What drives students’ successful reuse of online learning in higher education? A case of Google Classroom

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This study aims at proposing an integrated model based on the technology acceptance model, the information system success model, cognitive load theory, and personal characteristics to predict students' continued intention to reuse Google Classroom in the context of a developing country. To achieve this, we conducted quantitative research, empirically identifying the factors that could affect the continued intention of higher education students to reuse Google Classroom. Overall, 233 higher education students voluntarily participated in this research. Structural equation modelling was adopted as the method of analysis. The results showed that cognitive load significantly influenced perceived ease of use, whereas it had no impact on perceived usefulness or satisfaction. Furthermore, all personal characteristics significantly affected perceived ease of use. The outcomes likewise revealed that perceived usefulness, perceived ease of use, and satisfaction had a significant and positive effect on students’ continued intention to reuse Google Classroom. However, to enhance the generalisability of the findings, further research with a larger research sample is required. In addition, the predictability power of the proposed model could be improved by considering the role of other factors, such as engagement and learning effectiveness.

Implications for practice or policy:

- To ensure successful reuse of learning management systems (LMSs), course leaders should pay attention to students' perceptions.
- LMS developers should place greater emphasis on students’ individual differences, to maximise the effectiveness of LMS implementation.
- Instructors should ensure that the learning material does not require a high cognitive load, as this could produce learning fatigue.
- Educational institutions should consider students' satisfaction with particular learning technology, as this would affect students’ willingness to reuse it.

Keywords: Google Classroom; e-learning adoption; online learning; technology acceptance model; information system success model; cognitive load; personal characteristics

Introduction

The utilisation of learning management systems (LMSs) is one of the most significant advancements in information technology in higher education (Coates et al., 2005). LMS technology consists of self-contained, Web-based platforms that can be used purely for distance learning or to supplement the traditional teaching method (Al-Busaidi & Al-Shihi, 2012; Gautreau, 2011). This technology promotes a student-centred learning approach and facilitates the sourcing of learning materials (Gautreau, 2011). Among various LMSs, Google Classroom has received significant attention in contemporary education. According to Kumar et al. (2020), Google Classroom is rapidly being introduced into educational institutions. It facilitates students’ and instructors’ access to a user-friendly and secure learning environment. In particular, the platform permits the inclusion of more than one instructor per course. Hence, students can obtain information from multiple sources (Bhat et al., 2018). The popularity of Google Classroom may be attributed to its being free of charge for the end user. In turn, this could be the reason for its widespread use in developing countries, where financial resources are more limited (Azhar & Iqbal, 2018). Nevertheless, overall, the integration of LMSs is an endeavour that requires careful planning and a huge financial investment (Hussein et al., 2021; Sharma et al., 2017).

According to the literature, the continued intention to reuse particular LMSs is recognised as a key indicator of their success (Sharma et al., 2017). M. C. Lee (2010) noted that investigating the continued intention to reuse e-learning technologies is more important than researching e-learning acceptance. However, research has focused on initial acceptance, while only a few studies have examined the factors that could drive students' continued intention to reuse LMSs as this could facilitate effective integration of LMSs in higher education institutions beyond the stage of initial adoption and usage (Ashrafi et al., 2020; Sabah, 2020; Wu & Zhang, 2014). For example, Ashrafi et al. found that perceived usefulness was the strongest determinant of students' continuance intention, whereas learners' attitudes towards LMSs, and perceived satisfaction had no significant effect on this construct.

As a consequence, the core aim of this study was to help fill the research gap in the context of continued intention, proposing an integrated model based on the technology acceptance model (TAM; Davis, 1985), the information system success model (ISSM; DeLone & McLean, 2003), cognitive load theory (Paas et al., 2003), and learners' individual characteristics, namely personal innovativeness (Sharma et al., 2017), computer anxiety (Saadé & Kira, 2009) and computer self-efficacy (Compeau & Higgins, 1995). The rationale behind this integration is that these theories can complement each other in the context of e-learning. According to Al-Azawei (2017), although TAM is one of the most adopted theories in technology acceptance, the original TAM is no longer adequate for e-learning technologies, and this, in turn, invites further research to integrate theories and factors that are more relevant to educational technologies. Furthermore, TAM does not account for users' personal features (Al-Azawei et al., 2017), whereas this research incorporates constructs that could explain learners' differences. Furthermore, TAM neglects the effect of information, system and service quality on technology success, whereas this study suggests including such variables to understand technology reuse based on a wider perspective. Y. Wang et al. (2020) argued that TAM focuses solely on positive perceptions, while it neglects negative and boycotting factors, and, this, in turn, could limit its comprehensiveness. This research, however, addresses the issue of TAM's positive perception by examining the role of boycotting factors such as cognitive load and computer anxiety. For example, high cognitive load negatively impacts students' learning performance, satisfaction and information retention (Bradford, 2011; Hughes et al., 2018; Zhang, 2013). Concerning computer anxiety, Phelps and Ellis (2002) stated that computer anxiety could reduce students' success and their efforts to be successful, thus preventing a successful adaption of e-learning applications (Cidral et al., 2018; P. C. Sun et al., 2008).

This study, therefore, adds many contributions in comparison with previous literature. First, the model presented here is one of a few theoretical attempts to explore the domain of continued intention using such integration of different theories. Second, the predictability power of models proposed in earlier research to investigate continued intention to reuse LMSs was generally low (Chang, 2013; Islam & Azad, 2015; K. M. Lin, 2011; T. C. Lin & Chen, 2012); however, this research achieves a high prediction accuracy. Third, previous literature, for example, Ashrafi et al. (2020), Dağhan and Akkoyunlu (2016), M. C. Lee (2010), Li et al. (2012) and Wu and Zhang (2014), addressed the issue of limited explanatory power by designing more comprehensive frameworks, but they overlooked the role of students' cognitive load during the learning process. Thus, we expect that the outcomes of this study can extend the findings of previous research and provide a complementary understanding of factors contributing to continued intention to reuse LMSs, especially in developing nations.

