierrez, 2012); (c) the choice of intensive online learning (Tempelaar, Niculescu, Rienties, Gijselaers, & Giesbers, 2012); and (d) higher exam grades in the virtual world learning environment (Noteborn, Bohle Carbonell, Dailey-Hebert, & Gijselaers, 2012). A destructive impact of negative-deactivating emotions has also been shown consistently in various studies (Artino, 2009; Artino & Jones, 2012; Noteborn et al., 2012).

The empirical findings of negative-activating emotions were, in contrast, mixed. For illustration, we put forward here the contradicting results of frustration emotion. Pekrun, Frenzel, Goetz, and Perry (2007) classified frustration initially as negative-activating emotion in a three-dimensional taxonomy of achievement emotions. The preliminary empirical results showed that frustration predicted maladaptive behavior (Pekrun et al., 2004; Valiente et al., 2012), but later works failed to replicate this result. In particular, successive studies (Artino, 2009; Artino & Jones, 2012) showed that frustration positively predicts the use of meta-cognition, one of the most important self-regulation strategies in online learning. Moreover, Marchand and Gutierrez (2012) showed that frustration and anxiety failed to maintain a significant predictive power for meaningful learning strategies for distance education students, while they both negatively predicted the learning strategies in face-to-face groups. Even with these contradicting results, in their later work, Pekrun and Perry (2014) reclassified frustration under negative-deactivating emotions.

It has proven difficult for many researchers to interpret how negative emotions can lead to positive outcomes. For some, the findings were exceptional and inconclusive (Artino, 2009; Artino & Jones, 2012) and should be received with caution (Marchand & Gutierrez, 2012). For others, the variation of results could be due the nature of the learning context, online versus face-to-face (Marchand & Gutierrez, 2012; Zembylas, 2008). Some scholars chose to defect from the control-value theory and suggested that the effect of negative emotions is mediated by some factors (e.g., cognitive processes) or moderated by others (e.g., effortful control; Lane et al., 2005; Valiente et al., 2012). Valiente et al. (2012) additionally provided an interesting suggestion that the level of arousal may tamper with the positive effects of emotion. Accordingly, being angry at a teacher's activities, for example, could encourage one to exert more effort, but only when the anger does not rise up to the level at which no more cognitive capacity is left with which to complete the task itself.

Generally speaking, the field is active, yet under-researched regarding the impact of negative emotions. As far as we can tell, no previous study has demonstrated the prevalence and distribution of emotions in connectivist environments nor qualitatively tracked under which situations the negative emotions produce their positive effect on students' behavior. The current paper attempts to unravel some of the mysteries surrounding those objectives.

Methodology

Design and Procedure

Participants in this study were recruited from Palestinian higher education institutions (HEIs). There are three types of HEIs in Palestine: university, university college, and community college. Each type offers specific types of programs. For example, universities, in addition to postgraduate studies, can offer five undergraduate study programs: (a) four-year bachelor; (b) five-year bachelor (such as engineering); (c) six-year bachelor (such as medicine); (d) two-year diploma; and (e) one-year professional diploma. According to the *Higher Education Statistical Yearbook* for 2015/2016 (Ministry of Education and Higher Education, 2016), there are 50 accredited HEIs in West Bank and Gaza. The total number of students registered in HEIs for the academic year 2015/2016 was 216,028 (130,843 female) while the total number of newly enrolled students was 56,969 (33,292 female; Ministry of Education and Higher Education, 2016).

The current study employed aided retrospective think-aloud (RTA) as a main research method. An aided RTA is also known as "prompted retrospective protocol" (Kuusela & Paul, 2000, p. 398), "retrospective verbal protocol" (Ericsson & Simon, 1980, p. 226), and "stimulated retrospective think-aloud" (Guan, Lee, Cuddihy, & Ramey, 2006, p. 1253).

Upon inviting the participants to take part, the purpose of the research was clearly explained, and informed consent was collected. Each participant individually received ten tasks, one task after another. Participants were free to access any resource or to refer to anyone regarding the task, but they were asked to record their activities carefully (e.g., video recording of computer screen, screenshots of mobile conversation on *WhatsApp*, voice recording of face-to-face conversation with friends). A secondary consent was collected for any conversation involving other parties. Once completing the task, the participants took part in a follow-up RTA session, where they watched a recording of their activities and reported whatever was on their mind (Kuusela & Paul, 2000; Van Den Haak, De Jong, & Schellens, 2004). RTA sessions were video recorded.

