HLRC | HIGHER LEARNING RESEARCH COMMUNICATIONS

Higher Learning Research Communications
2021, Volume 11, Issue 0, Pages 72–87. DOI: 10.18870/hlrc.v11i0.1203

Original Research WALDEN UNIVERSITY

Special Issue: Implications of COVID-19 on Higher Education

Quality of Online Learning Participation in a Context of Crisis

Jorge Chávez, PhD
Universidad Andrés Bello, Santiago, Chile
https://orcid.org/0000-0001-7603-4766

Rosa Montaño, PhD
Universidad de Santiago de Chile, Santiago, Chile

Rosa Barrera, MA
Universidad de Santiago de Chile, Santiago, Chile

Jaime Sánchez, PhD
Universidad de Chile, Santiago, Chile

Jaime Faure, EdD
Universidad de Barcelona, Barcelona, Spain

Contact: jorge.chavez@unab.cl

Abstract

Objectives: The COVID-19 pandemic has forced educational institutions to adopt online tools to remotely teach and efficiently use virtual learning situations during the emergency. However, although these environments may serve to improve teaching processes, several issues must be considered to ensure quality student learning. The purpose of our study was to examine types of participation in virtual learning settings by analyzing the level of information contained in message posts and the depth of contributions made by students.

Method: We analyzed data from a computer programming module taught online using a learning management system during the first year of a computer science degree program at a Chilean university. We conducted a content analysis of the messages posted in the forums, followed by a statistical analysis of the codified data. For the latter, we used quantitative methods to identify relationships between the level of information contained in student contributions (information level) and a series of covariates, such as message length, perception of achieved learning, final grade, and message depth.

Results: Results show that Number of Words (B = 0.02, SE = 0.002), Final Grade (B = 0.45, SE = 0.22), and Student Self-Perceived Learning (B = -0.82, SE = 0.40) predict higher Information Level.

Conclusions: A clearer understanding of the relationship between forms of participation in online collaborative environments and the quality of participants' contributions would support activities that are conducive to improved participant learning.

Implication for Practice: Results revealed the need for guidelines that define online classroom activities, as these have a considerable influence on the generation of dialogue that is conducive to the attainment of new knowledge.

Keywords: *participation in online environments; learning in online environments; quality of contributions in online environments; learning in crisis or emergency contexts; COVID-19 pandemic*

Date Submitted: December 15, 2020 | Date Published: January 4, 2021

Recommended Citation

Chávez, J., Montaño, R., Barrera, R., Sánchez, J., & Faure, J. (2021). Quality of online learning participation in a context of crisis. *Higher Learning Research Communications, 11*, 72–87. https://doi.org/10.5590/10.18870/hlrc.v11i0.1203

Introduction

In the context of the ongoing international COVID-19 crisis, higher education institutions have been forced to adopt online environments as key spaces for interaction between teachers and students (Hodges et al., 2020). Although these online settings may contribute considerably to preserving interaction between instructor and pupil during the pandemic, other issues must be considered to ensure effective teaching and learning processes (Sánchez & Reyes Rojas, 2020). Two of the main hindrances to learning that are observed in virtual environments are the relatively few times students participate and the poor quality of the messages they post during collaboration (Dillenbourg et al., 2009; Hrastinski, 2009; Reimers et al., 2020).

Our study was framed in the research area of computer-supported collaborative learning and sought to explore the idea that participation is one of the fundamental variables that determines learning in online environments (Sivapalan & Cregan, 2005; Kent et al., 2016). This may be because (1) greater participation means a greater probability of student interaction, (2) greater participation means more communicative exchanges, or (3) greater participation leads to a better learning experience (Isohätälä et al., 2017; Kim & Ketenci, 2019). We defined participation as the capacity for students to involve themselves in virtual settings in a variety of ways and to differing degrees. This capacity was expressed through the contributions that students make as part of a collaborative process (Chávez & Romero, 2014; Hratinski, 2008). The scientific evidence regarding collaborative learning in virtual environments is categorical: (a) levels of student participation are low or at least unequal or (b) in the majority of cases, the quality of contributions is not sufficient for participants to achieve profound learning (Dlab et al., 2020; Schellens & Valcke, 2006; Sintonen et al., 2017; Stahl, 2015).

The scientific evidence suggests that to enhance student learning in online environments, the quality of participation must be improved (Hrastinski, 2009; Kurucay & Inan, 2017; Michailidis et al., 2018). However, there is disagreement as to how this may be achieved. In general terms, participation can be defined and thus measured at two levels: the structural level and the content level. The structural level can be defined as, for example, the number of times a student accesses an online platform, the number of responses to a given contribution, and/or the time spent on a given application. At the content level, participation is generally associated with the type of contribution made by the student or the depth of these contributions. Few researchers have chosen to adopt a more complex approach or, as in our particular case, to define participation as a complex activity that may include aspects of both structure and content (Dillenbourg et al., 2009; Stahl, 2015).

In relation to structural elements, analysis tends to be based primarily on the assumption that participation is associated with the number of times that a student accesses a platform, the number of messages that they post, and the length of these messages (Fu et al., 2016). However, it is difficult to discern from these indicators the degree of depth of participants' contributions (Chen et al., 2018; Dillenbourg et al., 2009).

