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The Influence of the Social, Cognitive, and Instructional Dimensions on Technology Acceptance Decisions among College-Level Students

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ABSTRACT
Technology acceptance models are primarily focused on the cognitive dimension of user beliefs. However, researchers have identified a range of situational and contextual factors that influence user attitudes and behavioral intention towards a given technology. We advance a situated model of e-learning acceptance among college students combining factors from the community of inquiry (COI) framework and the technology acceptance model (TAM), specifying core relationships within, and theoretically informed path relationships between the two frameworks. Using a sample of 121 respondents, we test a structural model using generalized structured component analysis. Collectively the situated model helped explain 63.7% variance in Behavioral Intention and 25% of the variance in Use suggesting that our model has strong explanatory power. Policymakers can leverage this information to boost acceptance of e-learning and platforms among their academic communities by promoting e-learning environments with strong Teacher, Social, and Cognitive Presence.

Keywords: community of inquiry, technology acceptance, e-learning

INTRODUCTION

E-learning arose in the latter half of the twentieth century as computing power grew exponentially and the world came online. Now, e-learning is a ubiquitous part of academic institutional mandates. Educational technology researchers have advanced many models to understand the imperatives behind constructivist e-learning environments. The community of inquiry framework (COI) is one of the most highly regarded in constructivist circles for understanding e-learning environments (Garrison, 2016). A COI "establishes procedures for critical inquiry and the collaborative construction of personal meaningful and shared understanding. It represents a process of designing and delivering deep and meaningful learning experiences through the development of three interdependent elements—social presence, cognitive presence and teaching presence" (Garrison, 2017, p.24-5). Social presence "is the ability of participants to identify with a group, communicate openly in a trusting environment, and develop personal and affective relationships" (Garrison, 2017, p.25). Cognitive presence "is a condition of higher-order thinking and learning focused on critical reflection and discourse" (Garrson, 2017, p.25) and refers to the extent that learners are able to construct meaning together through a process of scientific inquiry. Teaching presence concerns "the design, facilitation and direction of cognitive and social processes for the purpose of realizing personally meaningful and educationally worthwhile learning outcomes" (Anderson, Rourke, Garrison & Archer, 2001). In a recent study, a structural equation model of the community of inquiry framework demonstrated strong explanatory power, and confirmed the theorized factor structure and path relationships: teaching and social presence influence cognitive presence and teaching presence influences social presence (Garrison, Cleveland-Innes, & Fung, 2010). However, it is unclear how the three situational dimensions of the COI

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Contribution of this paper to the literature

- We advance a situated model of e-learning acceptance combining factors from the technology acceptance model (TAM) and the community of inquiry framework (COI).
- Our combined model explains 63.7% of variance in Behavioral Intention and 25% in Use.
- Acceptance of e-learning can be boosted by promoting e-learning environments with strong Teacher, Social, and Cognitive Presence.

influence student acceptance of e-learning. It is important to understand how these dimensions interact with learner technology acceptance beliefs to design and deliver e-learning solutions that are acceptable to users.

Competing frameworks of technology acceptance have largely focused on the cognitive dimension, focusing on the antecedent beliefs such as perceived usefulness or ease of use on attitude and behavioral intention for using specific technologies. Perceived usefulness is defined as "the prospective user's subjective probability that using a specific application system will increase his or her job performance" (Davis, Bagozzi & Warshaw, 1989, p.985). Whereas perceived ease of use is defined as "the degree to which the prospective user expects the target system to be free of effort" (Davis, Bagozzi & Warshaw, 1989, p.985). TAM research has largely ignored the influence of situational factors other than perceptions of voluntariness or social norm, "the perceived social pressure to perform or not to perform the behavior" (Azjen, 1991, p.188). However, recent research (Doleck, Bazelais, & Lemay 2017a, 2017b; Lemay, Doleck, & Bazelais, 2017) has argued for a situated perspective and shown how situational variables like belief modalities (e.g., needs vs. wants) influence the context of technology acceptance. User perceptions of the technology acceptance situation can influence user beliefs such that a perceived need such as self-expression or passion, in the case of social media, can have stronger effects on attitudes and behavioral intentions than core TAM factors perceived usefulness or ease of use. In the present study, we advance a situated model of e-learning acceptance among college-level students using a model combining the COI (Garrison, Cleveland-Innes, & Fung, 2010) and the TAM factors (Davis, 1989; Venkatesh, Morris, Davis, & Davis, 2003) and specifying core relations and theoretically informed path relationships specifying interactions between the two constructs.

