How Does Technology Anxiety and Technology Importance Influence Students' Adoption of the Learning Management System? A TAM Perspective

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Abstract

Learning management system has gained importance in the post-COVID-19 higher education era. However, just installing an LMS does not automatically guarantee that it is accepted by the students. Based on the Technology Acceptance Model, the current study explores the influence of Technology Anxiety on students' intention to adopt an LMS. The adoption-related beliefs, perceived ease of use, and perceived usefulness were mediators in the model, while perceived importance of technology is a moderator in the framework. Data were collected through an online survey from third- and final-year undergraduate students enrolled in Business and Economics departments of a large public-sector university in Punjab, Pakistan. After screening, 361 usable responses were analyzed using PLS-SEM (SmartPLS 4). The measurement model was fully established through reliability and validity. The structural model results provided support for all of the proposed hypotheses. Technology anxiety emerged as a significant psychological inhibitor, influencing both directly on intention and indirectly by shaping TAM beliefs. Importantly, perceived technology importance buffered the adverse role of anxiety, indicating that students who view technology as valuable for learning and future-oriented outcomes are less likely to let anxiety translate into negative adoption beliefs. This study integrates emotions with cognitive beliefs and intention towards technology. Practical implications for university administrators include designing usability-focused LMS interfaces, strengthening student support mechanisms, and cultivating technology importance beliefs to reduce anxiety towards the new system. Limitations and future research recommendations are also provided.

Keywords: Technology Anxiety; Technology Importance; Technology Acceptance Model; Learning Management System; Perceived Usefulness; Perceived Ease of Use.

INTRODUCTION

In the rapidly evolving era in which technology and academic interrelated, the learning management system (LMS) has gained immense traction as a component of teaching, learning, and academic administration. Post COVID-19, universities across the globe are increasingly relying on LMS platforms to deliver course content, manage assessments, facilitate student-teacher interactions, and maintain academic continuity. While there is immense improvement in the technical infrastructures of the LMS, and universities are investing in their deployment, the effectiveness of such systems depends largely on students' psychological responses and behavioral intentions towards their use. Prior research in technology adoption has consistently shown that mere availability of the technology does not guarantee its acceptance or usage (Davis et al., 1989; Venkatesh et al., 2003).

To study users acceptance and adoption of technology, the Technology Acceptance Model (TAM) (Davis et al., 1989) remains a popular framework, and can be applied to the LMS adoption in higher education settings. According to TAM, perceived usefulness (P-Usefulness) and perceived ease of use (P-EOU) shape users' attitude and intention towards technology adoption (Intentions). Extensive research shows the TAM is a robust model to explain students' acceptance of e-learning technologies across diverse cultures and institutional contexts (Raza et al., 2020; Sayaf et al., 2022). However, to date, there is a scarcity of studies that have explored the impact of negative emotions and psychological barriers that may inhibit technology adoption, particularly when discussing the adoption of new systems.

One such psychological barrier is technology anxiety (Tech_Anxiety), which can be defined as feelings of fear, discomfort, and even apprehension with the use of technological systems. Previous research indicates that technology-based anxieties negatively influence perceptions of the usefulness and ease of use of technology, thereby reducing the intention to adopt it (Venkatesh, 2000). Recent evidence further suggests that technology anxiety remains a persistent psychological barrier even among users with prior exposure to digital systems, affecting perceptions and intentions across various contexts (Kim et al., 2023). Therefore, it is plausible that in academic settings, students experiencing a high level of technology anxiety may struggle to fully engage with LMS platforms, despite institutional expectations and repeated use.

While anxiety can hinder the acceptance of technology, ingrained beliefs about the importance of technology for academia can be an important factor that mitigates the negative effect of anxiety on

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adoption beliefs and intentions. Technology importance (Tech_Impo) can be defined as the perceived relevance and value of technology for academic and learning outcomes (Pritchett et al., 2013). Students who perceive technology as important for academic success and skill development may be more willing to tolerate discomfort or anxiety associated with its use (Selwyn, 2007). However, there is a scarcity of research that explores the moderating role of technology importance in the relationship between technology anxiety and TAM beliefs.

Building on the prior work, this study researched undergraduate students and proposed a moderated TAM framework in which Tech_Anxiey is the antecedent, influencing intention to use LMS through P-EOU and P-Usefulness, while Tech_Impo acts as a moderator that dampens the negative influence of anxiety. The study integrates the emotional perspective into the TAM model, responding to recent calls for more psychology-informed models of technology adoption(Kim et al., 2023), particularly in post COVID-19 higher education scenario.