Participants

Fifteen students participated in the experiment and accepted the informed consent terms (Table 1 shows a list of participants); nine students completed the ten tasks in the experiment. Data generated from only those nine participants were included in the analysis. A small and purposive sample was chosen because of the difficulty in obtaining a larger sample for a think-aloud study, and in line with recommendations in the literature for online experiences, which make a strong case for selecting only those participants who show the desire and willingness to generate rich information about the phenomenon (Limbu & Markauskaite, 2015; Sharpe & Benfield, 2012). Each participant received about US$26 as a financial reward upon completing the tasks. The final sample included two males and seven females. The study also comprised data generated by 62 secondary participants to whom the main participants turned during the study.

Table 1

Participants' Information

Name[a]	Gender	Age	Field of study	GPA[b]	Tasks completed	Length (in days)[c]
Weaam	F	22	Pharmacy	87.95	10	30
M. AbuNour	M	20	Public Relations	76.20	1	46
K. AbuNour	M		Information Security		0	0
Khaled W.	M	21	Share'a and Law	76.80	10	194
Khaled D.	M	19	Journalism	81.50	10	183
Talla	F	19	English Literature	82.70	10	87
Sabha	F	21	Education	85.50	10	82
M. Musharawi	M		Share'a and Law		0	8
Redaa	F	20	Science Education	93.6	10	24
Salwa	F		Science Education		0	31
Neran	F	21	Math Education	80.74	10	37
Khoula	F	21	Math Education	82.00	0	7
Nawal	F	28	Arabic Literature	93.25	10	51
Khaled A.	M		English Literature		0	11
Amal	F	21	Math Education	80.50	10	42

Note. [a]All names used are pseudonyms. [b]GPA stands for Grade Point Average (in percent). [c]The number of days to complete the task(s).

Measures

We set the following four criteria for the experiment based on connectivist instructions and the recommendations of previous studies (Aldahdouh, 2019; Aldahdouh et al., 2015; Downes, 2009; Siemens, 2005):

1. A task should belong to the participant's daily life, inside or outside the academic context.

2. A task should be formulated in such a way so as to stimulate participants to search.

3. The experiment settings should empower the participants to do whatever they want to do in order to accomplish the task at hand.

4. Participants should receive tasks of different levels of difficulty.

The 10 tasks (i.e., Q1 to Q10) in the experiment were arranged based on their expected difficulty as follows: (Q1) an information search, (Q2) investigate a person, (Q3) a question in their field of study, (Q4) a self-motivation question, (Q5) validate information, (Q6) a compound task, (Q7) write an essay, (Q8) a design question, (Q9) a creativity question, and (Q10) a technical question. In creativity question (Q9) for example, a black circle covered a considerable part of a short story written by the researcher (see Figure 2). Participants were asked to recover the missing part using the shown text, so the whole story became consistent.

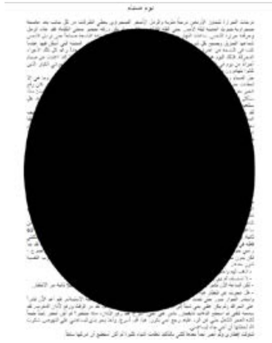

Figure 2. A snapshot of Q9.

Analysis

Throughout the experiment, the participants generated 1,364 files with a total storage size of 23 GB. This includes over 140 hours of video recordings and over 125 hours of audio recordings. Participants also produced text documents (doc, docx, and txt only) that totalled 93,255 words (*Facebook* and *Skype* chats were not included in this number).

Two theoretical frameworks guided the initial categorization process of emotions in this study. Connectivism—the first framework—identified three broad levels of learning networks, namely neural, conceptual, and external (Aldahdouh et al., 2015; Siemens & Tittenberger, 2009). The neural category was beyond the scope of our research, so our focus was solely on the conceptual and external levels of learning networks, hereafter referred to as internal and external, respectively. The other theoretical framework was the two-dimensional taxonomy of achievement emotions (Pekrun, 2014; Pekrun et al., 2007). Nevertheless, the aim of this study was to provide a detailed description of the higher-level categorization matrix proposed by the theoretical frameworks, rather than provide a rich description of the data set. The qualitative content analysis included the videos of RTA together with all other documented activities of the participants. ATLAS.ti 7 was used in the data analysis.