Aspects of content are generally associated with the depth of messages or the progression achieved by participants in terms of the meanings discussed during the collaborative activity (Ding et al., 2017). Proponents of this position suggest that participation is a process of establishing, maintaining, and growing relationships with others (Wenger, 1998). This is associated with the type or form of communication in which students engage and reflected in the quality of messages posted (Hrastinski, 2009; Michailidis et al., 2018).

Each of these structural and content-related aspects puts emphasis on different elements that are considered important to quality participation in online environments. However, there is a need to determine the role played by the different variables involved in students' participation. Research shows that forms of student participation in such contexts may have consequences in terms of the frequency and quality of participation and, in turn, of the quality of student learning (Dlab et al., 2020; Janssen et al., 2007; Phielix et al., 2010). More frequent participation may mean higher levels of interaction; however, to stimulate greater depth in terms of the ideas expressed by participants, this interaction must take a certain form.

We believe that identification and quantification of those variables that can help predict the quality of the messages posted by students as they interact in online learning contexts is vital. Progress on this issue is relevant as progress would (1) enable explanation of the learning that takes place when people collaborate in online learning contexts, (2) help guide and orient teaching practices in online environments, and (3) help with the resolution of certain problems currently faced by those teachers who find themselves required to conduct online teaching activities in the context of the COVID-19 pandemic.

Purpose of the Study, Research Questions, and Hypotheses

In view of the background presented in the previous section, the purpose of our study was to examine types of participation in virtual learning processes by analyzing the level of information contained in message posts and the depth of contributions made by students. As such, our research questions were as follows:

1. What types of messages were posted by students as they participated in collaborative activities in an online environment?
2. Was there a relationship between the type of message posted and (a) the depth of these messages, (b) the length of these messages, (c) the student's final grade, and (d) the student's perceived learning?
3. Which variables served to statistically predict the type of message posted by students when they participated in collaborative activities in an online environment?

There were three hypotheses corresponding to the research questions:

H1. There is a relationship between messages that rank higher in the hierarchy and the total number of messages posted by students during collaboration.

H2. There is a relationship between messages that rank higher in the hierarchy and a set of structural participation indicators.

H3. Certain structural participation variables are more relevant than others in the formulation of higher-ranking messages, and they may serve to predict the quality or type of message posted by students.

Method

Nature of the Study

A case study design was adopted for the present research (Spector et al., 2013; Stahl et al., 2011). In particular, the study analyzed two discussion forums on different subjects in a computer programming module offered during the first semester of a bachelor's degree program in computer science at a public university in Chile. Messages were gathered directly from the forums, which themselves were part of the virtual course environment. We conducted a content analysis of the messages posted in the forums, followed by a statistical analysis of the codified data (Johnson et al., 2007). For the latter, we used quantitative methods to identify relationships between the level of information contained in students' contributions and a series of covariates, such as message length, perception of achieved learning, final grade, and message depth. Subsequently, we fitted a theoretical ordinal logistic regression model that would make it possible to predict the types of messages that the students had posted in the module forums.

Context and Participants

The present research was conducted in the context of a computer science degree module consisting of 8 hours of online teaching via the Moodle platform. A total of 38 students took the module and participants were requested to sign an informed consent form. This included a brief explanation of the research objectives and specified that participation was voluntary and anonymous. All of them agreed to participate in the study. The objective of the module was to strengthen computational thinking for the implementation of algorithms designed to solve problems within the discipline and in everyday life. The module design included two forums. The first was intended for students to demonstrate their ability to efficiently address a computational problem. The second was for discussion of data searching and sorting methods. Each forum was open for 4 weeks and one of the most important rules of participation was that ideas must not be repeated. Another fundamental rule was that to encourage a high frequency and depth of messages, each student must comment on at least three posts made by their peers.

Instruments

To measure type of participation, several structural and content-level indicators were used. At the structural level (independent variables), a set of quantitative data was collected relating to the activity conducted via the platform. Activity was measured using the following structural indicators or independent variables: (a) the number of messages posted by the participant; (b) the number of words per message (i.e., message length); (c) the final grade awarded by the teacher; and (d) the student's self-perception of achieved learning. All these variables, except for perceived learning, were extracted from the Moodle platform. Perceived learning was measured by means of a survey that the students were required to complete at the end of the module. This covered (1) their management of the time given to complete the various tasks, (2) their management of the tasks themselves and the difficulty of the content, (3) their management of social participation or organization of the joint activity to complete the tasks, and (4)) their perception that these aspects served to help or hinder their learning over the course of the module. In terms of content or message type (dependent variable), a qualitative analysis of the contributions made was conducted. This was achieved by means of the framework presented in Appendix A, which was designed to facilitate differentiation between the different types of messages posted and the depth of each of them.

