Investigating Factors Influencing Personalized Mathematics Learning Adoption among Pre-university Students at the Maldives National University: An Extended UTAUT 2 Perspective

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ABSTRACT

Learning Management Systems (LMS) are widely used to promote personalized learning in mathematics. However, sustained adoption remains uneven, particularly when students' study routines and prior experience with formal e-learning vary. This study investigates the determinants of pre-university students' behavioural intention (BI) to adopt Moodle-supported Personalized Mathematics Learning (PML) at The Maldives National University (MNU), where PML is implemented through structured Moodle-based resources, practice, and feedback, using an extended UTAUT2-informed framework that incorporates learning- and engagement-relevant constructs. A cross-sectional survey design was employed (N = 120; population frame = 559). A total of 47 items measured performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, learning value, habit, student commitment, intrinsic motivation, and behavioural intention. Measurement quality was assessed using exploratory factor analysis (KMO = 0.871; Bartlett's χ^2 (1081) = 4856.158, $p < .001$; 10-factor solution; 74.887% cumulative variance explained) and internal consistency reliability (Cronbach's α range = 0.744 - 0.924 across constructs). Pearson correlations indicated that BI was positively associated with all predictors, with the strongest bivariate relationships observed for habit and student commitment. In multiple regression with diagnostic checks, the model explained substantial variance in BI ($R^2 = 0.628$; adjusted $R^2 = 0.598$), with habit ($\beta = 0.484$, $p < .001$), learning value ($\beta = 0.220$, $p = .023$), and student commitment ($\beta = 0.261$, $p = .017$) emerging as significant unique predictors. The findings suggest that adoption in this context is best supported by implementation strategies that strengthen perceived learning value, sustain commitment, and foster routinised engagement that can evolve into habit. Results are interpreted as associations, rather than causal effects, and future work should incorporate behavioural usage indicators and longitudinal designs to connect intention to actual adoption and learning outcomes.

Keywords: Moodle, Personalized Mathematics Learning, Behavioral intention, Habit formation, UTAUT2, Learning Management System, Technology acceptance, Maldives

1. Introduction

Digital learning platforms are now routinely positioned as key enablers of personalised learning in mathematics, particularly where institutions seek to support differentiated instruction, continuous practice, and timely feedback at scale (Major et al., 2021; Shemshack & Spector, 2020). However, the effectiveness of such systems depends on more than availability: learners must be willing to adopt and sustain use (Abbad, 2021; Salloum & Shaalan, 2019). In practice, many LMS implementations achieve initial exposure without achieving durable uptake, especially in contexts where students' prior experience with structured e-learning varies and where learning routines are still developing (Akwene, 2024; Al-Azawei et al., 2016; Brown et al., 2022).

In the Maldives, the national push toward digitally supported learning has expanded the use of Learning Management Systems (LMS) across education levels (Azlifa & Saeed, 2021). At The Maldives National University (MNU), Moodle has been utilised to support Personalized Mathematics Learning (PML) by delivering resources, structured practice, and interactive learning activities (Mohamed, 2020). In this study, Moodle-supported PML refers to the use of Moodle to organise mathematics learning through structured learning resources, repeated practice opportunities, interactive activities, and feedback processes intended to support sustained and differentiated student engagement in mathematics. Accordingly, the term does not refer to generic Moodle use in any course, but specifically to Moodle-supported mathematics learning as experienced by the pre-university students examined in this study. While Moodle provides a technically capable environment, the success of Moodle-supported PML depends on students' behavioural intention to engage with the platform consistently (Abbad, 2021; Raza et al., 2021). Understanding what most strongly aligns with students' intention is therefore practically important for instructional design, institutional planning, and sustainable LMS-supported innovation in mathematics education (Gamage et al., 2022; Ismail et al., 2021).

Research on technology adoption has frequently drawn on the Unified Theory of Acceptance and Use of Technology (UTAUT) and its extension, UTAUT2, which explain intention through constructs such as performance expectancy, effort expectancy, social influence, facilitating conditions, and habit (Venkatesh et al., 2003; Venkatesh et al., 2012; Venkatesh et al., 2016). However, evidence from educational settings has been mixed: predictors that perform strongly in workplace or consumer contexts do not always show the same explanatory pattern among students, particularly when learning value perceptions, motivational processes, and persistence mechanisms are central to engagement (Abbad, 2021; Bervell & Umar, 2017; Dwivedi et al., 2019).

In Moodle-supported learning environments, students may not adopt primarily because an LMS is "easy" or "useful" in general terms, but because the learning experience becomes valuable, personally meaningful, and integrated into their study routine (Ain et al., 2016; Ortiz de Guinea & Markus, 2009; Zacharis & Nikolopoulou, 2022). This study is positioned in relation to recent educational extensions of UTAUT2, particularly Ain et al. (2016), who foreground learning value, and Zacharis and Nikolopoulou (2022), who applied an extended UTAUT2 approach to e-learning platform adoption. What is distinctive, is the focus on Moodle-supported mathematics learning in the Maldivian pre-university context and the simultaneous examination of learning value, student commitment, and intrinsic motivation alongside the canonical UTAUT2 predictors to identify implementation-relevant priorities. To address this knowledge gap, this study examines pre-university students' behavioural intention to adopt Moodle-supported PML using an extended UTAUT2 model (Venkatesh et al., 2012; Zacharis & Nikolopoulou, 2022). In addition to the canonical predictors, the study foregrounds education-related drivers of engagement, especially learning value, student commitment, and intrinsic motivation, which can distinguish intention in a learning environment where sustained engagement is needed (Ain et al., 2016; San-Martín et al., 2020; Wilkins et al., 2016). The study provides empirical data on a setting underrepresented in the overall literature on LMS adoption by focusing on pre-university students in the Maldives (Adam, 2017; Mumthaz, 2021).

This study aims to identify which determinants are most closely associated with pre-university students' behavioural intention to adopt Moodle-supported PML. The study has three contributions: (1) a contextual contribution by providing evidence from the Maldives pre-university context, where the adoption of Moodle-supported PML is institutionally relevant (Adam, 2017; Azlifa & Saeed, 2021); (2) an applied contribution by determining which levers are most aligned with intention in this setting, which supports implementation priorities **for** administrators and instructors (Akwene, 2024; Brown et al., 2022); and (3) a theoretical contribution through refining a UTAUT2-based framework by incorporating value- and persistence-related constructs relevant to sustained learning engagement (Ain et al., 2016; San-Martín et al., 2020; Venkatesh et al., 2012; Zacharis & Nikolopoulou, 2022). Accordingly, the study addresses the following research questions: What are the levels of pre-university students' perceptions of Moodle-supported PML across the study constructs?