Literature review

Online learning

The rapid development in technology and Internet infrastructure has significantly transformed online learning (Dhawan, 2020). Recently, online learning has experienced enormous research interest and growth, as most educational institutes migrate online to provide continuity of learning during the COVID-19 pandemic (Hussein et al., 2021). Online learning is a broad concept associated with a wide range of terms such as open learning, Web-based learning, and LMSs (Dhawan, 2020). This instructional method is based on the delivery of learning material via laptops, personal computers, tablets or smartphones, thereby rendering the teaching and learning process more flexible and student-centred (Mayer, 2019).

Prior studies on the continued intention to reuse LMSs

A review of studies on students' continued intention to reuse LMSs revealed that this research area has been investigated using several different models and theories, which can be divided into three main categories based on the model or theory adopted. The first category consists of studies that have implemented a self-constructed model, without being grounded in any particular theory of technology adoption. The second category encompasses literature where variables have been adopted from one or two theories, and the third category comprises empirical studies where variables from three or more theories have been adopted.

Regarding the first category, Chang (2013) proposed a self-constructed model, which was focused solely on the information, system, and service quality of ISSM. However, Chang's model overlooked other variables that could have influenced students' continued intention to reuse. Likewise, Islam and Azad (2015) designed a self-constructed model that did not examine the relationships between the predictors of continued intention.

In terms of the second category, K. M. Lin (2011) and Lwoga and Komba (2015) developed a model based on TAM and the unified theory of acceptance and use of technology respectively. Nevertheless, these empirical studies narrowed the explanatory power of their models to the variables adopted from these two theories. Furthermore, they neglected other possible determinants, such as information quality, system quality, service quality, and satisfaction. T. C. Lin and Chen (2012) suggested a model based on TAM and ISSM. In their proposed model, however, they applied perceived usefulness and satisfaction as the sole predictors of students' continued intention..

In the third category, comprising studies where three or more theories were adopted, M. C. Lee (2010) designed a model based on TAM, the theory of planned behaviour, the expectation-confirmation model and flow theory. Although Lee's model employed four theories, it neglected the role of information quality, system quality, service quality, and individual features. Furthermore, Li et al. (2012) constructed a model based on TAM, ISSM and the self-efficacy theory. Although the model addressed students' self-efficacy, it focused only on one aspect of the students' characteristics. Moreover, it overlooked the role of satisfaction as a predictor of students' continued intention. Wu and Zhang (2014) employed three theories, namely TAM, ISSM and social motivation theory. Although Wu and Zhang considered ISSM, they did not adopt key variables of ISSM: service quality and satisfaction. Furthermore, Dağhan and Akkoyunlu (2016) proposed a model based on ISSM, the cognitive model, technology continuance, and the expectation-confirmation model, whereas Ashrafi et al. (2020) combined variables from TAM, the expectation-conformation model, social influence, and hedonic value. Although Dağhan and Akkoyunlu and Ashrafi et al. (2020) integrated four theories into the proposed models, they did not consider how students' cognitive load and personal characteristics could affect their intention to continue using LMSs.

Although the studies in the first and second categories provide useful insights, they include a limited number of predictors, which considerably inhibits their explanatory power. In contrast, the studies in the third category explored students' continued intention in greater detail. However, these models did not attempt to assess the role of cognitive load and allocated little research attention to students' personal characteristics. To address these gaps, the present study proposes an integrated model based on TAM, ISSM, cognitive load theory, and personal characteristics, in order to provide further empirical evidence of the constructs that could affect students' continued intention to reuse Google Classroom.

Proposed research model and hypotheses

To overcome the limitations of TAM and previous research studies in this domain, the present study incorporated ISSM, cognitive load theory, and personal characteristics into TAM. According to Aldholay et al. (2018), ISSM provides an overall evaluation of the quality and functionality of information systems. Hence, for a more in-depth exploration of the factors that could affect continued intention, Yan et al. (2021) observed a growing need to conduct further research to assess users' mental processes, given the increasing utilisation of online technologies. Moreover, although learners' individual differences have been thoroughly investigated in the area of technology adoption (Sabah, 2020), their effects on students' continued intention to reuse technology have received only limited interest. In addition, according to Sabah, studies investigating the impact of personal characteristics on students' continued intention have reported contradictory findings, inviting further research to offer a better understanding of the role of these factors on students' continued intention.

TAM

Among the various technology acceptance theories, Davis (1985) proposed TAM – now one of the most widely utilised frameworks for elucidating individuals' acceptance of new technology (Alhasan et al., 2020; Wang & Wang, 2009). TAM is grounded in the theory of reasoned action (Fishbein & Ajzen, 1977). Davis (1989) argued that perceived usefulness and perceived ease of use are the two key variables that can influence users' adoption of new technology. Figure 1 depicts the five variables of TAM.

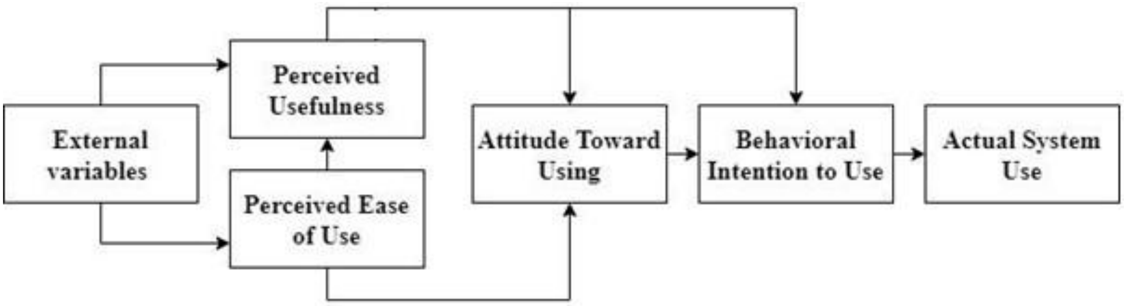

Figure 1. The architecture of TAM (Davis et al., 1989, p. 985)

Perceived usefulness measures the extent to which a person considers that using LMSs can promote their learning performance (Davis, 1989; Islam, 2015). Perceived ease of use signifies the degree to which an individual believes that using LMSs in their learning will be an effortless endeavour (Ashrafi et al., 2020; Davis, 1989; Islam, 2015).