LITERATURE REVIEW

Community of Inquiry

The COI model is a constructivist framework for understanding e-learning. The COI framework grew out of a need for a research framework that could capture the dimensions of computer conferencing in higher education (Garrison, Anderson, & Archer, 2010). Computer conferencing appeared to be a different kind of learning environment, one where the primary medium of communication was asynchronous and text-based, it was unclear whether it was as effective as oral and face-to-face. It is informed by research in communication, linguistics, and computer conferencing (e-learning) and grounded in Dewey's philosophy of education. The three dimensions of social, cognitive, and teacher presence overlap to create the conditions for an effective e-learning experiences, through supporting discourse, selecting appropriate content, and fostering a supportive climate (Garrison, 2017). The dimensions are complemented with a model of practical inquiry in four phases, triggering event, exploration, integration, and resolution. Teaching presence is central to COI and influences both social and cognitive presence.

Technology Acceptance Model

The TAM is based on the theory of planned behavior and the theory of reasoned action (Ajzen, 1991; Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1975), which posits that an individual's behaviors are a function of intentions and their antecedent beliefs. In the TAM, a user's attitude toward a technology provides a measure of their acceptance of the technology in terms of their behavioral attentions and use of the technology. The TAM is a parsimonious model made up of four core factors: perceived ease of use, perceived usefulness, attitude, and behavioral intention, which influence actual uptake (Davis, Bagozzi, & Warshaw, 1989; Legris, Ingham, & Collerette, 2003; Venkatesh & Davis, 1996). However, the model has been revised and extended, with the inclusion of social norm (Venkatesh & Davis, 2000; Venkatesh et al., 2003). More recently, the TAM has been subject to critical review and meta-analysis (Burton-Jones, & Hubona, 2006; King & He, 2006; Legris, Ingham, & Collerette, 2003; McFarland & Hamilton, 2006; Schepers & Wetzels, 2007; Sun & Zhang, 2006). These reviews find that the core TAM relationships are moderated by situational antecedents (Doleck et al., 2017a; Sun & Zhang, 2006) operating at the individual, social-organizational, and technological levels.

Technology acceptance has been primarily focused on user traits and beliefs, however a series of studies demonstrate (Doleck et al., 2017a, 2017b; Lemay et al., 2017) that situational determinants including personal needs and contextual conditions impact perceptions, attitudes, and behavioral intentions toward use. The TAM and its variants have been used to explore students' acceptance of e-learning and computer-assisted learning (Doleck et al., 2017b; Liaw, 2008; Teo, 2009). These studies support the core TAM constructs in the context of e-learning, that perceived usefulness and ease of use influence attitude and behavioral intention. However, the studies account for less than half the variance in use of e-learning. As the COI literature amply demonstrates, considerations of the social, cognitive, and teacher presence must be factored into our process descriptions of e-learning environments. Simply put, not all e-learning situations are equally effective and some of the variance in technology acceptance may be imputable to such variations in quality of social, cognitive, or teaching presence. We argue that a fuller description of students' perceptions of e-learning can be achieved by combining the COI and TAM frameworks. Indeed, we argue that the COI dimensions capture situational antecedents of effective e-learning environments, and thus can account for the natural variation across different e-learning situations and applications. Below we list the main hypotheses from the core COI and TAM relationships that we seek to reproduce in the present study. Further, we list the hypothesized interactions between the two models, with the situational COI factors as antecedent to the cognitive TAM factors. The hypothesized directions are supported by findings from meta-analysis supporting the moderating influence of situational factors on TAM relationships (Sun & Zhang, 2006).