RQ1: What are the bivariate relationships between behavioural intention (BI) and each predictor construct?

RQ2: Which constructs uniquely predict behavioural intention (BI) when all predictors are modelled simultaneously?

2. Literature Review and Conceptual Framework

Personalized learning in mathematics is often implemented through structured cycles of practice, feedback, and adaptive support, in which learners engage with content at an appropriate pace and level of difficulty (Major et al., 2021; Shemshack & Spector, 2020). Learning Management Systems (LMS) such as Moodle can operationalize these cycles by hosting learning resources, sequencing tasks, enabling formative assessment, and providing feedback loops that sustain engagement (Gamage et al., 2022; Ismail et al., 2021; Molins & García, 2023). Nevertheless, personalization facilitated by LMSs is not implemented automatically because the platform is there; instead, its adoption requires students to feel that the learning process is a worthy, manageable, and stable one, aligned with their study habits (Ain et al., 2016; Moorthy et al., 2019; Zacharis & Nikolopoulou, 2022). For this reason, adoption research in education frequently draws on theories of technology acceptance and use to explain why learners intend to engage with digital learning platforms (Abbad, 2021; Salloum & Shaalan, 2019).

A widely used theoretical lens is the Unified Theory of Acceptance and Use of Technology (UTAUT), which explains behavioural intention through performance expectancy, effort expectancy, and social influence, while acknowledging enabling conditions as drivers of use (Venkatesh et al., 2003). UTAUT2 extends this model by incorporating additional determinants, particularly hedonic motivation and habit, to improve explanatory power in contexts where users have discretion in adoption decisions (Venkatesh et al., 2012). The UTAUT2 model, based on Venkatesh et al. (2022) is presented in Figure 1.

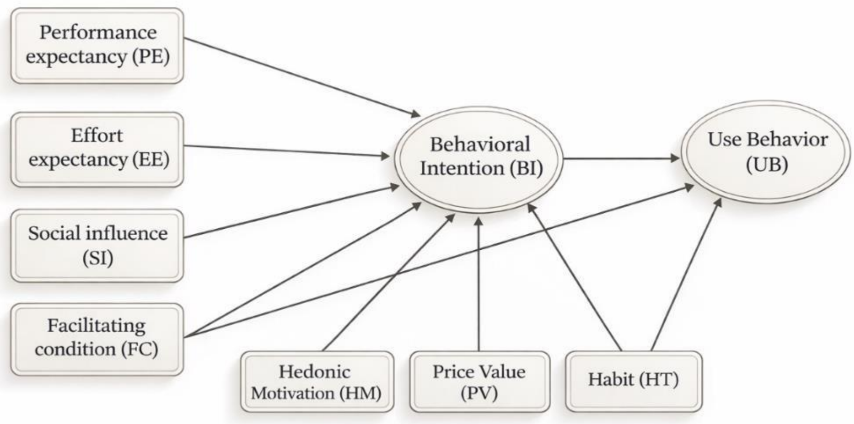

Figure 1. UTAUT2 Model (author's redrawing based on Venkatesh et al., 2012).

In educational settings, UTAUT2 has been applied to explain students' intention to use LMS platforms, digital learning tools, and online learning resources, largely because it offers a structured account of both instrumental beliefs (usefulness and ease) and experiential drivers (enjoyment and habit) (Abbad, 2021; Azizi et al., 2020; Raza et al., 2021; Salloum & Shaalan, 2019). Nevertheless, findings in education contexts have often been mixed: predictors that are robust in workplace or consumer settings do not always emerge as uniquely significant for students once multiple factors are modeled simultaneously (Abbad, 2021; Bervell & Umar, 2017; Zacharis & Nikolopoulou, 2022). This inconsistency is plausible because learning-related technology adoption is not only a "tool use" decision; it is embedded in self-regulation, persistence, and perceived learning payoff, which can overlap with or overshadow classic expectancy-based predictors when they are modeled together (Ain et al., 2016; Ortiz de Guinea & Markus, 2009; San-Martín et al., 2020). More specifically, prior studies suggest that expectancy- and support-related constructs such as performance expectancy, effort expectancy, social influence, and facilitating conditions do not always retain stable unique effects in educational LMS models once motivational and engagement-related predictors are considered, whereas habit, learning value, and context-specific persistence-related factors often remain more salient for continuance-oriented outcomes (Abbad, 2021; Ain et al., 2016; Bervell & Umar, 2017; Zacharis & Nikolopoulou, 2022). This pattern provides an empirical basis for extending UTAUT2 in learning instead of relying only on the canonical predictor set.

Against this background, the present study adopts a UTAUT2-informed foundation and extends it with education-relevant engagement constructs that are especially salient for sustained participation in Moodle-supported Personalized Mathematics Learning (PML) (Ain et al., 2016; Venkatesh et al., 2012; Zacharis & Nikolopoulou, 2022). Specifically, the model includes performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), hedonic motivation (HM), and habit (HT), and extends the framework by foregrounding learning value (LV), student commitment (SC), and intrinsic motivation (IM) as additional explanatory drivers of behavioural intention (BI) (San-Martín et al., 2020; Venkatesh et al., 2012; Wilkins et al., 2016; Zacharis & Nikolopoulou, 2022). The inclusion of these three constructs is deliberate. Learning value is retained as prior educational extensions have shown that students' judgments about the worth and utility of learning through an LMS can contribute beyond general usefulness perceptions (Ain et al., 2016; Zacharis & Nikolopoulou, 2022). Student commitment is included as mathematics engagement often depends on persistence, effort investment, and willingness to continue despite delayed rewards (San-Martín et al., 2020; Wilkins et al., 2016). While, intrinsic motivation considered as autonomous interest in learning activities may support voluntary participation in Moodle-supported practice even when external pressure is limited (Alamri et al., 2020; Deci & Ryan, 1985; Oudeyer & Kaplan, 2009).