In e-learning research, perceived usefulness has been identified as a key antecedent of students' satisfaction (Binyamin et al., 2017; Islam & Azad, 2015) and the continued intention to reuse LMSs (Islam & Azad, 2015; Li et al., 2012; Wu & Zhang, 2014). Perceived ease of use has also been found to have a significant impact on perceived usefulness (Binyamin et al., 2017; Li et al., 2012; Wu & Zhang, 2014), satisfaction (Ashrafi et al., 2020; Islam & Azad, 2015; T. C. Lin & Chen, 2012) and continued intention to reuse (Al-Busaidi, 20102; Li et al., 2012). Accordingly, we formulated the following hypotheses:

- H1: Satisfaction is positively and significantly influenced by perceived usefulness.
- H2: Continued intention to reuse is positively and significantly influenced by perceived usefulness.
- H3: Perceived usefulness is positively and significantly influenced by perceived ease of use.
- H4: Satisfaction is positively and significantly influenced by perceived ease of use.
- H5: Continued intention to reuse is positively and significantly influenced by perceived ease of use.

ISSM

DeLone and McLean proposed ISSM in 1992 and updated it in 2003 (DeLone & McLean, 1992, 2003). ISSM is a product of thorough research analysis on a large number of variables, connected with the success of information systems (Hussein et al., 2021). It represents one of the most established theories on information systems (W. T. Wang & Wang, 2009). Figure 2 illustrates ISSM, which constitutes six interrelated measures: information quality, service quality, system quality, intention to use, satisfaction, and net benefits.

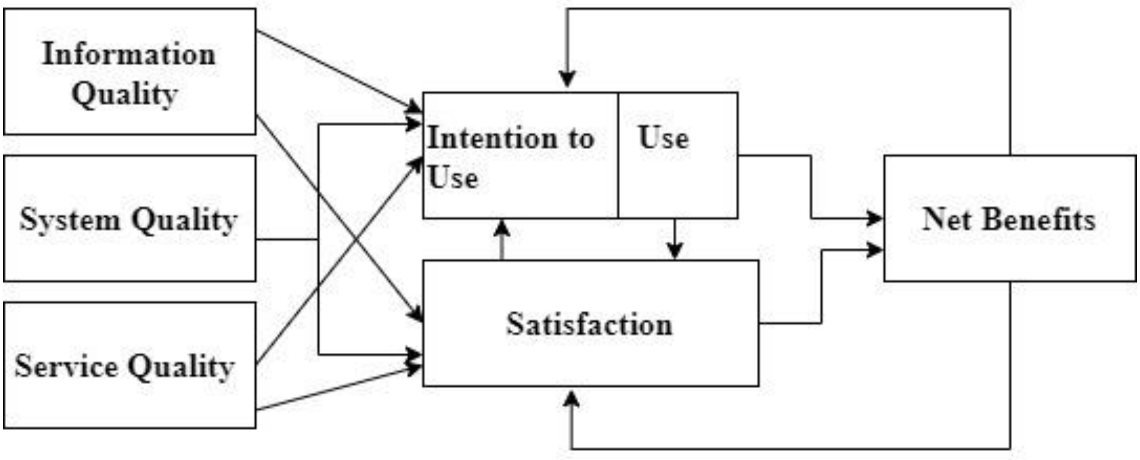

Figure 2. The architecture of the updated ISSM (DeLone & McLean, 2003, p. 24)

In this research, information quality refers to the accuracy and sufficiency of information that is obtained from LMSs (Koh & Kan, 2020; H. F. Lin, 2007). Meanwhile, service quality is primarily centred on the quality of technical support (Koh & Kan, 2020). Conversely, system quality relates to technical factors of LMSs, such as stability, reliability, interface design, and efficiency (H. F. Lin, 2007; Pituch & Lee, 2006). Satisfaction constitutes the extent to which a user considers that using LMSs will provide a positive learning experience and meet their expectations (Islam & Azad, 2015). Finally, continued intention to reuse is the extent to which an individual is inclined to continue using targeted LMSs for their learning activities in the future and to recommend LMSs to others (Bhattacherjee, 2001; Chang, 2013).

In the LMS literature, information quality is a key antecedent of perceived usefulness (Al-Busaidi, 2012; Wu & Zhang, 2012), whereas Al-Busaidi (2012) reported that service quality performs a decisive role in driving students' perceived ease of use. In addition, Al-Busaidi (2012) and T. C. Lin and Chen (2012) revealed that system quality has a significant impact on perceived usefulness and perceived ease of use. Furthermore, satisfaction is a key antecedent of students' continued intention (Chang, 2013; Dağhan & Akkoyunlu, 2016; Islam & Azad, 2015; T. C. Lin & Chen, 2012). Hence, we formulated the following hypotheses:

- H6: Perceived usefulness is positively and significantly influenced by information quality.
- H7: Perceived ease of use is positively and significantly influenced by service quality.
- H8: Perceived usefulness is positively and significantly influenced by system quality.
- H9: Perceived ease of use is positively and significantly influenced by system quality.
- H10: Continued intention to reuse is positively and significantly influenced by satisfaction.

Cognitive load theory

The key notion of the cognitive load theory is centred on addressing learners' limited cognitive processing abilities when designing instructional material (Paas et al., 2003; Spanjers et al., 2012). Ozcinar (2009) recommended considering this theory in the design of instructional practice. Cognitive load is classified into three categories: germane, intrinsic, and extraneous (Sweller, 2010). The present study focuses on extraneous cognitive load, as it refers to the additional effort that is demanded of students when they attempt poorly designed instructional tasks (Paas et al., 2010; Vandewaetere & Clarebout, 2013). Extraneous cognitive load is detrimental to the learning process, as it does not promote the construction of students' knowledge (Van Merriënboer & Sweller, 2005). Accordingly, we formulated the following three hypotheses:

- H11: Perceived ease of use is positively and significantly influenced by lower cognitive load.
- H12: Perceived usefulness is positively and significantly influenced by a lower cognitive load.
- H13: Satisfaction is positively and significantly influenced by lower cognitive load.