Results

Prevalence of Emotions in Connectivist Contexts

Participant's activities. Throughout the course of the experiment, the participants engaged in a wide array of learning activities and contacted various resources, as summarized in Table 2. The table was built based on the steps used in solving the tasks, as reported by the participants.

Table 2

Nodes' Distribution (Times of Occurrence)

<table>
<tr><td rowspan="2">Internal (80)</td><td colspan="4">Cognitive processes (34)</td></tr>
<tr><td colspan="4">Writing (46)</td></tr>
<tr><td rowspan="16">External (347)</td><td rowspan="2">Internet searching (169)</td><td colspan="3">Laptop or desktop (133)</td></tr>
<tr><td colspan="3">Mobile (36)</td></tr>
<tr><td rowspan="12">Ask people (139)</td><td rowspan="3">Face-to-face (48)</td><td colspan="2">Friends (9)</td></tr>
<tr><td colspan="2">Family members (26)</td></tr>
<tr><td colspan="2">Teachers (13)</td></tr>
<tr><td rowspan="9">Online (91)</td><td colspan="2">E-mail (2)</td></tr>
<tr><td rowspan="2">WhatsApp (10)</td><td>Friends (9)</td></tr>
<tr><td>Teacher (1)</td></tr>
<tr><td rowspan="4">Facebook Messenger (57)</td><td>Researcher (6)</td></tr>
<tr><td>Friends (26)</td></tr>
<tr><td>Family members (7)</td></tr>
<tr><td>Teachers (18)</td></tr>
<tr><td colspan="2">Facebook groups/pages (19)</td></tr>
<tr><td colspan="2">Skype call (3)</td></tr>
<tr><td colspan="4">Paper resource (30)</td></tr>
<tr><td colspan="4">Digital resource (9)</td></tr>
<tr><td colspan="5">Give up (7)</td></tr>
</table>

In Table 2, nodes are organized in a hierarchical manner. For instance, the participants asked people for help 139 times, and of these, 91 were through online communication. Online communication, in turn, took the form of e-mail twice, *WhatsApp* 10 times, and so forth. The implications of the activity distribution on theory and practice have been discussed in our previous work (Aldahdouh, 2018b, 2019). For this study, the list of activities was commingled with an emotion matrix to explore the distribution of emotions over activities.

Distribution of emotions. The participants expressed a diverse range of achievement emotions as shown in Figure 3 below.

	Activating (Occ=988, PoT=69,43)				Deactivating (Occ=435, PoT=30,57)			
	Emotion	Occ[a]	PoC[b]	PoT[c]	Emotion	Occ	PoC	PoT
Negative (Occ=1168, PoT=82,08)	Confusion	444	57,96	31,2	Frustration	183	45,52	12,86
	Anxiety	102	13,32	7,17	Hopelessness	140	34,83	9,84
	Irony	101	13,19	7,1	Boredom	61	15,17	4,29
	Anger	70	9,14	4,92	Sadness	11	2,74	0,77
	Shame	41	5,35	2,88	Regret	7	1,74	0,49
	Other NA	8	1,04	0,56				
		766	100	53,83		402	100	28,25
	Emotion	Occ	PoC	PoT	Emotion	Occ	PoC	PoT
Positive (Occ=241, PoT=16,94)	Enjoyment	67	30,18	4,71	Relief	33	100	2,32
	Hope	62	27,93	4,36				
	Surprise	51	22,97	3,58				
	Happy	36	16,22	2,53				
	Pride	6	2,7	0,42				
		222	100	15,6		33	100	2,32

Figure 3. Distribution of emotions in the experiment.

Note. Occ = times of occurrence; PoT = percentage of times of occurrence to the total number of emotions reported; PoC = percentage of times of occurrence to the number of emotions reported within the same category.

