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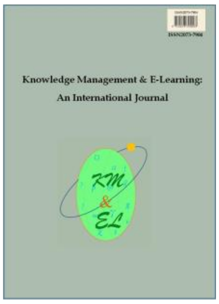

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Abstract: e-Learning acceptance has received considerable attention in the educational technology literature. In recent years, many frameworks have been proposed, modified, and applied to better understand the factors underlying students' acceptance of e-learning. Despite the important progress made with the acceptance literature, extant empirical examinations have unfortunately often produced discordant findings. Researchers frequently advance situational factors as possible moderating influences on technology to explain the high degree of variance unexplained in specific technology acceptance situations. Generalized models have been proposed that attempt to integrate situational variables to account for the high degree of situational variability that occurs across technology acceptance contexts. Abdullah and Ward proposed such a general extended technology acceptance model in the context of e-learning (GETAMEL). In the current paper, our objective is to quantitatively evaluate the GETAMEL, and consider it with respect to a situative perspective on technology acceptance in order to more fully characterize the dynamical relationships and situational factors influencing determinants of e-learning acceptance. This study, drawing on a survey of 132 college students, validates the GETAMEL employing a partial least square path modeling approach.

Keywords: Technology acceptance; e-Learning; CEGEP; Antecedents of technology use; Generalized models

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1. Introduction

What factors affect acceptance of e-learning? A considerable body of work has investigated the salient antecedents to e-learning acceptance (Chen & Tseng, 2012; Cheung & Vogel, 2013; Dečman, 2015; Doleck, Bazelais, & Lemay, 2017a; Lee, 2010; Liu, Liao, & Pratt, 2009; Park, 2009; Šumak, Heričko, & Pušnik, 2011). The general approach in this stream of work is to invoke an acceptance framework that explicates the impact that users' beliefs have on actual use and/or behavioral intention (in cases of absence of a measure of actual use). Among the gamut of technology acceptance frameworks, the technology acceptance model (TAM) (Davis, 1989) continues to enjoy much application and coverage (Abdullah & Ward, 2016; Bagozzi, 2007; Bazelais, Doleck, & Lemay, 2018). Early contributions using the TAM revealed the need for mitigating the limitations of the parsimonious characteristic of the TAM by accommodating additional external variables (Bagozzi, 2007; Legris, Ingham, & Collerette, 2003). In extending Davis' seminal work on the TAM, research has evolved by augmenting the model with various external factors to suit varied purposes and contexts (Abbad, Morris, & De Nahlik, 2009; Doleck, Bazelais, & Lemay, 2017b, 2017c; Lee, Hsieh, & Hsu, 2011; Lemay, Doleck, & Bazelais, 2017; Roca, Chiu, & Martínez, 2006; Sánchez & Hueros, 2010; Teo, Doleck, & Bazelais, 2017) resulting in innumerable different compositions of the TAM. However, much of the resultant literature—as is the case with the e-learning acceptance literature—has tended to present several limitations, as well as mixed findings (Liu et al., 2009; Šumak et al., 2011). Extant efforts have posed issues of non-generalizability, and underscored the importance and need for generalized frameworks. Thus, the formulation of adequately generalizable model that extends the core TAM factors, and that can explain more variability remains an important objective in this area.

A large literature in technology acceptance has focused on e-learning acceptance using the TAM and extended variations of it (Cheung & Vogel, 2013; Lee, Yoon, & Lee, 2009; Park, 2009; Persico, Manca, & Pozzi, 2014; Lee, Hsieh, & Hsu, 2011; Roca, Chiu, & Martínez, 2006; Sánchez & Hueros, 2010). Yet such studies do not provide much accordant evidence. Borne from such concerns, Abdullah and Ward (2016) brought together the empirical evidence, synthesizing the disparate pieces together via a meta-analysis, and proposed the general extended technology acceptance model for e-learning (GETAMEL). This generalized model has the potential to provide an accessible and calibrated framework for comparing e-learning acceptance as such a framework holds the potential of producing relatively consistent and comparable results on learners' acceptance behaviors. However, it should be noted that the authors did not empirically validate the model in their formulation. Thus, we undertake the empirical validation task using a sample of *Collège d'enseignement général et professionnel* (CEGEP) students (Bazelais, Lemay, & Doleck, 2016). The aim of the present study is to answer the following research question: Is a General Extended Technology Acceptance Model Generalizable to a CEGEP population?