Personal characteristics

The adoption of an LMS technology can be determined by the users' characteristics (Al-Busaidi & Al-Shihi, 2012). Such features are essential to investigate the role of users' traits in technology acceptance and success. This research integrates personal innovativeness, computer anxiety, and computer self-efficacy as individual features that can affect the reuse of LMSs.

Personal innovativeness refers to students' willingness to experiment with new technologies (Sharma et al., 2017; Venkatesh & Davis, 2000). Al-Busaidi (2012) and Agudo-Peregrina et al. (2014) noted that perceived ease of use was significantly predicted by personal innovativeness. Moreover, computer anxiety is manifested when students demonstrate their uneasiness, apprehension, or even fear at the prospect of using a computer (Abdullah et al., 2016; Igbaria & Parasuraman, 1989; Venkatesh & Davis, 2000). The literature shows that students with high computer anxiety may avoid e-learning technology, and in turn, this could negatively affect perceived ease of use (Al-Busaidi, 2012; J. C. Lee & Xiong, 2021; Saadé & Kira, 2009). Furthermore, computer self-efficacy indicates students' perceptions of their competence to perform certain tasks with a computer (Compeau & Higgins, 1995; J. C. Y. Sun & Rueda, 2012). As a result, computer self-efficacy can directly impact perceived ease of use (Binyamin et al., 2017; Yalcin & Kutlu, 2019). Accordingly, we identified the following hypotheses:

- H14: Perceived ease of use is positively and significantly influenced by personal innovativeness.
- H15: Perceived ease of use is positively and significantly influenced by computer anxiety.
- H16: Perceived ease of use is positively and significantly influenced by computer self-efficacy.

Figure 3 depicts the proposed research model in this study.

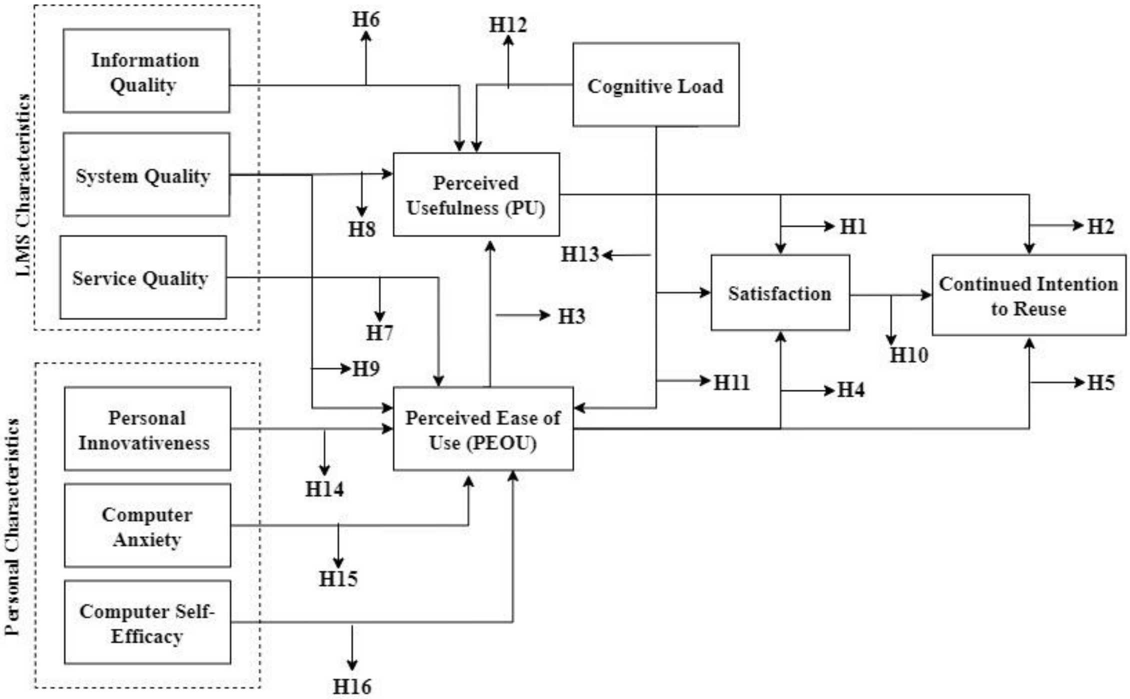

Figure 3. The proposed research model

Research methodology

To understand the process of technology reuse, this study proposed an integrated model based on TAM, ISSM, cognitive load, and individual characteristics. A quantitative research design was adopted for this work, focused on collecting and analysing quantitative data. The confirmatory factor analysis (CFA) test was performed to investigate the fit of the proposed research model.

Research instrument

The design of questionnaires plays a key role in research; therefore, the items should be short and concise (Ameen, 2017). In this study, we ensured that the design of the research instrument addressed the main research objectives.

The research questionnaire encompassed two sections. The first consisted of general questions about the participants' demographic information, such as students' age, gender, and e-learning experience. In the second section, there were 11 constructs and 43 items (see Appendix), perceived ease of use and perceived usefulness were adopted from TAM, and both constructs encompassed five items (Davis et al., 1989). Five constructs were adopted from ISSM. The first is system quality, which contained five items (Wang & Wang, 2009). Information quality and service quality contained four items (Dağhan & Akkoyunlu, 2016; Wang & Wang, 2009). Perceived satisfaction (DeLone & McLean, 2003) and continued intention to reuse (Bhattacherjee, 2001) consisted of three items. Concerning students' personal characteristics, only computer anxiety encompassed four items (Al-Busaidi & Al-Shihi, 2012), whereas personal innovativeness (Sharma et al., 2017) and computer self-efficacy (Chiu & Wang, 2008; Wang & Wang, 2009) encompassed three items. Finally, cognitive load consisted of four items which were derived from cognitive load theory (Hsu, 2015).

These items were rated using a 5-point Likert evaluation scheme ranging from 1 = *strongly disagree* to 5 = *strongly agree*. It should be mentioned here that each questionnaire item was translated into Arabic. Two experts examined the original items and their translation to ensure that both versions had the same meaning and that the aim of each item had not been changed during the translation process.

