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Engagement in cloud-supported collaborative learning and student knowledge construction: a modeling study

Noria Saeed Baanqud[1,2], Hosam Al-Samarraie[3,4*] , Ahmed Ibrahim Alzahrani[5*] and Osama Alfarraj[5]

*Correspondence:
h.alsamarraie@coventry.
ac.uk; myclasy@gmail.com;
ahmed@ksu.edu.sa
[3] School of Media
and Performing Arts,
Coventry University,
Coventry, UK
[5] Computer Science
Department, Community
College, King Saud University,
Riyadh, Saudi Arabia
Full list of author information
is available at the end of the
article

Abstract

Many universities, especially in low-income countries, have considered the potential of cloud-supported collaborative learning in planning and managing students' learning experiences. This is because cloud tools can offer students the necessary skills for collaboration with one another and improving communication between all users. This study examined how cloud tools can help students engage in reflective thinking, knowledge sharing, cognitive engagement, and cognitive presence experiences. The impact of these experiences on students' functional intellectual ability to construct knowledge was also examined. A quantitative questionnaire was used to collect data from 150 postgraduate students. A reflective–formative hierarchical model was developed to explain students' knowledge construction in the cloud environment. The findings revealed a positive influence of cognitive engagement, knowledge sharing, and reflective thinking on students' knowledge construction. Outcomes from this study can help decision makers, researchers, and academicians to understand the potential of using cloud-supported collaborative tools in developing individuals' knowledge construction.

Keywords: Distributed learning environments, Improving classroom teaching, Learning communities, Collaborative learning

Introduction

Collaborative learning is a social interaction that involves "a community of learners and teachers, where members acquire and share an experience or knowledge" Zhu (2012, p. 128). Recent studies have indicated that cloud computing technologies may provide an effective collaborative learning community (Ali et al. 2018; Ghazal et al. 2018). These technologies can also provide interaction in learning by engaging learners with new ideas, accelerating knowledge sharing, enhancing students' reflective thinking and analytical skills, and developing student capacity for "self-learning" (Aldoayan et al. 2019; Plisorn and Piriyasurawong 2019). Many universities have recently adopted cloud computing services such as Google Apps, Doc, and Space-Share in their educational system to stimulate sharing, reflection, communication, and to support collaboration between students (Al-Samarraie and Saeed 2018).
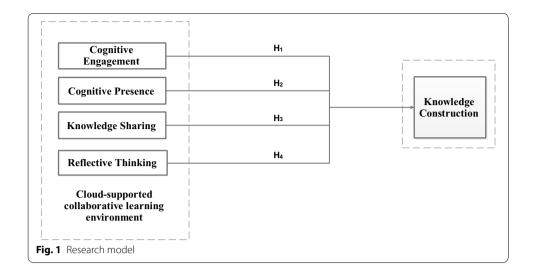
The use of cloud-supported collaborative learning tools in higher education can aid the teaching and learning processes (Martin et al. 2019). Meanwhile, cloud tools for collaborative learning may play a vital role in constructing a positive learning experience for students because its applications are more convenient for chatting, sending queries, recording audio meetings, processing documents, and delivering content (Zhaobin et al. 2013). It allows both instructors and students to construct and share knowledge and thus promote the latter's advanced thinking (Zeng 2016). The current literature on the application of cloud computing tools in collaborative learning shows a need to assess how students' engagement with these tools can stimulate students' knowledge construction, especially in low-income countries (Ghazal et al. 2019; Kaba and Ramaiah 2020; Yang et al. 2019). In addition, previous studies on collaborative learning have rarely examined the relationship between student engagement in cloud-supported activities and the main antecedents of knowledge construction, which may contribute to both synchronous and asynchronous forms of communication (Muthanna and Sang 2018). According to Aldholay et al. (2018), understanding ways to support knowledge transfer among students and instructors outside the classroom is notably lacking. Such deficiency is commonly due to the absence of online participation. The majority of empirical studies (e.g., Ali et al. 2018; Baragash and Al-Samarraie 2018a, b) have indicated that the adoption of cloud computing tools for collaborative learning can be shaped with regard to the emerging participation of students. Consequently, the impact of cloud computing tools on the collaborative learning activity should be assessed based on the development in students' knowledge and understanding in a specific situation (Xue et al. 2020).

This study constructed a new model to answer 'How cloud-supported collaborative learning tools contribute to students' knowledge construction in a university setting?'. Here, students' engagement in cloud-supported collaborative learning activities has been investigated based on constructs of cognitive engagement, cognitive presence, knowledge sharing, and reflective thinking. We examined the association between these factors and students' knowledge construction development. Participants were recruited from a public university in Yemen. Yemen is a developing country that faces a wide range of challenges in most areas of education. Therefore, the outcomes from this study can provide a better understanding for higher education institutions in Yemen and other low-income countries on how to integrate cloud-supported collaborative learning tools into the existing teaching practices. This study also offers some insights into the development of hybrid learning environments. It is also hoped that the proposed model can further improve individuals' engagement in online discussion, which seeks to improve the quality of online learning programs through the development of knowledge construction process.

Research model

The proposed research model was formed based on the relationships between cognitive engagement, cognitive presence, knowledge sharing, reflective thinking, and knowledge construction. The following subsections explain the model's factors and the relations between them (see Fig. 1).