In total, emotional indications were spotted 1,423 times, and of these 1,168 (82.08%) were marked as negative and 241 (16.94%) as positive. The negative-to-positive ratio in this study was about 4,85:1. Activating emotions were reported 988 times (69.43%) in comparison to deactivating emotions that appeared 435 times (30.57%). The negative-activating category had the biggest share of all emotions reported (766 times; 53.83%). Other categories in descending order were: (a) negative-deactivating (402 times; 28.25%); (b) positive-activating (222 times; 15.6%); and (c) positive-deactivating (33 times; 2.32%). The top five emotions reported were purely negative: (a) confusion (31.2%); (b) frustration (12.86%); (c) hopelessness (9.84%); (d) anxiety (7.17%); and (e) irony (7.1%). The positive emotions were mainly classified as activating: (a) enjoyment (4.71%); (b) hope (4.36%); (c) surprise (3.53%); (d) happy (2.53%); and (e) pride (0.42%). In this study, only relief was identified as a positive-deactivating emotion and was mentioned very little (33 times; 2.32%).

By reading the relative frequency within each category, it can be concluded that confusion (57.96%) and anxiety (13.32%) were the best representative of the negative-activating emotion, together constituting 71.28% of the total number of emotional expressions reported within the category. Similarly, frustration (45.52%) and hopelessness (34.83%) represented the negative-deactivating category with a total of 80.35%, while enjoyment (30.18%) and hope (27.93%) represented the positive-activating emotions with a total of 58.11%.

It is noteworthy that each distinct feeling was classified within its category mainly based on the work of Pekrun and colleagues (Pekrun et al., 2007; Pekrun & Perry, 2014) but also based on our analysis of emotions' co-occurrence table generated by ATLAS.ti. For example, surprise did occur jointly with negative and positive emotions, but it was classified as a positive-activating emotion because it co-occurred more often with the emotions within its group.

Distribution of emotions over activities. In order to help distinguish those activities that accounted for the bulk of emotional arousals, we were interested in assessing whether the pattern of emotional distribution varied across activities. Owing to the large number of end activities, similar activities were grouped together according to the hierarchy shown in Table 2. Figure 4 shows the distribution of emotions over the higher-level activities.

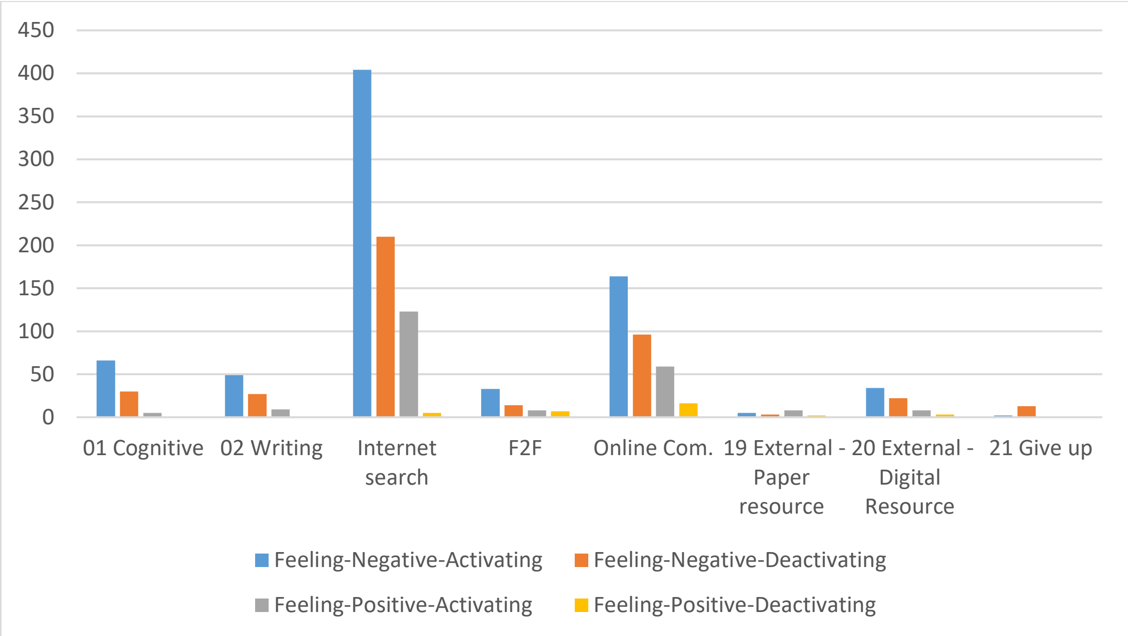

Figure 4. Emotion distribution over higher-level activities.