2. Background

As technology rapidly advances and transforms landscapes and practices across fields and in almost every facet of daily life, it should not be surprising that learners are increasingly relying on technology to support and facilitate their learning. e-Learning has been referred to as initiatives "which provide learning material in online repositories, where course interaction and communication and course delivery are technology mediated" (Johnson, Hornik, & Salas, 2008, p. 357) or, simply stated, as the "use of information and communications technology (ICT) in learning and teaching" (McGill, Klobas, & Renzi, 2014, p. 24). E-learning has garnered substantial interest and represents an important development in both technology-enhanced and learner-directed learning. In response, there has been growing emphasis and substantial upsurge in research contributions on e-learning. Indeed, in teaching and learning, research suggests that e-learning can: encourage self-management of learning; reduce costs; provide freedom and flexibility in learning; require less reliance on lecturers' time constraints; support and make dialogue between students and teachers more efficient; improve accessibility and availability of learning resources; enable on-demand training; and, complement face-to-face activities (Bell & Federman, 2013; Bouhnik & Marcus, 2006; Mohammadyari & Singh, 2015).

However, many issues and concerns have been identified, such as high attrition rates, underutilization, and in some cases poor satisfaction (Bell & Federman, 2013; Hong, Tai, Hwang, Kuo, & Chen, 2017; Tyler-Smith, 2006), that hinder the realization of the potential of e-learning and sustainability of e-learning (McGill et al., 2014). e-Learning's effectiveness, according to Bell and Federman (2013), "depends on how well it is designed to create the instructional experience that makes learning possible" (p. 170). A better understanding of factors that either impede or promote students' use of e-learning can provide instructional technology designers better guidelines for e-learning design and development. To the extent that acceptance and continued use of e-learning matter, examining and understanding the underlying mechanism that drives learners' e-learning acceptance—that is, the factors that affect the adoption and use of e-learning—becomes particularly salient.

2.1. e-Learning acceptance

Information systems literature has focused on the ever-increasing role of understanding the drivers of technology adoption (Legris et al., 2003; Taylor & Todd, 1995; Venkatesh, Thong, & Xu, 2012). There has been considerable work on mechanisms to explain IT acceptance and this stream of work has attracted attention and stimulated interest from other fields as well (Basnet, Doleck, Lemay, & Bazelais, 2018; Williams, Rana, & Dwivedi, 2015). There is now a general recognition and acknowledgement of the relevance and importance of understanding e-learning acceptance (Dečman, 2015; Park, 2009; Doleck, Bazelais, & Lemay, 2017d) and e-learning acceptance has become an active research strand in recent years in the educational technology literature. A better understanding of e-learning acceptance could contribute to "help teachers and vendors design strategies that are more likely to increase the use of e-learning" (Lee, 2010, p. 506).

The essence of technology acceptance is to unearth the drivers of technology use. Much of the e-learning acceptance literature draws from early and influential acceptance models such as the Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975), Theory of Planned Behavior (TPB) (Ajzen, 1991), and Technology Acceptance Model (TAM). Among the models, the TAM has been highly regarded and continues to enjoy much favor in the educational technology literature (Marangunić & Granić, 2014). Following the calls to augment the TAM by incorporating additional variables (Bagozzi, 2007; Legris et al., 2003), the subsequent literature has mainly focused on the overarching goal of accommodating and addressing the saliency and fit of external variables—such as accessibility, design of learning contents, instructor characteristics, teaching materials, playfulness, self-efficacy, subjective norm, to name but a few—for explicating e-learning acceptance with greater contextual specificity (Lee et al., 2009; Mcfarland & Hamilton, 2006; Park, 2009). While the core elements of the TAM exhibit some stability, refinement exercises introducing external variables have presented inconsistent and mixed findings, in part because departures from the original formulation of the TAM have resulted in widely varied models, causing much of the misalignment. Previous reviews have attempted to inventory exogenous moderating factors to help formulate more generalized models (Burton-Jones & Hubona, 2006; King & He, 2006; Sun & Zhang, 2006), and have distinguished between internal and external factors, or individual, organizational, and technology factors. It has been found that external factors can often have stronger effects than the core TAM constructs (Lemay, Doleck, & Bazelais, 2017) suggesting that the full-mediation of the core concepts is overstated (Burton-Jones & Hubona, 2006). In previous studies of social media acceptance (e.g. Doleck et al., 2017b; Lemay et al., 2017), we have advanced a situative model of technology acceptance and have shown that attention to situative factors like modalities of beliefs explains a greater amount of variance than the core model alone.