Core COI relationships (Garrison, Cleveland-Innes, & Fung, 2010):

H1 Teaching presence influences social presence

H2 Teaching presence influences cognitive presence

H3 Social presence influences cognitive presence

Core TAM relationships (Davis, 1989):

H4 Attitude influences behavioral intention

H5 Behavioral intention influences use

H6 Perceived usefulness influences attitude

H7 Perceived ease of use influences attitude

H8 Perceived usefulness influences behavioral intention

H9 Perceived ease of use influences perceived usefulness

Hypothesized interactions:

H10 Cognitive presence influences perceived usefulness

H11 Cognitive presence influences attitude

H12 Social presence influences perceived ease of use

H13 Teaching presence influences attitude

H14 Teaching presence influences behavioral intention

H15 Teaching presence influences use

Purpose

The purpose of this study was to describe the influence of situational factors on college-level students' acceptance of e-learning. Our research question was: "Can a combined COI-TAM model explain a larger amount of variance than the TAM alone?"

METHOD

Theoretical Framework

The present study is framed by situativity theory (Barwise, 1981; Barwise & Perry, 1981; Goffman, 1974; Greeno, 1994; 1998; Wenger, 1998) which is grounded in an interactionist account of human social activity. Rather than in the apposition of the individual to the collective, the interactionist perspective understands human activity as situated, that is, grounded in situations that determine the contours of the activity and that are subject to contextual affordances which enable and constrain beliefs, intentions, and actions (Greeno, 1994; 1998). A situated perspective on technology acceptance stipulates that human behavior is not simply a function of cognitions and beliefs but must be considered within the bounds of human social activity determining the situations and contexts of technology use.

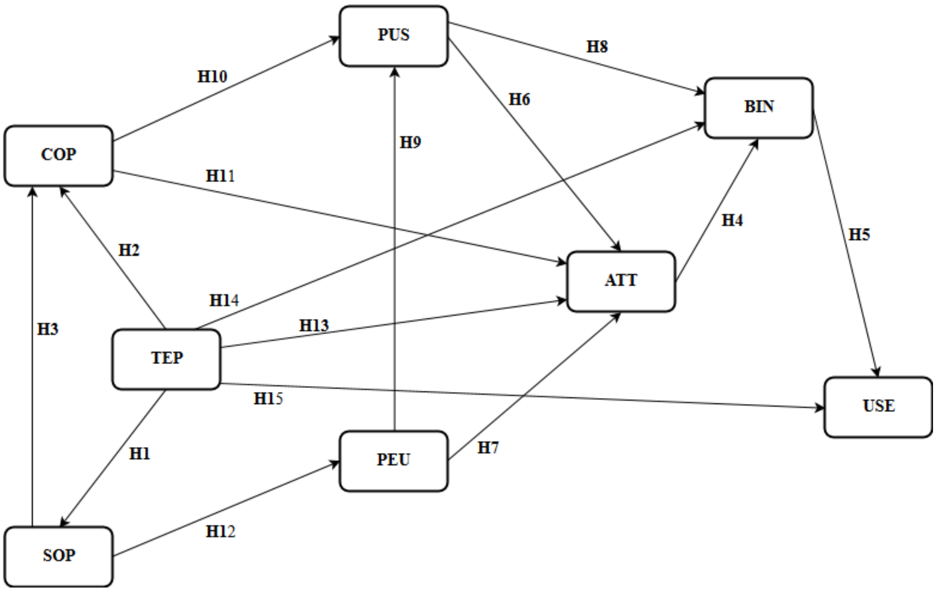

Figure 1. Research Model

Table 1. Constructs and abbreviation

Constructs	Abbreviation
Attitude toward use	ATT
Behavioral Intention	BIN
Perceived Ease of Use	PEU
Perceived Usefulness	PUS
Actual use	USE
Cognitive Presence	COP
Social Presence	SOP
Teaching presence	TEP

Research Design

Using a cross-sectional survey design, we test a structural equation model linking factors from TAM and COI using generalized structured component analysis (GSCA). To conduct data analyses, we employed GSCA due to its appropriateness for analyzing small sample sizes and because it does not require the multivariate normality assumption of indicators (Kim, Cardwell, & Hwang, 2016; Ryoo, & Hwang, 2017). Our proposed research model and hypothesized path relationships are presented in **Figure 1**.

