Online Learning Communities Amid the COVID-19 Pandemic: An Agent-Based Model

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Abstract: This study has adopted an agent-based model to examine the factors that influenced the learning experiences in online learning communities. A community of inquiry (CoI) is an online learning framework which posits that positive learning experiences are created through cognitive, social, and teaching dimensions. It is based on the distance learning system during the COVID-19 pandemic. During this challenging time, schools worldwide have shifted to the distance learning system. The factors of this model are carefully translated to correspond with the parameters from Netlogo's HIV model through a coherent approach. These are the number of contacts, the length of time for online unreadiness, and the absence of learner control measures. This paper used a three-factorial research design where a series of simulations are carried out in the Netlogo software. The generated data reveal how these factors significantly contribute to the students' meaningful learning experiences. It has shown that CoI supports deep learning and how it provides meaningful learning experiences. Hence, this paper calls for further research in online learning to sustain a quality online learning environment based on the CoI framework, equipping tutors to varying teaching methods in online learning and contextualizing CoI from perspectives across disciplines.

Keywords: Agent-based modeling, Netlogo HIV model, Community of Inquiry, Distance Learning

1. Introduction

When the COVID-19 pandemic has exploded in late 2019, the World Health Organization has declared its public health of international concern (WHO, 2020). Governments worldwide have developed drastic preventive measures to control and reduce its transmission. These include the mandatory use of personal protective measures such as wearing of face masks and shields, the practice of social distancing, travel restrictions, closure of workplaces and schools, and several others depending on the response intervention plan a given country has implemented (Guner et al., 2020; Rutayisire et al. 2020; Bellato et al. 2020). According to UNESCO (2020), close to 1.4 billion students were affected worldwide on school closure (i.e., closure rate at 64.43%) sometime in March 2020. Indeed, this pandemic has overwhelmingly affected all education systems at that time. As a response, distance learning solutions were immediately carried out.

Distance learning is an education system that involves the physical separation of teachers and students during teaching-learning activities and various teaching technologies in the learning process. Its essential characteristics include (1) it is school-driven, (2) physical and time separation, (3) interactive telecommunication, and (4) forms a learning group (Berg & Simonson, 2016). Various online learning platforms were used in the pandemic, such as digital learning management systems, self-directed learning, and flexible learning modality. Hence, distance learning has become an urgent necessity and a new learning modality (Dhawan, 2020; Dubey & Pandey, 2020; Nadeak, 2020). An important question then is, does this new learning modality ensure optimal learning outcomes for the learners?

The most recent studies have immediate issues and concerns in distance learning. Lassoued, Alhendawi & Bashitialshaaer (2020) have shown a need to upgrade e-learning applications and capacitate teachers through training to enhance student motivation for self-learning. The study of Dubey & Pandey (2020) has found problems on internet and technology accessibility, unprepared students on the shift to online learning, and teachers' instruction delivery. Almuraqab (2020) has strongly suggested a blended learning system. In fact, in the Philippine higher education system, the government has issued a memorandum to implement the flexible learning system (CHED, 2020). However, the issues and concerns that have not been addressed are the dynamics of learning groups in distance learning. In particular, there is less study on how the behavior of individuals interacts within the system. For instance, do individual learners interact in the same way during online and face-to-face classes? To understand the parameters involved in such interactions and how interdependent factors affect each other.

In the time of the COVID-19 pandemic, online learning has become the primary learning model. The most prominent and adapted model in the literature is the community of inquiry framework, known as *CoI* (Garrison, 2011). The study of Fiock (2020) uses the *CoI* framework to guide online instructional designers to foster learning objectives. Based on the framework of Dewey (1933), it represents an online learning environment that generates knowledge and learning experiences through the active presence of cognitive dimension (that is, to construct meaning), social dimension (that is, each one will share his/her expressions and values), and the teaching dimension (that is, teacher supports students' self-directed learning, acknowledge individual differences, and socio-environmental learning (Rubio and Tulang, 2016). Indeed, this is a massive challenge for teachers amidst

the COVID-19 pandemic. The teacher creates an online learning environment that "fills in" the missing links that students experience in a face-to-face learning modality.