2.2. General extended technology acceptance model for e-learning (GETAMEL)

The theoretical basis for the GETAMEL is the well documented TAM proposed by Davis (1989). The TAM posits that users' behavioral intentions predict actual use. The TAM entails three key belief constructs: perceived ease of use influences both perceived usefulness and attitude toward use directly, while exerting indirect influence on behavioral intentions; perceived usefulness influences both attitude toward use and behavioral intentions; and, attitude toward use is an immediate determinant of behavioral intention, that is in turn influenced by both perceived ease of use and perceived usefulness. In sum, the following constructs compose the original TAM: perceived usefulness (PUS), perceived ease of use (PEU), attitude toward use (ATT), behavioral intentions (BIN), and actual use (USE).

Abdullah and Ward (2016) conducted a meta-analysis by synthesizing the literature on e-learning acceptance drawing on the TAM as the foundational theorizing mechanism, and paid special attention to and consider the saliency of various external variables—as justified by the literature—to develop a generalized model for studying e-learning acceptance behaviors. The following constructs compose the external variables: computer anxiety, enjoyment, experience, self-efficacy, and subjective norm. They delineated the elements and formalized the model as depicted in Fig. 1. Below are the link specifications as stipulated in the GETAMEL. The variables in the original TAM include: perceived usefulness, perceived ease of use, attitudes, behavioral intentions, and actual use. The causal mechanisms of the original relationships are delineated as follows:

H1*: PUS is positively related to ATT*

H2*: PUS is positively related to BIN*

H3*: PEU is positively related to PUS*

H4*: PEU is positively related to ATT*

H5*: ATT is positively related to BIN*

H6*: BIN is positively related to USE*

Considering the external constructs of computer anxiety (ANX), enjoyment (ENJ), experience (EXP), self-efficacy (SEF), and subjective norm (SNM) in the TAM, the following link specifications were posited:

H7*: ANX is negatively related to PEU*

H8*: ENJ is positively related to PEU*

H9*: EXP is positively related to PEU*

H10*: SEF is positively related to PEU*

H11*: SNM is positively related to PEU*

H12*: ENJ is positively related to PUS*

H13*: EXP is positively related to PUS*

H14*: SEF is positively related to PUS*

H15*: SNM is positively related to PUS*

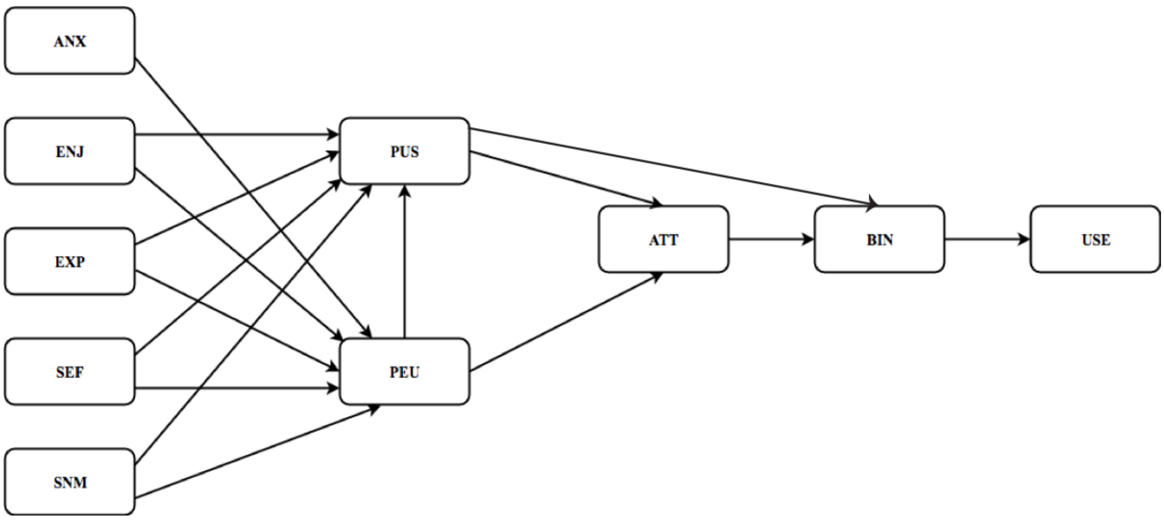

Fig. 1. GETAMEL. Adapted from Abdullah and Ward (2016)