The conceptual logic is that students are more likely to intend to adopt Moodle-supported PML when they expect the platform to support learning performance (PE), perceive it as manageable to use (EE), experience normative encouragement (SI), perceive adequate support and resources (FC), experience enjoyment during use (HM), perceive strong learning value from engagement (LV), possess commitment to persist (SC), experience intrinsic interest in learning activities (IM), and develop habitual engagement patterns that stabilize continued intention (HT) (Ortiz de Guinea & Markus, 2009; Tamilmani et al., 2019; Venkatesh et al., 2012). Performance expectancy refers to the extent to which students believe that using Moodle-supported PML will enhance their mathematics learning effectiveness or outcomes (Venkatesh et al., 2003; Venkatesh et al., 2012). Effort expectancy reflects perceived ease of use and the cognitive effort required to engage with the system (Venkatesh et al., 2003; Venkatesh et al., 2012). Although PE and EE often co-occur empirically, they are conceptually distinct: PE concerns the expected academic benefit of using Moodle-supported PML, whereas EE concerns the ease and mental effort involved in using it. A platform may be easy to use without being perceived as educationally valuable, and it may be educationally valuable while still requiring substantial effort. For this reason, both constructs are retained, while acknowledging that they may not always remain strongly discriminant in educational contexts. Social influence reflects perceived encouragement from instructors, peers, or the institution to use Moodle-supported PML (Venkatesh et al., 2003; Venkatesh et al., 2012; Raza et al., 2021). Facilitating conditions capture perceived access to necessary resources and support (such as reliable connectivity, access to devices, and guidance), enabling students to engage with Moodle consistently (Al-Azawei et al., 2016; Venkatesh et al., 2012). Hedonic motivation refers to the degree to which students experience enjoyment or positive affect while using Moodle-supported PML, which may strengthen their willingness to continue engaging (Tamilmani et al., 2019; Venkatesh et al., 2012). Habit reflects automaticity and routinized behaviour; as Moodle engagement becomes part of students' regular study pattern, intention becomes less dependent on deliberation and more dependent on continued routine (Moorthy et al., 2019; Ortiz de Guinea & Markus, 2009; Venkatesh et al., 2012).

Because Moodle-supported PML is also a learning practice that requires persistence over time, the model emphasises three education-relevant constructs. Learning value refers to students' appraisal of the usefulness and worthwhileness of the learning experience itself, whether Moodle-supported PML is perceived as beneficial, meaningful, and aligned with learning goals (Ain et al., 2016; Zacharis & Nikolopoulou, 2022). Student commitment captures the learner's willingness to persist, invest effort, and maintain engagement over time, particularly when tasks require repeated practice and delayed rewards (San-Martín et al., 2020; Wilkins et al., 2016). Intrinsic motivation refers to engagement driven by inherent interest or satisfaction in learning activities, consistent with motivational perspectives that emphasise autonomous interest as a driver of sustained learning engagement (Alamri et al., 2020; Deci & Ryan, 1985; Oudeyer & Kaplan, 2009). In Moodle-supported PML, intrinsic motivation can support voluntary engagement with practice activities and reinforce persistence when external pressures are minimal (Alamri et al., 2020). To reduce conceptual ambiguity, the three constructs are treated as related but non-equivalent. Learning value represents a cognitive appraisal that Moodle-supported PML is worthwhile for learning; student commitment represents persistence and sustained effort toward continued participation; and intrinsic motivation represents inherent interest and satisfaction in the learning activity itself. This distinction is also important for separating intrinsic motivation from hedonic motivation: HM refers primarily to enjoyment associated with using the platform, whereas IM refers to inherent interest in engaging with the mathematics learning activity supported by the platform. The two may overlap, but they are not conceptually identical, because enjoyment of system use does not necessarily imply autonomous interest in learning, and autonomous interest in learning does not necessarily depend on the platform being enjoyable in a hedonic sense.

The present study focuses on the main effects of these predictors on behavioural intention. Although UTAUT2 includes moderators such as age, gender, and experience, moderation testing typically requires larger sample sizes to preserve statistical power and to stabilize the estimation of interaction effects (Venkatesh et al., 2012). Given the study's sample size and its objective of identifying salient direct predictors of intention for applied implementation, moderators are not included in the model. They are prioritized for future work, particularly in follow-up designs that can incorporate prior LMS exposure and other contextual factors likely to shape transferability (Bervell & Umar, 2017; Dwivedi et al., 2019). The hypothesised model for the present study, adapted from UTAUT2 and extended with learning value, student commitment, and intrinsic motivation, is presented in Figure 2.

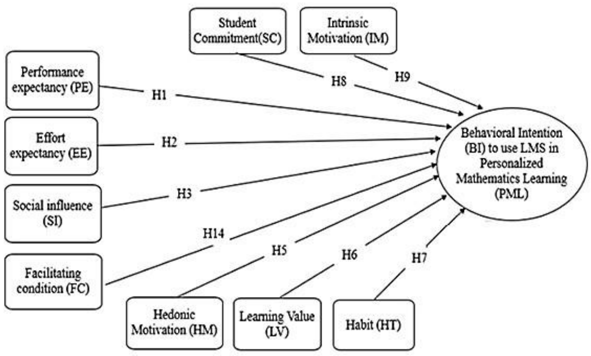

Figure 2. Hypothesised model for Moodle-supported PML adoption (adapted from Venkatesh et al., 2012).

Based on the conceptual framework, the study proposes the following hypotheses:

H_{a1}: Performance expectancy (PE) has a positive and significant effect on behavioural intention (BI) to adopt Moodle-supported PML.
H_{a2}: Effort expectancy (EE) has a positive and significant effect on behavioural intention (BI) to adopt Moodle-supported PML.
H_{a3}: Social influence (SI) has a positive and significant effect on behavioural intention (BI) to adopt Moodle-supported PML.
H_{a4}: Facilitating conditions (FC) have a positive and significant effect on behavioural intention (BI) to adopt Moodle-supported PML.
H_{a5}: Hedonic motivation (HM) has a positive and significant effect on behavioural intention (BI) to adopt Moodle-supported PML.
H_{a6}: Learning value (LV) has a positive and significant effect on behavioural intention (BI) to adopt Moodle-supported PML.
H_{a7}: Habit (HT) has a positive and significant effect on behavioural intention (BI) to adopt Moodle-supported PML.
H_{a8}: Student commitment (SC) has a positive and significant effect on behavioural intention (BI) to adopt Moodle-supported PML.
H_{a9}: Intrinsic motivation (IM) has a positive and significant effect on behavioural intention (BI) to adopt Moodle-supported PML.