It is evident that Internet searching and online communication (e-mail, *Facebook* groups/pages, *Skype* calls, *WhatsApp*, and *Facebook Messenger*) accounted for most of the emotional arousal in the experiment. This result somehow reflects the fact that the participants spent most of their time searching the Internet (see Table 2). Another interesting finding is the consistent pattern of emotions among almost all learning activities. In most categories, negative-activating was the highest followed by negative-deactivating, positive-activating, and finally positive-deactivating. The pattern of emotions participants experienced while thinking and writing was almost the same as that while consulting others or searching the Internet. An exception to this paradigm was when the participants gave up, which was dominated by negative-deactivating emotions.

Qualitative Analysis

Some examples of emotions reported in the experiment revealed how negative emotions affected the behavior of the participants positively. In the following, the participants' voices show how they experienced negative emotions. Interpretations and implications of participants' behavior are addressed in the Discussion section.

Confusion was accompanied by repeating the same content twice or more, random clicks on a Web page, and suspending the current activity to think of different options. The following excerpt from Khaled W., in Q6, shows how he started acting randomly.

Khaled W.: [visiting a Web page he had visited several times].

Researcher: Then you have decided to come back to the application page again, didn't you?

Khaled W.: I was going up and down through the page not because I was searching for something, No! I was thinking of what I should do at that moment.

The previous excerpt shows that confusion had a positive effect on Khaled W. since he began to consider other options to solve the task. The positive effect was also applicable to other negative-activating feelings such as anxiety. The following excerpt from Sabha, in Q2, clarifies how her anxiety led her to come up with a new idea and to establish a new connection with her friend.

Sabha: After closing the first video recording [for the experiment], I went to sleep. But I couldn't rest that night until I knew who he is [the Palestinian character under investigation]. So, I visited his Facebook page on my mobile and searched for other people who liked his page. Then, I figured out that a friend of mine was among his followers. So, I talked to her.

Another example of a negative-activating emotion was a *Facebook* conversation between Neran and her friend in regard to Q9. Neran sent the question along with the story file (PDF) to her friend and asked her to solve the task. Apparently, her friend did not try to fill in the missing parts of the story on her own. Instead, she searched the Internet, to no avail, which made her angry. In response, she began to search for help and established connections with other people to remove the black circle from the PDF file.

Her friend: I was about to have a heart attack.
Listen, I don't promise you I will solve it, but I promise you I will send it for more than one person. Don't worry.
[after a while]
Here I am, I've sent it!
I will try also to send it to experts in photo editing to remove that black thing; and it will appear.

Neran: Really 😭😭😭😭
I cried with happiness.

Neran's response revealed the level of frustration and hopelessness she reached and how she was waiting for a glimmer of hope.

The previous excerpts serve as examples of how negative-activating emotions, namely anxiety and anger, may lead to establishing new connections, as connectivism has assumed (Aldahdouh et al., 2015). However, in the experiment, negative-activating emotions did not always serve to establish connections to new thoughts or people. For some participants, developing the negative-activating emotions devolved to negative-deactivating emotions, especially for those with continuous failure. The following excerpt from Nawal, in Q6, shows that she reached a level of frustration, and maybe hopelessness, after experiencing anger in trying with no hope.

> Nawal: Frankly, the terms [of the scholarship] were all not applicable to me. And nothing went well, I mean nothing!
>
> Researcher: Aha.
>
> Nawal: There was a thing in the seventh video [a recording of her search on mobile]; I tried to click on 'Apply' [button] several times and I tried to click on anything on the webpage, but it was not working. Clicking on 'Apply' [button] has reloaded the page and brought me back to the same page. I do not know what else I can do now.

Negative-deactivating emotions were tightly coupled with giving up the task. In all these cases of giving up, the participants said they felt a high-level of frustration and hopelessness.