The model (Fig. 1) is provided as a framework that explicates the drivers of e-learning acceptance. However, the model has not yet been quantitatively evaluated yet—this is what we set out to do.

3. Methodology

3.1. Procedure and participants

In this cross-sectional study, students enrolled in pre-university science program at an English CEGEP in Montreal were invited to participate in the study. Participants responded to a questionnaire developed for assessing the constructs in the GETAMEL model. The questionnaires were administered to and completed by students during class hours. Students' participation in the study was voluntary. To ensure anonymity, students did not identify themselves. Additionally, no incentives were offered for participation. We received usable data from 132 students, which formed the sample for the final analyses. The convenience sample for the current study was comprised of 62 females and 70 males. Participants' had an average age of 17.93 years (*SD*=1.14).

3.2. Materials

This study employed a survey instrument for specifying the factors affecting e-learning acceptance, developed using items published in the literature on technology acceptance (Chen, & Tseng, 2012; Compeau & Higgins, 1995; Davis, 1989; Porter & Donthu, 2006; Taylor & Todd, 1995; Yi & Hwang, 2003). All items were scored on a 7-point Likert-type rating scale (1=*strongly disagree* to 7=*strongly agree*). The questionnaire also included questions on demographic characteristics (e.g., age and gender).

4. Data analysis and results

Partial Least Squares Structural Equation Modeling (PLS-SEM) (Henseler, Hubona, & Ray, 2016) has now become commonplace in the educational technology literature because of the affordances of the approach. We used PLS-SEM to test the hypothesized associations between the constructs. In the present study, all analyses were carried out using the WarpPLS tool (Kock, 2015a, 2015b). Some rules of thumb are proffered in the literature for ascertaining the sample size for conducting PLS analysis. We followed the guidelines prescribed by Hair, Ringle, and Sarstedt (2011): "(1) ten times the largest number of formative indicators used to measure one constructor (2) ten times the largest number of structural paths directed at a particular latent construct in the structural model" (p. 144). The sample size (*N*=132) in the present study was deemed adequate for conducing PLS analysis. We followed the standard two-step modeling process: measurement model and structural model (Gefen, Straub, & Boudreau, 2000; Hair et al., 2011; Henseler et al., 2016; Kock, 2015b).

4.1. Measurement model

The constructs in the research model are presented in Table 1. We examined model fit using multiple global fit indices (Table 2); we found acceptable fit of the data to the hypothesized model (Kock, 2015b).

The reliabilities for items are reported in Table 3. They were measured via the factor loadings, which all exceeded 0.70 (Chin, 1998), presenting a good indicator of the instrument's reliability. The composite reliability coefficients of the different measures (see Table 4) all exceeded the threshold value of 0.70 (Gefen et al., 2000). The Cronbach's alpha coefficients of the different measures (see Table 4) all exceeded the threshold value of 0.70 (Churchill, 1979). Thus, the reliability of the indicators was demonstrated. Composite convergent validity was assessed through the average variance extracted (AVE) test on the variables; all AVEs (see Table 4) exceeded the recommended threshold value 0.50 (Fornell & Larcker, 1981).