3. Methodology

3.1. Research Design and Setting

The study employed a quantitative, cross-sectional correlational research design to identify variables related to behavioural intention (BI) of pre-university students to use Moodle-based Personalised Mathematics Learning (PML) at The Maldives National University (MNU) (Pratama et al., 2023). Moodle is the institution's Learning Management System (LMS) used to facilitate the delivery of PML, learning resources, and student learning activities (Mohamed, 2020). For the purposes of this study, Moodle-supported PML refers to the use of Moodle to deliver structured mathematics learning resources, repeated practice opportunities, and feedback-oriented learning activities intended to support sustained and differentiated engagement in mathematics learning.

3.2. Participants, Sampling, and Data Collection

The study population comprised 559 pre-university students at the Maldives National University (MNU). All 559 eligible students were invited to participate via an online questionnaire administered using Google Forms, and recruitment was closed once the target sample size was achieved. A total of 120 students completed the survey, yielding a response rate of 21.5% (120/559). The inclusion criterion was enrolment as a pre-university student at MNU; no exclusion criteria were applied. Because participation was voluntary and no random selection procedure was used, the achieved sample is best interpreted as a self-selected, non-probability sample rather than as a statistically representative sample of the full invited population. Convenience sampling was adopted to allow efficient access to available students; however, this approach limits generalizability beyond the sampled cohort (Akwene, 2024). The survey was administered during the study period under institutional ethical approval (Approval No.: RR/2023/18).

3.3. Instrument Development and Measures

Data were collected using a structured questionnaire comprising 47 items measuring 10 constructs: PE, EE, SI, FC, HM, LV, HT, SC, IM, and BI. Items were rated on a five-point Likert scale ranging from Strongly disagree (1) to Strongly agree (5). The instrument was adapted from previously validated scales and refined for the PML/Moodle context (Ain et al., 2016; Venkatesh et al., 2012; Zacharis & Nikolopoulou, 2022). Content suitability and clarity were reviewed by five experts before administration. The final item wording and scale anchors are provided in Appendix A. Appendix A also reports the final retained items by construct and documents any items removed during post-administration measurement review.

3.4. Construct Validity and Internal Consistency

Construct validity was assessed using a staged measurement evaluation procedure. First, Exploratory Factor Analysis (EFA) was used to examine the factor structure of the predictor-item pool (PE, EE, SI, FC, HM, LV, HT, SC, and IM). To avoid circularity between predictor validation and outcome measurement, BI items were evaluated separately rather than being included in the same EFA as the predictor constructs. The suitability of the data for factor analysis was evaluated using the Kaiser–Meyer–Olkin (KMO) measure and Bartlett's test of sphericity. Factor extraction used Principal Axis Factoring, and rotation used Direct Oblimin. Because the constructs in this study were theoretically expected to correlate, an oblique rotation was preferred.

Factor retention and item adequacy were evaluated using factor loadings and cross-loadings; items with weak loadings or problematic cross-loadings were reviewed for potential removal. Items demonstrating weak primary loadings, problematic cross-loadings, or poor corrected item-total behaviour were reviewed for removal, and all retained and removed items are documented in Appendix A. Internal consistency reliability was examined using Cronbach's alpha for each construct. Where item removal improved reliability and measurement coherence, items were removed, and the revised reliability results were retained. The final reliability coefficients (and retained item counts) for each construct are reported in the Findings section, with the full measurement outputs available in the supplementary materials.

Given the size of the achieved sample (N = 120) relative to the original item pool, the EFA results are interpreted cautiously as an initial assessment of measurement structure rather than as definitive evidence of a fully stable factor solution. Discriminant validity was additionally evaluated using average variance extracted (AVE) and the Fornell–Larcker criterion for the final construct set.

3.5. Data Analysis Strategy and Diagnostic Checks

Data were analysed using IBM SPSS Statistics (Version 25). Descriptive statistics (means, standard deviations, skewness, and kurtosis) were computed to summarize construct distributions. Pearson correlation analysis was used to examine bivariate associations between behavioural intention (BI) and predictor constructs.

To test the multivariate model, multiple linear regression was estimated with BI as the dependent variable and PE, EE, SI, FC, HM, LV, HT, SC, and IM as predictors. Regression assumptions were evaluated and reported, including multicollinearity (Variance Inflation Factor and tolerance), independence of errors (Durbin–Watson), residual normality (histogram and P–P plot), and homoscedasticity/linearity (standardized residuals versus standardized predicted values). Collinearity diagnostics were further examined using condition indices and variance proportions as reported in the SPSS collinearity diagnostics output.

Given the number of predictors relative to the sample size (N = 120; nine predictors), the analysis is interpreted as identifying associations and estimating the relative unique contribution of predictors rather than as a definitive test of small effects (Pratama et al., 2023). While common rules of thumb (e.g., 10–15 cases per predictor) suggest the sample is acceptable for estimation, statistical power is limited for detecting small incremental effects and interaction terms. For this reason, the study focuses on main effects and prioritizes transparent reporting of coefficients, confidence intervals, and diagnostics.

Bivariate correlations are reported to describe relationships among constructs and to contextualize the multivariate findings. The regression model is treated as the primary inferential analysis, while correlations are interpreted as supportive rather than as independent hypothesis tests; accordingly, emphasis is placed on the consistency of evidence across regression and correlation results rather than on isolated p-values.

Although UTAUT2 includes canonical moderators (e.g., age, gender, experience, voluntariness), these were not modelled as interaction terms in the present study because moderation testing typically requires larger samples to support stable interaction estimation and adequate power (Venkatesh et al., 2012). Moderators are therefore positioned as a priority for future research, particularly in designs that can incorporate prior LMS exposure and other contextual constraints relevant to Moodle-supported learning (Bervell & Umar, 2017).

Lastly, robustness was addressed through diagnostic review and transparent reporting of findings, with a specific focus on the possibility of shared variance among predictors. To examine coefficient stability under correlated-predictor conditions, supplementary sensitivity analyses were performed using hierarchical regression. Still, the evidence most commonly used in this study is based on the reported OLS model and its diagnostic tests.

3.6. Ethical Considerations

Ethical approval was obtained from the Research Development Office (RDO) ethics committee at MNU (Approval No.: RR/2023/18). Participation was voluntary, and responses were anonymized for analysis. Data were stored securely and used exclusively for research purposes.