This paper used the *CoI* framework of Peacock & Cowan (2016) and adopted an agent-based model to mimic the participants' complex behavior in the *CoI* and the social dynamics of online learning. It uses a coherent approach in translating the community's complex social characteristics for HIV transmission to the constructed model. It is in faithful adherence to the underlying assumptions and the interaction of the parameters of the original Netlogo HIV model. The anchorage of this translation is based on *the CoI* framework of Peacock & Cowan (2016). A set of simulations is carried out from the Netlogo software, delving into the emergent phenomenon without necessarily obtaining actual raw data. The software (its interface is shown in figure 1) can construct a model based on a dynamic virus propagation. Hence, the purpose of this study is to create a theoretical model based on agents and examine how the factors influence the rate of students' learning experiences online.
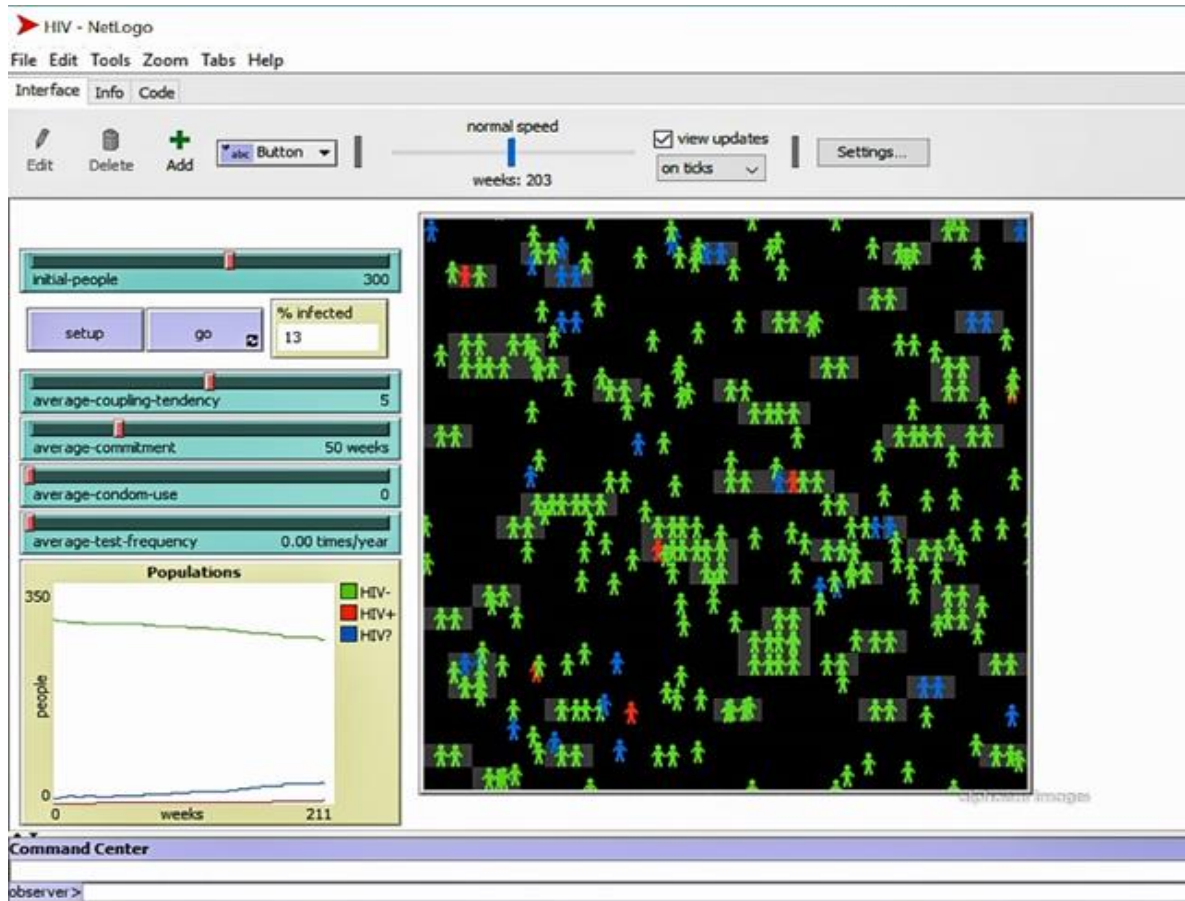
2. The Model