Fig. 1 Research model

Cognitive engagement

Cognitive engagement, as defined by Stoney and Oliver (1999), involves seeking, interpreting, analyzing, and summarizing information, and critiquing and reasoning through various opinions and arguments. According to Greene and Miller (1996), cognitive engagement can be further distinguished by the different behaviors that an individual experiences during a learning process. This delineation includes the continuum between deep and shallow engagement. Students who exhibit behaviors that allow them to master academic work are recognized as having deep cognitive engagement, whereas students who display behaviors such as rote memorization without developing mastery of the material are demonstrating shallow engagement. Zuh (2006) reported that cognitive engagement cannot be observed in an online learning environment, but it can be described as students' active engagement in online discussion with each other. Markauskaite et al. (2006) used a sample of 226 students to investigate and compare students' cognitive engagement with the personal and collaborative construction of knowledge in an online environment. The authors found that students were more engaged and likely to remember concepts better within an online collaborative learning environment than a traditional learning setting. Johnson and Delawsky (2013) examined the influence of project-based learning on chemistry students' behavioral, cognitive, and emotional engagement. The authors found that collaboration time can significantly influence the cognitive engagement of students. They emphasized that the use of different teaching pedagogies to distinguish between the various types of engagement would encourage students to attain an in-depth understanding of the learning process. Chi (2009) argued that students demonstrate a high level of cognitive engagement with learning material activities that connect to their prior knowledge and experience from observing videos and information. In addition, students engaged in limited cognitive activity are likely to experience a limited knowledge construction experience. Chou and Chen (2008) employed a Web 2.0 (Wiki) tool to promote student online collaborative learning in a programming course. The authors recruited a total of 55 college students majoring in information technology and management. The results indicated that the technological tool motivated students to engage in collaborative learning and improved their

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knowledge about the course. Since effective learning (e.g., subject matter learning) requires deep cognitive engagement with the content; hence, cloud-supported collaborative learning may potentially assist in offering students a means of sharing and constructing their knowledge in a meaningful manner (Lee et al. 2020). Empirical evidence denoted a positive relationship between cognitive engagement and knowledge construction in an online setting. Therefore, this study proposes the following hypothesis:

> H_1 *Students' cognitive engagement in a computer-supported collaborative learning environment has a significant relationship with their knowledge construction.*

Cognitive presence

Cognitive presence is a central dimension of an individual's thinking, which describes the learning phases from the initial practical inquiry to the eventual knowledge construction and problem solving. It offers a vital element for explaining the critical thinking process and outcomes that are commonly used in higher education (Wilhelm-Chapin and Koszalka 2020). Based on previous studies (e.g., Cheung et al. 2020; Kilis and Yildirim 2019), cognitive presence is created in a community of inquiry, which partly depends on students' communication (e.g., the use of asynchronous, text-based collaborative communication to facilitate deep and meaningful learning in higher education). Akyol and Garrison (2011) established a significant relationship between cognitive presence and knowledge construction when the students engaged in online discussion. Their study involved an online graduate course (16 students) on the topic of "Blended Learning." The authors found that cognitive presence connotes the extent of a student's ability to construct and approve meaning by constantly discussing solutions with others. In this context, Shea and Bidjerano (2009) involved a sample of 2159 university students participating in a multi-institutional fully online learning network. The authors identified higher levels of cognitive presence among students who establish connections with their classmates and thus promote effective collaborative knowledge construction. According to Gros and García-Peñalvo (2016), cognitive presence in an e-learning environment, provides a capacity to construct knowledge through learners' communication with their peers. This can lead to the conclusion that the innovative use of cloud resources for asynchronous communication and collaboration may offer both students and lecturers a means of promoting knowledge construction and extending learning within a developed community of inquiry (Eteokleous and Ktoridou 2012). Furthermore, facilitating cognitive presence in the collaborative space can be through suggestions, discussions, information sharing, and synthesis and application of new ideas (le Roux and Nagel 2018). Based on these observations, this study posits the following hypothesis:

> H_2 *Students' cognitive presence in a computer-supported collaborative learning environment has a significant relationship with their knowledge construction.*

Knowledge sharing

Knowledge sharing plays an important role in facilitating and improving students' understanding of basic concepts to construct knowledge (Lin et al. 2020; Wendell et al. 2019). According to Nandy (2015), students' knowledge sharing could be

improved by the "sense of self-worth," "communication," "attitude," and "willingness to support". Shin et al. (2018) investigated the effectiveness of visible-annotation types used in online discussions to enhance the accuracy of shared knowledge and the level of constructed knowledge in online environments. Using analysis of variance, Shin et al. (2018) reported a potential relationship between knowledge sharing and knowledge construction, suggesting that the accuracy of shared knowledge is an important factor for enhancing the level of knowledge construction in the online learning environment. Baraka (2012) examined the process of developing an e-learning environment that can support collaborative sharing and knowledge construction with greater participation of learners using "Share-Space." They concluded that information sharing among learners is an essential element for constructing knowledge. The willingness to share knowledge depends on the availability of tools that support students to engage in such a process (Xue et al. 2020). The current study assumes that cloud-supported collaborative learning tools can facilitate collaborative knowledge sharing among team members by encouraging them to participate in collaborative activities through a "sense of self-worth" and "willingness to support knowledge" that support knowledge sharing behavior to promote knowledge construction. Hence, this study proposes the following hypothesis:

H_3 Students' knowledge sharing in a computer-supported collaborative learning environment has a significant relationship with their knowledge construction.