Table 1
Constructs

Constructs	Abbreviation
Perceived Usefulness	PUS
Perceived Ease of Use	PEU
Attitude	ATT
Behavioural Intention	BIN
Use	USE
Computer Anxiety	ANX
Enjoyment	ENJ
Experience	EXP
Self-Efficacy	SEF
Subjective Norm	SNM

Table 2
Model fit statistics

Measure	Values	Recommended
Average path coefficient (APC)	0.282, $p < .001$	Acceptable if $p < .05$
Average R-squared (ARS)	0.521, $p < .001$	Acceptable if $p < .05$
Average adjusted R-squared (AARS)	0.510, $p < .001$	Acceptable if $p < .05$
Average block VIF (AVIF)	1.590	Acceptable if <= 5
Average full collinearity VIF (AFVIF)	2.516	Acceptable if <= 5

Table 4
Measurement scale characteristics

Construct	Composite reliability (CR)	Cronbach's alpha coefficients	Average variance extracted (AVE)
EXP	1.000	1.000	1.000
SNM	0.954	0.904	0.913
ENJ	0.960	0.938	0.889
ANX	0.900	0.831	0.750
SEF	0.932	0.902	0.774
PUS	0.928	0.903	0.721
PEU	0.935	0.913	0.743
ATT	0.946	0.923	0.814
BIN	0.974	0.946	0.949
USE	0.970	0.938	0.941

Table 3
Loadings of measurement items

	EXP	SNM	ENJ	ANX	SEF	PUS	PEU	ATT	BIN	USE	*p* value
EXP	**1.000**	0.000	-0.000	0.000	0.000	-0.000	-0.000	0.000	0.000	-0.000	<0.001
SNM1	-0.028	**0.955**	-0.037	0.011	-0.043	0.026	0.087	-0.005	-0.093	0.043	<0.001
SNM2	0.028	**0.955**	0.037	-0.011	0.043	-0.026	-0.087	0.005	0.093	-0.043	<0.001
ENJ1	-0.019	-0.033	**0.946**	-0.014	-0.002	0.041	0.121	-0.055	-0.037	0.147	<0.001
ENJ2	-0.036	0.032	**0.940**	-0.003	-0.069	-0.010	0.047	-0.110	-0.072	-0.053	<0.001
ENJ3	0.055	0.001	**0.943**	0.017	0.071	-0.032	-0.168	0.164	0.109	-0.095	<0.001
ANX1	-0.090	0.085	-0.165	**0.809**	0.133	-0.117	-0.073	0.357	-0.273	0.047	<0.001
ANX2	0.049	-0.070	0.302	**0.858**	-0.146	0.068	0.079	-0.292	0.039	0.013	<0.001
ANX3	0.033	-0.010	-0.136	**0.927**	0.019	0.039	-0.010	-0.041	0.202	-0.054	<0.001
SEF1	-0.054	-0.024	-0.185	0.168	**0.846**	-0.122	0.151	0.061	0.306	-0.025	<0.001
SEF2	-0.036	-0.011	0.154	0.095	**0.892**	0.033	0.206	-0.172	-0.045	0.038	<0.001
SEF3	0.042	-0.009	0.135	-0.151	**0.891**	0.078	-0.199	0.097	-0.194	-0.035	<0.001
SEF4	0.045	0.043	-0.114	-0.103	**0.889**	0.005	-0.150	0.018	-0.051	0.019	<0.001
PUS1	-0.067	-0.049	-0.064	0.036	-0.052	**0.824**	0.030	-0.107	0.140	0.041	<0.001
PUS2	0.072	0.040	-0.190	-0.069	-0.083	**0.848**	-0.077	0.231	0.092	0.081	<0.001
PUS3	-0.014	0.058	0.295	0.065	-0.006	**0.843**	-0.026	-0.239	-0.268	0.100	<0.001
PUS4	-0.086	0.018	0.092	-0.088	0.089	**0.872**	-0.065	-0.061	-0.230	0.057	<0.001
PUS5	0.095	-0.068	-0.134	0.059	0.048	**0.856**	0.140	0.173	0.272	-0.276	<0.001
PEU1	-0.087	-0.083	0.024	0.041	-0.075	-0.025	**0.843**	-0.153	0.302	-0.237	<0.001
PEU2	-0.050	-0.017	-0.449	0.090	0.246	-0.053	**0.878**	0.273	0.131	-0.096	<0.001
PEU3	0.075	0.011	-0.058	-0.048	0.049	0.063	**0.893**	-0.114	-0.066	0.169	<0.001
PEU4	0.047	0.027	0.357	-0.083	-0.256	0.079	**0.876**	-0.173	-0.290	0.240	<0.001
PEU5	0.012	0.062	0.138	0.002	0.034	-0.070	**0.818**	0.174	-0.068	-0.094	<0.001
ATT1	-0.011	-0.002	-0.148	-0.073	-0.152	0.078	0.171	**0.902**	0.121	-0.049	<0.001
ATT2	0.031	0.100	-0.006	0.016	0.158	-0.173	-0.148	**0.868**	-0.340	0.054	<0.001
ATT3	-0.094	-0.031	0.015	0.042	-0.036	0.034	0.113	**0.927**	0.143	0.005	<0.001
ATT4	0.077	-0.061	0.138	0.015	0.036	0.053	-0.144	**0.910**	0.059	-0.007	<0.001
BIN1	-0.006	0.019	0.026	0.022	0.022	0.020	-0.043	0.006	**0.974**	0.048	<0.001
BIN2	0.006	-0.019	-0.026	-0.022	-0.022	-0.020	0.043	-0.006	**0.974**	-0.048	<0.001
USE1	0.016	-0.000	0.038	-0.036	-0.002	-0.038	0.009	0.007	0.029	**0.970**	<0.001
USE2	-0.016	0.000	-0.038	0.036	0.002	0.038	-0.009	-0.007	-0.029	**0.970**	<0.001