In this research, the generated model is based on the parameters of the Netlogo (version 6.1.1), a multi-agent ready-made program for various fields of modeling environments (Wilensky, 1999). One of its dynamic social behavior models is the human immunodeficiency virus (HIV). Simulations through the software mimic the spread of HIV via sexual contacts across individuals in a given population. This model explains how sexual behavior changes over specific parameters. However, it does not consider the biological and physiological characteristics of the individuals. It assumes that HIV spreads according to the lifestyle of individuals. For instance, if the couple is faithful to each other, they are less likely to get infected, and that the spread of HIV becomes minimal. Also, the more preventive measures are being practiced by the couple, such as sexual abstinence or use of condoms, or avoid using drugs; the spread is likely to reduce. This behavior is identical to the *CoI* framework in certain ways. Peacock & Cowan (2016) suggests that the participants of the *CoI* encourage the group and individuals to engage in self-regulation, metacognition, and management of emotional response to collaborative online learning. Hence, the HIV model is adapted and is translated as specified in table 1:

Table 1: Translation of Netlogo Parameters

HIV Model	Learning Communities Model

- *The number of people*. In the Netlogo, the *couples* represent two people engaged in a sexual relationship. With this behavior, it is possible to transmit the deadly HIV; a color represents its presence: *green* (the healthy ones), blue (the infected ones); however, their infection is not known, and *red* (the infected ones where their infection is known). That is,

HIV (+) infected
HIV (–) uninfected
HIV (?) not known

The number of individuals is set at 500.

- *Average coupling Tendency*. The tendency for individuals to be involved in sexual couples. It is the same as the average number of sexual partners. In this parameter, it is set into a maximum of 10 sexual partners.

- *Average commitment*. The length of time (in weeks) the individuals stay as a couple. The longer they stay as a couple (e.g., exclusivity), the less likely they will be infected by HIV.

- *Average condom use*. The tendency of the individual to practice safe sex. The use of condoms assumes 100% protection from HIV. A value of 0 indicates no condom used during sexual contact.

- *The number of participants*. Garrison (2011) describes a community of inquiry (*CoI*) as socially worthwhile and personally meaningful. The participants of the *CoI* comprise the population such as learning designers and the online learners. They are "engaged" as a pair (i.e., couples) in terms of *tutor-learner* and the pair *student-student*. It is then assumed that positive and meaningful learning experiences are possible when the three dimensions (cognitive, social, and teaching) are present. Hence, the translation

(+) meaningful learning experiences
(–) low meaningful learning experiences
(?) learning experiences not known

- *The number of contacts*. Fiock (2020) stresses that one of the best practices in an online learning environment is the effective *tutor-learner* (including *learner-learner*) contacts which focus on the interaction between these "couple." It is assumed that "the higher the number of contacts, the greater the social presence (i.e., strong relationships spur social interaction), which encourages motivation to learn, mentoring, feedback, and emotional support." Further, there is a more significant cognitive presence (that is, it sustains a reflective learner, individual differences are being addressed (through scaffolding methods) since students interact most diversely. Similarly, if there is more teacher presence in the learning group (that is, the teacher designs and then redesigns the learning structure based on the learners' outputs), positive learning outcomes are produced.