LITERATURE AND FRAMEWORK

LMS Adoption and TAM in Higher Education

LMS, a kind of management information system (Alias & Zainuddin, 2005) is nowadays a core part of the e-learning system in modern universities. LMSs are extensively used in universities, where they support e-learning by supplementing traditional teaching methods and enhancing the learning environment. Generally, an LMS provides following features: 1) content management; they provide a centralized platform for managing educational content. Allow educators to upload and organize material efficiently. 2) interactive learning environment: they offer various interactive tools such as quizzes, assignments, and discussion forums to engage learners and facilitate active participation. 3) They provide tracking of student progress and performance such as marks, attendance, etc. Modern LMS are web-based applications that enable every stakeholder to access their enabled front end at ease of any device and place (Irfandi et al., 2023; Ramzy & Najimudeen, 2025). It is noteworthy that the adoption of LMS not only aids in teaching but also leads to efficient administration as well as lead to sustainable paperless practices (Alturki & Aldraiweesh, 2021; Camilleri & Camilleri, 2022). However, as discussed earlier, universities face a common issue that LMS installation does not automatically convert into student acceptance. In most cases, students' willingness to adopt the LMS is an important factor that determines the success of the implementation and the university's investment (Zwain, 2019).

To study the technology acceptance, TAM (Davis, 1989) remains a popular choice among academicians because of its logical and generic approach to understanding the adoption and acceptance of technology. TAM proposes that various contextual and personality antecedents translate into intention and actual use of technology via mediating paths of technology beliefs; P-usefulness of the technology under consideration, and P-EOU of the technology. Earlier studies report its extensive use in applications like LMS and e-learning contexts (Sayaf et al., 2022). Recent bibliometric evidence also documents the dominance of the TAM model across various types of technology adoptions.

Conceptually, P-Usefulness reflects the belief that using the system enhances performance, whereas PEOU reflects the expectation that using the system requires less effort (Davis et al., 1989). Now these two beliefs are contingent upon various internal and contextual factors. In the LMS context, these beliefs are based upon the notion of whether students believe LMS improves their academic performance (usefulness) and whether the system feels manageable (ease of use)alongside traditional academic routines (Kim et al., 2009) and other technologies in use. According to the TAM model, when applied to LMS adoption, we posit with related to intention to use LMS that:

H1: P-EOU is positively related to intentions.

H2: P-Usefulness is positively related to intentions.

Technology Anxiety in LMS Use

Tech_Anxiety basically refers to the feeling of insecurity, fear, and apprehension when an individual is engaged with any kind of technology (Bhattacharyya, 2024; Falk, 2024). Various factors, such as generational technology divide, cognitive decline, physical limitations, cybersecurity threats, and insufficient training and support, can lead to this anxiety (Falk, 2024). Although university students are considered digitally savvy and comfortably use technologies like smartphones or social media, this does not necessarily imply comfort when interacting with institutional systems such as LMS. Academic based systems are typically complex, compulsory, and can trigger apprehension even among frequent technology users. Prior work conceptualizes technology anxiety as a negative emotional reaction experienced during actual or anticipated interaction with technology (Bozionelos, 2001). Even among younger, digitally experienced users, anxiety can exist when systems are complex or tightly linked to performance outcomes (Chow et al., 2022).

The relevance of Tech_Anxiety related to LMS can be more pronounced among youth in the post-COVID-19 academic environment. During and even after the pandemic, students were consistently exposed to an intense digital learning ecosystem that may have been overwhelming for some students. It involved multiple platforms, frequent system changes and updates, online assessments, and continuous monitoring (Maatuk et al., 2022). Moreover, it made them move out of their comfort zone of a traditional paper and pen environment and compelled them to adopt that medium for studies, which was previously mostly utilized for entertainment and pleasure. Limited empirical evidence collected during COVID-19 suggests that compulsory use of the e-learning system increases students technology related anxiety and negatively influences their perceptions of system ease and engagement, even among populations generally assumed to be digitally competent (Alkhawaja et al., 2021).

Technology anxiety and the TAM model

Emotional factors such as anxiety can shape technology-related beliefs (Venkatesh, 2000). User anxiety can be an important emotional antecedent in the TAM model, influencing how users perceive and adopt new technologies. In a meta-analytic study, Dönmez-Turan and Kır (2019) highlight that anxiety negatively impacts P-Usefulness and P-EOU; however, the impact on P-EOU was lower than P-Usefulness. These findings suggest that anxious users tend to perceive technologies as more effortful and, consequently, less beneficial.

