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Technology enhanced learning acceptance among university students during Covid-19: Integrating the full spectrum of Self-Determination Theory and self-efficacy into the Technology Acceptance Model

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Abstract

This study proposes a unified theoretical model to integrate the full spectrum of Self-Determination Theory, self-efficacy, and the Technology Acceptance Model in understanding the acceptance of technology enhanced learning among university students during the Covid-19 pandemic. In the proposed theoretical model, 7 hypotheses were tested to understand the acceptance of technology enhanced learning. A total of 303 university students participated in this study. The Heterotrait-Monotrait (HTMT) ratio of correlation was applied to measure Discriminant Validity for the Covariance-Based Structural Equation Model. Based on the results, the unified theoretical model provided better insight to understanding acceptance of technology enhanced learning ($R^2 = .71$). Intrinsic motivation (IM), amotivation, motivation, and technology enhanced self-efficacy (TELSE) were identified as significant determinants of students' perceived ease of use (PEU). Amotivation, motivation and TELSE were significant determinants of students' perceived usefulness (PU) towards technology enhanced learning. During the Covid-19 pandemic, students had internalised external regulation and identified regulation. The empirical results also revealed that the relationship between amotivation and PEU were moderated by gender. Gender also played a role in moderating the effects of amotivation and motivation relationships towards PU. However, the relationships between IM and motivation toward PEU and TELSE to PU were vulnerable towards the moderating effects of gender and students' field of study. In conclusion, students' view on technology acceptance have changed since the pandemic, therefore, their participation in design, development, and implementation of learning resources is much needed than before to improve their psychological motivation.

Keywords Self-Determination Theory · Self-efficacy · Technology Acceptance Model · Technology enhanced learning · Heterotrait - Monotrait (HTMT)

Introduction

The incorporation of technology into learning in higher education was catalysed by the recent Covid-19 pandemic. Technology enhanced learning was intensified globally due to the pandemic as university students heavily relied upon technology in learning and social life. Now, technology enhanced learning supersedes the once-popular terminology of "computer-based learning" and "e-learning" in education due to its reputation. Technology enhanced learning is an emerging research area with various definitions coined by scholars. This study adopted the definition of technology enhanced learning from Law et al. (2016) as "learning in an environment that is enriched by the integration of digital technologies". Technology enhanced learning involves the integration of technologies into education to assist teaching and facilitate communication between students and instructors with online education, ubiquitous learning, mobile learning, and other types of internet-assisted or medium learning are approaches that are categorized as technology enhanced learning (Tsai, 2017). It enriches the dynamics of

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learning, whereby students transcend from passive behaviour to taking the initiative of exploring knowledge which induces improvement in thinking skills. Education in the information age nurtures thinking skills as it is imperative in determining an individual's ability to grasp knowledge. Technology enhanced learning not only brings technology into the classroom but is also about bridging education and technology. It is flexible, interactive, and can balance the need for face-to-face (f2f) and online interaction between instructors and students (Ibrahim et al., 2015). Technology enhanced learning is in line with the inspiration of the digital native generation, hence, online education can be deemed as the pinnacle of modern education (Alshammari et al., 2016).

Previous literature have investigated the implication of technology enhanced learning towards performance (Fowler et al., 2021) and thinking skill enhancement (Lim, 2021; Ramlee et al., 2019). Scholars have also reported that technology enhanced learning is not suitable for students with different cognitive styles (Fırat et al., 2021) as the instructor's approach might lead to mismatched learning styles (Stec et al., 2020). Hence, the potentiality of technology enhanced learning usage in the future, especially to assist learning needs attention. The pros of technology enhanced learning are continuously evolving as it is pivotal in the development of futuristic assessment (Jopp, 2020). As such, the research and application of technology enhanced learning has been accepted in Europe (Stadler et al., 2020), where universities have begun implementing technology enhanced learning extensively as an effort to cushion the impact of Covid-19 (Skulmowski & Rey, 2020). Although the same application of technology enhanced learning has been occurring outside of Europe, not much research has been conducted on this matter.

Nevertheless, little is known about the factors that could lead to the acceptance or rejection of technology enhanced learning especially in the affective aspects of human beings such as motivation, feelings, and perceived efficacy. University students have begun learning remotely or in open distance learning mode due to Covid-19. The need for the adoption of an alternative learning method became imperative. However, the suitable factors supporting the incorporation of technology enhanced learning that suit the psychological aspect of the students remain largely unknown. Although a larger group of mindsets is needed to avoid bias in technology enhanced learning environment (Smith et al., 2020), students is the main end-users of technology enhanced learning. Hence, the quality and sustainability of education during the Covid-19 pandemic from the students' point of view needs to be understood.

The present study serves to fill the research gap by identifying and studying the factors influencing the behavioural intention (BI) of university students in using technology enhanced learning environments during Covid-19. The Technology Acceptance Model (Davis, 1989) with improvement and a combination of important external variables from psychological perspective was employed to examine the perceived usefulness (PU), perceived ease of use (PEU), and actual usage (AU). These variables serve as predictors to the BI to use technology enhanced learning among university students. Technology Acceptance Model that was a proven, robust, and parsimonious model in explaining the usage intentions but was only documented at 40% of variance explained (Venkatesh & Davis, 2000). Thus, Technology Acceptance Model needs support from suitable external variables to improve its strength in explaining acceptance (Scherer & Teo, 2019).

On the other hand, motivation is an imperative affective element in humans when it comes to incorporating new technology based on the Self-Determination Theory pioneered by Deci and Ryan (1980). The theory had played important roles in psychology and was introduced into education a decade later (Deci et al., 1991). Previous study reported relationship between motivation and acceptance of technology (Li et al., 2021). However, the implications of motivation from the tenets of full spectrum of Self-Determination Theory towards the acceptance of technology enhanced learning remain a question.

Self-efficacy theory was introduced by Bandura (1977). Self-efficacy is among the factors that are believed to influence the acceptance of technology enhanced learning among students. Self-efficacy influences students' selection, motivational, and cognitive processes, which all have an effect on their academic behaviours, such as their ability to regulate their learning and master academic activities (Bandura, 1993). Synchronously, students' PEU is expected to be influenced by prior experience from a self-efficacy perspective (Venkatesh, 2000). Self-efficacy theory is defined as an individual's beliefs about their ability to produce a specified level of performance (Lyons & Bandura, 2018). Self-efficacy is one of the popular external variables for the Technology Acceptance Model (Angelica et al., 2020). Based on the extant literature, self-efficacy is deemed as the main factor influencing the usage of technology in learning such as mobile learning (Qashou, 2021) and learning management system (Rivers, 2021). Students who understand the effects of self-efficacy can benefit from using technology enhanced learning. However, it is unclear how self-efficacy from the perspective of technology enhanced learning self-efficacy (TELSE) could affect the usage and acceptance of technology enhanced learning, especially in the current pandemic situation.

This study aims to address the gaps by improving the Technology Acceptance Model with several psychological variables like motivation and self-efficacy into a unified theoretical model before empirically testing using modelling techniques to study the acceptance of technology enhanced learning. Self-Determination Theory, self-efficacy, and the Technology Acceptance Model will be discussed further in the theoretical framework. This study makes a number of theoretical and practical implications. To begin, this is the first study to our knowledge that integrates the full spectrum of Self-Determination Theory into the Technology Acceptance Model, as previous studies have focused exclusively on the original form of Self-Determination Theory by focusing exclusively on the basic psychological needs of autonomy, competence, and relatedness. Second, this research examines the role of TELSE in advancing current self-efficacy application. As technology has evolved, research on self-efficacy beyond the integration of computer self-efficacy into the Technology Acceptance Model has become scarce. Third, this research expanded the Technology Acceptance Model to incorporate a broader perspective of psychological factors, as the model has been criticised for being oversimplistic, and there is a scarcity of studies on the acceptance of technology enhanced learning based on the Technology Acceptance Model. Finally, these efforts have implications for the use of technology enhanced learning applications in universities. The factors that contribute to students' acceptance and the ways in which their learning can be supported technologically and psychologically will be understood.