Reflective thinking

Numerous studies have pointed out that reflection plays an important role in the knowledge construction process (Renner et al. 2020; Tremblay et al. 2019). Reflective thinking refers to purposeful thought in which learners engage in active, persistent, and careful consideration of ideas for deeper understanding (Wilson and Murdoch 2013). Online tools are another means of promoting reflective thinking in collaborative learning activities. The review of the literature indicated that collaboration learning may contribute to increased reflective thinking (Brendel 2017), deep learning, and knowledge construction (Joshi and Chugh 2009). According to Xiao et al. (2008), promoting reflective thinking during collaborative learning activities can be achieved by supporting the active sharing of information among group members. Furthermore, a deeper understanding of reflective thinking processes would help students to progress in their collaborative tasks (Xiao and Carroll 2015). For instance, Khalid et al. (2015) conducted a study on 151 university students taking the Computer in Education course. The authors concluded that reflective thinking is not spontaneous but should be deliberately stimulated by a supported environment and group discussions, which may induce the construction of better knowledge and skills among students. The literature review on reflective thinking demonstrated that any changes to individual reflective thinking can be reasonably attributed to the learning environment. Thus, this study proposes the following hypothesis:

H_4 Students' reflective learning in a computer-supported collaborative learning environment has a significant relationship with their knowledge construction.
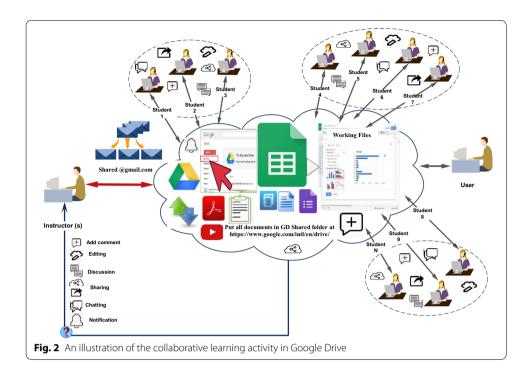
Method

A quantitative research approach was used in this study to collect the data through an online survey questionnaire. A reflective–formative hierarchical model was developed for the knowledge construction construct in Partial Least Square-Structure Equation Modeling (PLS-SEM). The present study was approved by the first author's institution. We also obtained informed consent from all respondents.

Sample

The preceding guidelines for using the G*Power software were used to determine the appropriate sample size as recommended by Faul et al. (2007). With an anticipated effect size of ($d = 0.15$, alpha $= 0.05$, and power $= 0.95$), the projected sample size required was 138. The sample size estimates were also informed by previous studies that adopted similar strategies. Yet, this study considered a bigger sample size of 180 students as it was believed that some students may refuse to accept or share responsibility for the group's work, or may not participate for personal reasons. The sample consisted of postgraduate students of several disciplines at Aden University in Yemen. Students were recruited using a purposive sampling strategy. A 2-month online collaborative learning activity was given to all students.

Procedure

A total of 180 students from different disciplines have participated in this study. The collaborative learning activity was managed and monitored by four instructors. The collaborative learning task was about performing advanced mathematical calculations using Google Drive Sheets. Six classes were formed, each class comprising 30–35 students. Students in these classes were divided into groups of 5–7 students. In each group, there was one group leader to lead the collaborative learning activity. Prior to the learning activity, the respondents received a brief demonstration of the purpose of the study via email. All students were given a 90-min demonstration on the first day of the cloud tool to explain the learning process. The cloud tool used in this study was Google Drive. Google Drive-Sheets is a free Google Cloud platform, which supports essential programming elements (formulas, functions, conditional formatting, and scripting) and allows for simultaneous collaboration and editing among online users. All the course materials (such as an e-book, spreadsheets syllabus, PDF files, and videos prototypes) were uploaded into a Google Drive's shared folder (see Fig. 2). Students of the one group were encouraged to work with each other to make the necessary adjustments in the shared files, solve problems, comment, and discuss learning topics relevant to the course. These activities were believed to improve knowledge sharing and reflective thinking among students. The students were given 2 months to complete the learning activities that were managed by the four instructors. After completing the learning activity, "Revision history" data from Google Drive were used to track students' participation in the collaborative learning activity. Then, students were asked to respond to an online questionnaire assessing the influence of the collaborative learning activity in Google Drive on their knowledge construction. Out of

Fig. 2 An illustration of the collaborative learning activity in Google Drive

the 180 students, only 150 students were able to complete the collaborative learning activity and submit their responses.

Instrument

We adapted items from previous studies that are related to the use of online tools and modify to be appropriate for our study's setting. The questionnaire consisted of 69 items that were divided into two separate parts. The first part asked about the respondents' demographic background (e.g., level of study, gender, age group, discipline, and Internet experience). The second part asked about the main variables:

- Cognitive engagement is a second-order reflective construct, consisting of two first-order reflective constructs adapted from Greene and Miller (1996). Several published studies have validated this construct. This construct was measured using six items that assessed shallow and meaningful cognitive engagement.
- Cognitive presence was assessed using 12 items adapted from the community of inquiry instrument by Garrison et al. (2001). These items examined aspects related to "triggering event," "exploration," "integration," and "resolution or application".
- Knowledge sharing is a second-order reflective construct with two first-order reflective sub-constructs: "sense of self-worth" and "willingness to support." A total of nine items were adapted from Nandy (2015) to measure this construct.
- Reflective thinking was assessed using 16 items adapted from the reflective thinking questionnaire by Kember et al. (2000). The construct was measured using four first-order reflective sub-constructs named habitual action; understanding; reflection; and critical thinking.
- Knowledge construction is a second-order formative construct that was measured with three first-order reflective constructs: "problem understanding," "achieving per-

spective," and "commitment." A total of 20 items from Tillema and van der Westhui-zen (2006) were used to measure this construct. The subconstruct of problem under-standing consisted of seven items that evaluate the individual professional's growth in understanding the topic and insights gained from the discussions. The subconstruct of achieving perspective consisted of seven items that evaluate the ideas expressed by others during team discussions. The subconstruct of commitment consisted of six items focusing on the active involvement of individuals during the discussion.