Discriminant validity was assessed using the Fornell-Larcker criterion (Fornell & Larcker, 1981). Table 5 illustrates that the Fornell-Larcker criterion is met, as all the diagonal values are greater than the off-diagonal numbers in the corresponding rows and columns.

Overall, the acceptability of the psychometric properties of the measurement model was established.

Table 5
Discriminant validity check

	EXP	SNM	ENJ	ANX	SEF	PUS	PEU	ATT	BIN	USE
EXP	**1.000**	0.083	0.164	-0.034	0.121	0.206	0.218	0.211	0.235	0.151
SNM	0.083	**0.955**	0.353	0.040	0.297	0.272	0.145	0.329	0.326	0.318
ENJ	0.164	0.353	**0.943**	-0.069	0.573	0.664	0.519	0.787	0.713	0.541
ANX	-0.034	0.040	-0.069	**0.866**	-0.232	-0.066	-0.265	-0.085	-0.173	0.015
SEF	0.121	0.297	0.573	-0.232	**0.880**	0.451	0.712	0.466	0.451	0.391
PUS	0.206	0.272	0.664	-0.066	0.451	**0.849**	0.473	0.774	0.622	0.504
PEU	0.218	0.145	0.519	-0.265	0.712	0.473	**0.862**	0.593	0.429	0.370
ATT	0.211	0.329	0.787	-0.085	0.466	0.774	0.593	**0.902**	0.714	0.535
BIN	0.235	0.326	0.713	-0.173	0.451	0.622	0.429	0.714	**0.974**	0.664
USE	0.151	0.318	0.541	0.015	0.391	0.504	0.370	0.535	0.664	**0.970**

4.2. Structural model

Having established the adequacy of the measurement model, the structural model was evaluated to test the relationship between the constructs. The variance inflation factors (VIFs) between the constructs were checked to detect multicollinearity. Since all VIFs were below the suggested threshold of 5, multicollinearity was not an issue (Kock, 2015b). Furthermore, the predictive relevance associated with each endogenous variable in the model was assessed and all Q^2 coefficient values were greater than zero, demonstrating an acceptable level of predictive relevance (Kock, 2015b). The path estimation results are illustrated in Fig. 2.