In the academic context, particularly post-COVID-19, Tech_Anxiety has gained more relevance. A recent scoping review highlights that technology anxiety is consistently associated with users' perceptions and intentions across wide contexts, indicating that it is not age-specific but more situational and psychological in nature (Kim et al., 2023). When anxiety negatively influences P-EOU and P-Usefulness, this is expected to lower behavioral intentions. Previous research regarding e-learning and self-service supports the indirect pathway, showing that anxiety weakens intention primarily by distorting core TAM beliefs, along with acting as a direct deterrent (Dönmez-Turan & Kır, 2019; Venkatesh, 2000). Based on this theoretical and empirical ground, the following hypotheses are proposed: propose the following hypothesis:

H3: Tech_Anxiety is negatively associated with Intentions

H4: Tech_Anxiety is negatively associated with P-EOU

H5: Tech_Anxiety is negatively associated with P-Usefulness

H6: P-EOU mediates the negative influence of Tech_Anxiety on Intentions

H7: P-Usefulness mediates the negative influence of Tech_Anxiety on Intentions.

Moderating Role of Technology Importance

Users' general beliefs towards technology may shape how anxiety influences TAM beliefs. Beyond perception of usefulness and ease of use, prior research has highlighted the importance of value based belief of perceived importance or relevance of technology for growth, learning and academic success(Selwyn, 2007; Teo, 2011) Tech_Impo in the context of this study reflects the extent to which individuals perceive technology as relevant, valuable, and essential for achieving academic or future-oriented goals. A study conducted on school administrators revealed that technology was considered important for various functions within the school such as communication, instruction, data sharing, and management. The instructors considered it as a resource for administrative tasks as well as students' learning (Waxman et al., 2013). Similarly, in another study on teachers, their perception of Tech_Impo was crucial for its effective integration into education (Ertmer & Ottenbreit-Leftwich, 2010).

In the post-COVID academic environment, while technology anxiety can undermine students' system related beliefs (P-usefulness and P-EOU), its impact is unlikely to be uniform across all students. According to the expectancy value theory, individuals weigh perceived costs against perceived value when deciding to perform a task or duty (Wigfield & Eccles, 2000). When taking the context of LMS, students who already attach high importance to technology would cognitively re-frame inherent technology anxiety as a bearable cost, thereby diminishing its negative effect on P-Usefulness and P-EOU. A recent review study has also emphasized that emotional barriers interact with belief systems and contextual expectations (Kim et al., 2023), leading to our proposal that perceived technology importance serves as a boundary condition that shapes how anxiety influences TAM beliefs. Evidence suggests that students' positive beliefs about the role of technology in academia and skill growth strengthen their favorable technology perceptions and intentions, even if the conditions are demanding (Teo, 2011). Therefore, technology acceptance belief is included as a moderator in the TAM model.

H8: Tech_Impo acts as a moderator between Tech_Anxiety and P-EOU, such that for high Tech_Impo, the negative relationship is weaker.

H9: Tech_Impo acts as a moderator between Tech_Anxiety and P-Usefulness, such that for high Tech_Impo, the negative relationship is weaker.

Furthermore, we also believe that the indirect effect of Tech_Anxiety on intentions via P-EOU and P-Usefulness is non-uniform across multiple students due to their beliefs regarding Tech_Impo in their academic life. From a TAM perspective, emotional factors such as anxiety affect intention indirectly via core cognitive beliefs rather than exerting a direct, strong influence (Venkatesh, 2000). When perceived value is high, individuals are more likely to persist despite emotional barriers, and this effect would also help to overcome the cognitive barriers (Wigfield & Eccles, 2000). Students who perceive technology as important for learning, skill enhancement, or even future employability may be able to cope better with their anxiety, consider it among functional stressors, rather than taking it as a signal to disengage. As a result, the negative effect of anxiety on perceived ease of use and perceived usefulness is attenuated, weakening its downstream indirect effect on intention. This makes us propose our conditional indirect effect (moderated mediation effect).

H10: Tech_Impo moderates the indirect effect of Tech_Anxiety on Intentions via P-EOU such that the indirect effects are weaker when Tech_Impo is high

H11: Tech_Impo moderates the indirect effect of Tech_Anxiety on Intentions via P-Usefulness, such that the indirect effects are weaker when Tech_Impo is high

The following is the diagram of the proposed framework:

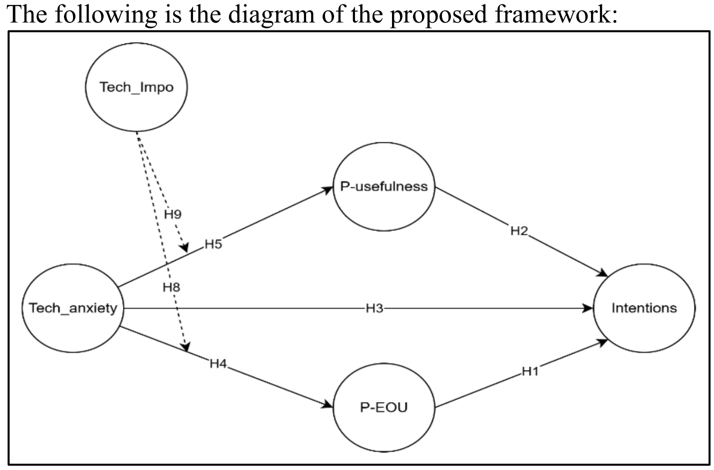

Figure 1: proposed framework of the study (Source: authors creation)

METHODOLOGY

Sampling and data collection

To empirically test the proposed framework and its associated hypotheses, this study employed a quantitative research design relying on survey data. The target population consisted of third and final-year undergraduate students from the Business and Economics departments of a major public-sector university in Pakistan. This university is large-scale public-sector university operating five administrative divisions and nine campuses throughout Punjab, the country's most populous province.