A five-point Likert scale was used to assess students' perceptions of these constructs. To examine the validity of the questionnaire, two university professors with more than 30 years of experience were approached to validate the study instrument.

Data analysis

We used SEM to test the research hypotheses. The Smart PLS software was used for the overall data analysis and testing for the validity and reliability of the study instrument and the research model. Three steps were followed for analyzing the collected data. In the first step, we analyzed the reflective measurement model to indicate the internal con-sistency reliability, convergent validity, and discriminant validity (Hair et al.2011, 2014). In the second step, we analyzed the hierarchical model. In the third step, we applied four criteria for assessing the structural model to measure the hypothesized relation-ships between the constructs namely: coefficient of determination (R^2), path coefficients, effect size (f^2), and predictive relevance (Q^2).

Results and discussion

Demographic results

Table 1 presents the frequencies and percentages of the demographic data. The respond-ents involved in this study were postgraduate students (89.3% Master and 10.7% Ph.D). A total of 80 students were male and 70 were female. The majority of students were over 30 years old (76%), 31 students were between 28 and 30 years, and only five students were between 25 and 27 years old. A total of 87 respondents had a high level of internet experience.

Measurement model evaluation and specification

Here, we used a regression analysis based on 150 cases (rows). The number of latent var-iables in the model was five. The number of indicators used in the model was 63 items. There were no items from reflective and formative latent variables removed. These items were sufficient for the analysis because they were used to measure the latent variables as expected. Factor loadings of 0.71 and above is considered excellent; 0.55 is considered good and very significant; 0.45 is considered fair 0.32, and below 0.32 is considered poor (Comrey and Lee 2013).

The measurement items and constructs were tested using reflective–reflective hierar-chical component model (see Table 2). The first and second order constructs were con-sidered as a reflective construct in this study. For example, the second-order construct of 'cognitive engagement' was manifested by two first-order constructs of cognitive engagement (shallow and meaningful) (see Additional file 1: Appendix S1, Fig. S1). Only

Table 1 Demographics characteristics

Measure	Category	Frequency	Percentage (%)
Level of study	Master	134	89.3
	Ph.D	16	10.7
Gender	Male	80	53.3
	Female	70	46.7
Age group	25–27	5	3.3
	28–30	31	20.7
	Over 30	114	76.0
Discipline	Education	48	32.0
	Art	37	24.7
	Engineering	12	8.0
	Medicine	12	8.0
	Pharmacy	3	2.0
	Economics	3	2.0
	Administration	4	2.7
	Law	3	2.0
	Computer Science	17	11.3
	Agriculture	6	4.0
	Women Studies	5	3.3
Internet experience	Low (0–2 years)	11	7.3
	Medium (3–5 years)	42	28.0
	High (over 5 years)	97	64.7

Table 2 Description of relational transaction practices and outcomes

Second order constructs	First order	Items	Measurement items no
Cognitive engagement	Shallow	1–3	6
	Meaningful	4–6	
Cognitive presence	Triggering event	1–3	12
	Exploration	4–6	
	Integration	7–9	
	Resolution	10–12	
Knowledge sharing	Sense of self-worth	1–4	9
	Willingness to support	5–9	
Reflective thinking	Habitual action	1, 5, 9, and 13	16
	Understand	2, 6, 10, and 14	
	Reflection	3, 7, 11, and 15	
	Critical reflection	4, 8, 12, and 16	
Knowledge construction	Problem understanding	1–7	20
	Achieving perspective	8–14	
	Commitment	15–20	

knowledge construction was measured using reflective–formative hierarchical component model. The first and second order constructs were tested using reflective and formative model (see Additional file 1: Appendix S1, Fig. S2). However, removing any pair would violate the validity of the second-order construct. The reason for using the reflective–formative type of hierarchical component model for the dependent variable

(knowledge construction) was because the relationship between problem understanding, achieving perspective, commitment, and knowledge construction was formative in nature, whereby each construct is measured by reflective indicators (Petter et al. 2007). This method of specifying the dependent constructs was also adopted by many previous studies (e.g., Hair et al. 2016; Petter et al. 2007; Ringle et al. 2012).

Convergent validity

Convergent validity here was tested by extracting the factor loadings, cross-loadings, composite reliability (CR), and average variance extracted (AVE) of all the items on their respective constructs (see Table 3). It was illustrated that the validity of the measurement scale was convergent because of the high item loadings (i.e., greater than or equal to 0.5) on their associated latent variables. All values were found to be above the 0.5 thresholds, meaning that the measurement constructs produced adequate convergent validity. In addition, the internal reliability was also assessed using Cronbach's alpha and composite reliability, which should be greater than 0.7 for the reliability to be considered acceptable, 0.80 to be adequate and 0.90 to be excellent (Hair et al. 2014; Kock and Verville 2012). Table 3 shows the Cronbach's alpha and the composite reliability results for the reflective latent variables. The composite reliability values were ranged between 0.77 and 0.93 which surpasses the prescribed estimation of 0.7. These coefficients are considered high, shown good support for the convergent validity.

Discriminant validity

Discriminant validity is the degree to which items differentiate among constructs or measures distinct concept by examining the correlation between the measures of potentially overlapping constructs (Fornell and Larcker 1981). In addition, the AVE of the latent variable should be higher than the squared correlations between the latent variable (Chin 1998, 2010; Fornell and Larcker 1981). Table 4 shows the latent variable correlation based on Fornell-Larcker criterion, where the values of the square root of AVE were higher than inter-correlation value between constructs.