Theoretical framework

Self-Determination Theory

Self-Determination Theory, one of the most thoroughly researched psychological theories (Ryan & Deci, 2019), represents a paradigm shift in our understanding of motivation, autonomous extrinsic motivation, psychological motivation, and the factors that facilitate these components, by emphasizing an individual's intrinsic motivational proclivities rather than "outside" control (Ryan & Deci, 2020). Initially, Deci and Ryan (1980) proposed three psychological needs to support the individual's learning in their organismic nature theory: autonomy, relatedness, and competence. Autonomy refers to the ownership of a decision, competence to an individual's sense of success, and relatedness to belonging and connection (Ryan & Deci, 2020). However, over time, the theory expanded to encompass intrinsic motivation (IM), extrinsic motivation, and amotivation—a concept we refer to as the full spectrum of Self-Determination Theory. IM is a term that refers to activities that are undertaken for the inherent interest and enjoyment of students; it is likely responsible for the predominance of human learning throughout the lifespan (Ryan & Deci, 2020). Extrinsic motivation refers to behaviour that is motivated by factors other than the students' inherent satisfaction. It is comprised of four types of regulation: external regulation (ER), identified regulation (ID), introjected regulation, and integrated regulation (Deci et al., 1991). However, only ER and ID were included in this research as suggested by Guay et al. (2000). Amotivation, which is placed at the outer end of the theory refer to lack of intentionality (Ryan & Deci, 2020). In the context of this study, motivation is defined as the synthesis of the basic psychological needs of autonomy, relatedness, and competence into a single construct. Based on this premise, a review of the literature revealed a significant knowledge gap.

Over decades of research, researchers combined Self-Determination Theory and the Technology Acceptance Model to gain a better understanding of technology acceptance through the inclusion of human psychological perspectives (Hew & Kadir, 2016; Lee et al., 2015). To that end, Self-Determination Theory variables were linked to the Technology Acceptance Model as predictors of PU and PEU (Nikou & Economides, 2017), as these two factors were significant antecedents to BI in the Technology Acceptance Model (Huang & Teo, 2021). While Self-Determination Theory may help explain the psychological factors underlying technology acceptance, because its theoretical perspective is highly correlated with acceptance of technology enhanced learning (Fathali & Okada, 2018). Prior research is unlikely to have examined explanations from the standpoint of external motivation and amotivation – a perspective that Self-Determination Theory encompasses in its full spectrum. While prior research has established the two theories' compatibility (Lu et al., 2019; Tsai et al., 2021), surprisingly little attention has been paid to the integration of the entire spectrum of Self-Determination Theory into the Technology Acceptance Model.

Although Racero et al. (2020) argued that Self-Determination Theory, in its initial form, is compatible as an external variable for the Technology Acceptance Model for educational research that integrates both technological acceptance and psychological components for educational application. Their conclusion is limited to the Self-Determination Theory's influence on technology in education based on autonomy and relatedness in general. Though this finding suggests that the Technology Acceptance Model could be expanded to include external variables from Self-Determination Theory such as autonomy, relatedness, and competence, the finding is not conclusive.

Racero et al. (2020) adopt the same perspective as Fathali and Okada (2018) when they combine the Self-Determination Theory and the Technology Acceptance Model to better understand technology enhanced out-of-class language learning. They concluded, through quantitative analysis of Structural Equation Model, that determinants from Self-Determination Theory could significantly predict the PU and PEU constructs from the Technology Acceptance Model, with perceived competence from Self-Determination Theory being the most influential factor. This once again demonstrates the suitability of Self-Determination Theory in its original form (Deci & Ryan, 1980) as a complement to the Technology Acceptance Model (Davis, 1989).

However, previous studies such as Fathali and Okada (2018) and Racero et al. (2020) focused exclusively on the psychological needs of autonomy, relatedness, and competence. This is not an unusual scenario, as previous research has focused almost exclusively on basic psychological needs (Hew & Kadir, 2016; Lee et al., 2015; Lu et al., 2019; Tsai et al., 2021). As Self-Determination Theory has been expanded from its original form (Deci & Ryan, 1980) to include extrinsic motivation and amotivation (Ryan & Deci, 2000, 2019), but the research in Technology Acceptance Model appears to exclude this expansion, a gap in our current knowledge has been created. Thus, it may be beneficial to fully investigate Self-Determination Theory to ensure that understanding of technology acceptance can keep pace with the development of psychological theory.

As Ryan and Deci (2019) had expanded their theory from intrinsic motivation (IM) to permutation of intrinsic and extrinsic motivation with amotivation, which transformed the theory into its new full-fledged state. Self-Determination Theory's Taxonomy of Motivation (Ryan & Deci, 2020) suggested that the full spectrum Self-Determination Theory embraces IM, extrinsic motivation, and amotivation. The extrinsic motivation was then divided into four subtypes namely external regulation (ER), identified regulation (ID), introjection regulation, and integrated regulation. Internalization increases from introjection through identification to integration (Ryan & Deci, 2020).

Given Self-Determination Theory's central role, it is critical to establish the relationship between IM, ER, ID, and amotivation. The relationships between the stated variables were examined by Guay et al. (2000) using as sample size of 907 Fresh Canadian college students. However, because previous research was conducted decades before the Covid-19 pandemic, which now necessitates widespread implementation and use of technology enhanced learning, it may not fully explain the relationship between the factors in Self-Determination Theory in the digital age. To our knowledge, no prior research has examined the influence of Self-Determination Theory on technology acceptance through the lens of the relationships between IM, ER, ID, and amotivation toward PU and PEU. Although some researchers advocated for incorporating the Self-Determination Theory into the Technology Acceptance Model by integrating only IM (Sun & Gao, 2020). This would result in a negligible psychological contribution to technological acceptance. Rather than relying on previous research, it is now necessary to examine these relationships among today's university students. Not only is it worthwhile to investigate the relationships and incorporate them into the Technology Acceptance Model. It is also consistent with organismic philosophy's vision for integrating Self-Determination Theory with other appropriate frameworks (Ryan & Deci, 2017). While Self-Determination Theory is a widely accepted theory in psychology, studies attempting to incorporate it into an understanding of the psychological component of technology acceptance have been insufficient.

This will also address an intriguing question in this context: What role do psychological factors based on full spectrum Self-Determination Theory play in determining whether technology enhanced learning is accepted using the Technology Acceptance Model? This study aims to integrate the full spectrum of Self-Determination Theory into the Technology Acceptance Model in order to better understand not only the acceptance of technology enhanced learning, but also the relationship between the two theories when the full spectrum of Self-Determination Theory is used. This paper fills a knowledge gap by examining the roles of the full spectrum of Self-Determination Theory when combined with the Technology Acceptance Model in university students' acceptance of technology enhanced learning during Covid-19. We hypothesized that students' acceptance of technology enhanced learning while studying in a pandemic situation based on PU and PEU of Technology Acceptance Model would be influenced by IM, ER, ID, Amotivation, and Motivation. To ensure that no elements of Self-Determination Theory were overlooked in this study, the basic physiological needs for autonomy, relatedness, and competence were combined into a construct called Motivation. ER and ID were later dropped due to the issue of Discriminant Validity. We had formulated the following hypotheses in response to the highlighted gap and argument:

Hypotheses 1a: *IM is positively associated with the university students' PU towards technology enhanced learning*

Hypotheses 1b: *IM is positively associated with the university students' PEU towards technology enhanced learning*

Hypotheses 2a: *Amotivation is negatively associated with the university students' PU towards technology enhanced learning*

Hypotheses 2b: *Amotivation is negatively associated with the university students' PEU towards technology enhanced learning*

Hypotheses 3a: *Motivation is positively associated with the university students' PU towards technology enhanced learning*

Hypotheses 3b: *Motivation is positively associated with the university students' PEU towards technology enhanced learning*

Technology Enhanced Learning Self-Efficacy (TELSE)

Self-efficacy is a critical perception that is necessary for technology adoption to succeed. However, this study concentrated on a subset of self-efficacy known as TELSE. TELSE is defined as an individual's beliefs about his or her ability to perform using technology enhanced learning media, tools, and devices, based on Lyons and Bandura (2018) definition of self-efficacy.