3.7. Data/Materials Availability

The questionnaire instrument (item wording and anchors) is provided in Appendix A. The de-identified dataset is deposited in an appropriate repository and is referenced in the Data Availability statement in this manuscript.

4. Findings

4.1. Measurement Quality: Construct Validity and Internal Consistency

Construct validity was assessed using exploratory factor analysis (EFA) of the predictor constructs, with behavioural intention (BI) evaluated separately from the predictor-item pool to avoid circularity between predictor validation and outcome measurement. Sampling adequacy was strong (KMO = 0.871), and Bartlett's test of sphericity was significant (χ^2 (1081) = 4856.158, $p < .001$), indicating that the correlation matrix was suitable for factor analysis. Using Principal Axis Factoring with Direct Oblimin, a 10-factor solution consistent with the conceptual model was retained. The 10 factors explained 74.887% of the cumulative variance. Item performance was acceptable overall, with rotated factor loadings ranging from 0.420 to 0.824 and communalities ranging from 0.580 to 0.854.

Internal consistency (reliability) was assessed using Cronbach's alpha for each construct. Items demonstrating weak or negative corrected item–total behaviour (typically negatively keyed items) were removed to improve internal consistency. The final retained items and the item-retention log are reported in Appendix A. The final reliability coefficients and retained item counts are reported in Table 2.

4.2. Descriptive Statistics

Construct-level descriptive statistics (N = 120) are presented in Table 1. Behavioural intention (BI) was generally high (M = 3.948, SD = 0.762). Facilitating conditions (FC) and student commitment (SC) recorded the highest mean levels, indicating that students generally perceived strong support and commitment regarding Moodle-supported PML. By contrast, social influence (SI) had the lowest mean (M = 3.077, SD = 0.997), suggesting that relative to other constructs, perceived peer, instructor, or institutional encouragement was less strongly endorsed in this sample. This pattern is descriptively noteworthy because it suggests that students' intentions may be shaped more strongly by individual engagement-related perceptions than by external social pressure. In addition, FC showed the highest mean (M = 4.121) and a relatively high kurtosis value (3.911), indicating a possible ceiling effect and restricted variability in perceived support conditions. This restricted range may help explain why FC correlates positively with BI but does not emerge as a unique predictor in the full multivariate model.

Table 1. Descriptive Statistics For Study Constructs (N = 120)

Construct	N	Mean	SD	Skewness	Kurtosis
PE	120	3.971	0.783	-0.253	-0.665
EE	120	3.921	0.821	-0.787	1.035
SI	120	3.077	0.997	0.127	-0.543
FC	120	4.121	0.636	-1.124	3.911
HM	120	3.590	0.902	-0.580	0.454
LV	120	3.731	0.787	-1.055	1.910
HT	120	3.583	0.869	-0.523	0.322
SC	120	4.005	0.751	-0.893	1.565
IM	120	3.915	0.828	-1.069	2.137
BI	120	3.948	0.762	-0.878	2.026

Note. Values are based on final retained items for each construct.

4.3. Reliability

Final internal consistency estimates met acceptable thresholds across constructs. The strongest reliabilities were observed for HM, PE, EE, and BI, while FC remained acceptable. Full reliability results are reported in Table 2.

Table 2. Internal Consistency Reliability by Construct (Final Retained Items)

Construct	Items retained (k)	Cronbach's α
PE	4	0.911
EE	4	0.908
SI	4	0.817
FC	4	0.744
HM	4	0.924
LV	4	0.831
HT	3	0.874
SC	5	0.849
IM	4	0.867
BI	4	0.900

4.4. Correlation Analysis (Pearson Correlations)

Pearson correlations among constructs are reported in Table 3. Behavioural intention (BI) showed the strongest positive associations with habit (HT) and student commitment (SC), followed by learning value (LV), intrinsic motivation (IM), and hedonic motivation (HM). These correlations support the expectation that commitment, habitual engagement, and motivational/value beliefs align with intention to adopt Moodle-supported PML. At the same time, several inter-predictor correlations were relatively high, notably PE–EE ($r = 0.798$), HM–HT ($r = 0.757$), HM–LV ($r = 0.728$), and SC–IM ($r = 0.713$), indicating substantial shared variance among conceptually related constructs. These patterns are important for interpreting the multivariate regression results, particularly where bivariate associations do not translate into unique regression effects.

Table 3. Pearson Correlation Matrix (Construct Level, N = 120)

	PE	EE	SI	FC	HM	LV	HT	SC	IM	BI
PE	—									
EE	0.798***	—								
SI	0.355***	0.345***	—							
FC	0.312***	0.387***	0.113	—						
HM	0.685***	0.624***	0.526***	0.387***	—					
LV	0.561***	0.488***	0.501***	0.477***	0.728***	—				
HT	0.508***	0.475***	0.441***	0.352***	0.757***	0.618***	—			
SC	0.627***	0.556***	0.321***	0.461***	0.713***	0.617***	0.709***	—		
IM	0.533***	0.479***	0.325***	0.445***	0.615***	0.593***	0.530***	0.713***	—	
BI	0.461***	0.413***	0.244**	0.460***	0.569***	0.600***	0.704***	0.694***	0.574***	—

Note. Lower triangle reported. Two-tailed tests. *** $p < .001$, ** $p < .01$, * $p < .05$.

4.5. Multiple Regressions Predicting Behavioural Intention (BI) + Diagnostics

Multiple linear regression was estimated with BI as the dependent variable and PE, EE, SI, FC, HM, LV, HT, SC, and IM as predictors. The model was statistically significant and explained substantial variance in BI ($R = 0.792$, $R^2 = 0.628$, Adjusted $R^2 = 0.598$, $F(9, 110) = 20.635$, $p < .001$).

As shown in Table 4, habit (HT) was the strongest unique predictor of BI (standardized $\beta = 0.484$, $p < .001$), followed by learning value (LV) ($\beta = 0.220$, $p = .023$) and student commitment (SC) ($\beta = 0.261$, $p = .017$). Other predictors were not statistically significant after controlling for the full set of constructs. Accordingly, Ha6, Ha7, and Ha8 were supported, whereas Ha1, Ha2, Ha3, Ha4, Ha5, and Ha9 were not supported in the multivariate model.