The selection of this specific institution was deliberate, driven by its history of Learning Management System (LMS). Unlike many institutions that rushed to adopt technology during the pandemic, this university had initiated LMS implementation prior to COVID-19. However, the previous system did not had much interaction with student except for checking their examination records etc. The system handled basic administrative tasks, such as course allocation, attendance, and exam scheduling for teachers. However, the four-semester lockdown period saw a heavy reliance on a hybrid of the internal LMS, Google Classroom, and Google Meet. Since returning to on-campus instruction, the administration has planned to roll out an in-house LMS custom-built to replace the previous LMS, which was sourced from a third party. Because our study focuses on psychological constructs related to technology, it was crucial to select respondents with a relatively uniform exposure to these digital tools to minimize external variables. At the time of data collection in 2024, an in-house LMS had started to be operational, and the students were given initial access to it.

Given their exposure to online learning during COVID-19, the students were well-versed in LMS environments, ensuring they could provide meaningful responses. To prevent any ambiguity, a brief primer was included at the start of the survey defining the scope and core features of an LMS. Before the main roll-out, the instrument underwent a validity check by two faculty members, one from IT department and one from the business management department. The purpose was to ensure the terminology of the survey were relevant and clear for the students.

Data collection was conducted in the third week of Jan 2024, just as the fall semester was ending. Questionnaires were distributed via Google Forms through official class WhatsApp groups. The sampling frame included ten selected classes with a total headcount of 397 students. Participation was strictly voluntary without academic incentives; It was explicitly stated that there were no "correct" answers and guaranteed anonymity and confidentiality. All participants provided informed consent before proceeding. The survey window remained open for two weeks, with a single reminder sent to encourage participation.

The drive yielded 372 total responses.A rigorous screening process was then condusted, discarding submissions with over 10% missing data, obvious inattentive patterns, or incomplete sections. This resulted in a final dataset of 361 valid responses.SPSS ® was utilized for data entry, screening, and demographic profiling, while the structural model and hypotheses were tested using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 4.

The demographic profile of the final sample was fairly balanced, comprising 51.5% male students (n = 186) and 47.4% female students (n = 171). Four participants opted not to disclose their gender. The average age of the respondents was 22.07 years (SD = 1.78), and they held a mean GPA of 3.41 (SD = 0.29). None of the respondents were married.

Measures

Tech_Anxiety was measured with a modified version of the computer anxiety scale, which is a part of the computer attitude scale by Loyd and Gressard (1984). A sample item is "working with technology makes me nervous. Measured on five points Likert scale. The scale for Tech_Impo was measured from the perspective of the perception of use of technology in academia. The following items were used:" How important is it for you that your instructor uses new, cutting-edge technology?" "How important is it for you that more or better technology was available to learn, study or complete coursework?", How important is it for you that you were better trained or skilled at using available technologies to learn, study or complete coursework?". The importance was measured on 4 points scale from very important to not at all important. The questions related to TAM variables: P-EOU, PUsefulness, Technology Attitude, and Intentions were adapted from earlier studies (Davis, 1989; Davis et al., 1989), and various previous studies on TAM have repeatedly used these questions by slightly rephrasing them to the context of the specific type of technology system emphasized in a study (Kim et al., 2009; Venkatesh, 2000; Venkatesh & Bala, 2008; Venkatesh & Davis, 2000; Venkatesh et al., 2003). Five items served as the P-EOU measurement tool. A sample item is "I find LMS easy to use." P-Usefulness was measured with four items. Finally, the intention was calculated with five items. A sample item is 'As I am given access to more features in LMS, I intend to use them'. A five-point Likert scale was used to score the responses for all of the TAM variables (Strongly Disagree to Strongly Agree).

RESULTS

Reliability and Convergent Validity

The results for reliability and convergent validity are reported in Table 2. Overall, the measurement model shows an acceptable level of internal consistency and convergent validity across the constructs, although some variations can be observed among individual measures. Except for Tech_Impo (α = 0.655) and Tech_Anxiety (α = 0.659), all other constructs had Cronbach's α greater than 0.7. However, composite reliability, which is a more robust assessment of internal consistency, was greater than 0.7 in all constructs. Convergent validity was assessed using the average variance extracted (AVE). The AVE values for all constructs are above the minimum threshold of 0.50, implying that each construct explains more than half of the variance of its indicators. Therefore, convergent validity was established.