Data collection

Prior to the commencement of this research, the ethical guidelines of Iraqi public-sector higher education institutes were considered. Moreover, the students were informed that their involvement was purely voluntary and that they could withdraw their participation at any time. The students were also informed that all their responses would be anonymous; that the data collected would remain confidential; and that these data would be used solely for research purposes. Finally, the students were informed in the first section of the questionnaire that their consent to take part in the study would be deemed to have been granted once they had completed and submitted the questionnaire. An online instrument was implemented in this study to survey full-time university students from a public-sector university in Iraq. The instrument was sent to students via email and short message service. In terms of the sampling approach, a non-probabilistic convenience sample was selected, as it would have been a very challenging and time-consuming task to gain access to the whole population (L. Cohen et al., 2007).

Participants

Table 2 presents background information on the research participants. Overall, 233 undergraduate students participated in this study (see Table 2). According to Hair et al. (2016), a research sample greater than 200 is appropriate for structural equation modelling analysis. Out of the total sample, 142 respondents were female. Moreover, most of the respondents were aged 23 years or above (n = 132). However, the students' experience of using LMSs was very limited, with 221 respondents having 0–1 year of LMS experience.

Table 2
Participants' background (*N* = 233)

Item	Frequency
Gender	
Female	142
Male	91
Age	
18	14
19	26
20	17
21	20
22	24
23 or above	132
E-learning experience (years)	
0	151
1	70
2	8
3	2
4 or more	2

Data analysis

The Anderson and Gerbing (1988) data analysis protocol was adopted. In the first phase, SPSS was utilised to examine the reliability and validity of the data. In the second phase, AMOS statistical software was implemented to perform SEM as a means of assessing and testing the structural model.

Results

Descriptive statistics

Table 3 presents the descriptive statistics of the proposed research model variables. It demonstrates that service quality received the lowest mean score of 2.56 out of 5. This may indicate that the students did not receive enough services from Google Classroom. Conversely, cognitive load registered the highest mean score of 3.39 out of 5. This could suggest that the students were obliged to exert high mental effort while learning via Google Classroom. Besides, the data were normally distributed, as the values of skewness and kurtosis fell within the threshold of ±2 (Liu et al., 2019).

Table 3
Descriptive statistics

Variable	Skewness	Kurtosis	Mean	Standard deviation
Perceived ease of use	-0.644	-0.496	3.20	1.10
Perceived usefulness	-0.166	-0.939	2.76	1.07
System quality	-0.365	-0.727	2.87	0.99
Information quality	-0.254	-0.924	2.82	1.03
Service quality	-0.176	-0.824	2.56	0.88
Computer self-efficacy	-0.475	-0.877	2.83	1.03
Personal innovativeness	-0.403	-0.593	3.21	1.11
Computer anxiety	0.194	-0.957	2.78	1.17
Cognitive load	-0.489	-0.220	3.39	1.04
Perceived satisfaction	-0.090	-0.899	2.74	1.12
Intention to reuse	0.204	-1.14	2.60	1.24

Evaluating the measurement model

To investigate the overall load of the questionnaire items on their latent variables, CFA was used (Teo & Zhou, 2014). According to Hair et al. (1998), each construct should include at least two items. Furthermore, the acceptable factor load should be greater than 0.40. Table 4 demonstrates that the values of all factor loadings fell between 0.583 and 0.901, which exceeds the recommended value.

To investigate the internal consistency of the research questionnaire, Cronbach's alpha was calculated. According to Nunnally and Bernstein (1994), Cronbach's alpha values are considered satisfactory if they reach or surpass the 0.70 threshold. Table 4 demonstrates that the Cronbach's alpha values of the model's factors were between 0.850 and 0.949. Thus, the recommended value was surpassed.

The validity of the research instrument was measured by computing composite reliability (CR) and average variance extracted (AVE). Fornell and Larcker (1981) recommended that CR and AVE values should be above 0.70 and 0.50, respectively. Table 4 illustrates that all values of CR and AVE were higher than the recommended thresholds. Hence, we can conclude that all constructs used in this study were reliable and valid.

Table 4
Reliability of the questionnaire constructs

Item	Factor loading	CR	AVE	Cronbach's alpha
System quality (SYS-Q)		0.830	0.718	0.855
SYS-Q1	0.767			
SYS-Q2	0.616			
SYS-Q3	0.726			
SYS-Q4	0.758			
SYS-Q5	0.727			
Service quality (SRV-Q)		0.894	0.701	0.855
SRV-Q1	0.742			
SRV-Q2	0.688			
SRV-Q3	0.618			
SRV-Q4	0.759			
Information quality (INF-Q)		0.715	0.808	0.902
INF-Q1	0.806			
INF-Q2	0.824			
INF-Q3	0.839			
INF-Q4	0.765			
Perceived ease of use (PEOU)		0.762	0.788	0.937
PEOU1	0.763			
PEOU 2	0.805			
PEOU3	0.777			
PEOU4	0.789			
PEOU5	0.806			
Perceived usefulness (PU)		0.866	0.771	0.902
PU1	0.731			
PU2	0.762			
PU3	0.815			
PU4	0.712			
PU5	0.837			
Personal innovativeness (PI)		0.829	0.642	0.859
PI1	0.713			
PI2	0.583			
PI3	0.630			

Computer anxiety (CA)		0.773	0.850	0.922
CA1	0.819			
CA2	0.825			
CA3	0.901			
CA4	0.855			
Computer self-efficacy (CSE)		0.831	0.759	0.852
CSE1	0.832			
CSE2	0.741			
CSE3	0.705			
Cognitive load (CL)		0.886	0.712	0.850
CL1	0.615			
CL2	0.643			
CL3	0.822			
CL4	0.768			
Satisfaction		0.709	0.828	0.908
Satisfaction1	0.839			
Satisfaction2	0.833			
Satisfaction3	0.814			
Continued intention to reuse (CIR)		0.841	0.713	0.949
CIR1	0.709			
CIR2	0.696			
CIR3	0.736			

The present study used five fit indices to examine the research model's goodness-of-fit index (GFI). Table 5 demonstrates that the chi-square/degree of freedom had a value of 1.520. This is less than the maximum recommended threshold of three (Wang & Wang, 2009). The root mean square error of approximation (RMSEA) had a value of 0.023, which is below the approved threshold of 0.07 (Wang & Wang, 2009). Moreover, the GFI and the adjusted GFI (AGFI) registered values of 0.964 and 0.926, respectively, which was above the suggested level of 0.90 and 0.80, respectively (Wang & Wang, 2009). Furthermore, the comparative fit index (CFI) had a value of 0.953, which exceeded the recommended value of 0.90 (Wang & Wang, 2009). Thus, the values of all fit indices met their recommended levels, meaning that the proposed model was a good fit.