Data Gathering and Analysis Procedure

All messages posted by the students in the two forums were gathered. We then conducted two phases of analysis. The first was a content analysis to codify the messages, which were classified according to content type and depth level. Qualitative analysis of the messages was conducted by three specialists using an adapted version of the method proposed by Chávez et al. (2016) for analysis of discussion forum messages (see Appendix A). Messages were categorized according to a hierarchical structure consisting of five levels (lowest to highest): analysis of peer information (PI); idea contribution (IC); learning content processing (CP); situation of the task or problem within a broader framework of knowledge, experiences, and information (TS); and motivation to comply with and understand the task (M). The highest-ranked message type in the hierarchy was task situation (TS), as it indicates the student's capacity to take into consideration other knowledge in the resolution of a given problem. The motivation (M) type focuses on the student's attribution of meaning to the task rather than specific content creation, which was the central element of the study. Consequently, M was not included in the analysis.

The classification hierarchy was validated by experts, and all data were entered into a quantitatively codified database. Each message was classified according to its depth level using a 5-point Likert-type scale, where 1 indicates superficiality and 5 indicates profundity. Given the quantity of information obtained, we ultimately decided upon a three-level depth classification: *Low* for messages categorized as 1 or 2, *Medium* for messages categorized as 3, and *High* for messages categorized as 4 or 5. To establish perceptions of achieved learning, we applied an ad hoc self-perception survey at the end of the semester. The survey employed a 5-point Likert-type scale ranging from 1 (*very low*) to 5 (*very high*).

Once all data codifications had been validated by the experts according to the message categorization system (Appendix A), a series of quantitative analyses were conducted. In this second phase of the research, we calculated bivariate correlations and analysis of variance (ANOVA) to explore Research Questions 1 and 2. Ordinal logistic regression was used to explore Research Question 3, the purpose of which was to assess the behavior of those structural variables that best predict the depth level and quality of messages. Logistic models are suitable for situations in which there is a need to explain the probability of the occurrence of a given event by means of certain independent or explanatory variables. Given that we have information as to which structural participation variables best reflect the level of message depth, this should permit us to measure the type of message posted by participants. These models reveal the probability, according to the different independent variables, of achieving a certain level of information, or the logit of the level in relation to previous ones. We calculated five different models, whose dependent variable was message type (i.e., level of information). Number of words, final grade, and perceived achievement were then added sequentially as covariates. The process resulted in an optimal model with low standard deviation, in which the estimated parameters enabled prediction of the type of message that participants can formulate, according to the covariates.

Results

The results presented in this section are organized according to the research questions specified earlier. Initially, we describe the types of messages constructed by students when they participate in collaborative course activities. We then explore the relationships between the different variables addressed in the study. Finally, we present the linear regression results.

Question 1: What types of messages are posted by students as they participate in collaborative activities in an online environment?

Message classifications according to type and depth are presented in Table 1 and Figure 1. As shown in Table 1, half of the posted messages fall into the lowest information level category (PI = 48.2%). The following two categories contain a similar number of messages (IC = 18.1%; CP = 18.6%). These three levels indicate that the students post primarily low-ranking messages involving limited argumentation or idea development that reflect little more than response to information provided by their peers (PI).

A much smaller number of messages fell into the two highest-information-level categories. Messages situating the task or problem within a broader framework of knowledge (TS) accounted for 13.6% of all posts. Messages motivating students to comply with and understand the task (M) accounted for only 1.5% of posts. As each student was permitted to post more than one message, we decided to include the total number of participants at each level. Most students (66%) fall into the two lowest-information-level categories (PI and IC).

Table 1: *Number of Messages by Information Level*

Information Level (Lowest to Highest)	Number of Messages	%	Number of Students	%
PI (Peer Information)	96	48.2	31	81.6
IC (Idea Contribution)	36	18.1	22	57.9
CP (Content Processing)	37	18.6	24	63.2
TS (Task Situation)	27	13.6	19	50.0
M (Motivation)	3	1.5	2	5.3
Total	199	100.0		

Question 2: Is there a relationship between the type of message posted and (a) the depth of these messages, (b) the length of these messages, (c) the student's final grade, and (d) the student's perceived learning?

Figure 1 provides a graphical representation of the relationship between the different types of messages and their depth level (Chávez et al., 2016). Almost all message types can be seen to behave in a similar way, beginning with low percentages at the lowest depth level and gradually increasing to higher percentages at the highest depth level. The only exception is CP-type messages, where distribution remains the same for the first two depth levels and increases only at the high level. Based on this information, we can see that the largest number of messages posted by students fell into the highest depth-level category, regardless of message type. As such, the students made contributions that, for the most part, involve more profound ideas.