Table 1: Reliability and Convergent validity of the measurement model

Construct	Cronbach's α	Composite Reliability	AVE
P-EOU	0.843	0.890	0.619
Intentions	0.863	0.895	0.550
Tech_Impo	0.655	0.813	0.592
P-Usefulness	0.886	0.922	0.748
Tech_Anxiety	0.659	0.812	0.591

Discriminant Validity

Table 3 shows discriminant validity using both the Fornell–Larcker (FL) criterion and the HTMT ratio. Starting with FL criteria, It can be seen that square root of AVEs (bold diagonal in Table 3) are greater than the correlations between constructs. This suggests that the constructs are empirically distinct from each other. Similarly, the HTMT correlation was in all of the cases less than the conservative threshold of 0.85. Therefore, with both criteria, discriminant validity is established.

Table 2: Discriminant Validity: Fornell–Larcker Criterion and HTMT Ratios

Construct	1	2	3	4	5
1. P-EOU	0.787	0.709	0.363	0.513	0.592
2. Intention	0.606	0.742	0.383	0.643	0.601
3. Tech_Impo	0.275	0.291	0.769	0.325	0.511
4. P-Usefulness	0.437	0.563	0.250	0.865	0.312
5. Tech_Anxiety	−0.455	−0.464	−0.340	−0.240	0.769

Note. Diagonal elements (bold) represent the square roots of the average variance extracted (AVE). Values below the diagonal are inter-construct correlations (Fornell–Larcker criterion). Values above the diagonal are heterotrait–monotrait (HTMT) ratios.

Direct Effects and Moderation

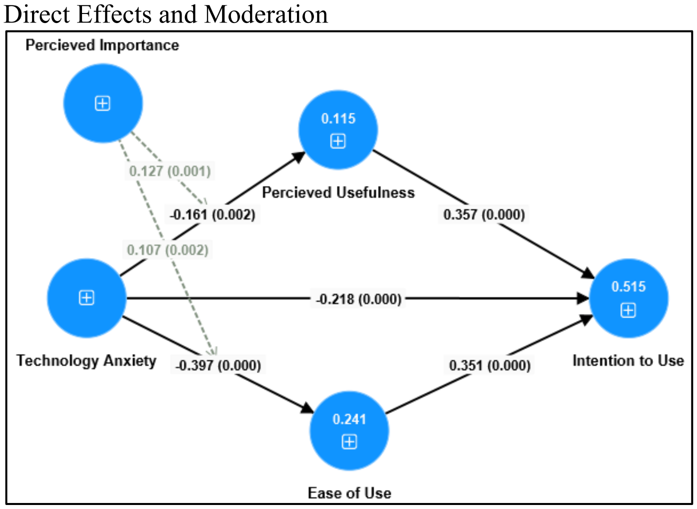

Figure 2: SMART PLS diagram for the structural model

Table 4 and Figure 2 present the results of the structural model, reporting the direct and moderating effects of the proposed model. Overall, the findings provide fairly consistent support for the proposed relationships. It can be seen that P-EOU ($\beta = 0.351$, $p < .001$) and P-Usefulness ($\beta = 0.357$, $p < .001$) show strong and positive effects on the Intentions, suggesting that H1 and H2 were accepted. . Tech_Anxiety shows a significant negative effect on the Intentions ($\beta = -0.218$, $p < .001$), P-EOU ($\beta = -0.397$, $p < .001$) and P-Usefulness ($\beta = -0.161$, $p = .002$). Therefore, H3, H4 and H5 were accepted.

Table 3: Path Coefficients, Significance Values, confidence intervals and effect size

Path	β	p	95% CI [LL, UL]	f²
P-EOU → Intention	0.351	< .001	[0.269, 0.433]	0.172
Tech_Impo → P-EOU	0.097	0.018	[0.025, 0.178]	0.01
Tech_Impo → P-Usefulness	0.144	0.004	[0.056, 0.236]	0.019
P-Usefulness → Intention	0.357	< .001	[0.281, 0.435]	0.212
Tech_Anxiety→ P-EOU	−0.397	< .001	[−0.481, −0.317]	0.182
Tech_Anxiety→ Intention	−0.218	< .001	[−0.312, −0.126]	0.078
Tech_Anxiety→ P-Usefulness	−0.161	0.002	[−0.251, −0.071]	0.026
Tech_Impo × Tech_Anxiety→ P-EOU	0.107	0.002	[0.039, 0.160]	0.024
Tech_Impo × Tech_Anxiety→ P-Usefulness	0.127	0.001	[0.051, 0.184]	0.028

The interaction effects show a positive moderation by P-Importance for both relationships, between technology anxiety and P-EOU, and technology anxiety and P-Usefulness. The same relationships are shown in Figures 3 and 4, respectively. This means high perceived importance of technology dampens the negative relationship between technology anxiety and P-EOU, and between technology anxiety and P-Usefulness of the technology. Hence moderation hypothesis, H8 and H9 were accepted in our case.