- *Length of Time for Online Unreadiness*. Firat & Bozkurt (2020) used the term *e-readiness* to mean the degree to which learning groups (i.e., *CoI*) are readily prepared to participate in online learning. In this paper, online readiness would denote the degree of preparedness in terms of policies and standards (i.e., flexible learning modality), online resources (i.e., technology, connectivity, communication, etc.), and human resources (that is, *learner-learner* readiness). However, in adherence to the description of Netlogo, this parameter is reversed to *unreadiness* (that is, as the degree of online unreadiness increases, the rate of learning experiences declines).

- *Absence of Learner Control Measures*. A student-controlled instruction is an online learning strategy through which the learners exercise certain levels of control in online learning (Hannafin, 1984; Simsek, 1993). Several studies have found significant enhancement of online learning experiences via learner control (Ka Yuk Chan et al., 2012). Its presence plays an essential role in *CoI* shaping learners' meaningful learning experiences. However, this paper uses the term "absence" is placed for the word "presence." This reversal is necessary for adherence to the description of

Netlogo's parameter. In this model, it is assumed that the absence of learner control via *CoI* there is less likely a student receives a positive learning experience. So, in this case, when the level is 0, then it indicates that learner control is present.

- Frequency of Testing (per year). The average frequency an individual will check their HIV status in a year.

- *Learning Success Indicator.* The number of times a learner is tested with successful learning results (that is, meaningful learning experiences are drawn via *CoI* framework) has become successful in propagating knowledge during the pandemic. In this model, the value is set to 1.00 time per year (i.e., once a year only).

3. Methodology

This paper used a three-factorial research design to determine the effects of the generated model's factors on the response variable. In Netlogo's HIV model, the rate of infection (i.e., in percentage) resulting from the agents' interaction was translated as the rate of learning experiences. A set of simulations is carried out by adjusting the levels of each of the Netlogo parameters.

The initial number of people in the population is set at the maximum level of 500. The first parameter is the *average coupling tendency* which is set from 1 to a maximum of 5. That is, low values are at 1–5, and high values at 6–10. The second parameter is the *average commitment* with values from 1 up to 200 weeks. Low values are at 1–99, and high values at 100–200. The third parameter is *average condom use* with low values set at 1–5 and high values at 6–10. The descriptions of these parameters are found at the information window of the Netlogo model. Then a series of ten simulations of each of the different combinations across the parameters is performed. The rate of learning experiences is presented in Table 2 and the graph in figure 1.

4. Results and Discussion

Table 2. Rate of Learning Experiences (%)

		Factor 1							
		Low				High			
	Factor 2	Low		High		Low		High	
Factor 3	Low	2.80	3.00	3.80	3.80	22.20	14.60	5.00	4.20
		2.60	3.40	3.80	3.60	19.20	19.60	4.40	4.40
		2.80	3.20	3.80	3.60	17.20	16.80	4.40	4.40
		3.00	2.60	3.80	4.20	17.20	20.20	5.00	4.80
		3.80	2.80	3.60	4.40	12.00	16.40	4.40	4.60
	High	3.60	2.60	4.00	4.60	8.40	6.40	4.80	4.20
		3.80	3.40	3.80	4.40	5.40	7.00	4.40	4.40
		3.20	4.60	3.40	4.00	6.60	5.40	4.20	4.60
		3.20	3.00	4.80	4.80	6.20	5.00	4.80	4.60
		3.60	2.80	4.20	4.00	6.00	7.00	4.40	4.20