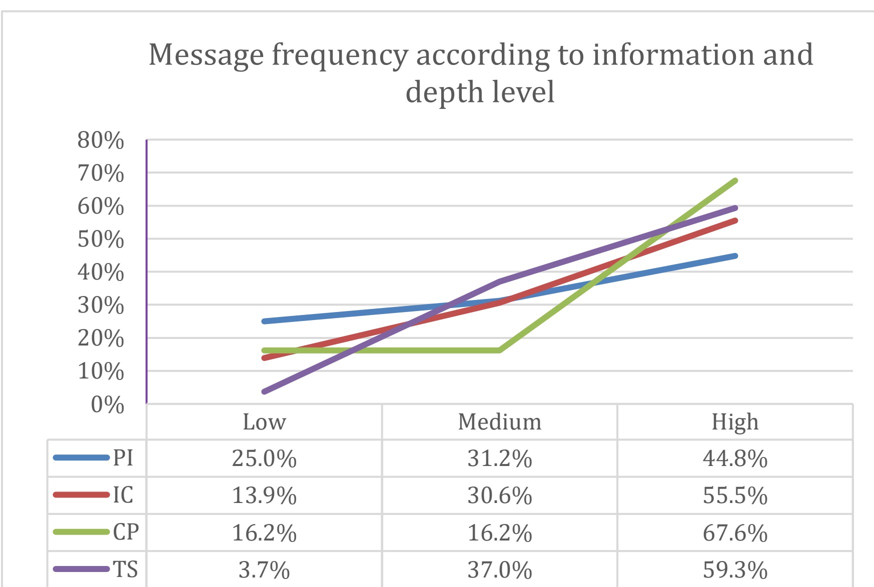


Figure 1*: Frequency of Messages According to Information and Depth Level*
Note: the colored lines represent the different types of messages posted by participants. *Low* includes messages categorized as "superficial" and "somewhat more than superficial." *Medium* includes messages

categorized as "neither superficial nor deep." *High* includes messages categorized as "somewhat deep" and "deep."

Table 2 presents the average message word count for each information level, along with their respective standard errors. The results show a gradual increase in the average number of words from the bottom to the top of the message type hierarchy. In other words, messages higher up the hierarchy require a greater number of words. As shown in Table 2, PI-type messages have the lowest average number of words ($\bar{X}$ = 69.02, *SD* = 4.2), while TS-type messages have the highest ($\bar{X}$ = 232.29, *SD* = 44.6). Closer analysis of the results reveals statistically significant differences between average number of words per message type ($F = 19.63$, $p < 0.01$). From this we can conclude that the level of information achieved in a message is directly related to the number of words used.

Table 2: *Number of Words According to Information Level*

	Number of words summary	
Information level	Mean	Standard error
PI (Peer Information)	69.02	4.2
C (Idea Contribution)	94.37	9.7
CP (Content Processing)	126	12.6
TS (Task Situation)	232.29	44.6
Total	130.42	

We then analyzed for statistically significant relationships between Message Type and the Grade achieved by students at the end of the module. The Chilean grade system ranges from 1 (lowest) to 7 (highest). Table 3 presents the average grade and standard error for each message type. The grade is awarded by the teacher at the end of the module based on the student's performance in the various tasks. The grade assigned was not related to the level. As the differences were statistically significant ($F = 3.53$, $p = 0.016$), we conducted a Duncan test to specifically identify them. The test revealed differences between PI and IC messages (which had average final grades of 4.3) and TS and CP messages (with higher average final grades of 4.6 and 4.8, respectively). We also found differences between CP messages and PI messages and between CP messages and IC messages. Despite these differences, the analysis only enables us to conclude that the students who achieved a higher final grade also posted messages that were categorized toward the top of the proposed hierarchy.

Table 3: *Average Final Grades According to Information Level*

Information level	Average final grade	Standard error
PI (Peer Information)	4.3	0.09
IC (Idea Contribution)	4.3	0.13
CP (Content Processing)	4.8	0.16
TS (Task Situation)	4.6	0.18

Finally, Table 4 presents self-perception of achieved learning for each information level. The results show no significant association ($\chi^2_{gl=6} = 8.06$; $p > 0.203$) between self-perceived learning and the level of information contained in messages.

Table 4: *Self-Perception of Achieved Learning According to Information Level*

Information Level	Self-perception scale		
	Low (%)	Medium (%)	High (%)
PI (Peer Information)	35.4	34.4	30.2
IC (Idea Contribution)	40.0	25.7	34.3
CP (Content Processing)	46.0	43.2	10.8
TS (Task Situation)	48.2	29.6	22.2

Question 3: Which variables serve to statistically predict the type of message posted by students when they participate in collaborative activities in an online environment?

Five logistic regression models were tested. Ordered logit models are used to estimate relationships between an ordinal dependent variable and a set of independent variables. The dependent variable is Information Level. The first contained no covariates; then, each of the remaining four models added one covariate sequentially (Message Depth Level; Number of Words; Final Grade; and Student Self-Perceived Learning.) Table 5 shows the significant coefficients in bold. In Model 5, the results show that Number of Words (B = 0.02, SE = 0.002), Final Grade (B = 0.45, SE = 0.22), and Student Self-Perceived Learning (B = -0.82, SE = 0.40) predict higher Information Level.