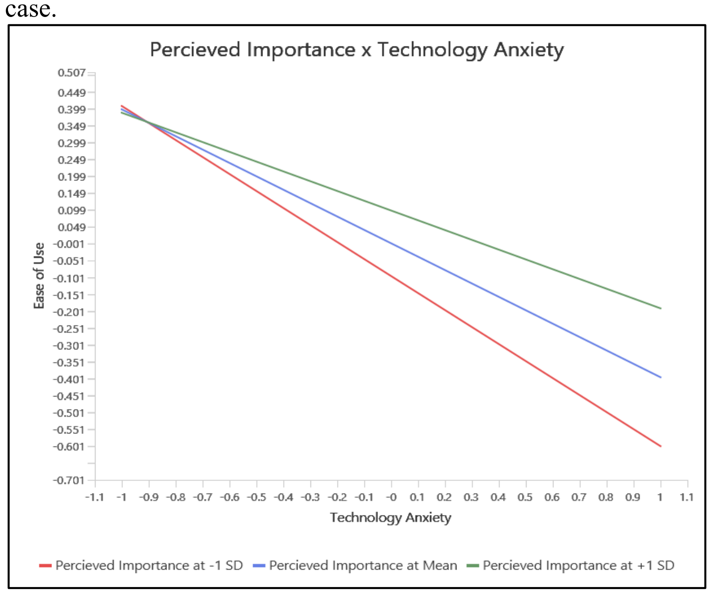

Figure 3: Moderation Slope of Tech_Impo between Tech_Anxiety and P-EOU

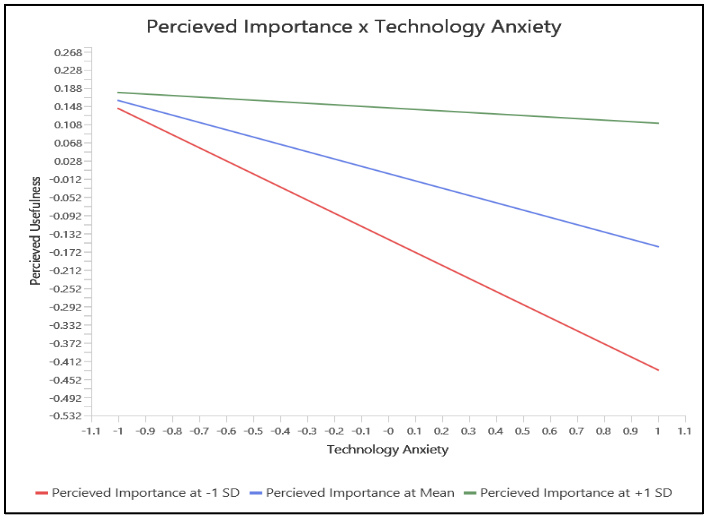

Figure 4: Moderation Slope of Tech_Impo between Tech_Anxiety and P-Usefulness

Explanatory Power

The explanatory power of the structural model can be assessed using the coefficient of determination (R^2) along with the effect sizes (f^2). For effect size, the benchmark is such that the effect is small for f^2 of greater than 0.02 and less than 0.15, medium for f^2 of greater than 0.15 and less than 0.35, and large for f^2 greater than 0.35. Among our results, P-EOU (f^2= .172) and P-Usefulness (f^2 = .212) had a medium effect on intention. Similarly, Tech_Anxiety had a medium effect on P-EOU (f^2 = .182) but a small effect on P-Usefulness (f^2 = .026) and Intentions (f^2 = .078).

The model explains a substantial portion of variance in Intentions (adjusted R^2 = 0.511). This figure in the table shows that all the exogenous variables explain more than 50% of the variance in Intentions. For P-EOU, the model explains a moderate variance of 24.1%, and for P-Usefulness, the model explains a relatively low variance of 11.5%.

Table 4: Coefficient of Determination

	R-square	R-square adjusted
Intention	0.515	0.511
P-EOU	0.241	0.235
P-Usefulness	0.115	0.107

Predictive Relevance

Q2 and PLS-predict was used to assess the predictive relevance of the model (Liengaard et al., 2021). The procedure examines out-of-sample prediction accuracy through Q²predict values and a comparison of prediction errors between the PLS-SEM model and a linear regression (LM) benchmark. At the construct level, all Q2predict were greater than zero, depicting a minimum benchmark fulfilled. At the indicator level, most of the PLS-SEM RMSE and MAE values are generally lower than those of the linear regression model for the majority of indicators. Therefore, strong predictive relevance can be assumed. The results are shown in Table 5.