Self-efficacy is a frequent external variable used in the Technology Acceptance Model (Angelica et al., 2020). Self-efficacy becomes irrelevant as a factor influencing human behaviour as technology advances if it is not adapted to newer technology. A closer examination of the literature on self-efficacy and technology acceptance, however, reveals a significant gap, as the majority of studies have focused exclusively on computer self-efficacy. Teo (2009) integrated computer self-efficacy into the Technology Acceptance Model to simulate pre-service teachers' technology acceptance in Singapore. Teo (2009) revealed a direct relationship between computer self-efficacy and technology acceptance among pre-service teachers with a favourable attitude toward computers. Similarly, self-efficacy was found to positively influence computer self-efficacy among 286 teachers in Greece (Paraskeva et al., 2008). As a result of the repercussions of digital surfaces, new terms such as digital media self-efficacy (Hammer et al., 2021) and creative self-efficacy (Akbari et al., 2021) have emerged. Given that previous research in education has focused exclusively on computer self-efficacy (Paraskeva et al., 2008; Sayaf et al., 2021; Teo, 2009), what is the impact of TELSE on technology enhanced learning? Continue to be a mystery.

Although computer self-efficacy leads to better learning performance and technology acceptance as previous studies by Paraskeva et al. (2008), Sayaf et al. (2021) and Teo (2009) was conducted prior to the Covid-19, these cannot be considered conclusive. TELSE is a relatively new concept; it exists in conjunction with computer self-efficacy, which has been the subject of a few studies (Hatlevik & Bjarnø, 2021; Tzafilkou et al., 2021). However, when compared to computer, technology enhanced learning is significantly more complex and composite. Hence, TELSE may deviate from the current behaviour exhibited by computer self-efficacy. This raises an important question: Is TELSE a significant predictor of university students' acceptance of technology enhanced learning during Covid-19? Therefore, the purpose of this study was to examine the relationship between TELSE and technology acceptance by incorporating TELSE as an external variable into the Technology Acceptance Model. We hypothesized that TELSE would influence students' acceptance of technology enhanced learning in a pandemic situation. We had formulated the following hypotheses in response to the highlighted gap and argument:

Hypotheses 4a: *TELSE is negatively associated with the university students' PU towards technology enhanced learning*

Hypotheses 4b: *TELSE is positively associated with the university students' PEU towards technology enhanced learning*

Technology Acceptance Model

Technology Acceptance Model is the first model of technology acceptance proposed by Davis (1989) and turn out to be the popular one. This model was extensively tested (Davis & Venkatesh, 1996; Venkatesh et al., 2003) and has been comprehensively researched in education (Lavidas et al., 2020; Qashou, 2021; Yunus et al., 2021). However, the model has been criticized for being too conservative to provide practical advice on how to improve PU and PEU (Luo et al., 2021; Wong, 2016). At the same time, it was also criticized for being overly simplistic when used in the absence of external variables (Huang & Teo, 2021). As a result, significant effort has been made to expand the Technology Acceptance Model by adding factors and incorporating external factors that contribute to researchers' understanding of technology acceptance, such as variables found in online ecosystems (Abdullah et al., 2016). While numerous studies have been conducted on the acceptance of online ecosystems for educational purposes, little research has been conducted on the acceptance of technology enhanced learning.

Although research about specific types of technology in education is emerging, such as Huang and Teo (2021) who had identified that the extended model based on the Technology Acceptance Model was suitable to investigate the intention of English teachers in Chinese universities to use technology. As well as, Hanham et al. (2021) who reported the infusion of the Technology Acceptance Model and Social Cognitive Theory to assess the relationships between academic perception, academic capabilities, and performance towards online tutoring among undergraduate students in Australia. The study of technology enhanced learning is limited because too much emphasis has been placed on specific technologies such as Learning Management Systems, e-learning, mobile applications, and mobile learning.

As Covid-19 altered the landscape of higher education in the modern era. The demand for technology enhanced learning has increased as a strategy to mitigate the curfew imposed as a result of Covid-19 (Skulmowski & Rey, 2020). It is necessary to conduct a systematic study in order to comprehend technology enhanced learning acceptance using the tenets of the Technology Acceptance Model. It is a perfect window of opportunity to investigate university students' acceptance and BI towards technology enhanced learning. This is important, as the main user of technology needs to be understood by the developers, institutions, or policy makers to ensure the effectiveness and success of the technology introduced. This raised the following question: According to the Technology Acceptance Model, what is the level of acceptance for technology enhanced learning? As such, the purpose of this study was to determine, using the Technology Acceptance Model, the level of acceptance of technology enhanced learning among university students during Covid-19.

The Technology Acceptance Model is composed of three constructs: PU, PEU and BI. Davis (1989) proposed that PU and PEU are precursors to BI that results in actual usage (AU) among the users. PU denotes the extent to which a user believes that using technology increase task productivity, while PEU denotes the extent to which a user believes that using technology is effort-free (Huang & Teo, 2021). This premise has been tested and analysed for over 30 years of intensive research, but the proposed relationship has been established as solid and correct (Huang & Teo, 2021; Kaewsaiha & Chanchalor, 2021). The debate over the fundamental relationships between these Technology Acceptance Model constructs continues to centre on the question of whether PU or PEU is a more significant predictor in the model (Aburagaga et al., 2020; Lu et al., 2019). There is limited disagreement about the roles of PU and PEU in relation to BI. In our research, we proposed that PU and PEU positively associated with university students' BI to use technology enhanced learning. Previously, we included IM, amotivation, and motivation as predictors of PU and PEU in order to incorporate the full spectrum of Self-Determination Theory into the Technology Acceptance Model. The extension of the Technology Acceptance Model to include appropriate psychological variables was necessary to further investigate the variables and interactions of external variables in the Technology Acceptance Model (Scherer & Teo, 2019), particularly in the context of Covid-19. In response to the highlighted gap and argument, we formulated the following hypotheses:

Hypotheses 5: *PEU is positively associated with university students' PU towards technology enhanced learning*

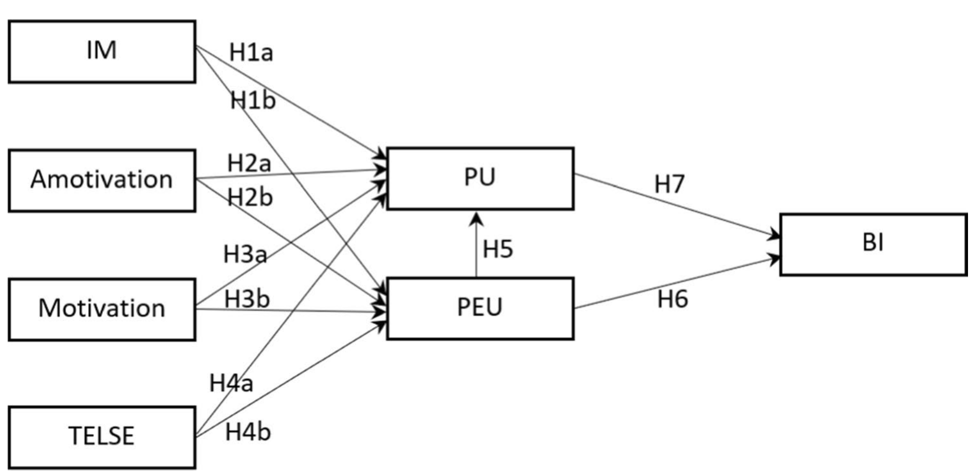
Hypotheses 6: *PEU is positively associated with university students' BI to use technology enhanced learning*

Hypotheses 7: *PU is positively associated with the university students' BI to use technology enhanced learning*

The significant hypotheses will be tested for the moderating effect of gender and field of study on acceptance of technology enhanced learning in order to gain a better understanding of this phenomenon. Additionally, as Lakhal and Khechine (2021) and Stolk et al. (2021) suggest, when students study online, there is likely to be a moderating effect on the gender relationships being investigated.