Discussion and Conclusions

The initial objectives of this current study were to identify the distribution of emotions in connectivist learning environments and explore the effect of negative emotions on the participants' behaviors. The findings revealed that the emotions experienced in this environment were particularly negative. The feelings of confusion, frustration, hopelessness, and anxiety dominated, and there was almost no room for feeling relief. Other positive emotions barely appeared and hardly reached one sixth of the total emotions decoded. The yields of negative emotions in this investigation were high. The overall negative-to-positive emotion ratio was found to be 4.85:1, far higher than that of previously reported ratios (Pekrun et al., 2004; Valiente et al., 2012). Moreover, the findings of the current study did not support previous research in terms of the top emotions experienced. In the study by Pekrun et al. (2004), for example, the most frequently reported negative emotions were, in descending order: (a) anxiety, (b) anger, (c) shame, and (d) hopelessness. This is in comparison to our results: (a) confusion, (b) frustration, (c) hopelessness, (d) anxiety, and (e) irony. We attribute this variation to the context of the experiment (problem-solving in connectivist environments vs. taking an examination on campus) and invite researchers to take the context into account before applying their measures. Our results, in contrast, support the connectivist hypothesis that engaging in connectivist environments greatly arouses learners' negative emotions (Aldahdouh, 2019; Downes, 2019; Kop et al., 2011; Mackness & Bell, 2015).

What is interesting about the data in Figure 3 is that they revealed a shared pattern of emotions across all activities, although the intensity of feelings differed significantly. It can be seen that the greatest share is for negative-activating and negative-deactivating emotions, followed by positive-activating and positive-deactivating. A possible explanation for this might be that the learning process itself triggers this pattern, regardless of the activity performed.

The single most striking observation to emerge from the qualitative analysis is that in each indication of negative-activating emotion we detected, the emotion showed a positive effect on the participants' performance, particularly at first. The participants thought of alternative solutions, sought help, and employed higher-levels of thinking. This finding should not be completely surprising, however, since control-value theory suggests that emotions lying on the activating dimension will most likely induce one to act. What is remarkable about this finding is that these actions seem to be sufficient for one engaging in connectivist environments. Basically, learners in such contexts are not forced to rely solely on their own cognitive capacity (Downes, 2007; Wang et al., 2014), and thus, identifying the consumption of one's cognitive capacity as a negative consequence does not apply in this context (Pekrun & Perry, 2014). This could possibly explain why negative emotions positively predicted meta-cognition strategies (Artino, 2009; Artino & Jones, 2012), but not students' grades (Pekrun et al., 2004; Valiente et al., 2012). The destructive effect of negative-activating emotions did occur, but only when the failure was constantly happening. More often than not, the negative effect manifested itself in transforming the negative-activating to negative-deactivating emotion. So, confusion becomes boredom and anger becomes hopelessness. It can thus be suggested that undesirable effects of negative-activating emotions are mediated by negative-deactivating emotions, where the continuous failure can be thought of as a moderator.

The results of the present study are significant in at least two major respects. For researchers, the findings highlight the importance of targeting the top frequent negative and positive emotions listed in the results, especially for those who seek to identify the effect of emotions in connectivist learning environments using large samples. It makes little sense to study the effect of less frequent emotion such as sadness, although it is a primary emotion (see also the results of Pekrun et al., 2004), because this entails a decrease in its predictive power. For teachers in connectivist environments, a note of caution is due here since the level of negative emotions is certainly high. Although our results suggest the positive impacts of negative-activating emotions, this does not imply that the learning environment should be designed so as to arouse them. Rather, the role of teacher is to keep one's eyes open for frequent failure by students and to intervene before the negative-activating emotion develops to negative-deactivating emotion. Considering a possibly large number of learners in a regular connectivist learning environment (e.g., cMOOC), the teacher still has an option to inform the participants of the high level of negative emotions they may feel. Raising the participants' awareness is perhaps useful in any stage of the course and might help them to exert control over their emotions.

The findings of the current study are limited by a number of deficiencies. A small sample size is the clearest source of bias. Being qualitative in nature, this study should not, and cannot, prove or deny the generalizability of the model presented to interpret how negative-activating emotions take their effects. The literature is still in need of a large study that rolls out the effect of frequent failure, and examines the mediation role of negative-deactivating emotions between negative-activating emotions and the undesired outcomes. Another source of uncertainty is that we did not measure the level of emotional arousal. Therefore, we do not know as yet whether a high-arousal level manipulates the emotional effects as suggested by Valiente et al. (2012). Moreover, this study failed to track the distribution of emotions over time. An extended problem-solving context, like the one presented in this study, involves a continuous emotional arousal which fluctuates repeatedly over time. A study to plot the development of each emotion and the interaction among emotions over the course of the experiment would therefore be interesting. Despite these shortcomings, a combination of findings in the present study provides some support for the conceptual premise of connectivism and control-value theory in that negative-activating emotions somehow produce positive consequences, although not always.

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