Figure 1. Histogram of the Data
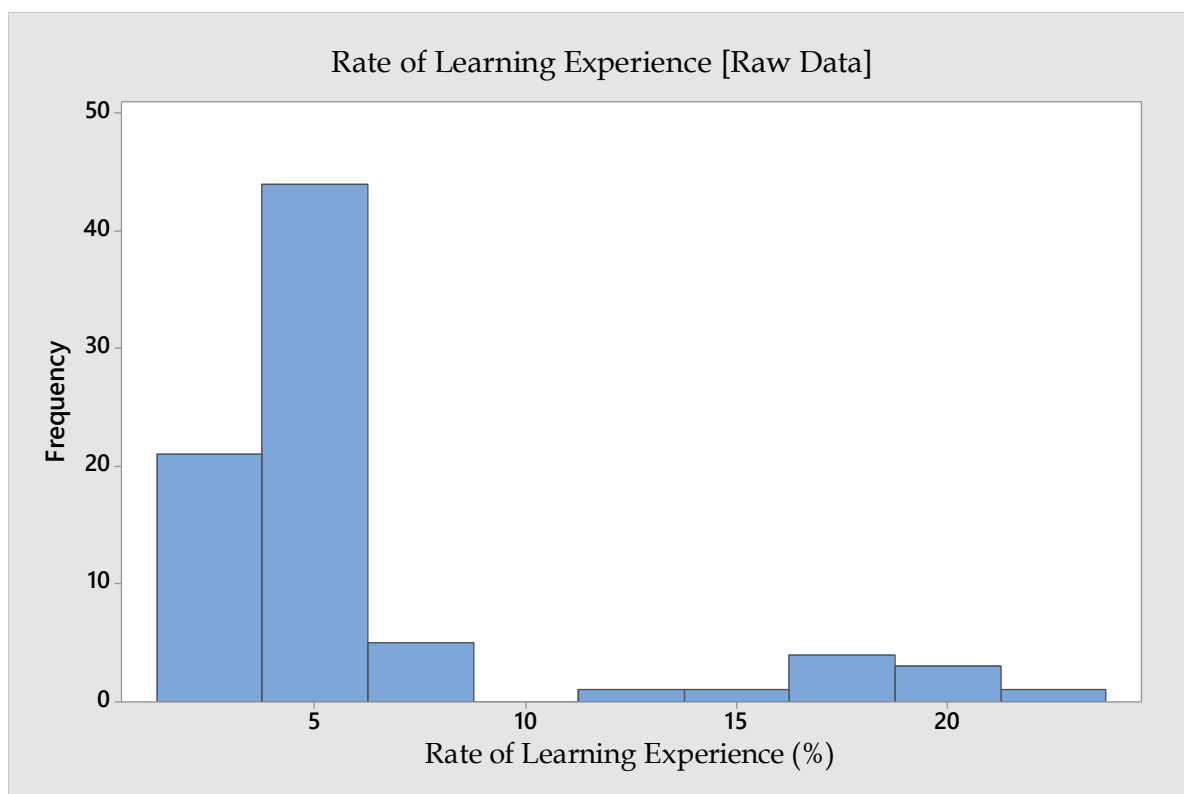
In table 2, the simulated data reveal that the rate of the learning experience tends to increase ($M = 17.60$, $SD = 2.972$) when there is a large number of contact times (factor 1) of the participants of the *CoI*, despite a low absence of learner control measures, and have lesser time for the learner to be online unready. In other words, when *CoI* participants meet "frequently" online and that the learners are online ready (i.e., *e-ready*) where the online learning platform has learner control, then the rate of the learning experience is likely to increase. According to Fiock (2020), *tutor-learner* and *learner-learner* contacts provide social presence through an instructional strategy primarily by online interaction activities (i.e., coupling tendency) and reduces learner isolation. Peacock & Cowan (2016) stresses that tutors initiate collaborative discourse and task-based online activities. Tutors should design their learning environments such that effective interaction across participants is evident, including the pedagogical stimulus in critical thinking, inquiry, and reflective thinking. The presence of types of interaction such as *learner-content* or *learner-learner*, when integrated into online learning, increases learning outcomes (Redmond, 2014; Hodges et al.,2020). Indeed, the interaction within *CoI* supports active learning through feedback and other reflective activities, mentoring, and microlearning groups. The interaction across learners could provide collaboration and informal social interaction, increasing a positive learning climate in an online environment.