What role does full spectrum Self-Determination Theory play in determining whether technology enhanced learning is accepted using the Technology Acceptance Model? Is TELSE a significant predictor of university students' acceptance of technology enhanced learning during the Covid-19? What is the acceptance for technology enhanced learning, according to the Technology Acceptance Model? These are the scientific questions that remain unanswered to this day due to the research gap and limitations of previous studies. To fully understand university students' acceptance of technology enhanced learning during Covid-19, it is critical to conduct research to close these gaps. Thus, this research sought to close these gaps by incorporating the full spectrum of Self-Determination Theory, including IM, ER, ID, amotivation and motivation, and self-efficacy in the form of TELSE, into the Technology Acceptance Model to better understand the acceptance of technology enhanced learning among university students in Covid-19. Figure 1 depicts the proposed theoretical model for this study, which excludes ER and ID due to their internalisation into IM, as indicated by the Heterotrait-Monotrait (HTMT) ration of correlation results obtained later in the study. Additionally, AU was

Fig. 1 Proposed theoretical model with hypotheses



excluded from the theoretical model because it did not meet the required Convergence Validity.

Research methodology

This study employed a correlational research design. The questionnaire was the only instrument involved in this study. Data were collected using questions on demographics along with the variables stated in the theoretical framework and model. The hypotheses were analysed using IBM SPSS Amos via Covariance-Based Structural Equation Model.

Respondents

There were a total of 303 undergraduate students from a university in south Peninsular Malaysia. Data were collected in two cohorts, where the first cohort involved 230 respondents. Data was collected from the questionnaires distributed in the first quarter of 2021. The second cohort comprised 73 respondents who were provided with the same set of the questionnaire in the second quarter of 2021. Since no repetitions were ensured among respondents, chances for the same individual to be involved in both cohorts was extremely low.

All the respondents were learning using technology enhanced learning environments due to the global outbreak of Covid-19. Most of these respondents depend solely on technology enhanced learning as they were homebound. Whereas, a small proportion of these respondents were on campus with limited f2f classes and maximum usage of the online medium for teaching and learning purposes as part of the Ministry of Higher Education's effort to minimize the risk of Covid-19 infection among students. Online learning is the enabling factor for Malaysia success in combating the pandemic (Yong & Sia, 2021).

The collected data were complete with no missing response because the online questionnaire was set to require a response from the respondents before they could submit their responses. Prior to sending out the questionnaires, an invitation with an explanation about technology enhanced learning, the content of the questionnaire, and the purpose of the study were sent to the respondents. All respondents who participated in this study were recruited voluntarily. The demographic information of the respondents is tabulated in Table 1.

Instrumentation

The questionnaire was administered through Google Form because this application is familiar among the respondents as it is frequently used for class activities, evaluations, and assessments. All the items were implemented using the 5-point Likert scale except for an item from AU construct.

Table 1 Demographic information

Demographic data	Number, *n*	Percentage, %
Age		
19 years old	87	28.7
20 years old	61	20.1
21 years old	61	20.1
22 years old	51	16.8
23 years old	33	10.9
24 years old	8	2.6
25 years old and older	2	0.7
Gender		
Male	167	55.1
Female	136	44.9
Field of Study		
Social Science	108	35.6
Engineering, Science & Technology	195	64.4

The first part of the questionnaire (Part A) collected demographic data like age, gender, year of study, and faculty. Meanwhile, Part B consisted of 22 items. The sections that measured IM consisted of 4 items, ID had 4 items and another 4 items for ER. Part B also measured amotivation ($n = 4$ items). These items were adapted from Guay et al. (2000). Another 6 items were adapted from Chen et al. (2015) to measure motivation from the perspective of basic psychological needs. Part C consisted of 4 items to measure TELSE (Abdullah & Ward, 2016; Compeau & Higgins, 1995; Compeau et al., 1999; Delgosha & Hajiheydari, 2021). Part D consisted of 4 items from Technology Acceptance Model to measure PU (Davis, 1989; Huang et al., 2020; Mutambara & Bayaga, 2021; Sivo et al., 2018), 4 items for PEU (Davis, 1989; Huang et al., 2020; Sivo et al., 2018), 5 items for BI (Davis, 1989; Huang et al., 2020; Mutambara & Bayaga, 2021; Sivo et al., 2018), and 3 items for AU (Park et al., 2019; Sivo et al., 2018). The questionnaire (Part B, C and D) is as in Appendix.

Data analysis

Data analyses were performed using descriptive and inferential approaches. The descriptive data analysis was performed to elaborate on the demographic data of the respondents. While the inferential analysis involved the execution of three levels of Structural Equation Model analysis namely Confirmatory Factor Analysis (CFA), Measurement Model, and the Structural Model.

To ensure that each item belonged to its assigned construct, CFA was employed where the Convergent Validity and Construct Reliability were calculated. In this analysis, items with standardized factor loading lower than 0.5 were removed (Hair et al., 2010). Whereas the Measurement Model involved the testing of combined latent variables for a fit model. The Discriminant Validity was assessed before proceeding with the Structural Model. Fit Indices were referred to for model fitness (Byrne, 2016).

The data were checked to ensure that they conformed to the CFA and SEM assumptions. The analysis was performed under the assumption of multivariate normality, the absence of missing data, and an appropriate sample size. Using the skewness and kurtosis of each construct, the multivariate normality assumption was examined. When using a Structural Equation Model, skewness between -3 and + 3 and kurtosis between -10 and + 10 are considered acceptable (Griffin & Steinbrecher, 2013). Then, skewness and kurtosis values indicate that this study meets the multivariate normality assumption, with skewness values ranging from -0.919 to -0.024 and kurtosis values ranging from 1.569 to -0.548. There are no missing data in our dataset because data collection was conducted using a Google Form and respondents were required to respond to all items before submitting their response. As a result, this study satisfies the assumption of no missing data. Kline (2015) recommends a minimum sample size of 200 for SEM, which this study meets. Hence, we concluded that our dataset meets the necessary assumptions.

Result

Confirmatory Factor Analysis (CFA)

CFA was performed for each construct. To produce a robust output, the Cronbach's alpha (α) was calculated for each of the constructs apart from its Construct Reliability (CR) and Average Variance Extracted (AVE) as listed in Table 2. ID and ER remain constructs at this point until their Discrimination Validity is discovered to be violated.

Item ER3 was deleted as it indicated negative load to ER during CFA. The CR value was set to a minimum benchmark value of 0.7 (Hair et al., 2010), while the AVE was set to a benchmark value of 0.5 (Fornell & Larcker, 1981). According to Table 2, the constructs and items used in this study fulfilled the set benchmarks except for AU. Table 2 also demonstrated that the instrument possessed a good Convergent Validity and we had dropped AU from further testing.

Measurement Model

The Measurement Model for this study involved 9 latent variables as depicted in the theoretical framework and model (AU was dropped due to poor CR and AVE values). This study implemented the fitness indices suggested by Hu and Bentler (1999). The fit indices for the measurement model were acceptable with $\chi^2 = 1562.390$, $\chi^2/df = 2.484$, CFI = 0.903, RMSEA = 0.070. Improvements were made to the model to correlate errors between error for item Motivation3 and error for item Motivation4 and error for item Motivation5 with error for item Motivation6. The new fit indices for the improved measurement model were good ($\chi^2 = 1402.190$, $\chi^2/df = 2.236$, SRMR = 0.0447, CFI = 0.919, RMSEA = 0.064).

The Discriminant Validity was assessed using HTMT ration of correlation instead of the dominant practices of Fornell-Larcker criterion. Henseler et al. (2015) recommended a new criterion to assess the Discriminant Validity for Variance-Based Structural Equation Modeling method namely the Partial Least Squares (PLS) as an alternative to the criterion proposed by Fornell and Larcker (1981). Although the application of HTMT for Covariance-Based Structural Equation Modeling is scarce, it is still applicable (Hosen et al., 2021). Also, Fornell-Lacker criterion is not the only guideline used to assess Discriminant Validity (Rönkkö & Cho, 2020). Therefore, this study explored the suitability of HTMT for Covariance-Based Structural Equation Model as a manoeuvre to spearhead the evolution of Discriminant Validity assessment for Social Sciences research. This study also suggested the application and exploration of new techniques using CI_{CFA}(sys) and χ^2(sys) proposed by Rönkkö and Cho (2020) for future studies. Table 3 summarizes the Discriminant Validity obtained using HTMT for this study.