Assumption/diagnostic checks. Multicollinearity was within acceptable bounds (VIF range 1.53–4.23; see Table 4). Independence of errors was supported (Durbin–Watson = 1.833). Residual diagnostics (normality and homoscedasticity checks) did not indicate violations severe enough to invalidate inference for the present model.

Table 4. Multiple Regression Predicting BI (N = 120)

Predictor	**B**	**SE(B)**	**β**	**t**	**p**	**95% CI for B**	**VIF**
PE	0.033	0.107	0.034	0.313	.755	[-0.179, 0.245]	3.57
EE	-0.024	0.094	-0.026	-0.255	.799	[-0.210, 0.162]	3.02
SI	-0.082	0.055	-0.107	-1.488	.139	[-0.191, 0.027]	1.54
FC	0.127	0.086	0.106	1.477	.143	[-0.043, 0.298]	1.53
HM	-0.169	0.101	-0.201	-1.677	.096	[-0.370, 0.031]	4.23
LV	0.213	0.092	0.220	2.311	.023	[0.030, 0.396]	2.68
HT	0.424	0.086	0.484	4.935	<.001	[0.254, 0.595]	2.84
SC	0.265	0.109	0.261	2.423	.017	[0.048, 0.481]	3.43

IM	0.097	0.081	0.106	1.204	.231	[-0.063, 0.258]	2.28

Note. DV = BI. Unstandardized coefficients (B), standard errors, standardized coefficients (β), and 95% CIs are reported. VIF = variance inflation factor.

To facilitate interpretation, Table 5 summarizes the hypothesis-testing outcomes based on the multivariate regression model.

Table 5. Hypothesis Testing Summary

Hypothesis	Path	β	p	Decision
Ha1	PE → BI	0.034	.755	Not supported
Ha2	EE → BI	-0.026	.799	Not supported
Ha3	SI → BI	-0.107	.139	Not supported
Ha4	FC → BI	0.106	.143	Not supported
Ha5	HM → BI	-0.201	.096	Not supported
Ha6	LV → BI	0.220	.023	Supported
Ha7	HT → BI	0.484	<.001	Supported
Ha8	SC → BI	0.261	.017	Supported
Ha9	IM → BI	0.106	.231	Not supported

5. Discussion

5.1. Interpreting the Dominant Predictors: Habit, Learning Value, and Student Commitment

The most important interpretive result of this study is that behavioural intention to adopt Moodle-supported PML was explained primarily by habit, learning value, and student commitment rather than by the full canonical set of UTAUT2 predictors. The multivariate model explained substantial variance in BI ($R^2 = 0.628$; Adjusted $R^2 = 0.598$), indicating that the extended UTAUT2-based model provided a strong account of intention in this setting (Venkatesh et al., 2012; Zacharis & Nikolopoulou, 2022). This level of explanatory power is strong in relation to comparable educational UTAUT2 studies, although it is not unusually high. For example, El-Masri and Tarhini (2017) reported that their extended UTAUT2 e-learning model explained 68% of the variance in behavioural intention in the Qatari sample and 63% in the USA sample. In addition, recent synthesis work has noted that UTAUT2-based models can explain up to 74% of the variance in behavioural intention in technology-use contexts (Venkatesh et al., 2012; Zheng et al., 2025). Against this benchmark, the present model's R^2 of 0.628 indicates solid explanatory performance in this pre-university mathematics setting, while also suggesting that some relevant contextual or motivational influences remain outside the current model. Habit (HT) emerged as the strongest unique predictor, followed by student commitment (SC) and learning value (LV), suggesting that intention in this context is shaped most strongly by routinised engagement, persistence, and perceived worthwhileness of the learning experience. This pattern is also consistent with broader educational UTAUT2 evidence. Zheng et al. (2025), in a meta-analytic review of 91 higher-education e-learning studies involving 37,910 participants, found that habit was the most influential antecedent of behavioural intention toward e-learning. The same review also notes that Zacharis and Nikolopoulou (2022) identified habit as the strongest predictor in their university e-learning study.

Habit being the strongest predictor aligns with evidence in technology adoption showing that repeated use reduces deliberative effort and supports continuance intentions over time (Ortiz de Guinea & Markus, 2009; Venkatesh et al., 2012; Moorthy et al., 2019). In the present study, this suggests that once Moodle-supported mathematics learning becomes embedded in students' regular study routines, continued intention depends less on one-time judgments about the system and more on the stability of those routines. This is especially relevant in pre-university settings, where study patterns may still be forming and where repeated exposure to structured digital tasks can gradually normalize platform use.

Student commitment and learning value also emerged as significant unique predictors of BI (Table 4). Together, these results point to an adoption mechanism that is both self-regulatory and instrumental (San-Martín et al., 2020; Wilkins et al., 2016; Ain et al., 2016; Zacharis & Nikolopoulou, 2022). Students appear more likely to intend continued use when they perceive Moodle-supported PML as genuinely beneficial for mathematics learning and when they are psychologically prepared to persist with the required engagement. This pattern is theoretically important because it suggests that in learning-specific technology contexts, value and persistence constructs may operate as more proximal drivers of intention than the more general expectancy constructs that dominate the original UTAUT2 formulation.

The differential pattern across the three extension constructs is also informative. Learning value and student commitment were significant, whereas intrinsic motivation was not. This suggests that not all education-specific extensions add explanatory power equally. In this sample, intention appears to depend more on whether students judge the learning process to be worthwhile and are willing to persist with it than on whether they experience inherent interest in the learning activity itself after other related predictors are controlled. Accordingly, future educational adaptations of UTAUT2 may benefit from prioritizing value- and persistence-related constructs over broader motivational constructs unless the latter are shown to contribute distinct variance in the specific learning context under study.

5.2. Why The Canonical UTAUT2 Predictors Were Not Uniquely Significant

Several UTAUT2 constructs showed meaningful bivariate associations with BI (Table 3), but none remained significant in the multivariate model (Table 4). This pattern is common when predictors share variance and suggests that their influence may be indirect or subsumed by more proximal determinants (Dwivedi et al., 2019; Bervell & Umar, 2017). The present findings therefore do not suggest that performance expectancy, effort expectancy, social influence, facilitating conditions, and intrinsic motivation are unimportant in absolute terms; rather, they suggest that their explanatory role was not unique once learning value, student commitment, and habit were entered simultaneously.