Table 5
Values of fit indices

Notation	Recommended value	Model value
Chi-square/degree of freedom	< 3	1.520
RMSEA	< 0.07	0.023
GFI	> 0.90	0.964
AGFI	> 0.80	0.926
CFI	> 0.90	0.953

Path analysis

As a confirmatory statistical approach, SEM is recommended for examining several different hypotheses of a research model and then individually considering each hypothesis (Hoyle & Smith, 1994; Ullman & Bentler, 2003).

In structural equation modelling, R-squared (R^2) is a good indicator of the model's explanatory power. R^2 refers to the degree of variance explained by the independent variables (Islam & Azad, 2015; Wu & Zhang, 2014). According to Ferguson (2009), in the social sciences, if the R^2 value is higher than 0.64, a strong effect is indicated. Table 6 demonstrates that the R^2 values of the research variables were as follows: 1) R^2 of perceived ease of use = 0.769, 2) R^2 of perceived usefulness = 0.711, 3) R^2 of satisfaction = 0.723, and 4) R^2 of continued intention to reuse = 0.656. These values suggest that the dependent variables were adequately predicted by their antecedents.

The effect size was also calculated to assess the extent to which the dependent variables were influenced by the independent variables (Chin, 1998; J. Cohen, 1988). According to Chin (1998) and Gefen et al. (2000), if the effect size value ranges between 0.02 and 0.150, 0.150 and 0.350, or is greater than 0.350, it indicates that the independent variable has a small, medium or large effect on the dependent variable respectively. Table 6 shows that information quality had a weak effect on perceived usefulness, whereas perceived ease of use and cognitive load had no effect. Concerning perceived ease of use, only service quality had a medium effect. Conversely, system quality, personal innovativeness and computer anxiety had weak effects, whereas cognitive load had no effect. Concerning students' satisfaction, the result demonstrated that both perceived usefulness and perceived ease of use had medium effects, while cognitive load had no effect. Finally, perceived usefulness had a medium effect on students' continued intention to reuse Google Classroom, while perceived ease of use and satisfaction had weak effects on this intention.

In addition, the probability value (*p* value) was used to investigate whether a particular independent construct predicted the dependent constructs, wherein, if the *p* value was equal to or less than 0.05, it meant that the construct was a predictor of the dependent variable (Greenland et al., 2016; Jacobs, 2019). Overall, Table 6 reveals that personal innovativeness, computer self-efficacy, and system quality contributed significantly to perceived ease of use ($p < 0.001$). Moreover, service quality and cognitive load also had a significant influence on perceived ease of use ($p < 0.05$). Moreover, information quality and system quality significantly influenced perceived usefulness ($p < 0.001$). However, perceived ease of use and cognitive load had no significant effect on perceived usefulness ($p > 0.05$). Furthermore, perceived usefulness and perceived ease of use significantly influenced satisfaction ($p < 0.001$), but cognitive load had no significant impact on satisfaction ($p > 0.05$). Finally, perceived usefulness and satisfaction significantly determined students' continued intention to reuse Google Classroom ($p < 0.001$), as did perceived ease of use ($p < 0.05$). Figure 4 illustrates the findings of the hypothesised path analysis.

Table 6
Summary of the findings

Dependent variable	**Path**	**Effect size**	R^2	***P* value**	**Findings**
Perceived usefulness (PU)			0.711		
	Information quality → PU	0.135		0.001	Supported
	System quality → PU	0.204		0.001	Supported
	PEOU → PU	0.000		0.098	Rejected
	Cognitive load → PU	0.000		0.463	Rejected
Perceived ease of use (PEOU)			0.769		
	Service quality → PEOU	0.333		0.012	Supported
	System quality → PEOU	0.026		0.001	Supported
	Personal innovativeness → PEOU	0.035		0.001	Supported
	Computer anxiety → PEOU	0.043		0.001	Supported
	Computer self-efficacy → PEOU	0.060		0.001	Supported
	Cognitive load → PEOU	0.017		0.015	Supported
Satisfaction			0.723		
	Cognitive load → Satisfaction	0.000		0.065	Rejected
	PU → Satisfaction	0.259		0.001	Supported
	PEOU → Satisfaction	0.217		0.001	Supported
Continued intention to reuse			0.656		
	PEOU → Continued intention to reuse	0.023		0.018	Supported
	PU → Continued intention to reuse	0.159		0.001	Supported
	Satisfaction → Continued intention to reuse	0.113		0.001	Supported