Based on the results, Discriminant Validity was present except between ID and IM, and between ID and ER with HTMT values of 0.990 and 1.214, respectively. The same goes to ER and IM and between ER and Motivation with HTMT values of 1.08 and 0.976. These values indicated a strong correlation between these constructs, where they were are almost indistinguishable. It had violated Discriminant Validity (Voorhees et al., 2016). The suitable threshold value indicating the existence of Discriminant Validity between constructs was HTMT ratio value of 0.90 (Henseler et al., 2015). The respondents might perceive ID and ER as internal factors as they perceived IM. Therefore, the construct of ID and ER were dropped from the Measurement Model and Structural Model. Since ID and ER were dropped, Measurement Model was performed again. The new Measurement Model exhibited better goodness of fit ($\chi^2 = 874.271$, $\chi^2/df = 2.127$, TLI = 0.929, CFI = 0.937, RMSEA = 0.061, and SRMR = 0.0453).

Main Structural Model

The fitness indices value for the Main Structural Model are $\chi^2 = 894.129$, $\chi^2/df = 2.155$, CFI = 0.935, TLI = 0.927, PGFI = 0.835, SRMR = 0.0480, RMSEA = 0.062. The Main Structural Model goodness of fit was good based on the cut-off indices proposed by Hu and Bentler (1999). The hypotheses were tested based on the results generated by the Main

Table 2 Convergent validity

Construct	Item	Factor Loading	Cronbach's alpha, α	Construct Reliability (CR)	Average Variance Extracted (AVE)
Intrinsic Motivation (IM)	IM1	0.71	0.855	0.859	0.606
	IM2	0.72			
	IM3	0.89			
	IM4	0.78			
Identified Regulation (ID)	ID1	0.79	0.875	0.877	0.640
	ID2	0.82			
	ID3	0.81			
	ID4	0.78			
External Regulation (ER)	ER1	0.80	0.842	0.842	0.640
	ER2	0.82			
	ER3	-0.02[a]			
	ER4	0.78			
Amotivation	A1	0.66	0.812	0.813	0.522
	A2	0.82			
	A3	0.69			
	A4	0.71			
Motivation	Mot1	0.67	0.894	0.889	0.578
	Mot2	0.63			
	Mot3	0.68			
	Mot4	0.71			
	Mot5	0.92			
	Mot6	0.90			
Technology Enhanced Learning Self-Efficacy (TELSE)	TELSE1	0.81	0.842	0.846	0.581
	TELSE2	0.81			
	TELSE3	0.80			
	TELSE4	0.61			
Perceived Usefulness (PU)	PU1	0.87	0.933	0.934	0.781
	PU2	0.90			
	PU3	0.94			
	PU4	0.82			
Perceived Ease of Use (PEU)	PEU1	0.79	0.891	0.892	0.673
	PEU2	0.83			
	PEU3	0.83			
	PEU4	0.83			
Behavioural Intention (BI)	BI1	0.86	0.944	0.944	0.771
	BI2	0.90			
	BI3	0.88			
	BI4	0.88			
	BI5	0.87			
Actual Usage (AU)	AU1	0.51	0.572	0.617	0.458
	AU2	0.81			
	AU3	0.42[a]			

[a] Item deleted due to negative load to construct during CFA

Structural Model. The results of the hypotheses testing were summarized in Table 4.

The direct relationship from IM to PU was insignificant ($\beta = 0.033$, SE = 0.152, $p = 0.756$) but positive and significant to PEU ($\beta = 0.275$, SE = 0.126, $p < 0.05$). Amotivation to PU was negatively significant (β =—0.103, SE = 0.049, $p = 0.013$); Amotivation to PEU possessed a significantly negative influence (β =—0.089, SE = 0.040, $p < 0.05$); Motivation was positively significant with PU ($\beta = 0.505$, SE = 0.173, $p < 0.001$); Motivation was positively associated to PEU, with significant ($\beta = 0.312$, SE = 0.138, $p < 0.05$); TELSE was negatively associated to PU with a significant relationship (β =—0.222, SE = 0.090, $p < 0.05$); TELSE was positively associated to PEU with a significant relationship ($\beta = 0.402$, SE = 0.065, $p < 0.001$); PEU was positively associated with PU and was significant ($\beta = 0.569$, SE = 0.125, $p < 0.001$); PU was positively associated to BI and was significant ($\beta = 0.461$, SE = 0.075, $p < 0.001$); PEU was positively significant with BI ($\beta = 0.417$, SE = 0.093, $p < 0.001$). Therefore, H1b, H2a, H2b, H3a, H3b, H4a, H4b, H5, H6 and H7 were supported, while H1a was not supported. This theoretical model explained 71% of the variance

Table 3 Discriminant validity using HTMT

Construct	IM	ER	ID	Amotivation	Motivation	TELSE	PU	PEU	BI
IM									
ER	1.08								
ID	0.990	1.214							
Amotivation	0.134	0.445	0.113						
Motivation	0.839	0.976	0.836	0.146					
TELSE	0.588	0.801	0.632	0.055	0.681				
PU	0.777	0.824	0.788	0.038	0.801	0.600			
PEU	0.755	0.817	0.738	0.017	0.771	0.786	0.839		
BI	0.753	0.820	0.771	0.000	0.774	0.589	0.815	0.789	

Table 4 Hypotheses results

Hypothesis	Relationship	Estimate	β	SE	CR	p	Conclusion
H1a	IM → PU	0.047	0.033	0.152	0.311	0.756	Rejected
H1b	IM → PEU	0.319	0.275	0.126	2.537	0.011	Accepted
H2a	Amotivation → PU	-1.21	-0.103	0.049	-2.498	0.013	Accepted
H2b	Amotivation → PEU	-0.086	-0.089	0.040	-2.136	0.033	Accepted
H3a	Motivation → PU	0.663	0.505	0.173	3.822	***	Accepted
H3b	Motivation → PEU	0.336	0.312	0.138	2.423	0.015	Accepted
H4a	TELSE → PU	-264	-0.222	0.090	-2.928	0.030	Accepted
H4b	TELSE → PEU	0.392	0.402	0.065	6.009	***	Accepted
H5	PEU → PU	0.693	0.569	0.125	5.528	***	Accepted
H7	PU → BI	0.427	0.461	0.075	5.712	***	Accepted
H6	PEU → BI	0.471	0.417	0.093	5.090	***	Accepted

ER and ID were not tested due to lack of Discriminant Validity

for BI ($R^2 = 0.71$), 79% variance for PU ($R^2 = 0.79$) and 77% variance for PEU ($R^2 = 0.77$). The Main Structural Model is as in Fig. 2.

Multigroup Structural Equation Modeling

To understand the moderation effects of gender and field of study to the strength of the causal relationship between the exogenous and endogenous variables, Multigroup Analysis was performed. The Multigroup Analysis produced three models that were used for further analysis namely the unconstrained, structural weights, and measurement residuals models.

Based on the analysis, the *p*-values for structural weight for multigroup analysis between males and females were significant, $p = 0.00$ and $p < 0.05$, respectively. Further comparison between the χ^2 values of the unconstrained and measurement residuals indicated that the unconstrained model was better ($\chi^2 = 1547.872$) than the measurement residuals ($\chi^2 = 1822.548$) with significant *p*-values each. Meanwhile, the model comparison measured for assuming model unconstrained to be correct, $\chi^2 = 274.676$; $df = 112$; $p = 0.000$ for measurement residuals. Therefore, a moderating effect of gender was identified. The fitness indices of the unconstrained model are $\chi^2 = 1547.872$, $\chi^2/df = 1.865$, CFI = 0.907, TLI = 0.896, PCFI = 0.809, SRMR = 0.0584 and RMSEA = 0.054. The fitness indices of the measurement residuals model are $\chi^2 = 1822.548$, $\chi^2/df = 1.935$, CFI = 0.886, TLI = 0.887, PCFI = 0.897, SRMR = 0.0696, and RMSEA = 0.056.

For the analysis of individual paths, criteria suggested by Hair et al. (2010) was used to make a decision. Table 5 summarises the results for the individual paths.

Models based on gender demonstrated different significant relationships compared to the Main Structural Model. Gender played a moderating role in the relationships between IM to PEU, amotivation to PU, amotivation to PEU, motivation to PU, motivation to PEU, TELSE to PU, and PU to BI.