Performance expectancy (PE) and effort expectancy (EE) may have functioned as necessary but not differentiating conditions in this setting. Students reported relatively high mean levels on these expectancy constructs (Table 1), which may have reduced their ability to distinguish between students with stronger and weaker adoption intentions once more engagement-proximal variables were controlled. This interpretation is consistent with observations that expectancy constructs in educational LMS research may matter most at the stage of initial acceptance, while continuance-oriented outcomes depend more heavily on value, commitment, and routine (Abbad, 2021; Zacharis & Nikolopoulou, 2022).

Facilitating conditions (FC) also correlated positively with BI (Table 3) but did not retain unique significance in the full model (Table 4). This result is possibly linked to the descriptive pattern observed in Table 1: FC had the highest mean ($M = 4.121$) and a high kurtosis value (3.911), indicating a possible ceiling effect and restricted variability. When support conditions are already broadly perceived as adequate, they may cease to function as the primary differentiator of intention, leaving more variance to be explained by students' engagement-related judgments and routines (Akwene, 2024; Al-Azawei et al., 2016).

Social influence (SI) showed the lowest mean of all constructs ($M = 3.077$) and only a modest association with BI. This is substantively important for institutional interpretation. In this cohort, adoption appears to be less strongly driven by peer or authority encouragement than by students' own developing routines, perceived learning value, and persistence. In practical terms, this suggests that in this setting, institutional messaging alone is unlikely to be sufficient; social encouragement may help at the margins, but it is unlikely to substitute for instructional designs that make Moodle-supported PML useful, repeatable, and worth sustaining. This finding may also reflect the individualized nature of mathematics practice, where continued engagement depends less on social visibility and more on task integration into students' private study behaviour.

Intrinsic motivation (IM) correlated positively with BI (Table 3) but became non-significant in the multivariate model (Table 4), implying that its explanatory role overlapped with learning value, commitment, and hedonic experience rather than remaining distinct after adjustment. This is consistent with the broader theoretical implication noted above: in this sample, sustained intention appears to be explained more directly by "this helps me learn" and "I will persist with this" than by "I am inherently interested in this activity" once the shared variance across motivational constructs is accounted for.

These results suggest that in this cohort, the canonical UTAUT2 constructs functioned more as background conditions than as decisive differentiators of intention. This does not disconfirm UTAUT2; rather, it indicates that when the model is applied to a learning-specific context that requires sustained effort, theory may need to foreground engagement continuity, perceived learning payoff, and persistence more explicitly.

5.3. Reconciling Hedonic Motivation: Positive Bivariate Association but Negative Multivariate Coefficient

A key concern is the apparent contradiction that hedonic motivation (HM) correlated positively with BI (Table 3) but showed a negative, non-significant coefficient in the multivariate model (Table 4). This is not necessarily an error; it is consistent with shared variance or suppression when correlated motivational predictors are entered simultaneously (Dwivedi et al., 2019; Tamilmani et al., 2019).

HM overlapped strongly with other engagement-related predictors, particularly HT, SC, and LV. When these correlated constructs were estimated simultaneously, the HM coefficient reflected the unique component of enjoyment not shared with habit, commitment, or value. In the present model, that unique remainder was negative and non-significant. Substantively, this suggests that enjoyment may support intention mainly through its contribution to routine formation, persistence, and perceived worth of the learning experience, rather than through an independent direct pathway of its own. Once those more proximal engagement constructs were controlled, "pure enjoyment" did not add unique explanatory value and may have inverted slightly because of shared variance and suppression (Tamilmani et al., 2019; Deng & Yu, 2023).

This interpretation should nevertheless be treated cautiously. The current evidence supports a plausible suppression explanation, but stronger confirmation would require the additional sensitivity analyses requested by the reviewers. For the present study, the most defensible conclusion is that HM was positively related to BI at the bivariate level but did not retain a stable independent role once the broader engagement pathway was modeled.

5.4. Practical implications for Moodle-supported PML in the Maldives context

The findings suggest that increasing BI in this setting is best approached by designing for habit formation, strengthening commitment, and making learning value salient and experienced, not merely asserted (Ortiz de Guinea & Markus, 2009; Ain et al., 2016; San-Martín et al., 2020; Zacharis & Nikolopoulou, 2022). The practical implication is not that institutions should abandon support, expectancy-building, or social encouragement, but that these should be treated as enabling supports rather than as the primary levers of adoption in similar contexts.

Table 6 provides a prioritized action-oriented implementation map. These indicators are suggested as monitoring tools rather than as validated outcome measures and should therefore be piloted and adapted in context.

Table 6. Policy and Practice Priority Actions Derived from Results

Priority action	Stakeholder	Evidence strength	Cost/Effort	Timeline	Rationale linked to findings	Illustrative KPI(s)
Design a weekly "PML routine" workflow inside Moodle (fixed schedule, predictable task pattern, low-friction access)	Instructors + LMS admins	Strong	Medium	Short-term (4–8 weeks)	Builds habit (HT), the strongest unique predictor of BI	Weekly active user rate; proportion of students completing scheduled weekly PML tasks for 4–8 consecutive weeks
Embed quick feedback cycles (auto-graded quizzes + immediate explanations)	Instructors + LMS admins	Strong	Medium	Short-term	Increases experienced learning value (LV) and sustained engagement	Average quiz completion rate; average number of repeat practice attempts per student per week
Commitment supports: progress dashboards, goal-setting prompts, milestone badges tied to learning goals (not "fun only")	LMS developers + instructors	Strong	Medium	Short–mid-term	Reinforces student commitment (SC); helps engagement persist until habitual	Goal completion rate; proportion of students maintaining engagement across a defined monitoring period (e.g., 6 weeks)
Align PML tasks to exam-relevant competencies and show "why this matters" explicitly	Instructors + curriculum leads	Strong	Low–Medium	Short-term	Strengthens learning value (LV); makes utility concrete	Student-reported perceived usefulness of task alignment; completion of competency-linked activities
Orientation and "first 2 weeks" scaffolding (walkthroughs + guided first tasks)	Administrators + instructors	Moderate	Low	Short-term	Helps move students from initial use to routine use (habit	Orientation completion rate; first-two-week platform login consistency

					formation)	
Social influence interventions (peer study groups, mentor prompts)	Administrators	Weak–Moderate	Low	Mid-term	SI had a weaker unique role; used as support rather than a core lever	Participation in peer-support activities; proportion of students responding to mentor prompts
Infrastructure-only initiatives (devices/connectivity) as a standalone adoption strategy	Policymakers/administrators	Weak (as a standalone)	High	Long-term	FC correlates with BI but does not uniquely predict BI once engagement constructs are accounted for	Device/connectivity access coverage; service reliability indicators

Note. "Evidence strength" reflects alignment with significant predictors in the multivariate model (Table 4) and consistent bivariate support (Table 3). The KPI examples are illustrative and intended for short-cycle monitoring in pilot implementation rather than as definitive evaluative standards.