Participants

In the present study, a total of 121 usable responses were included in the final analysis. Respondents ranged between 17 and 20 years of age at the time of the data collection (M = 18.15 and *SD* = 0.78) and gender composition consisted of 72 females and 49 males. Participants were students attending a pre-university college institution in the North-Eastern North America.

Instrument

We constructed a survey combining items from the COI and from the TAM instruments. Items for each construct were selected from the following studies: Perceived Usefulness (Davis et. al, 1989); Perceived Ease of Use (Davis et. al, 1989); Attitude (Taylor & Todd, 1995); Intention (Taylor & Todd, 1995); Use (Porter & Donthu, 2006); Community of Inquiry (Arbaugh et al., 2008).

Analysis

The research model was tested using the generalized structured component analysis (GSCA; Hwang & Takane, 2004) approach in the GeSCA software (Hwang, 2008). The analysis was executed and assessed using the standard two-step modeling approach, namely: measurement and structural model. The constructs and abbreviations are presented in **Table 1**.

Table 2. Model fit statistics

Measure	Values
FIT	0.647
AFIT	0.640
GFI	0.992
SRMR	0.070
NPAR	69

RESULTS

Measurement Model

The fit of the model (**Table 2**) was found to be acceptable according to the criterion suggested by Hwang (2011). GeSCA provides various fit measures. We consider the most widely accepted measure SRMR (an acceptable model fit is determined by an SRMR value ≤.08). Given that SRMR = 0.070 (see **Table 2**), the research model had adequate fit with the data.

The loadings (after dropping low loading values), construct reliabilities (Cronbach's alpha measure), and composite convergent validity (average variance extracted (AVE) test on the variables) are presented in **Table 3**. The estimates were all deemed acceptable according to guidelines in the literature (Hwang, 2011): loadings should exceed the threshold value of 0.70 (Chin, 1998); Cronbach's alpha of the different measures should exceed the recommended threshold value 0.70 (Churchill, 1979); and, AVE of the different measures should exceed the recommended threshold value 0.50 (Fornell & Larcker, 1981).