Female students are affected by the relationship between IM and PEU. Even though the impact of amotivation was almost similar between males and females, it was significant only for female students ($\beta =$ —0.124, $p = 0.045$). However, Motivation yielded a bigger impact among female students ($\beta = 0.456$) towards their PU compared to male students ($\beta = 0.403$, $p > 0.05$). Whereas, the influence of TELSE was larger among male students ($\beta =$ —0.253) than their female counterparts ($\beta =$ —0.153, $p > 0.05$). However, only

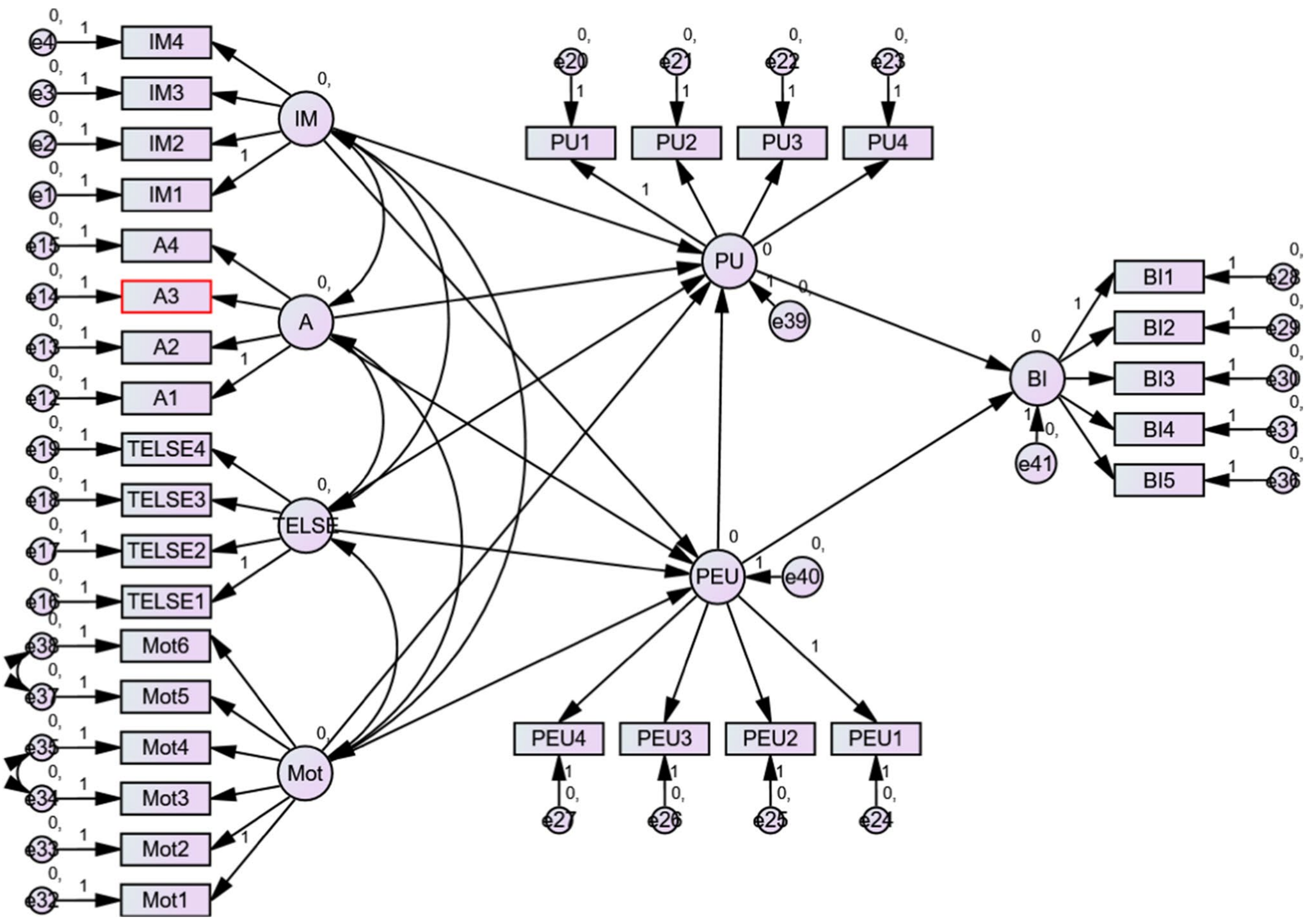


Fig. 2 Main structural model

the relationship in the male model was significant with $p = 0.037$. As for BI, PU was greater for males ($\beta = 0.690$, $p < 0.001$) than females ($\beta = 0.197$, $p = 0.136$).

The *p*-values for unconstrained and measurement residuals models for social sciences and engineering, science & technology multigroup analysis were significant, $p = 0.00$ and $p < 0.05$. The unconstrained model yielded a smaller χ^2 with $\chi^2 = 1631.499$ to bigger value for measurement residuals model at $\chi^2 = 1844.052$. The model comparison shows that $\chi^2 = 212.553$; $df = 112$; $p = 0.000$. In short, there was some level of moderation effects between the field of study and the model. The fit indices measured for both models were unconstrained model ($\chi^2 = 1631.499$, $\chi^2/df = 1.966$, CFI = 0.897, TLI = 0.885, PCFI = 0.800, SRMR = 0.0647, and RMSEA = 0.057) and measurement residuals model ($\chi^2 = 1844.052$, $\chi^2/df = 1.958$, CFI = 0.884, TLI = 0.885, PCFI = 0.895, SRMR = 0.1009, and RMSEA = 0.056. Analysis of individual path results was summarized in Table 6.

On the other hand, the field of study also played a moderating role in the model tested but limited only to the relationship between IM to PEU, motivation to PEU and TELSE to PU. Whereby IM positively influenced social sciences students compared to its effects on PEU ($\beta = 0.594$, $p < 0.05$), but not for engineering, science, and technology students. PEU among engineering, science, and technology students is significantly influenced by motivation but TELSE influence PU for social science students. As for the rest of the relationships, the field of study did not indicate the presence of moderating effects. The magnitude and impact of each variable are the same between students from social sciences group and engineering, science & technology group.

Discussion

This study aimed to study the factors contributing to university students' acceptance of technology enhanced learning from the perspectives of Self-Determination Theory, TELSE, and the Technology Acceptance Model. Although scholars have recognized the positions of Self-Determination Theory in the Technology Acceptance Model, the focus was limited to the intrinsic components of autonomy, relatedness, and competence (Chiu, 2021; Racero et al., 2020). Not much of existing literature investigated the Self-Determination

Table 5 Individual path analysis for moderation effect of gender

Moderator	Group	Path	Standardized Regression Weights, β	p	Conclusion
Gender	Male ($n = 167$)	IM → PEU	0.122	0.508	Moderated
		IM → PEU	0.375	0.005	
		Amotivation → PU	-0.108	0.062	Moderated
		Amotivation → PU	-0.124	0.045	
		Amotivation → PEU	-0.068	0.233	Moderated
		Amotivation → PEU	-0.124	0.048	
		Motivation → PU	0.403	0.054	Moderated
		Motivation → PU	0.456	0.005	
		Motivation → PEU	0.339	0.094	Moderated
	Female ($n = 135$)	Motivation → PEU	0.391	0.019	
		TELSE → PU	-0.253	0.037	Moderated
		TELSE → PU	-0.153	0.080	
		TELSE → PEU	0.524	***	Not
		TELSE → PEU	0.219	0.019	
		PEU → PU	0.629	***	Not
		PEU → PU	0.436	0.001	
		PU → BI	0.690	***	Moderated
		PU → BI	0.197	0.136	
		PEU → BI	0.229	0.012	Not
		PEU → BI	0.644	***	

Table 6 Individual path analysis for moderation effect of field of study

Moderator	Group	Path	Standardized Regression Weights, β	p	Conclusion
Field of Study	Social Sciences ($n = 108$)	IM → PEU	0.594	0.012	Moderated
		IM → PEU	0.138	0.278	
		Amotivation → PU	-0.043	0.542	Not
		Amotivation → PU	-0.095	0.063	
		Amotivation → PEU	-0.110	0.092	Not
		Amotivation → PEU	-0.072	0.184	
		Motivation → PU	0.829	0.021	Not
		Motivation → PU	0.456	0.005	
		Motivation → PEU	0.012	0.964	Moderated
		Motivation → PEU	0.471	0.003	
	Engineering, Science & Technology ($n = 195$)	TELSE → PU	-0.446	0.010	Moderated
		TELSE → PU	-0.156	0.081	
		TELSE → PEU	0.370	0.003	Not
		TELSE → PEU	0.373	***	
		PEU → PU	0.863	***	Not
		PEU → PU	0.466	***	
		PU → BI	0.386	0.006	Not
		PU → BI	0.508	***	
		PEU → BI	0.530	***	Not
		PEU → BI	0.348	***	