Table 5: *Results of Tests of Ordinal Logistic Regression Models*

	Model 1	Model 2	Model 3	Model 4	Model 5
	*B (SE)	B (SE)	B (SE)	B (SE)	B (SE)
Cut-off points					
Const1	-0.04 (0.14)	0.71 (0.34)	1.52 (0.38)	3.89 (1.00)	3.23 (1.05)
Const2	0.72 (0.15)	1.50 (0.35)	2.45 (0.40)	4.86 (1.02)	4.19 (1.07)
Const3	1.83 (0.21)	2.63 (0.39)	3.90 (0.47)	6.36 (1.07)	5.75 (1.12)
Independent variables					
Depth level					
Low (reference)					
Medium		0.66 (0.43)	0.32 (0.44)	0.36 (0.44)	0.53 (0.46)
High		1.06 (0.39)	0.22 (0.41)	0.12 (0.42)	0.25 (0.43)
Number of Words			0.02 (0.002)	0.02 (0.002)	0.02 (0.002)
Final Grade				0.55 (0.21)	0.45 (0.22)
Student Self-Perceived Learning					

Low (reference)					
Medium					-0.65 (0.35)
High					-0.82 (0.40)
Goodness of fit measurement					
AIC	495.5	491.1	438.6	433.7	428.7
Deviance		481.1	426.6	419.7	410.7

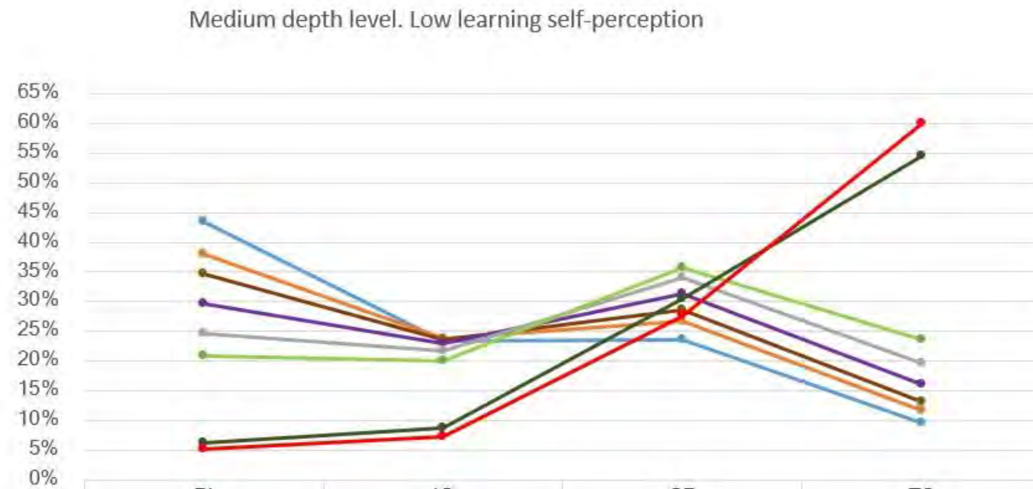
*Note: Beta (regression) coefficients are not standardized to preserve the nature of the measured characteristic.

An example to explain Table 5 is presented in Figure 2, which shows the probabilities of obtaining different information levels according to variations in message word count, that is, message length (Wn) and average final grade[1] (Fg) at a constant medium depth level and low self-perception of achieved learning. The probability of obtaining a TS-type message (the highest information level in the hierarchy) rises with the number of words and the average final grade. As such, when messages have 69 words and an average final grade of 4.3, the probability of obtaining TS-type messages is 9.4%, increasing to 11.5% when the average final grade is 4.8. When messages have 232 words (higher than the total mean) and an average final grade of 4.3, the probability of obtaining TS-type messages is 54.5%, increasing to 60% when the average final grade is 4.8.

By contrast, the probability of obtaining a PI-type message (the lowest information level in the hierarchy) falls as the number of words and the average final grade increase. As such, when messages have 69 words and an average final grade of 4.3, the probability of obtaining PI-type messages is 43.5%. When messages have 232 words and an average final grade of 4.8, the probability of obtaining PI-type messages decreases to 5.1%.

This shows that, at a medium depth level and a low self-perception of achieved learning, the effect of message word count on the probability of obtaining TS-type messages is significant. Average final grade also has an effect, but this is considerably smaller.

[1] It should be noted that the values chosen for the number of words and for the average final grade were based on the cut-off points in Tables 2 and 3, respectively.



	PI	IC	CP	TS
Wn=69 y Fg=4.3	43,5%	23,5%	23,6%	9,4%
Wn=69 y Fg=4.8	38,1%	23,7%	26,6%	11,5%
Wn=94 y Fg=4.3	34,6%	23,6%	28,6%	13,2%
Wn=94 y Fg=4.8	29,7%	23,0%	31,4%	16,0%
Wn=126 y Fg=4.3	24,7%	21,6%	34,0%	19,7%
Wn=126 y Fg=4.8	20,7%	20,0%	35,7%	23,5%
Wn=232 y Fg=4.3	6,3%	8,7%	30,5%	54,5%
Wn=232 y Fg=4.8	5,1%	7,3%	27,6%	60,0%

Figure 2: *Probabilities of Obtaining Messages With Different Information Levels*

Discussion

Our aim was to analyze participation and learning in a group of students as they engaged in a virtual environment. Specifically, we analyzed how collaborative participation related to depth of the messages that they exchanged and to other variables associated with a variety of structural aspects: message length, final grade awarded, and self-perception of achieved learning. The scientific evidence published to date indicates that students' participation in collaborative activities designed by the teacher does not guarantee learning (Isohätälä et al., 2017). In accordance with our work, Hrastinski (2008; 2009) highlighted the need to consider participation not only as synonymous with speaking or writing, but as a complex process of participation and relationships with others, together with the support of attractive activities. This points to a need to identify the principal aspects that must be developed as part of an online teaching process. In this same line, we assert that further research is needed into the specific characteristics of a form of participation that would yield improved depth of students' contributions and, in turn, a better quality of learning (Hrastinski, 2009; Järvelä et al., 2016).