In order to assess the collinearity value, the values of the variance inflation factors (VIFs) were obtained for all the latent variables and employed to measure discriminant validity. The collinearity values for all latent variables were lower than 3. This means that adequate VIFs were achieved for the reflective and formative latent variables, thus, sufficient discriminant validity.

Based on the results, it can be said that the measurement model was valid in terms of measuring the first order constructs through the measurement items. Then, we examined the hierarchical model in an attempt to determine the validity of measuring the second order constructs using the first order constructs. Figure 3 shows the research framework of the measurement model and the relationships between the latent variables.

Hierarchical model results

The second-order construct approach was used in this study, as recommended by Wetzels et al. (2009), for the development of the proposed model. First, two types of hierarchical latent variable model were reported in this study (e.g., reflective–reflective for independent variables and reflective–formative type for dependent variable).

Table 3 Construct and measurement model

Constructs	Items		Loading	Cronbach's Alpha	AVE	CR	References
Cognitive engagement (CE)	Shallow	CE1	0.901	0.892	0.823	0.933	Greene and Miller (1996)
		CE2	0.912				
		CE3	0.911				
	Meaningful	CE4	0.907	0.884	0.812	0.928	
		CE5	0.897				
		CE6	0.899				
Cognitive presence (CP)	Triggering event	CP1	0.834	0.772	0.686	0.867	Garrison et al. (2001)
		CP2	0.842				
		CP3	0.808				
	Exploration	CP4	0.843	0.799	0.714	0.882	
		CP5	0.815				
		CP6	0.876				
	Integration	CP7	0.833	0.789	0.703	0.877	
		CP8	0.844				
		CP9	0.839				
	Resolution	CP10	0.845	0.779	0.693	0.872	
		CP11	0.828				
		CP12	0.825				
Knowledge sharing (KS)	Sense of self-worth	KS1	0.828	0.850	0.690	0.899	Nandy (2015)
		KS2	0.799				
		KS3	0.847				
		KS4	0.848				
	Willingness to support	KS5	0.881	0.913	0.742	0.935	
		KS6	0.846				
		KS7	0.883				
		KS8	0.823				
		KS9	0.872				
Reflective thinking (RT)	Habitual action	RT1	0.840	0.850	0.690	0.899	Kember et al. (2000)
		RT5	0.821				
		RT9	0.787				
		RT13	0.873				
	Understanding	RT2	0.829	0.867	0.715	0.909	
		RT6	0.858				
		RT10	0.857				
		RT14	0.839				
	Reflection	RT3	0.855	0.859	0.703	0.904	
		RT7	0.870				
		RT11	0.785				
		RT15	0.842				
	Critical reflection	RT4	0.854	0.867	0.715	0.909	
		RT8	0.873				
		RT12	0.846				
		RT16	0.808				

Table 3 (continued)

Constructs	Items		Loading	Cronbach's Alpha	AVE	CR	References
Knowledge construction (KC)	Problem understanding	KC1	0.767	0.874	0.569	0.902	Tillema and van der Westhuizen (2006)
		KC2	0.730				
		KC3	0.791				
		KC4	0.722				
		KC5	0.777				
		KC6	0.719				
		KC7	0.772				
	Achieving perspective	KC8	0.843	0.912	0.656	0.930	
		KC9	0.806				
		KC10	0.776				
		KC11	0.788				
		KC12	0.811				
		KC13	0.794				
		KC14	0.848				
	Commitment	KC15	0.830	0.910	0.690	0.930	
		KC16	0.808				
		KC17	0.837				
		KC18	0.858				
		KC19	0.844				
		KC20	0.794				

Second, we communicated aspects related to the approach used to estimate the hierarchical latent variable model (e.g., repeated indicator or two-stage approach for estimating knowledge construction). Figure 4 shows the second stage of the hierarchal model by reducing the reflective–formative constructs (problem understanding, achieving perspective, and commitment) into only one output (knowledge construction).
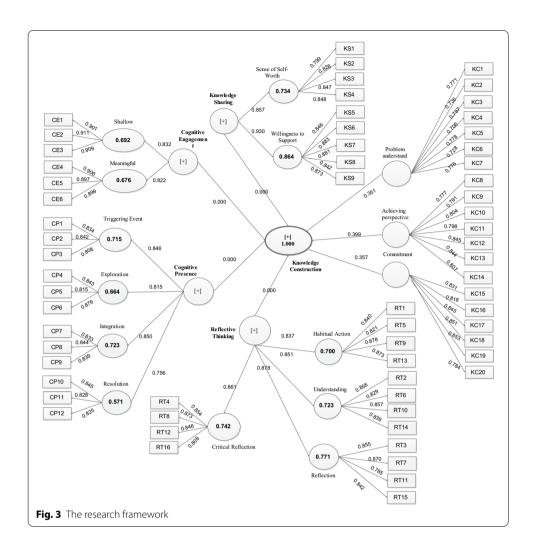
All path coefficients for the hierarchical model were significant (t-value > 2.56). It is worth mentioning that the values of R^2 were very high, indicating that the variance of second order constructs can be fully explained by the first order constructs. This is because measurement items were repeated in the second order constructs (Wetzels et al. 2009). The values of Q^2 were greater than zero, indicating that the first order constructs are robust to predict the second order constructs (see Table 5).