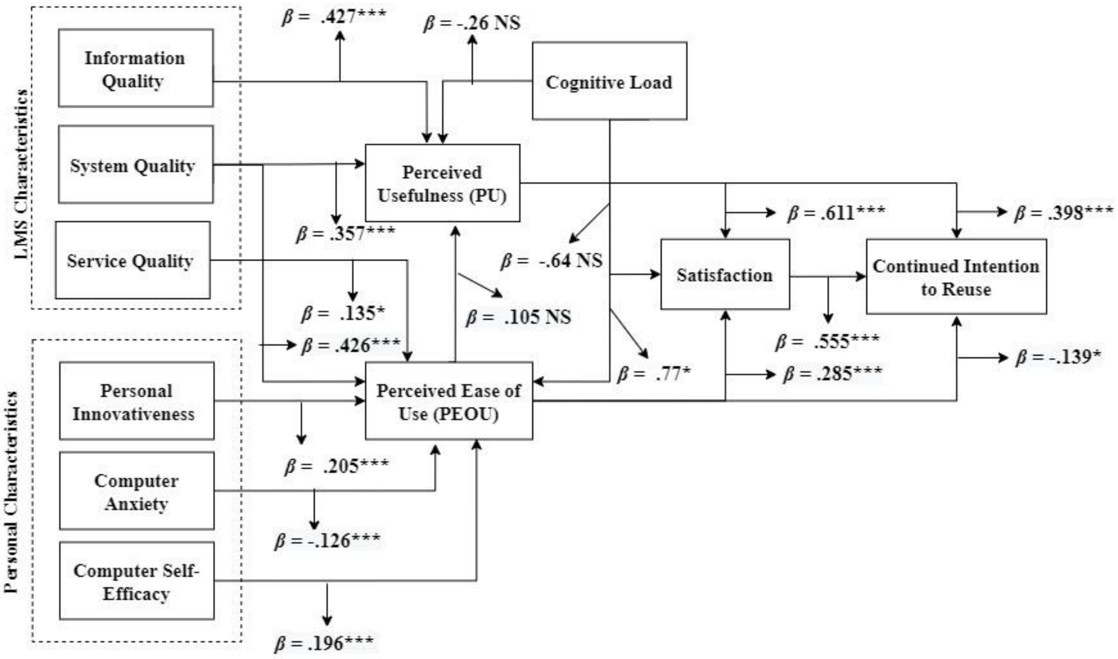

Figure 4. Outcomes of hypotheses tests

Discussion

The key aim of this research was to predict and explain the variables that can influence students' continued intention to reuse Google Classroom. The study proposes an integrated model of TAM, ISSM, cognitive load theory, and individual characteristics, namely, personal innovativeness, computer anxiety, and computer self-efficacy.

The findings show that system quality and information quality significantly affected perceived usefulness. Such results are consistent with previous research (Al-Busaidi, 2012; Wu & Zhang, 2014). This may mean that if LMS technology is reliable and stable, and provides helpful information, students will consider it useful. Additionally, cognitive load and perceived ease of use were not found to have a significant effect on perceived usefulness. This finding is incompatible with the outcomes of Binyamin et al. (2017) and Wu and Zhang (2014), who reported that perceived ease of use had a positive relationship with perceived usefulness. However, it is in line with the results of Ashrafi et al. (2020), which could be attributed to students' limited experience of using Google Classroom, as the overwhelming majority had only about 1 year's experience of e-learning. Besides, the students may have found Google Classroom to be a useful learning platform, regardless of the required cognitive load to process the information.

Concerning perceived ease of use, service quality, personal innovativeness, computer anxiety, computer self-efficacy, system quality, and cognitive load were significant antecedents of perceived ease of use. These observations correspond to outcomes reported by Al-Busaidi (2012) and T. C. Lin and Chen (2012), namely that when students find LMS technology to be stable and to provide effective support, they can recognise its ease of use. The results also reveal that personal characteristics were significant determinants of perceived ease of use. If students are open to experimenting with new learning methods (Al-Busaidi, 2012; Agudo-Peregrina et al., 2014), have no reluctance or hesitation to use computers (Al-Busaidi, 2012; Saadé & Kira, 2009), exhibit confidence in their ability to use computer technology (Binyamin et al., 2017; Yalcin & Kutlu, 2019), and are not overwhelmed with an excessive overflow of information by the learning technology (Paas et al., 2010; Vandewaetere & Clarebout, 2013), they will perceive the technology as easy to use.

The outcomes reveal that students were more likely to feel satisfied with Google Classroom based on its usefulness and ease of use, which is consistent with the results of other studies (Ashrafi et al., 2020; Binyamin et al., 2017; Islam & Azad, 2015; T. C. Lin & Chen, 2012). Such observations suggest that public-sector universities should ensure that their students have enough e-learning or computer experience to use Google Classroom.

The continued intention to reuse Google Classroom appears to be significantly driven by perceived ease of use, perceived usefulness, and satisfaction. These outcomes correspond to the results of prior literature, which concluded that if students recognise LMS technology as easy to use (Al-Busaidi, 2012; Li et al., 2012), useful (Li et al., 2012; Islam & Azad, 2015) and satisfying their learning requirements (Chang, 2013; Dağhan & Akkoyunlu, 2016; Islam & Azad, 2015), they will continue to reuse it in future.

Two interesting remarks can be highlighted here. The cognitive load had no significant relationship with perceived usefulness. Similarly, the cognitive load had no significant effect on students' satisfaction. This could be reasonably credited to the effect of split attention, which occurs when learners obtain information from multiple sources (Florax & Ploetzner, 2010). In this research, the students received their instructions primarily via Google Classroom. In numerous instances, however, they needed to seek and retrieve additional information from textbooks, the Internet, and other written or digital resources. Interaction with physically distanced information (for example, on screen and in print) can result in an extraneous cognitive load that is unnecessary for knowledge construction (Kalyuga, 2012). Another plausible explanation for this, as well as for the high scores that students displayed for cognitive load, could be attributed to the influence of transient information. This issue arises when information disappears before it is appropriately processed by learners (Wong et al., 2012). In the research context, students frequently receive long and complex instructional information. Hence, they can experience difficulties in processing such information, thereby producing further extraneous cognitive load (Leahy & Sweller, 2016).

Conclusion, implications and limitations

At the level of higher education, online learning has received considerable attention. However, most of the literature has primarily focused on initial acceptance of LMSs, with only very few studies examining the variables that could determine students' continued intention to reuse LMSs such as Google Classroom. To address this research gap, the present study extendsTAM with ISSM, cognitive load theory, and personal characteristics, namely, personal innovativeness, computer self-efficacy, and computer anxiety. To validate the proposed framework, an empirical study was conducted, using data gathered from 233 undergraduate students in a public-sector university in Iraq. The findings reveal that system and information quality predicted students' perceived usefulness. In addition, all personal characteristics, system and information quality, and cognitive load had a significant and positive impact on perceived ease of use. However, satisfaction was predicted only by perceived usefulness and perceived ease of use. Finally, the students' continued intention was successfully explained by perceived usefulness, perceived ease of use, and satisfaction.