Our main finding is that it is possible to predict the type of participation or depth level of messages in a virtual environment using a generalized linear model. By means of this model, we sought to identify a group of variables that increase or decrease the likelihood of obtaining a higher-ranking message type. Our model took into consideration several variables, which we have termed structural participation variables. This enabled us to identify key variables, such as message length, students' final grades, and self-perception of achieved learning. The modeling results show, for example, that the contribution of message length is significant. In other words, students who write longer messages also produce messages of a higher level in terms of information and depth, while shorter messages are less likely to demonstrate a high degree of complexity. However, it is important to note that these messages must demonstrate certain other characteristics, such as simplicity and precision of the ideas expressed. This implies the need for students not only to develop ideas as they collaborate, but also for these ideas to be articulated as clearly as possible for them to be of use to their peers. As such, it would be interesting for future works to explore the usefulness to peers of messages posted in a given forum (e.g., Järvelä et al., 2016).

Analysis of other variables that could help to predict messages that rank more highly within the proposed hierarchy revealed an association among students' grades, message types, and message quality. We were able to identify significant differences between the levels of information contained in messages in relation to the average final grades achieved. Students who participate more actively with longer messages also obtain higher grades at the end of the module. In other words, students whose grades are below the total average post messages that rank lower in the hierarchy (PI and IC), while those whose grades are above the total average post higher-level messages (TS and CP). As such, there is a positive relationship between the teacher's evaluation of student learning and the level of information contained in messages posted by the students.

Another prominent covariate identified by the study is self-perception of achieved learning, which refers to the students' own evaluation of their knowledge achievement during the module. The results show that students with a strong perception of their own learning are not necessarily those who make the highest-level contributions or acquire the most complex knowledge. A possible explanation for this is that these students may be highly demanding of themselves when it comes to tackling a task and, as such, are more critical in their self-evaluation. This demonstrates the need for teachers to provide motivation and acknowledge the value of messages posted by students during collaboration in an online environment. Teacher presence is relevant, as it contributes to students' sense of self-worth.

Limitations of the Study

The study has several limitations. First, given the small sample size, the results need to be replicated in larger populations. Second, additional covariates or structural activity indicators must be considered to explore in greater depth the relationship between these and the quality of contributions. Third, the presence of the teacher in these types of activities and the mediating role of the teacher and fellow students over the course of the task are also important factors that we were unable to explore in the present study.

Implications for Theory and Practice

The present study contributes by considering some of the key elements that should be considered when designing a training process for use in an online environment. These include task elements such as the guidelines that steer dialogue within the activity, as this must be conducive to the achievement of new, high-quality knowledge. There are also several criteria that serve to increase levels of participation and the quality of contributions. These include guidelines that provide students with a clear idea of concepts, deadlines for participation, and the link between contributions and a satisfactory grade, all of which are key factors in the achievement of complex knowledge (Ludvigsen et al., 2016). As a final point, we believe that the organization of the activity, the rules of participation, and acknowledgment by the teacher of that participation are key aspects in the planning of an online learning process.

Conclusion

The present study suggests that online environments are becoming increasingly demanding. This is particularly noticeable in relation to the level of information and quality of contributions required of participants (Chávez, 2020). Greater clarity as to the relationship that exists between forms of participation in online collaborative environments and the quality of participants' contributions would support the generation of activity models that are conducive to improved quality of participant learning.

One of the main challenges posed by the COVID-19 pandemic is for students to engage in online learning environments. Our results suggest that technology is a particularly important resource in the current situation in that it enables people to continue their educational activities with as little disruption as possible. Furthermore, our study points to the existence of certain elements that contribute to improving the quality of participation in online environments and, as such, to more productive learning processes (Dlab et al., 2020; Schellens & Valcke, 2006; Kentz et al., 2017; Stahl, 2015).

Acknowledgments

This research was supported by DICYT project number 041733BC from the Vice-Rectory for Research, Development and Innovation, Universidad de Santiago, Chile; by PIED (Educational research projects) from the Pro-Vice-Chancellor's Office (Research), Faculty of Education, Universidad Andres Bello, Chile; and by the Chilean National Research and Development Agency's (ANID) Basal Funding for Scientific and Technology Centers of Excellence, project number FB0003.