According to Garson (2016, p. 236), when applying the repeated indicator approach for reflective–reflective (input) models, the first order component (FOCs) was found to explain nearly all the variance in the second order component (SOC) (R^2 approach 1.0). Therefore, a two-stage approach is recommended: (1) first the repeated indicator approach is used to get factor scores for the FOCs, then (2) the FOC factors scores are used as indicators for the SOC. In both stages, other latent variables should be

Table 4 Latent variable correlations

Code	CE		CP				KS			RT				KC		
	SH	MF	TE	E	I	RES	SSW	WS	HA	U	REF	CR	PU	AP	C
SH	0.907														
MF	0.368	0.901													
TE	0.103	0.107	0.828												
E	0.193	0.115	0.591	0.845											
I	0.249	0.157	0.660	0.591	0.839										
RES	0.169	0.145	0.500	0.485	0.523	0.833									
SSW	0.242	0.138	0.262	0.210	0.176	0.233	0.831								
WS	0.241	0.148	0.130	0.156	0.043	0.150	0.606	0.862							
HA	0.147	0.119	0.112	0.195	0.085	0.131	0.520	0.476	0.831						
U	0.104	0.195	0.167	0.214	0.163	0.115	0.446	0.520	0.592	0.846					
REF	0.099	0.128	0.140	0.269	0.139	0.145	0.463	0.439	0.686	0.651	0.839				
CR	0.146	0.179	0.103	0.231	0.138	0.100	0.438	0.519	0.608	0.666	0.669	0.846			
PU	0.271	0.240	0.201	0.119	0.110	0.269	0.614	0.596	0.589	0.548	0.546	0.562	0.919		
AP	0.200	0.212	0.204	0.180	0.147	0.296	0.440	0.601	0.501	0.626	0.530	0.605	0.736	0.755	
C	0.269	0.208	0.055	0.115	0.021	0.111	0.447	0.492	0.459	0.543	0.546	0.535	0.752	0.687	0.830

CE: cognitive engagement, SH: shallow, ME: meaningful; CP: cognitive presence, TE: triggering event, E: exploration, I: integration, RES: resolution; KS: knowledge sharing, SSW: sense of self-worth, WS: willingness to support; RT: reflective thinking, HA: habitual action, U: understanding, REF: reflection, CR: critical reflection; KC: knowledge construction, PU: problem understanding, PU: problem understanding, AP: achieving perspective, C: commitment

Fig. 3 The research framework

included in the model as well (Hair et al. 2016, p. 236). Figure 5 shows the final simple model after carrying out a two-stage approach.

Structural model results

To assess the structured model, we used SMART PLS to generate five test fit indices; the path coefficient—hypothesis test, the coefficient of determination (R^2), effect size (f^2), predictive relevant (Q^2), and goodness of fit (GOF). The result of the R^2 coefficient of the endogenous latent variable or dependent latent variable (knowledge construction) was 0.598, reflecting a moderate effect. This means that the proportion of variation in the dependent variable (knowledge construction) can be moderately explained by all predictor variables (CE, CP, KS, and RT). The effect size (f^2) indicates the relative effect of a particular exogenous (independent) latent variable on endogenous (dependent) latent variable(s) by means of a change in the R^2. Table 6 provides a summary of the effect size results, indicating that reflective thinking has the largest effect on knowledge construction, while knowledge sharing and cognitive engagement had medium and small effect respectively, with no effect of cognitive presence on knowledge construction.
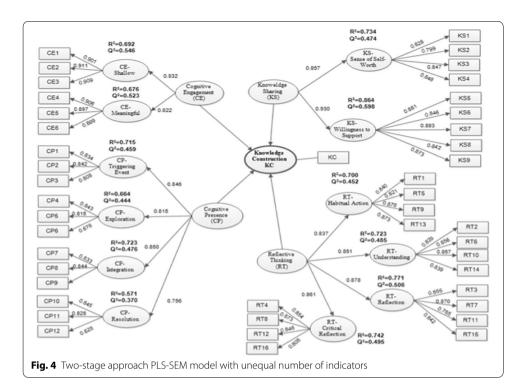
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Fig. 4 Two-stage approach PLS-SEM model with unequal number of indicators

Table 5 Evaluation of hierarchical model result

Path	Path coefficient	T-value	R^2	Q^2	Effect
CE → SH	0.832	33.691	0.692	0.546	High effect
CE → ME	0.822	30.996	0.676	0.523	High effect
CP → TE	0.846	21.088	0.715	0.459	High effect
CP → E	0.815	17.903	0.664	0.444	High effect
CP → I	0.850	22.037	0.723	0.476	High effect
CP → RES	0.756	14.480	0.571	0.370	Moderate effect
KS → SSW	0.857	28.349	0.734	0.474	High effect
KS → WS	0.930	76.255	0.864	0.598	High effect
RT → HA	0.837	23.525	0.700	0.452	High effect
RT → U	0.851	25.078	0.723	0.485	High effect
RT → REF	0.878	30.997	0.771	0.506	High effect
RT → CR	0.861	26.266	0.742	0.495	High effect

Then we examined the significance of the path coefficient-hypothesis. The analysis data in Table 7 showed that the relationship between cognitive engagement and knowledge construction seems to have the smallest impact, with significant level ($\beta = 0.137$, $P < 0.05$), and weak effect size ($f^2 = 0.042$). The path coefficient from cognitive presence to knowledge construction was found to be non-significant ($\beta = 0.011$, $P = 0.883$), and had no effect on the knowledge construction ($f^2 = 0.000$). This means that knowledge construction was not predicted by the cognitive presence. The results also showed that the path coefficient from knowledge sharing to knowledge construction was significant ($\beta = 0.326$, $P < 0.001$). This means that students' knowledge construction can be moderately predicted by their knowledge sharing in the
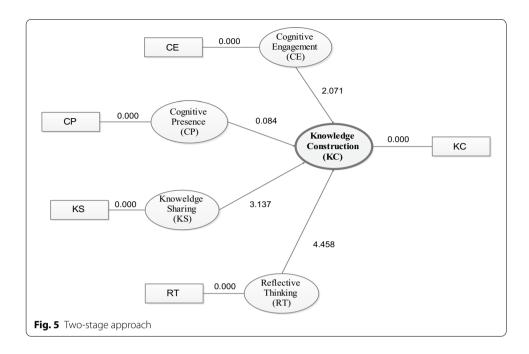
Fig. 5 Two-stage approach