This study is important from both a theoretical and practical perspective. Theoretically, it provides support for the integration of TAM, ISSM, cognitive load theory, and personal characteristics. To our knowledge, this analysis is one of just a few studies on the continued intention to reuse LMSs based on integrated theories. Thus, this research attempts to provide useful information on the continued intention to reuse educational technologies, potentially enhancing the quality of the teaching and learning experience. In the proposed model, we assume that cognitive load is a predictor of perceived usefulness, perceived ease of use, and satisfaction; however, the research outcomes reveal that it was not a determinant of perceived usefulness or of perceived satisfaction. Accordingly, to understand the role of cognitive load properly and ensure that students are not loaded unnecessary information during the learning process, it is essential to examine what variables could predict cognitive load in an educational learning environment.

Several practical implications may also be inferred from the research outcomes. First, the study demonstrates that personal characteristics significantly explained perceived ease of use. Therefore, LMS developers could consider providing students with a dynamic learning platform that can be adjusted to address learners' individual needs, thereby providing them with a personalised learning experience. This could be achieved by allowing students to construct profiles that correspond to their area of study, background knowledge, and learning styles. Thus, the potential advantages of LMSs could be harnessed more effectively. In addition, D. Lee et al. (2018) argued that learning environments that offer learners a high degree of personalisation were associated with better attitudes and a higher rate of utilisation. By providing personalised learning experiences, LMS developers may help increase the interest of higher education institutes in such learning technologies. Moreover, both learners and instructors would be more receptive towards LMSs.

Second, the findings show that cognitive load did not predict either perceived usefulness or perceived satisfaction. However, it was a significant predictor of perceived ease of use. Hence, instructors need to ensure that the learning content delivered to students is easy to process and comprehend, to satisfy the students' learning goals and improve their perceptions of the usefulness of LMSs (e.g., Google Classroom). To illustrate this further, instructors could form small groups of learners to address the challenges faced by students while learning via LMSs. In groups of this nature, instructors could also encourage students to exchange information and ideas, thereby improving their understanding and enabling them to absorb the learning content effectively. Such interaction could also improve students' communication skills, especially with other peers and instructors.

Finally, the findings demonstrate that perceived ease of use did not predict perceived usefulness. This may indicate that the students benefitted greatly from the Google Classroom platform, regardless of their abilities or experience. The utilisation of the LMS allowed the students to depart from a traditional method of teaching and learning towards a modernised, Internet-based instructional approach. Consequently, the students endeavoured to overcome numerous challenges that are native to online learning adoption in Iraq, such as poor Internet connectivity, lack of experience, and a dysfunctional power grid. As a result, this study helps close the gap with other nations that have made significant progress in their e-learning adoption.

Regardless of the significant outcomes of the present study, as discussed above, it has certain limitations. First, the participants were recruited from just one public-sector university in Iraq. Further studies could therefore be conducted in other public-sector universities to improve the generalisability of the results, or even in other developing countries to compare the findings and further confirm the validity of the proposed model. Second, the proposed model predicted 65.6% of the students' continued intention to reuse Google Classroom. However, studies are encouraged to consider other factors, such as learners' engagement or learning effectiveness. Moreover, the current study did not consider the role of other individual differences. Consequently, additional research is recommended to examine how such variables could produce different outcomes. Finally, the adoption of qualitative analysis would highlight other factors that could affect technology adoption, given that only quantitative analysis was conducted in this research.

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Appendix: The survey items

Construct	Source
System quality Google Classroom offers flexibility as to time and place of use. I have appropriate and sufficient software and hardware on my personal computer to use Google Classroom. I can easily access Google Classroom anytime I need to use it. Google Classroom enables interactive communication between instructors and students. Google Classroom has well-designed user interfaces.	Pituch & Lee (2006); Sharma et al. (2017); W. T. Wang & Wang (2009)
Service quality The services provided by the Google Classroom support team can enhance my ability to use Google Classroom. I can communicate with Google Classroom support when I encounter technical problems and require quick responses. Google Classroom support team can quickly fix my technical problems. The service quality provided by Google Classroom matches my expectations.	Dağhan & Akkoyunlu (2016); W. T. Wang & Wang (2009)
Information quality Google Classroom can provide me sufficient information to enable me to do my assignment tasks. Google Classroom presents the information in an appropriate format. The information contained in Google Classroom is very good. The information from Google Classroom is up to date enough for my learning purposes.	Dağhan & Akkoyunlu (2016); W. T. Wang & Wang (2009)
Perceived ease of use Google Classroom is easy to use. Google Classroom is easy to learn. Google Classroom is easy to access. It is easy for me to become skilled at using Google Classroom. It is easy for me to understand how to perform tasks using Google Classroom.	Davis et al. (1989); Mohammadi (2015); W. T. Wang & Wang (2009)
Perceived usefulness Google Classroom helps to save time. Google Classroom helps to improve my performance. Google Classroom helps to improve my knowledge. Google Classroom helps me to be self-reliable. Overall, I find Google Classroom to be useful.	Davis et al. (1989); Mohammadi (2015); W. T. Wang & Wang (2009)
Personal innovativeness I like to experiment with new information and communication technologies. Among my peers, I am usually the first person to try new technologies. I am not hesitant to try new technologies.	Sharma et al. (2017)

Computer anxiety I believe that working with computers is very difficult. Computers make me feel uncomfortable. Working with a computer would make me very nervous. Computers make me feel uneasy and confused.	Al-Busaidi & Al-Shihi (2012)
Computer self-efficacy I could complete my learning activities using Google Classroom If I had never used a system like it before. I could complete my learning activities using Google Classroom If I had only the system manuals for reference. I could complete my learning activities using Google Classroom If I had seen someone else using it before trying it myself.	Chiu and Wang (2008); W. T. Wang & Wang (2009)
Cognitive load I have difficulty concentrating on the materials presented on Google Classroom platforms. I feel pressure when learning with the materials presented on the Google Classroom platform. I have to put into efforts to understand the functionality of Google Classroom technologies. I have to put into efforts to understand the contents delivered by Google Classroom technologies.	Hsu (2015)
Satisfaction I am generally satisfied with my experience with the use of Google Classroom. My decision to use Google Classroom was a wise one. Google Classroom has met my expectations.	DeLone & McLean (2003); Hussein et al. (2021); Mohammadi (2015)
Continued intention to reuse If I could, I would like to continue using Google Classroom in my learning activities in the future. I will likely continue using Google Classroom in the future. I expect to continue using Google Classroom in the future.	Bhattacherjee (2001)