Table 3. Estimates of loadings, AVE, and Cronbach's alpha

Variable	Loading			Weight			SMC		
	Estimate	SE	CR	Estimate	SE	CR	Estimate	SE	CR
COP				**AVE = 0.666, Alpha =0.499**					
COP2	0.777	0.069	11.32*	0.553	0.050	11.07*	0.604	0.098	6.17*
COP3	0.853	0.032	26.77*	0.668	0.062	10.84*	0.727	0.054	13.54*
TEP				**AVE = 0.613, Alpha =0.840**					
TEP1	0.836	0.035	23.61*	0.246	0.028	8.93*	0.699	0.058	12.1*
TEP2	0.749	0.057	13.15*	0.289	0.030	9.62*	0.561	0.082	6.81*
TEP3	0.795	0.037	21.38*	0.233	0.038	6.17*	0.632	0.058	10.91*
TEP4	0.793	0.053	14.93*	0.305	0.034	8.84*	0.629	0.082	7.66*
TEP5	0.738	0.059	12.59*	0.204	0.031	6.65*	0.544	0.083	6.52*
SOP				**AVE = 0.735, Alpha =0.625**					
SOP1	0.852	0.032	26.97*	0.574	0.044	13.04*	0.726	0.053	13.71*
SOP4	0.862	0.030	28.29*	0.593	0.043	13.66*	0.744	0.052	14.32*
PUS				**AVE = 0.680, Alpha =0.882**					
PUS1	0.781	0.048	16.33*	0.233	0.021	11.17*	0.609	0.073	8.3*
PUS2	0.845	0.034	25.19*	0.263	0.026	10.13*	0.713	0.056	12.7*
PUS3	0.861	0.028	30.32*	0.227	0.029	7.71*	0.742	0.048	15.3*
PUS4	0.853	0.031	27.21*	0.224	0.027	8.3*	0.727	0.053	13.81*
PUS5	0.780	0.052	15.1*	0.270	0.022	12.04*	0.608	0.080	7.59*
PEU				**AVE = 0.735, Alpha =0.907**					
PEU1	0.859	0.025	34.3*	0.226	0.025	9.08*	0.738	0.043	17.17*
PEU2	0.838	0.028	30.19*	0.189	0.025	7.44*	0.702	0.047	15.03*
PEU3	0.891	0.019	47.22*	0.232	0.027	8.53*	0.794	0.034	23.68*
PEU4	0.868	0.030	28.84*	0.270	0.026	10.33*	0.753	0.052	14.6*
PEU5	0.830	0.032	25.62*	0.248	0.025	9.98*	0.689	0.054	12.88*
ATT				**AVE = 0.828, Alpha =0.931**					
ATT1	0.926	0.018	52.73*	0.327	0.031	10.53*	0.858	0.032	26.56*
ATT2	0.865	0.032	27.08*	0.195	0.027	7.26*	0.749	0.055	13.71*
ATT3	0.933	0.013	72.29*	0.254	0.053	4.79*	0.871	0.024	36.23*
ATT4	0.913	0.017	53.24*	0.319	0.039	8.13*	0.834	0.031	26.8*
BIN				**AVE = 0.925, Alpha =0.923**					
BIN1	0.981	0.005	180.16*	0.654	0.040	16.39*	0.962	0.011	90.29*
BIN2	0.943	0.015	64.16*	0.380	0.040	9.43*	0.889	0.028	32.21*
USE				**AVE = 0.870, Alpha =0.854**					
USE1	0.955	0.010	98.38*	0.621	0.041	15.1*	0.912	0.018	49.37*
USE2	0.911	0.023	39.33*	0.447	0.039	11.51*	0.829	0.042	19.9*

*Note. CR** = significant at .05 level

Finally, discriminant validity was established via the Fornell-Larcker criterion (Fornell & Larcker, 1981). In **Table 4** (which presents the correlations of latent variables), the Fornell-Larcker criterion is met when all the diagonal values (the square root of the AVEs highlighted in bold) are greater than the off-diagonal numbers in the corresponding rows and columns. Thus, the criterion for discriminant validity was satisfied.

Table 4. Discriminant Validity Check

	Correlations of Latent Variables (SE)							
	COP	TEP	SOP	PUS	PEU	ATT	BIN	USE
COP	**0.816**	0.562	0.472	0.404	0.268	0.298	0.298	0.304
TEP	0.562	**0.783**	0.546	0.262	0.161	0.122	0.118	0.139
SOP	0.472	0.546	**0.857**	0.326	0.350	0.328	0.211	0.133
PUS	0.404	0.262	0.326	**0.825**	0.675	0.746	0.645	0.393
PEU	0.268	0.161	0.350	0.675	**0.857**	0.713	0.602	0.328
ATT	0.298	0.122	0.328	0.746	0.713	**0.910**	0.794	0.440
BIN	0.298	0.118	0.211	0.645	0.602	0.794	**0.962**	0.494
USE	0.304	0.139	0.133	0.393	0.328	0.440	0.494	**0.934**

Table 5. R^2 of Latent Variables

Measure	Values
COP	0.354
TEP	0
SOP	0.299
PUS	0.510
PEU	0.122
ATT	0.644
BIN	0.637
USE	0.250