References

Chávez, J. (2020). Space-time in the study of learning trajectories. *Learning: Research and Practice*. https://doi.org/10.1080/23735082.2020.1811884

Chávez, J., Montaño, R., & Barrera, R. (2016). Structure and content of messages in an online environment: An approach from participation. *Computers in Human Behavior*, *54*, 560–568. https://doi.org/10.1016/j.chb.2015.08.046

Chávez J., Romero M. (2014, September 2–5) The relationship between group awareness and participation in a computer-supported collaborative environment. In: L. Uden, J. Sinclair, Y. H. Tao, & D. Liberona (Eds.) *Learning Technology for Education in Cloud. MOOC and Big Data* (Conference Proceedings). LTEC 2014. Communications in Computer and Information Science, Vol. 446. Springer, Cham. https://doi.org/10.1007/978-3-319-10671-7_8

Cheung, W. S., Hew, K. F., & Ling Ng, C. S. (2008). Toward an understanding of why students contribute in asynchronous online discussions. *Journal of Educational Computing Research*, *38(*1), 29–50. https://doi.org/10.2190/EC.38.1.b

Dillenbourg, P. (2013). Design for classroom orchestration. *Computer Education, 69*, 485–492. http://dx.doi.org/10.1016/j.compedu.2013.04.013

Dillenbourg, P., Järvelä, S., & Fischer, F. (2009). The evolution of research on computer-supported collaborative learning. From design to orchestration. In N. Balacheff, S. Ludvigsen, T. Jong, A. Lazonder, & S. Barnes (Eds.), *Technology-enhanced learning* (pp. 3–19). Springer. https://doi.org/10.1007/978-1-4020-9827-7_1

Ding, L., Kim, C., & Orey, M. (2017). Studies of student engagement in gamified online discussions. *Computers & Education*, *115*, 126–142. https://doi.org/10.1016/j.compedu.2017.06.016

Dlab, M. H., Boticki, I., Hoic-Bozic, N., & Looi, C. K. (2020). Exploring group interactions in synchronous mobile computer-supported learning activities. *Computers & Education*, *146*, 103735. https://doi.org/10.1016/j.compedu.2019.103735

Fu, E. L. F., van Aalst, J., & Chan, C. K. K. (2016). Toward a classification of discourse patterns in asynchronous online discussions. *International Journal of Computer-Supported Collaborative Learning*, *11*(4), 441–478. https://doi.org/10.1007/s11412-016-9245-3

Hodges, C., Moore, S., Lockee, B., Trust, T., & Bond, A. (2020). The difference between emergency remote teaching and online learning. In: *Educase Review.* https://er.educause.edu/articles/2020/3/the-difference-between-emergency-remote-teaching-and-online-learning.

Hrastinski, S. (2009). A theory of online learning as online participation. *Computers & Education*, *52*(1), 78–82. https://doi.org/10.1016/j.compedu.2008.06.009

Hrastinski, S. (2008). What is online learner participation? A literature review. *Computers & Education*, *51*(4), 1755–1765. https://doi.org/10.1016/j.compedu.2008.05.005

Isohätälä, J., Järvenoja, H., & Järvelä, S. (2017). Socially shared regulation of learning and participation in social interaction in collaborative learning. *International Journal of Educational Research*, *81*, 11–24. https://doi.org/10.1016/j.ijer.2016.10.006

Janssen, J., Erkens, G., Kanselaar, G., & Jaspers, J. (2007). Visualization of participation: Does it contribute to successful computer-supported collaborative learning? *Computers & Education*, *49*(4), 1037–1065. https://doi.org/10.1016/j.compedu.2006.01.004

Järvelä, S., Kirschner, P. A., Hadwin, A., Järvenoja, H., Malmberg, J., Miller, M., & Laru, J. (2016). Socially shared regulation of learning in CSCL: Understanding and prompting individual- and group-level shared regulatory activities. *International Journal of Computer-Supported Collaborative Learning*, *11*, 263–280. https://doi.org/10.1007/s11412-016-9238-2

Johnson, R. B., Onwuegbuzie, A. J., & Turner, L. A. (2007). Toward a definition of mixed methods research. *Journal of Mixed Methods Research*, *1*(2), 112–133. https://doi.org/10.1177/1558689806298224

Kent, C., Laslo, E., & Rafaeli, S. (2016). Interactivity in online discussions and learning outcomes. *Computers & Education*, *97*, 116–128. https://doi.org/10.1016/j.compedu.2016.03.002

Kentz, M. B., Sintonen, S., & Lipponen, L. (2017). Vertaisoppiminen digitaalisessa toimintaympäristössä. Tapaustutkimus kahden viisivuotiaan Minecraft-luomisesta. *Kasvatus & Aika*, *11*(1). https://journal.fi/kasvatusjaaika/article/view/68705

Kim, M. K., & Ketenci, T. (2019). Learner participation profiles in an asynchronous online collaboration context. *The Internet and Higher Education*, *41*, 62–76. https://doi.org/10.1016/j.iheduc.2019.02.002

Kurucay, M., & Inan, F. A. (2017). Examining the effects of learner–learner interactions on satisfaction and learning in an online undergraduate course. *Computers & Education*, *115*, 20–37. https://doi.org/10.1016/j.compedu.2017.06.010