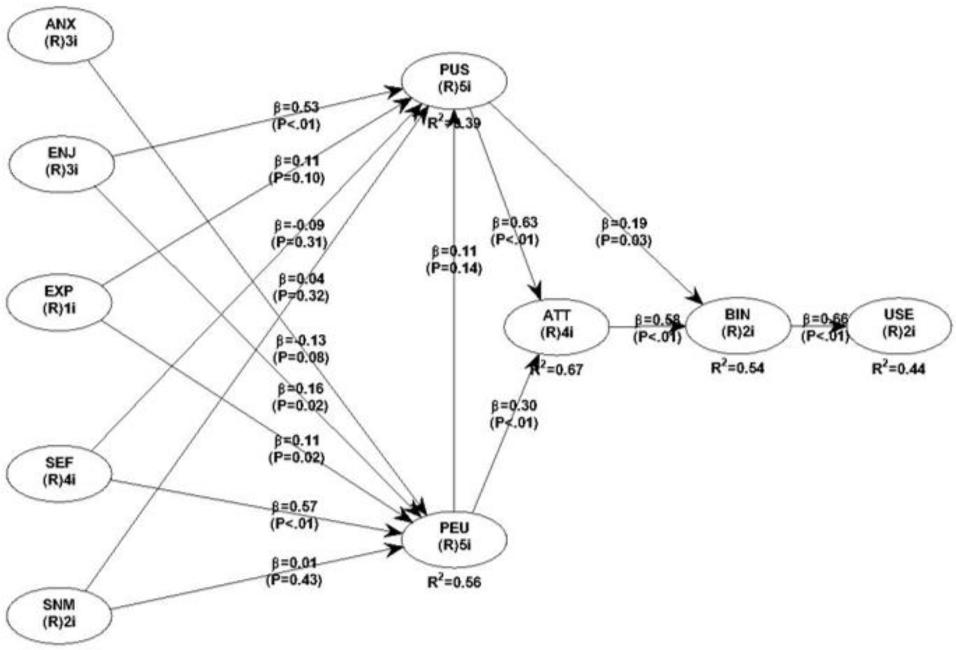

Fig. 2. PLS Results

Table 6
Hypotheses testing

Hypothesis	Path	Path coefficient (β)	*p* value	Effect size (f^2)	Result
H1	PUS → ATT	0.635	p<0.001	0.492	Supported
H2	PUS → BIN	0.187	p=0.032	0.119	Supported
H3	PEU → PUS	0.109	p=0.139	0.053	Not Supported
H4	PEU → ATT	0.300	p<0.001	0.179	Supported
H5	ATT → BIN	0.581	p<0.001	0.422	Supported
H6	BIN →USE	0.665	p<0.001	0.442	Supported
H7	ANX → PEU	-0.128	p=0.079	0.037	Not Supported
H8	ENJ → PEU	0.162	p=0.025	0.085	Supported
H9	EXP → PEU	0.114	p=0.024	0.027	Supported
H10	SEF → PEU	0.573	p<0.001	0.409	Supported
H11	SNM → PEU	0.012	p=0.427	0.002	Not Supported
H12	ENJ → PUS	0.526	p<0.001	0.350	Supported
H13	EXP → PUS	0.110	p=0.100	0.025	Not Supported
H14	SEF → PUS	-0.092	p=0.313	0.044	Not Supported
H15	SNM → PUS	0.035	p=0.320	0.011	Not Supported

The coefficient of determination, R^2, is 0.44 for USE; thus, BIN explains 44% of the variance in USE. The coefficient of determination, R^2, is 0.54 for BIN; thus, the two latent variables (PUS and ATT) explain 54% of the variance in BI.

The path coefficients (β) and path significance (p-value) were examined to reveal the relationships between the constructs in the research model. The results of the hypotheses testing, including effect sizes (f^2), are summarized in Table 6. f^2 values of 0.35, 0.15, and 0.02 are deemed as large, medium, and small, respectively (Cohen, 1988).

5. Discussion

The results of the study supported nearly all the core TAM construct relationships but only some of the external relationships proposed by the GETAMEL are supported by the data. Specifically, the links between experience, enjoyment, and self-efficacy and perceived ease of use were supported but not those from social norm, or anxiety to perceived ease of use. Neither are the relationships supported between the external factors experience, self-efficacy, or social norm and perceived usefulness, although we find support for a link between enjoyment and perceived usefulness. Finally, the only core relationship we did not reproduce was the contested link between perceived ease of use and perceived usefulness.

While putting in question the stability of the GETAMEL, we find in these data support for the situative perspective, which posits that increased explanatory power requires models to be sensitive to the modulating effects of situational factors such as modality of beliefs (Doleck et al., 2017a, 2017b; Lemay et al., 2017) as contextual factors can systematically influence the way underlying beliefs influence technology acceptance beliefs, such that specific needs can trump other beliefs all else being equal. A common finding in the TAM literature is that the degree of voluntariness is an important moderating factor for technology end-users. Indeed, voluntariness has been advanced as a core factor in extended models of technology acceptance (Venkatesh, Morris, Davis, & Davis, 2003). Furthermore, in our studies of social media acceptance, we found that necessity beliefs such as need for self-expression (Doleck et al., 2017b) or passion (Lemay et al., 2017) can have stronger effects on behavioral intention and use than the core TAM constructs themselves.