Furthermore, the use of technology also increases interaction and motivation (Seckman, 2018). Skills in the utilization of technology such as simulation activities through software are enhanced. When interaction is carried out effectively in online learning, it stimulates cognitive presence (Redmond, 2014). Similarly, since learner control is present in learning groups, the tutor's presence also shapes this control (i.e., effective designs of online learning environments).

Figure 1 depicts the graph of the data from the set of simulations. The data are framed in terms of the relationship between the predictors (i.e., the defined factors) and the dependent variable (i.e., rate of learning experiences) in a linear model. Its purpose is to examine how the factors affect the response variable. Also, the assumptions of the model need to be satisfied. Hence, data transformation is required to construct the final model (Bolker et al.,2008). Using a Box-Cox transformation with estimated rate parameter $\lambda = -1.58$, the results are shown in Table 3.

Table 3. Results of Stepwise Multiple Regression of the Model

Predictors	Unstandardized Coefficients		T	p-value
	B	Std. Error		
Constant	0.1018	0.002	44.80	0.000
F1: Number of Contacts	0.0382	0.002	16.85	0.000
F2: Length of Time for Online Unreadiness	−0.0013	0.002	−0.57	0.567
F3: Absence of Learner Control Measures	−0.0007	0.002	−0.33	0.745
F1 x *F2*	0.0283	0.002	12.45	0.000
F1 x *F3*	0.0112	0.002	4.96	0.000
F2 x *F3*	−0.0035	0.002	−1.57	0.121
F1 x *F2* x *F3*	0.0069	0.002	3.04	0.003

Stepwise multiple regression was used to test if the defined factors in this study could significantly predict the rate of learning experiences. The transformed response variable is now expressed as (Rate of Learning Experiences)$^{-1.58}$. The general linear model has explained 86.85% of the variance, and it was a significant predictor of the rate of the learning experience with $F(6, 73) = 79.02$, $MSE = 0.000$, $p = 0.000$. The results have also revealed that the main contributing predictor is the number of contacts (factor 1) in online learning for about 51.83% of the model. It is followed by the interaction factor $F1xF2$ (that is, the number of contacts and the length of time in online unreadiness) with a 28.32% contribution. All factor interactions have significantly contributed to the model, except for one (that is, $F2xF3$), as shown in table 3. The model's final regression equation is

$$\text{(Rate of Learning Experience)}^{-1.58} = 0.1018 + 0.0382F1 + 0.0283F1xF2 + 0.0112F1xF3 + 0.0069F1xF2xF3$$

Although the learning experience rate is an outcome, the student's learning outcomes are not directly measured in this present study. Nevertheless, they are embedded in the online learning environment framed under *CoI*. The rate of the learning experience is a form of system outcome since the increase (or decrease) of this rate is being determined and measured (Bakia et al., 2012). So, when there are high contact times with the *CoI* participants, there is likely an increase in the rate of the learning experience. For example, time tasks are given to the students, such as assignments and projects, to contact *student-student* interactions. They engage in shared discussions and possibly exhaustive debate, review and propose active plans, and create strategies to develop the best output. This interaction could provide a meaningful sharing of thoughts, positive emotions, and experiences that the members would cherish. However, the interaction across *CoI* participants could be disastrous when misunderstanding and disappointment take place and may not be discounted. The tutor's role could serve as the "neutralizer," Hence, learner control is vital in *CoI*. Jiang & Koo (2020) suggest that online tutors should be visible most of the time (i.e., high contact times) by posting images attractive to learners and may provide videos as welcome messages or any inspiring messages for the *CoI* participants, and may give purposeful immediate positive feedback.