Table 6 Effect sizes for path coefficients

Independent variables	f^2	Effect size assessment
CE → KC	0.042	Small effect
CP → KC	0.000	No effect
KS → KC	0.155	Medium effect
RT → KC	0.350	Large effect

Table 7 Path coefficient of the research hypotheses

Hypo	Relationship	Std. beta*	Std. error	T-value	P-values	Decision
H1	CE → KC	0.137	0.06	2.071	0.043	Supported*
H2	CP → KC	0.011	0.08	0.084	0.889	Not supported
H3	KS → KC	0.326	0.09	3.137	0.002	Supported**
H4	RT → KC	0.481	0.11	4.458	0.000	Supported**

Significant at $P^{**} = {<}0.01$, $P^* < 0.05$

cloud-supported collaborative learning environment. The path coefficient from the students reflective thinking to the knowledge construction was significant ($\beta = 0.481$, $P < 0.001$), and also showed a large effect size ($f^2 = 0.350$).

To find the predictive relevance of the structural model, we used the Stone-Geiser Q^2 test of the independent latent variables (Roldán and Sánchez-Franco 2012). The result indicated that the Q-squared coefficients for the predictive relevance (validity) were associated with each latent variable in the model, through the dependent latent variables ($Q^2 = 0.543$). Finally, we calculated the goodness of fit GoF using the following formula:
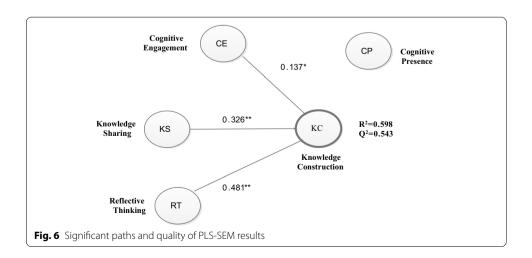
$$\text{GoF} = \text{square root of} : (\text{average R} - \text{squared}) \times (\text{average AVE})$$
$$\text{GoF} = \sqrt{R2} * \text{Average communality (AVE)}$$
$$\text{GoF} = \sqrt{0.498} * \text{Average communality}(0.707) = 0.593.$$

The outcome value of GoF was 0.593 for this study's model. Thus, it can be concluded that the GoF model of this study was sufficient. Figure 6 shows the significant paths, quality of PLS-SEM results, and the relationships of cognitive engagement, cognitive presence, knowledge sharing and reflective thinking with knowledge construction.

Discussion

This study found a significant relationship between students' cognitive engagement and knowledge construction in the cloud space. This positive relationship might be due to the role of the environment in promoting students' interaction and engagement in an active discussion, during which they constructed new understanding and knowledge. Our results likewise imply that a shallow cognitive engagement can be considered an extension of students' learning in the cloud, which may potentially support the collaborative knowledge construction process. This finding supports previous studies such as that of Zuh (2006), indicating that stimulating individuals' interaction and cognitive engagement during online-discussion activity is critical for constructing new understanding and knowledge. It also supplement the work of Mason (2011) denoting that cognitive engagement presented represents a conceived span of a crucible within which a rich mix of cognitive activities occurs and from which new knowledge emerges. This study assumes that using cloud-supported collaborated learning may allow students to become flexible in terms of communicating and learning about the topics taught anytime and anywhere to construct meaningful knowledge. This assumption similarly adds to the work of other scholars such as Shukor et al. (2014), which recommend that further research should comprehensively explore the influence of different variables on students' strategies for constructing knowledge with regard to the cognitive engagement level.

The relationship between cognitive presence and knowledge construction, however, was not significant. This result is not in line with previous research such as the study of Kupczynski et al. (2010), which demonstrate the effectiveness of cognitive presence

Fig. 6 Significant paths and quality of PLS-SEM results

in allowing students to construct and confirm meaning through reflection and discourse. Öztürk (2015) posits that individuals' level of experience in using the technology can potentially influence their level of cognitive presence. Building on this basis is the assumption that a high level of cognitive presence requires students to exercise critical thinking skills and entails communication with others based on engagement in collaborative learning activities. These conflicting findings may emanate from the students' efforts in communicative processes (e.g., discussions, sending instant messages, and chats) and course tasks (e.g., quizzes, assignments, course projects) and activities that they are more likely to experience.

The results also showed a significant relationship between knowledge sharing and knowledge construction in the cloud space. This significant relationship was observed through frequent communication and the sharing of important information between students, which assisted to boosting their collaboration level and building strong ties with the learning community. The result extends the work of Stacey (2002), which found that students in the online collaborative environment can construct new knowledge by sharing and listening in a context that promotes effective interactions and collaborative practices. The results therefore suggest the students' willingness to support and share knowledge with team members, which is reflected in the establishment of interpersonal and trusting relationships between group members, thereby spurring knowledge construction. This finding supports previous studies such as the work of Wang and Noe (2010) which measured the willingness to share knowledge and behaviors to understand individuals' motivation to participate in online learning activities. Furthermore, it consistent with the finding of Dalkir and Beaulieu (2017), which denotes that one important type of knowledge sharing that occurs in a community involves the evolution of a best practice (an improved means of doing things) or lessons learned (learning from both successful and unsuccessful events).