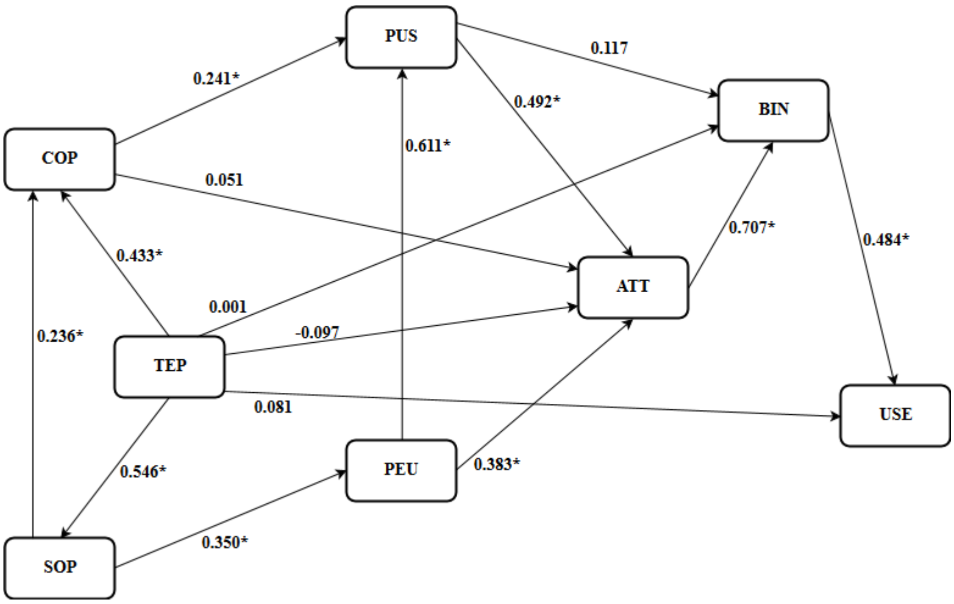

Figure 2. Path analysis results
* Significant at .05 level

After establishing the reliability and validity of the measurement model, we proceed to the structural model.

Structural Model

The structural model was examined to assess the significance of each hypothesized path in the research model. Specifically, the following were examined: the estimates of coefficients of determination (R^2), path coefficients, and the critical ratios (CR). The R^2 values of the endogenous latent variables are presented in **Table 5**. The antecedent variables helped explain 63.7% variance in behavioral intention and 25% of the variance in use. In testing the research hypotheses, the CR values were used to determine the significance of each path. The results of the path analysis are presented in **Figure 2**.

The results of the hypotheses testing are provided in **Table 6**. A total of 10 out of 15 hypotheses were supported by the data.

Table 6. Hypothesis Testing

Hypotheses	Path	Estimate	SE	CR	Result
H1	**TEP→SOP**	0.546	0.071	7.72*	Supported
H2	**TEP→COP**	0.433	0.098	4.42*	Supported
H3	**SOP→COP**	0.236	0.109	2.16*	Supported
H4	**ATT→BIN**	0.707	0.097	7.26*	Supported
H5	**BIN→USE**	0.484	0.078	6.23*	Supported
H6	**PUS→ATT**	0.492	0.091	5.39*	Supported
H7	**PEU→ATT**	0.383	0.074	5.2*	Supported
H8	**PUS→BIN**	0.117	0.105	1.12	Not Supported
H9	**PEU→PUS**	0.611	0.079	7.78*	Supported
H10	**COP→PUS**	0.241	0.081	2.98*	Supported
H11	**COP→ATT**	0.051	0.078	0.66	Not Supported
H12	**SOP→PEU**	0.350	0.066	5.3*	Supported
H13	**TEP→ATT**	-0.097	0.068	1.41	Not Supported
H14	**TEP→BIN**	0.001	0.074	0.01	Not Supported
H15	**TEP→USE**	0.081	0.066	1.22	Not Supported

*Note. CR** = significant at .05 level

DISCUSSION

An interesting picture emerges from the addition of the COI factors as situational antecedents to the TAM. For COI, all the core COI relationships were supported as well as both H10 COP→PUS and H12 SOP→PEU between the two models. The core COI and TAM path relationships have been reproduced in earlier e-learning models (Garrison, Cleveland-Innes, & Fung, 2010; Liew, 2008; Teo, 2009).

For TEP both H1 TEP→SOP and H2 TEP→COP were supported. TEP did not have a direct impact on TAM factors. Of the COP, only H10 COP→PUS was supported, H11 COP→ATT was not supported. Thus, we find that teacher presence only has an indirect influence on attitudes and behavioral intention as it is mediated by social presence to perceptions of ease of use and from cognitive presence to perceptions of usefulness.