The present study supports the validity of the situative thesis as these apparent contradictory findings can be explained as variations in modalities of beliefs. In other words, CEGEP students' technology acceptance appears dictated to some extent by the influence of the context of use on the modality of beliefs. Therefore, perceived usefulness is likely evaluated with respect to course constraints and institutional decisions, rather than experience, self-efficacy, or social norm. Hence, the perceived usefulness of e-learning would be derived from the activity it supports, and not necessarily some intrinsic quality of the technology itself—beyond the perceived enjoyment derived from technology-supported learning situations. Whereas the relationships of enjoyment, experience, and self-efficacy to perceived ease of use hold as expected, as perceived ease of use remains a function of prior experience and may not necessarily be modulated by institutional constraints. Importantly, neither social norm nor anxiety appear to influence perceived ease of use either, suggesting that constrained contexts of adoption typical of e-learning situations restrict the influence of affective factors on e-learning adoption. These findings are supported by two recent studies where we compared computer-based learning in the Nepali and North-American educational contexts (Doleck et al., 2017a). We argued that important situational differences, both in terms of the degree of voluntariness, and in the degree of adoption of information and communication technologies, strongly moderated the core TAM relationships. Whereas, students in the North American contexts were surveyed on their voluntary use of computer-based learning environments and were found to be influenced primarily by perceived usefulness, students in the Nepali context were surveyed on their use in more constrained classroom settings, and were found to be primarily influenced by perceived enjoyment. Furthermore, in the latter context, we could not reproduce the core links between perceived usefulness and behavioral intention, nor between attitude and behavioral intention. Taken together, these results strongly suggest the contextual sensitivity of the TAM must be included in the formulation of a generalizable model for e-learning. As multiple reviews of the technology acceptance literature have demonstrated (King & He, 2006; Burton-Jones & Hubona, 2006; Sun & Zhang, 2006), situational factors have important moderating effects on the core TAM constructs, beyond the particularities of specific technology applications.

The situative perspective offers some pathways to assess the influence of situations on technology acceptance. It is outside of the scope of the present study, but it would be valuable to compare how the external factors of the GETAMEL vary systematically across adoption contexts, for instance, with different degrees of voluntariness. Comparative studies across contexts could increase our understanding the influence of situative factors on technology acceptance and help develop more robust, contextually sensitive, technology acceptance models.

The limitations of the study also provide directions for future research avenues. A major limitation of this study is the use of self-reports from a single sample—giving rise to potential measurement inaccuracies and bias. Since the sampling for our study was limited to a CEGEP in Montreal, it is difficult to extrapolate our findings to other samples and we exercise caution as to the generalizability. However, our study does raise questions concerning the generalizability of the GETAMEL, as we could not reproduce all the theorized relationships. Future research needs to be conducted from additional sources and across contexts and populations. The second limitation regards the general relatedness of the constructs. Given the cross-sectional nature of the study design, causal conclusions cannot be drawn. Furthermore, we did not examine the voluntariness of e-learning use, as it was not part of the proposed GETAMEL model. Future research could profit by focusing on the influence of voluntariness by comparing different contexts of use. These limitations notwithstanding, the present study contributes to the literature on technology acceptance and extends our understanding of factors underlying e-learning acceptance.

6. Conclusion

A considerable body of research has examined the factors affecting e-learning acceptance, yet this stream of research has resulted in discordant findings. The GETAMEL model was offered as an effort to provide a generalizable model for examining e-learning acceptance to reconcile the disparate findings in the extant literature. The aim of this study was to examine and validate the GETAMEL model. While the model did fit the data, not all the hypotheses were supported. The present study highlights the difficulty in formalizing such a generalizable mechanism. While a generalizable model, such as the GETAMEL, could potentially be valuable for providing a simple yet reliable way for ascertaining and explicating e-learning acceptance, it appears that technology acceptance is highly context-specific and that any generalizable model will need to account for the high degree of situativity inherent in technology acceptance decisions.

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