In addition, a significant relationship between reflective thinking and students' knowledge construction was also found. It is assumed that students' engagement in the cloud-supported collaborative learning activity enabled learners to develop their higher-order thinking skills by prompting them to construct new knowledge, thus enabling individuals to test their constructed views on others and discuss their ideas through the available communication tools. The result of the present research also implied that students acquired both significant reflection benefits and valuable practical learning skills through online discussions. This result is consistent with the findings of Thaiposri and Wannapiroon (2015) that social networks and cloud computing offer various useful services available on the Internet, enhancing students' critical thinking skills through teaching and learning activities by communicating and collaborating with one another. Furthermore, this result is in line with previous studies (e.g., Khalid et al. 2015; Murugaiah and Thang 2010) that thinking practices in the online learning environment would help students to foster the processes in collaborative learning activities and to become responsible for constructing their own knowledge. The results of this work imply that student reflection and critical reflection in the cloud environment encourage students to engage in reflective activities, thus contributing to the development of knowledge construction processes.

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Implications of the study

This study demonstrated the potential of cloud tools in the formulation process of the collaborative activity itself. The most significant outcome was that the cloud environment is able to foster the development of students' knowledge while learning how to collaborate online. With respect to instructional design, developing online courses with the aid of cloud computing technologies is essential for supporting collaborative knowledge construction in the cycle of deepening inquiry. Outcomes from this study may help in aligning different cloud adoption strategies to the practices of universities and learning institutions. In addition, this study offers a novel model that includes all the variables that are deemed necessary for promoting the knowledge construction process in online settings. The proposed model can help educational technologists to create a more sophisticated understanding of the relationship between the variables that influence the construction of collaborative knowledge in online, hybrid, and face-to-face settings. It is also possible that the use of online collaborative learning tools, such as Google Drive-Sheet, can promote the learning of advanced mathematical calculations for students enrolled in different university disciplines. For example, cloud-supported collaborative learning can be an important aspect of dialogic knowledge construction in that it allows students to interact with each other rather than with a computer. This can help students to engage in multiple dialogic communications that can be recorded and reflected upon later.

Limitations and future works

Despite the results, this study poses some limitations. First participants in this study included postgraduate students from only one university. Future studies could collect and examine data from different universities, by providing a large sample size. Additionally, this study could be replicated for undergraduate students or students in K-12 to determine whether the practices and activities in cloud-supported collaborative learning within higher education apply to the practices in K-12. The second limitation is related to students' use of cloud-supported collaborative learning tools (e.g., Google Drive-Sheet) to learn advanced mathematical calculations, and therefore not generalizable to other subjects. Despite the existence of other cloud learning environments such as Microsoft Azure, Baihui, and Zoho, sheets course was only selected in this study without considering other Google Drive applications such as GD-Docs or GD-Slides. The final limitation is the use of linear statistical methods such as PLS-SEM. The relational transactions may be more complex in reality. For example, the relationship among variables and the outcomes may not be linear. Future research that adopts nonlinear statistical methods, experimental settings, or qualitative data to triangulate the findings is therefore recommended.

The findings of this study added to the current literature on technology utilization in higher education by demonstrating the forms of relationships exploring the key factors that influence knowledge construction. A comparative study using the same data instruments could be conducted to ascertain the similarities and differences between students' knowledge construction in an identical environment (e.g., collaborative learning-based cloud computing). This study aimed to gain a deeper knowledge of the effects

of cloud collaborative tools on student's knowledge construction through active cognitive engagement, cognitive presence, knowledge sharing, and reflective thinking. In this regard, future research should consider additional success factors such as self-efficiency, which could also play a crucial role in improving knowledge construction and productivity. Finally, this work endeavored to address certain gaps and open some avenues to new areas in education, expecting to encourage further research on collaborative knowledge. The findings of this study alone would not do justice to this comprehensive research context. Future studies on the effects of different types of knowledge are thus recommended.

Conclusion

This study primarily aimed to provide an extensive vision of the implementation of cloud-supported collaborative tools to substantially improve students' collaboration by promoting the active discussion, sharing, and editing of learning resources to construct knowledge. The study addressed the factors contributing to students' knowledge construction. The results indicated that students' cognitive engagement, knowledge sharing, and reflective thinking in a cloud-supported collaborative learning environment had a significant relationship with knowledge construction. However, the findings also revealed the lack of any significant relationship between cognitive presence and knowledge construction in a cloud-collaborative environment. These outcomes may be related to the students' efforts in communicative processes and course tasks. From a practical viewpoint, the findings provide an understanding of the cloud-supported collaborative tools in the higher education context toward developing students' knowledge construction; at the same time, the findings highlight the importance of cognitive engagement, cognitive presence, knowledge sharing, and reflective thinking relationships within knowledge construction.

Supplementary information

Supplementary information accompanies this paper at https://doi.org/10.1186/s41239-020-00232-z.

Additional file 1: Appendix S1. Fig. S1. An example of reflective–reflective hierarchical construct model of CE. **Fig. S2.** An example of reflective–formative hierarchical construct model of KC. **Table S1.** Questionnaire.

Author details
[1] Faculty of Computing and Information Technology, University of Aden, Aden, Yemen. [2] Centre for Instructional Technology and Multimedia, Universiti Sains Malaysia, Gelugor, Penang, Malaysia. [3] School of Media and Performing Arts, Coventry University, Coventry, UK. [4] Centre for Arts, Memory, and Communities, Coventry, UK. [5] Computer Science Department, Community College, King Saud University, Riyadh, Saudi Arabia.

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