On the factor $F1xF2$ (that is, the number of contacts in online learning and the length of time in online unreadiness), Liu (2019) suggests that online readiness directly affects learner's motivation, self-efficacy, self-directed learning, and learner control. This study has shown that the (interaction) factor with a high contact time and low online unreadiness is a significant contributor to the rate of the learning experience (see Table 3). Hence, it has supported the dimension of social presence in *CoI*. Yu & Richardson (2015) have shown constructs for social competencies with instructor and co-learners (that is, *tutor-learner* and *learner-learner* interactions), technical and communication competencies. This result also confirms the study of Liu (2019) so that the aspects of the learners' social interaction with the teachers online and their classmates (that is, social competencies across the *CoI* participants) are strengthened. Hence, the assumption on more contact times with the participants of the *CoI* and more online readiness are supported.

The factor $F1xF2xF3$ (that is, the number of contacts in online learning, the length of time in online unreadiness, and the absence of learner control measures) is a significant predictor; however, it gives only a small percentage (1.68%) of contribution to the model. In this case, the integration of learner control (that is, combining $F1xF2$ with $F3$) in the model reduces the percentage contribution to the model as a whole. Factor 3 (the absence of learner control measures) is a non-significant predictor of the model (Table 3).

There is a pedagogical implication of the *CoI* framework to the online learning platform and is crucial. Although the difference between online learning and face-to-face learning is noticeable, they differ mainly in pedagogy and learning environments. However, both could provide better learning opportunities such that the following aspects are given. These are broad access to resources and experience, active learning engagement, differentiated instruction, and maximized teacher-student time. According to Fiock (2020), teacher-student contact is one of the best practices in an online environment. The results of this study have supported Peacock and Cowan

(2016), that is, online contact times provide learner's self-managed learning activities coupled with tutoring, encouragement, nurturing of self-efficacy, and independent learning.

Moreover, Seckman (2018) has shown that teaching and social presence significantly predict cognitive presence. It implies that the dimensions of teaching and social presence on *CoI* are essential elements of *CoI* itself. The interaction of all *CoI* dimensions creates learning opportunities and develops a relationship. It allows the spread of knowledge when shared with other individuals outside of their *CoI*. Hence, the model in this present study is saying that online learning using the *CoI* framework provides positive and meaningful learning experiences. For as long as the dimensions are present or influence (social, tutoring, and cognitive), deep learning in online environments is addressed. Further, learning goals received from face-to-face learning is a possibility.

Finally, this paper intends to recommend conducting a further study in sustaining a quality online learning environment, equipping tutors to varying teaching methods in online learning, and contextualizing *CoI* from across disciplines.

5. Conclusion

Distance learning system has become a necessity amid the COVID-19 pandemic. Online learning replaces face-to-face learning to prevent the discontinuity of knowledge. One of the most influential online learning frameworks is the *CoI*. The active and collaborative online activities of *CoI* posit positive and meaningful learning experiences, as described in several studies. This study constructed a model to predict the rate of learning experiences for students online. This study adopted Netlogo's HIV model to mimic the social behaviors across the individuals in a population by translating its parameters into the predictors of this study. Using a three-factorial design, the factors are the number of contacts (factor 1), the length of time for online unreadiness (factor 2), and the absence of learner control measures (factor 3). The data show that factor 1 has significantly contributed 51.63%, and the interaction factor $F1xF2$ has contributed 28.32% to the rate of the learning experience. Although other factors are significant predictors to the model, yet their contribution rate is significantly low. It was found that when participants of the *CoI* frequently meet online, such that the learners are online ready and where the online learning platform has learner control, then the rate of the learning experience is likely to increase. The result of this study has pedagogical implications. Online learning using the *CoI* framework provides a positive and meaningful learning experience when all its dimensions (social, tutoring, and cognitive) are present. Deep learning contexts in online environments are also addressed. Hence, this study recommends further study in sustaining quality online learning environments and contextualizing CoI from the perspective of different disciplines.

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