All the original TAM constructs and relationships were supported except for H8 PUS→BIN which was not supported. The absence of a link from perceived usefulness to behavioral intention and the unsupported relation H11 COP→ATT taken together suggests that the e-learning context only indirectly influences attitudes and behavioral intentions. Social, cognitive, and teaching presences influence perceptions of usefulness and ease of use but do not directly influence attitudes or behavioral intentions toward e-learning. However, the antecedent variables collectively helped explain 63.7% variance in behavioral intention and 25% of the variance in use suggesting nonetheless that our model has strong explanatory power. TAM formulations generally explain less than half the variance (Venkatesh et al., 2003). The integration of COI adds variance explained by situational antecedents with respect to behavioral intentions and to a lesser extent use. We interpret the difference between behavioral intentions and use by invoking students' limited agency in e-learning offerings. Although the situation has improved, instructional programs are overwhelmingly offered through face-to-face meetings, and despite the rise of MOOCs, students have limited choice in opting for e-learning over classroom learning at most traditional colleges or universities. In forced-choice contexts, behavioral intention takes on a slightly different connotation, as technology acceptance refers more to an appreciation rather than an intention to use. In other words, confronted with having to use e-learning platform in a course context, a behavioral intention may be understood as an intention to capitalize on the platform's affordances for learning. However, in the literature, variance explained in use is generally lower than behavioral intention, reflecting the difference between saying one will do x and actually doing x. Given the situational links to COI, we can understand students' behavioral intention to accept e-learning as grounded in the dimensions of teacher, social, and cognitive presences. Their decisions are not solely grounded in perceptions of usefulness and ease of use as these are influenced by the e-learning context afforded by the three presences. All core TAM factors are moderated at least indirectly by the teacher's decisions and actions for creating a supportive social and cognitive presence in the e-learning environment. This is interesting in light of another recent study (Doleck, Bazelais, & Lemay, 2018) demonstrating no link between social norm, self-efficacy, and perceived usefulness in e-learning situations, suggesting that some of the variance in technology acceptance of e-learning is attributable to determinants in the learning environment that transcend particular technological affordances and concern the overall effectiveness of the e-learning situations created and maintained by the teacher. Thus, not all e-learning environments can be considered interchangeable from a technology standpoint as they depend heavily on social, cognitive, and teacher presence. Indeed, it appears that the cognitive and social presence that the teacher creates in the e-learning environment influences perceptions of usefulness and ease of use of e-learning technology.

A series (Doleck et al., 2017a, 2017b; Lemay et al., 2017; Lemay, Morin, Bazelais, & Doleck, 2018) of studies has argued for a situated perspective on technology acceptance and demonstrated that situational determinants have an important influence on user beliefs. Perceived needs like a desire for self-expression, or following a passion, can exert a stronger influence on technology acceptance decisions compared to core factors like perceived usefulness or perceived ease of use. In the present study, we combined the TAM with the COI to capture the influence of the e-learning environment on technology acceptance beliefs. We observed a strong influence from the teacher dimension, mediated by the social and cognitive dimensions, of the e-learning situation on beliefs about e-learning's ease of use and usefulness. Policymakers can leverage this information to boost acceptance of e-learning and platforms among their academic communities by promoting e-learning environments with strong teacher, social, and cognitive presence.

Limitations

This study is limited by its cross-sectional nature and its reliance on a convenience sample. It's based on self-report data that can affect its reliability. We did not query past experiences or check conceptions of e-learning although these almost certainly influenced the way students responded.

Conclusions and Future Direction

More research is needed to develop a situated model of technology acceptance across different technologies and use contexts. Although originally formulated for the adoption of computer-based technologies, the TAM is first grounded on individual beliefs, but it can be extended to understanding technology acceptance situations more broadly. Its roots in theories of action, suggests that the TAM can and really ought to be applied to the uptake of other forms of technology, from physical to intellectual tools, in human social activity generally, and in learning applications specifically. More longitudinal work is needed that can trace the uptake of technologies over time.

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