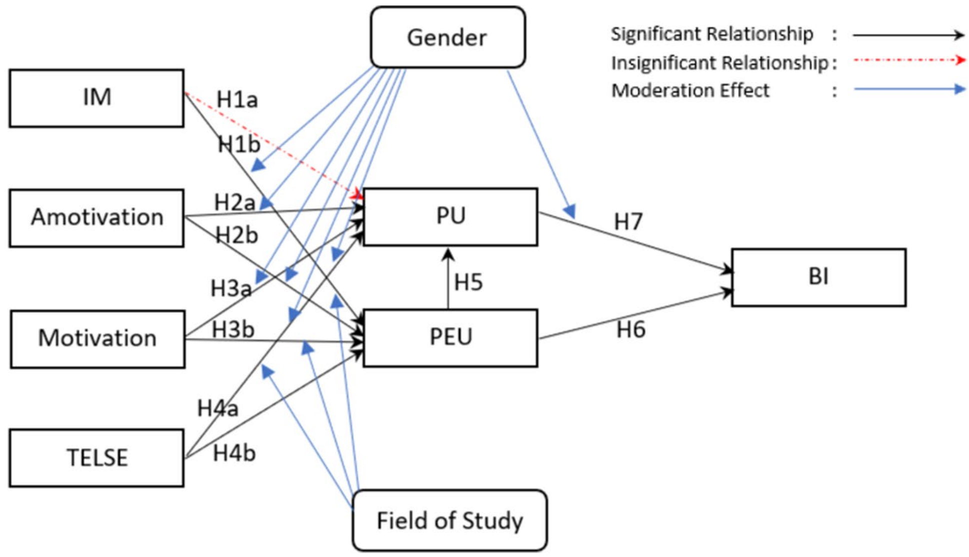


Fig. 3 Visual Representation of the Findings

Theory in full spectrum involving IM, ER, ID and amotivation. Hence, the lack of knowledge was perceived as a research gap and was assessed in the present study. This study is among the first to implement full spectrum Self-Determination Theory into Technology Acceptance Model. For that purpose, this study employed the constructs of IM, ER, ID and amotivation to complement the autonomy, competence, and relatedness that were already combined into the motivation construct. At the same time, this study examines the influence of TELSE on the Technology Acceptance Model and fills a research gap on the acceptance of technology enhanced learning using the Technology Acceptance Model tenet.

Furthermore, this study also assessed two moderating factors namely gender and field of study on the constructed model. To achieve the stated purpose, a correlational research design was applied using the Covariance-Based Structural Equation Model on university students who are actively using technology enhanced learning globally due to the impacts of Covid-19. Based on the previous literature, studies on technology enhanced learning were mainly focusing on the effectiveness, performance, thinking skills, and learning process. Thus, the acceptance of technology enhanced learning, psychological factors influencing its usage, together with the effects of gender and field of study towards acceptance are regarded as a research gap. The visual representation of the findings is as in Fig. 3.

The full spectrum of Self-Determination Theory's influence on the Technology Acceptance Model

The study's aim is to incorporate the full spectrum of Self-Determination Theory into the Technology Acceptance Model. The relationship between IM, amotivation, and motivation toward PU and PEU was examined using three hypotheses. The hypotheses tests established a positive association between IM and PEU, amotivation toward PU and PEU, and motivation toward PU and PEU. However, this positive association between IM and PEU contradicted a previous study (Sun & Gao, 2020) which reported that IM did not influence the usage of mobile devices in terms of PEU, although mobile devices are linked to technology enhanced learning. Nevertheless, Abdullah and Ward (2016) suggested that IM (in form of enjoyment) does play a substantial influence in the adoption of e-learning. The analysis reported no support for H1a, hence, there was no positive association between IM and PU. This result contradicted the findings by Abdullah and Ward (2016) and Li et al. (2021). Although the respondents were actively using technology enhanced learning, they did not regard their IM to be a significant predictor to PU of technology enhanced learning. Probably, there could be other factors influencing the PU and degrading the association of IM.

The analysis also exhibited ER and ID were related to IM. These results contradicted a previous study (Rahi & Abd. Ghani, 2019) which demonstrated that ER, as proposed by Self-Determination Theory, predicted the continuance intention to use the information system. A similar observation could not be noted in this study probably because the dynamic relationships might differ for the use of technology enhanced learning in online distance learning. In the current Covid-19 situation, the externally controlled motivation might no longer be relevant as students might perceive the use of technology to be purely essential.

A previous study indicated a negative relationship between amotivation and continuance intention to use information systems (Donaldson & Duggan, 2013). Compared to the relationships between amotivation and other constructs of motivation, amotivation demonstrated negative relationships towards IM, ID, and ER (Guay et al., 2000). Motivation is due to an individual's uncertainty about what they do and its consequences are often associated with several negative outcomes (Donaldson & Duggan, 2013). Hence, H2b yields a negative association, in line with available literature. The negative association in H2b was also supported in a previous study (Ferrer et al., 2020), indicating the effects of amotivation towards the attitude on online learning, online engagement, and intellectual engagement – which are highly related to learning in technology enhanced learning ecosystem.

A higher perceived use for technology enhanced learning could create a clear and positive impact on the user through these technologies, thus, reducing their amotivation. Malinauskas and Pozeriene (2020) also supported the inference that amotivation is lower in the online environment compared to the traditional approach. This observation could be the reason for the acceptance of H2a, where amotivation in technology enhanced learning ecosystem is negatively significant in influencing PU. According to Algharaibeh (2020), higher amotivation depicted that students were not keen on excelling in learning. Hence, the negative relationship identified in this study indicated that students are looking forward to excelling in technology enhanced learning.

Based on the results, this study suggested that motivation based on Self-Determination Theory significantly contributed to PU, thus, supporting H3a. This observation is in line with previous research (Lu et al., 2019), including a study related to technology application but not in an educational setting (Tsai et al., 2021). Motivational elements from Self-Determination Theory can also influence BI to use Virtual Learning Environment (Hew & Kadir, 2016), a variation of technology enhanced learning. Moreover, autonomy and relatedness are significant predictors of perceived enjoyment (Lee et al., 2015) which is a form of IM. However, the current study did not investigate this relationship, hence, could be explored in the future.

H3b was supported, concluding that PEU be influenced by motivational elements of Self-Determination Theory. One possible interpretation could be that technical elements such as access to the Internet and user-friendly interface of the learning materials maintain the relationship between the two constructs. Previous studies conducted in setting that education is not negatively impacted by the pandemic (Al-Maroof et al., 2021) showing the relationship in line with our finding. A study in Mexico and the USA revealed that motivation among students in higher educational institutions decreased due to the Covid-19 pandemic (Patricia Aguilera-Hermida et al., 2021). The probable degradation of motivation due to the pandemic could reduce motivation, but motivation is still a crucial precursor for the PEU of a learning environment. Thus, psychological supports are highly needed in boasting the motivation.

The relationships of TELSE to PU and PEU

The statistical results supported H4a and H4b. Negative associations existed between TELSE and PU, but positive between TELSE and PEU. In short, the more the students who perceived themselves good at using technology enhanced learning, the higher their PEU. Our statistically significant relationships between these variables were largely coherent with the findings from previous research on technology acceptance, particularly on technology enhanced learning. The relationships between the attributes of computer self-efficacy (Sayaf et al., 2021) and online academic self-efficacy (Rivers, 2021) to PU and PEU was first suggested by Davis (1989). Self-efficacy is a well-established predictor for PU and PEU (Angelica et al., 2020). Therefore, TELSE is a major component that needs to be emphasized by higher educational institutes in establishing a successful implementation of technology enhanced learning. However, its negative association toward PU need further exploration in the future.