Ludvigsen, S., Cress, U., Law, N., Rosé, C. P., & Stahl, G. (2016). Collaboration scripts and scaffolding. *International Journal of Computer-Supported Collaborative Learning*, *11*(4), 381–385. https://doi.org/10.1007/s11412-016-9247-1

Michailidis, N., Kapravelos, E., & Tsiatsos, T. (2018). Interaction analysis for supporting students' self-regulation during blog-based CSCL activities. *Journal of Educational Technology & Society*, *21*(1), 37–47. https://www.jstor.org/stable/26273866

Phielix, C., Prins, F. J., & Kirschner, P. A. (2010). Awareness of group performance in a CSCL-environment: Effects of peer feedback and reflection. *Computers in Human Behavior*, *26*(2), 151–161. https://doi.org/10.1016/j.chb.2009.10.011

Reimers, F., Schleicher, A., Saavedra, J., & Tuominen, S. (2020). Supporting the continuation of teaching and learning during the COVID-19 pandemic. Annotated resources for online learning. *OECD*, *1*(1), 1–38. https://www.oecd.org/education/upporting-the-continuation-of-teaching-and-learning-during-the-COVID-19-pandemic.pdf

Sánchez, J., & Reyes Rojas, J. (2020). MOOCs in Latin America: Trends and issues (2019). In K. Zhang, C. Bonk, T. Reeves, & T. Reynolds (Eds.), *MOOCs and open education around the world in emerging economies: challenges, successes, opportunities* (pp. 98–112). Routledge/Taylor & Francis.

Schellens, T., & Valcke, M. (2006). Fostering knowledge construction in university students through asynchronous discussion groups. *Computers & Education*, *46*(4), 349–370. https://doi.org/10.1016/j.compedu.2004.07.010

Sivapalan, S., & Cregan, P. (2005). Value of online resources for learning by distance education. *CAL-laborate. International Journal of Innovation in Science and Mathematics Education, 14*(1), 23–27. https://openjournals.library.sydney.edu.au/index.php/CAL/article/view/6037/6688

Spector, J. M., Merrill, M. D., Elen, J., & Bishop, M. J. (Eds.). (2013). *Handbook of research on educational communications and technology* (4th ed.). Springer.

Stahl, G. (2015). A decade of CSCL. *International Journal of Computer-Supported Collaborative Learning*, *10*(4), 337–344. https://doi.org/10.1007/s11412-015-9222-2

Stahl, G., Spada, H., Miyake, N., & Law, N. (2011). Introduction to the Proceedings of CSCL 2011. In *Connecting Computer-Supported Collaborative Learning to Policy and Practice: CSCL2011 Conference Proceedings (vol. 1)*. Springer.

Wenger, E. (1998). *Communities of practice: Learning, meaning, and identity*. Cambridge University Press. https://doi.org/10.1017/CBO9780511803932

Appendix A

Information levels and depth of messages

Indicator	Superficial	Somewhat more than superficial	Neither superficial nor deep	Somewhat deep	Deep
	1	2	3	4	5
PI Peer Information	The participant accepts the ideas or statements passively	The participant mentions fragments of the idea without coherence	The participant repeats the same idea using different words	The participant contrasts the ideas using their perception, but without justification	The participant critically analyses others' ideas and statements, using justification, judgment, interpretation, and inference
IC Idea Contribution	The participant expresses an idea without any justification	The participant describes an idea derived from the support material	The participant states an idea	The participant supports their own idea without connecting it to information from others	The participant uses arguments and their own ideas, relating their solutions to information from others
CP Content Processing	The participant focuses on memorizing facts	The participant identifies the facts relevant to the algorithm	The participant outlines facts relevant to solution of the algorithm	The participant analyses the facts relevant to solution of the algorithm	The participant works toward conclusions and hypotheses
TS Task situation (situation of the algorithm within a broader framework of knowledge, experiences, and information)	The participant is unable to view the algorithm within this broader framework and does not refer to information beyond the algorithm	The participant views the algorithm within a broader framework without adding further information	The participant identifies the algorithm within a broader framework	The participant relates the algorithm with a broader perspective but is unable to relate it to information beyond the group discussion	The participant relates the algorithm with a broader perspective, the search for connections between different parts of the task, or the search for information beyond the group discussion

Indicator	Superficial	Somewhat more than superficial	Neither superficial nor deep	Somewhat deep	Deep
M Motivation (motivation to comply with and understand the task)	The participant focuses on the minimum assessment requirements	The participant memorizes the requirements to comply with the assessment	The participant carries out the task according to self-imposed goals	The participant explains and clarifies the solution presented to their peers	The participant understands the task on their own, demonstrating inherent motivation

The *Higher Learning Research Communications* (*HLRC*), is a peer-reviewed, online, interdisciplinary journal indexed in Scopus, ERIC, JGATE and Directory of Open Access Journals (DOAJ). It is an open access journal with an international focus published by Walden University, USA. Its aim is to disseminate both high quality research and teaching best practices in tertiary education across cultures and disciplines. *HLRC* connects the ways research and best practice contribute to the public good and impact the communities that educators serve. *HLRC* articles include peer-reviewed research reports, research briefs, comprehensive literature reviews, and books reviews.