Table 5: Q2 Predict and PLS-Predict

	Q²predict	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE
P-EOU	0.222				
EaseUse1	0.123	0.923	0.724	0.931	0.734
EaseUse2	0.158	1.002	0.777	1.023	0.794
EaseUse3	0.137	1.03	0.85	1.048	0.866
EaseUse4	0.066	1.01	0.838	1.023	0.848
EaseUse5	0.198	0.93	0.737	0.936	0.734
P-Usefulness	0.096				
PU1	0.054	1.052	0.812	1.067	0.827
PU2	0.093	0.963	0.731	0.983	0.759
PU3	0.071	1.022	0.822	1.039	0.826
PU4	0.068	1.064	0.822	1.087	0.852
Intentions	0.223				
Int_use1	0.125	0.906	0.717	0.909	0.72
Int_use2	0.076	0.904	0.689	0.901	0.694
Int_use3	0.049	1.117	0.914	1.118	0.921
Int_use5	0.148	0.929	0.708	0.935	0.722
Int_use6	0.187	0.843	0.652	0.859	0.672
Int_use7	0.125	0.956	0.777	0.962	0.776
Int_use8	0.127	1.129	0.921	1.132	0.907

Indirect and Conditional Indirect Effect

Table 6: Indirect Effect Coefficient, Significance Values and Confidence Interval

Indirect Path	β	P	95% CI [LL, UL]
Tech_Anxiety→ P-Usefulness → Intention	−0.057	0.005	[−0.098, −0.024]
Tech_Impo → P-EOU → Intention	0.034	0.025	[0.008, 0.065]
Tech_Impo × Tech_Anxiety→ P-Usefulness → Intention	0.045	0.001	[0.018, 0.067]
Tech_Anxiety→ P-EOU → Intention	−0.139	< .001	[−0.186, −0.100]
Tech_Impo × Tech_Anxiety→ P-EOU → Intention	0.038	0.003	[0.013, 0.058]
Tech_Impo → P-Usefulness → Intention	0.052	0.007	[0.020, 0.089]

Table 6 lists the indirect and conditional indirect effects of the study variable on the dependent variable. There were two serial mediators in the framework. The results show that P-usefulness (β = −0.057, p = .005) and P-EOU (β = −0.139, p < .001) are significant mediators between Tech_Anxiety and Intentions. Therefore, H6 and H7 were substantiated. However, as the beta values suggest, a greater effect is passed through P-EOU, while the combined mediating effect is smaller than the direct effect.

Table 6 also lists the conditional indirect effects with moderated mediation results. The interaction between Tech_Impo and Tech_Anxiety shows significant positive indirect effects on Intention via both P-usefulness (β = 0.045, p = .001) and P-EOU (β = 0.038, p = .003). This shows that the perceived Tech_Impo weakens the negative indirect influence of Tech_Anxiety on Intentions. Hence Hypothesis H10 and H11 are accepted.

DISCUSSION

Previous management research has highlighted that addressing Tech_Anxiety through adequate training and open communication is essential for managers to alleviate these concerns among employees(Bhattacharyya, 2024). However, this study is the first of its type that focuses on the anxiety about technology among university students. The study examined how Tech_Anxiety shapes students' intention towards adaptation of a newly deployed LMS by adopting the core TAM model. TAM beliefs of P-EOU and P-Usefulness were the mediators, while Tech_Importance was considered as a boundary condition. Overall, ample support is found of our proposed hypothesis emphasizing that emotional factors are relevant in shaping technology adoption decision in academia. In total, all of the study's hypotheses were accepted with low to medium effect sizes and substantial R2 values.

Starting with LMS-related beliefs and intention, the study found that the relationship is established as expected in the TAM model (Davis et al., 1989; Venkatesh & Bala, 2008), with P-Usefulness being a stronger predictor than P-EOU. However, both beliefs had a medium effect on students' intentions to adopt LMS. Tech_Anxiety as an antecedent, the researchers found that it is a significant inhibitor of students' willingness to adopt LMS. these findings are consistent with previous literature, which also indicates that individual intention to adopt technology decreases when they feel more anxious and overwhelmed (Bozionelos, 2001). However, the direct effect of anxiety on intention had a lower effect size than TAM beliefs, which indicates that emotional factors exert their influence by first shaping cognitive beliefs and have less influence is directly on behavioral intentions (Venkatesh & Bala, 2008). This also shows that even in presence of emotional trigger, intentions are primarily altered by cognitive beliefs even in academic settings (Raza et al., 2020).