Relationships between constructs of Technology Acceptance Model

This study also assessed the relationships between variables from Technology Acceptance Model. Based on the results, PEU yielded almost as strong relationship to BI (H6) of using technology enhanced learning compared to PU of the technology (H7). The findings deviated from the original relationship reported by Davis (1989). Since the high influence of PEU is not rare, the difference might be due to the familiarity of the respondents to the technology enhanced learning environment (Lu et al., 2019). Also, the respondents in this study could have perceived technology from a different paradigm compared to those in pioneering research (Davis, 1989). Overall, technology acceptance in this study was congruent with previous study on technology acceptance (Mutambara & Bayaga, 2021), whereby several studies reported only one of the two constructs being a significant predictor (Aburagaga et al., 2020; Barrett et al., 2021) or with indirect effect (Baber, 2021). The findings were consistent with previous literature on the relationship between PEU and PU as in H5

(Zardari et al., 2021), with some exceptions (Hanham et al., 2021). Hence, when a useful and user-friendly ecosystem is offered through technology enhanced learning, university students will have high intentions to using the platform for learning purposes.

Moderating effects of gender and field of study

The second objective of this study was to investigate the moderation effect of gender on the relationships proposed by our theoretical model. The calculated multigroup analysis demonstrated some of relationships were moderated by gender. Our findings partially substantiated the outcome in (Lakhal & Khechine, 2021) which reported gender differences in online course. A previous study (Stolk et al., 2021) revealed that gender differences exist in learning among students of higher education institutions. Hence, universities should try their best to minimize amotivation and maximize motivation regardless of gender based on Self-Determination Theory as it could lead to successful adoption of technology enhanced learning among students. Moreover, the moderation effect of gender can also be detected in the relationship between TELSE and PU. Curiously, the higher students perceived they have good TELSE; their PU is going lower. The effect is bigger for males. This needs further investigation in the future.

The final research objective probed the possible moderation effects of the study field towards the adoption of technology enhanced learning. The PEU among engineering, science & technology students were heavily influenced by their motivation. PU among social sciences students was chiefly being inversely influenced by their TELSE, while it was minimal among students from engineering, science & technology background. Therefore, higher education institutions should design their learning system to be user-friendly with the highest level of ease of use to gain and sustain a quality virtual, online, and distance education.

Theoretical implications

Several implications suitable to enhance the theoretical foundation were derived based on the data analysis along with the practice of technology enhanced learning during Covid-19. This study proposed a model of technology enhanced learning acceptance among university students by extending the renowned Technology Acceptance Model (Davis, 1989), Self-Determination Theory (Ryan & Deci, 2019), and self-efficacy (Bandura, 1977). The new model is among the major implication to the existing fundamental theories involved. This proposed model offered a deeper insight into the integration of Self-Determination Theory into technology acceptance model by including IM, ER, ID and amotivation components, which were rarely incorporated in technology acceptance. This step aided in expanding our knowledge on the functions of Self-Determination Theory in the age of digital education. We also added the contemporary TELSE into the new model to augment existing literature (Compeau & Higgins, 1995; Compeau et al., 1999). Furthermore, the questionnaire adapted, developed, and tested in this study could be used to explore the theoretics of this study.

Practical implications

Developing an effective learning ecosystem that supports the needs of digital age education and the economy remains a persistent and pervasive challenge in terms of financial, technical, and implementation. Therefore, a well-formulated plan is required to predict the acceptance of users and factors of rejection for such learning ecosystems (Abdullah et al., 2016).

Based on the findings, university students' BI to use technology enhanced learning was predicted by their PEU ($\beta = 0.417$, $p < 0.001$). Thus, universities and other higher education institutions should involve their students in the development of an effective learning medium and materials for technology enhanced learning. This step could improve students' PEU because improvements will be made based on their input (Abdullah et al., 2016). In addition, it is also recommended to produce learning supports such as tutorial videos on how to use the technology enhanced learning in and off-campus to increase student's familiarity with the system. The user interface and navigation design of the technology enhanced learning should also be updated frequently based on students' responses.

Moreover, PEU was also identified to positively impact PU ($\beta = 0.569$, $p < 0.001$). Hence, it is imperative for higher education institutions to involve students into the design and development of technology enhanced learning to boost higher level of PEU. Technology enhanced learning which is user-friendly, easy to use, combined with excellent design, and navigational design would automatically encourage university students to use the system. A high level of motivation from the perspective of self-determination could boost PU ($\beta = 0.505$, $p < 0.001$). This observation reinforces the practical implication to involve students in the development, design, and implementation to increase relatedness, autonomy, and competence (Deci et al., 1991).

This study also indicated that students' IM ($\beta = 0.275$, $p < 0.05$) revealed a sizable influence on their PEU towards technology enhanced learning. This finding supported the concept introduced by Ryan and Deci (2000) where they theorized that IM could deliver better learning outcome influenced by effective activities conducted during the teaching and learning session to improve student's motivation. At the same time, internal motivation among students needs to be enriched because IM refers to individual satisfaction in using the learning material, tool, and device. Hence, system breakdown, unstable connection and degraded fluidity of the media could lead to frustration that jeopardizes IM. Therefore, regular maintenance of technology enhanced learning-related devices and service providers is highly recommended. Technology enhanced learning offered by the university must also promote performance feedback, freedom of choice in learning, and free from evaluations that might demean students to enable competence and autonomy that facilitate IM (Ryan & Deci, 2000).

Another substantial predictor for PEU is TELSE ($\beta = 0.402$, $p < 0.001$), where it suggested that self-efficacy will nurture self-confidence and self-control (Bandura, 1986). Some students might still be unfamiliar with technology enhanced learning prior to their registration as university students. Thence, the university could provide basic hands-on workshops for new students to achieve self-efficacy in interacting with technology enhanced learning. Introducing a peer support system might also be beneficial in facilitating the development of self-efficacy. Furthermore, appraisals by instructors and universities on a student's ability to use, interact, and manipulate technology enhanced learning for learning purposes as suggested by Lyons and Bandura (2018) could induce TELSE.

Limitations and direction for future work

This study identified a few associated limitations that need to be addressed for future work. Firstly, the respondents who were recruited in this study were all from a single university. Therefore, more universities can be involved in future studies to aid with larger-scale generalization. Secondly, only 6 variables from two different theories (Self-Determination Theory and self-efficacy) were included in the theoretical model as predictors to technology acceptance using the Technology Acceptance Model. Hence, other variables affecting technology enhanced learning acceptance could be included in the future. We also recommend the extension of our theoretical model to encompass additional theories and factors in future studies. In the model we had tested, 29% of the variance for BI to use technology enhanced learning among university students are still unknown. The same thing goes for PU with 21% of the variance and PEU with 23% of the variance are still unexplained by the model.

Next, the data in this study was collected across samples using a correlational research design. Thus, experimental designs using pre-post tests and longitudinal studies could be integrated in the future to measure the presence of any differences. Finally, although the sample size used in this study was sufficient for the structural equation model, future study designs could use a bigger sample size to avoid any decline in TLI and CFI indices when the multigroup analysis is used to examine the theoretical model, as these indices are sample size sensitive.

Conclusion

Despite the tsunami of challenges due to the Covid-19 pandemic, a window of opportunities in the advancements of higher education was also evident. Technology acceptance among university students for teaching and learning has now entered a different landscape than before. As such, Extrinsic motivation is now internalized toward intrinsic motivation more than before and low amotivation is good for the new approach of education. Gender and field of study play moderation effect, these group of students need different psychological and learning support. Self-efficacy in interacting with technology enhanced learning need attention to ensure high level of PEU and PU. PEU has the same place PU as the main determinant of BI as a new norm. Therefore, universities and instructors need to pay attention to the elements of self-efficacy and motivation based on Self-Determination Theory, basic psychological needs, and reduction of amotivation among students in planning, designing, and implementing technology enhanced learning.

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Authors' contributions Mohd Shafie Rosli: conceptualization, theory, instrument, data analysis and writing – original draft preparation. Nor Shela Saleh: instrument, literature, methodology and revising.

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Data availability The dataset generated and analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethical approval All the data collection procedures were in accordance with the ethical practices. Ethical approval was not required in accordance with the current institutional requirement where the data were collected.

Informed consent Respondents answered the questionnaire voluntarily and were informed about the research purposes before they agreed to answer the questionnaire.

Competing interest The authors declared that they have no competing interest.

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