Therefore, we also tested for the indirect effect via the technology beliefs and had interesting findings. First, there is a significant relationship of Tech_Anxiety on P-EOU and P-Usefulness, with the effect being more pronounced on Ease of Use. Previous TAM literature also indicates that anxiety increases the perception of effort and difficulty of the system, leading to a high perception of the system being intricate to handle and operate (Venkatesh, 2000). When students feel anxious that they have to operate an education-based computer system, it appears to be more complicated and demanding, even if functional benefits are recognized. Meta analytic finding also suggest that anxiety related feeling are stronger associated with ease of system rather then usefulness across various technology adoption contexts (Dönmez-Turan & Kır, 2019). The mediation of TAM beliefs was eventhough partial, it suggest the emotion-cognition-intention model in which anxiety first shape the technology-related adoption beliefs which then shape the intention toward adoption.

A key contribution of the current study is to test and Tech_importance belief works as a boundary spanning cognitive condition that weakens the negative influence of anxiety related to new technology adoption on adoption-related beliefs. The moderation effects indicate that anxiety does not uniformly distort students' perceptions; rather, its impact depends on how strongly students value technology in their academic lives. This is aligned with expectancy-value theory and in the LMS context, Tech_importance represents a value-based belief that reframes anxiety as a management demand rather then disengaging factor. Our study was not done in isolatin as prior research in educational technology indicated that strong beliefs about the importance of technology promote persistence and adaptive coping, even under challenging conditions (Ertmer & Ottenbreit-Leftwich, 2010; Selwyn, 2007; Teo, 2011).

Beyond moderation at the emotion-belief level, the study also provides evidence for conditional indirect effects with moderation at the emotion-belief-intention level, indicating that the mediating role of P-EOU and P-Usefulness varies across levels of Tech_Impo. The beta coefficients of the indirect path show that it is more substantial through P-EOU rather than P-Usefulness. Similarly, when technology is perceived as important, its buffering role is particularly effective in mitigating anxiety-driven perceptions of difficulty, which then translates into a weaker negative impact on intention. This is consistent with studies in TAM model, which show that emotional factors influence intentions through indirectly and through different belief channels (Venkatesh & Bala, 2008).

Collectively, our findings challenge a rather simplistic belief that university students' digital exposure makes them comfortable with technology. However, in the post-COVID academic environment, when students were overwhelmed with technology in academia, the LMS adoption now is shaped by a complex interplay of anxiety, beliefs, and perceived importance of the technology in academia by the students.

Practical Implications

In addition to the theoretical contributions as discussed earlier, this study has various practical implications, especially for the university administration, academic managers, and ICT managers who are responsible for implication of LMS and other e-learning technologies. First, the results suggest that technology anxiety is a barrier to LMS adoption even among our sample who are Generation Z, the second most tech-savvy generation until now, and are generally considered digitally competent. Second, the role of P-EOU among the model suggests that students are concerned with how manageable and easy the LMS is to use in their daily academic routine. Therefore, it is suggested that the software designed should be user-centered with simple navigation, a consistent interface, and clear instructions. Any usability issues, even seemingly trivial ones, may have a disproportionate influence on anxiety, thereby undermining the willingness to engage with the LMS. Third, the buffering role of Tech_Impo suggest that if we shape students belief system to understand that technology in general is useful for their learning, growth and future success, this can immensely reduce the negative consequences of anxiety. This is going to be useful as there is no escape from technology now. With the emergence of generative and general artificial intelligence and its related challenges, success is possible if students have strong positive beliefs towards technology. Finally, the results indicate that training related to systems should not be only technical-based. The trainer and academicians need to go beyond technical knowledge and address emotional and psychological concerns as well.

Limitation and Future Research

The study comes with several limitations, which should be overcome by future researchers. First, the sample was drawn from a single public sector university, which may limit the generalizability. However, the university was chosen because it was in a transition period while implementing a new LMS system, which was just operational, and students needed to understand the importance of the LMS for their academic endeavors. Such a situation was ideal for understanding what happens if the LMS is rolled out at a much larger scale. This study relied on use of cross-sectional data and invite future researchers to adopt longitudinal designs and a more diverse sample. While the antecedent, technology anxiety, is unique, the fact is appreciated that the majority of recent studies have focused on emotional distress factors such as techno-stress or techno-uncertainty. Future studies can focus on different stressors to understand the relationship in a better way. Moreover, positive emotions can also be integrated. Last, we acknowledge that the study was based on intention to use, rather than actual behavior to use LMS. However, once the LMS is completely rolled out, the researcher intends to study the actual adoption behavior by teachers, students, and administrators, differentiating between compelled adoption and voluntary adoption.

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