5.5. Contextual Interpretation and Transferability

The Maldives presents a distinctive educational and infrastructural context. Practical adoption may be affected by variability in connectivity reliability, students' prior LMS exposure, and the extent to which digital learning is institutionalized across schools and pre-university programs (Azlifa & Saeed, 2021; Mumthaz, 2021). While facilitating conditions and expectancies matter in principle, the present results suggest that once baseline access is present, the differentiating drivers of intention are engagement-based: students intend to adopt Moodle-supported PML when it becomes routine, valued, and supported by commitment mechanisms (Ortiz de Guinea & Markus, 2009; Ain et al., 2016; San-Martín et al., 2020).

These implications should not be generalized without caution. The present findings come from a single institutional cohort with a modest response rate, and they therefore support recommendations for piloting and monitored implementation in similar contexts rather than universal prescriptions across all institutions. Settings with substantially lower access or weaker institutional embedding of Moodle may see FC and EE play larger roles, consistent with barrier-and-enabler patterns reported in other constrained contexts (Al-Azawei et al., 2016; Akwene, 2024). Conversely, contexts with mature LMS integration may show the same pattern observed here: expectancy constructs become necessary but not sufficient, while habit- and value-based engagement dominate (Zacharis & Nikolopoulou, 2022; Moorthy et al., 2019).

The low mean for SI also has context-specific policy implications. If social influence is comparatively weak in this sample, institutional strategies in similar settings may need to rely less on one-way encouragement campaigns and more on embedding Moodle-supported PML into routine instructional design, feedback cycles, and visible academic relevance. In other words, students may need to experience the platform as educationally useful and habit-supporting rather than simply being told that they should use it.

5.6. Methodological Considerations: OLS Versus SEM and Statistical Inference

The study used OLS regression to estimate the association between the predictor set and BI because it provides transparent coefficient interpretation and aligns with the study's objective of identifying key determinants of intention. Regression diagnostics indicated acceptable collinearity and residual behaviour for inference (Table 4). However, UTAUT-type models are commonly estimated with SEM, which explicitly models latent variables and measurement error (Venkatesh et al., 2012; Venkatesh et al., 2016). SEM may therefore yield more precise parameter estimates and allow simultaneous testing of the measurement model and structural relationships (Venkatesh et al., 2012).

The choice of OLS in the present study should therefore be understood as a pragmatic analytical decision rather than as a claim that OLS is the optimal method for all UTAUT-based research. It was selected because it supports direct interpretation of coefficients for applied audiences and is compatible with the study's main objective of identifying relative predictor salience. To address the issue of multiple testing, the regression model is treated as the primary multivariate test, and bivariate correlations as descriptive context rather than as independent hypothesis tests.

5.7. Limitations and Future Research

Several limitations should guide interpretation. First, the cross-sectional design limits causal inference; behavioural intention is a proximal predictor and does not confirm actual Moodle usage or learning performance outcomes (Venkatesh et al., 2012). Second, reliance on self-report measures introduces the potential for common-method bias. Third, the achieved sample was based on voluntary participation and a 21.5% response rate, which limits generalizability beyond the sampled cohort and raises the possibility of non-response bias. Fourth, while collinearity diagnostics were acceptable, moderate intercorrelations among motivational constructs likely contributed to suppression patterns (e.g., HM) (Dwivedi et al., 2019; Tamilmani et al., 2019). Fifth, if the measurement model continues to rely primarily on EFA rather than a full CFA-based validation strategy, conclusions about construct distinctiveness should remain appropriately cautious.

Future research should (i) measure actual Moodle usage logs and learning outcomes, (ii) adopt longitudinal designs to track habit formation over time, (iii) test potential moderators such as prior Moodle experience and connectivity constraints, and (iv) estimate the model using SEM for latent-variable inference where sample size permits (Venkatesh et al., 2012; Venkatesh et al., 2016). Future studies should also compare the explanatory performance of extended UTAUT2 models across different educational contexts to clarify when value- and commitment-based constructs outperform expectancy-based constructs as predictors of sustained adoption.

6. Conclusion

This study set out to understand what most strongly aligns with pre-university students' intention to adopt Moodle-supported Personalized Mathematics Learning (PML) in the Maldives. The evidence points to a clear pattern: intention is not driven primarily by whether students think the platform is useful or easy in the abstract, but by whether the learning experience becomes meaningful, sustained, and routine. When students perceive real learning value in PML, feel personally committed to staying engaged, and develop habitual patterns of using Moodle for their mathematics work, intention is markedly stronger. At the same time, the findings also suggest that the canonical UTAUT2 predictors, performance expectancy, effort expectancy, social influence, and facilitating condition, may function more as supportive background conditions than as the strongest unique drivers of intention in this learning-specific context. This implies that educational technology adoption models may need to place greater emphasis on value, persistence, and routinised engagement when the focus is sustained learning use rather than initial acceptance alone.

PML supported by Moodle should be perceived as more than the introduction of a certain platform and the expectation that students will use it. The crucial practical consideration is whether the learning experience is structured so that students can revisit it periodically, with clear tasks, visible progress, and consistent feedback that supports persistence. Once these conditions have been established, it becomes easier to maintain further use and may slowly evolve into habitual interaction. For institutions, this means that adoption is unlikely to be secured through a single initial orientation or one-time sensitisation effort; rather, it depends on the consistent integration of Moodle-supported PML into teaching, practice routines, and feedback processes that sustain continued student use over time.

These findings should also be interpreted with caution. The study is cross-sectional and focuses on behavioural intention rather than actual usage or learning outcomes. The results, however, do not imply causal influences but instead suggest associations. The evidence can be further enhanced in the future by monitoring students' use of Moodle over time, including learning analytics and log data, and by examining whether maintaining Moodle-supported PML use is related to improvements in mathematics learning outcomes.

These limitations notwithstanding, the study has a definite implication for LMS-based personalised learning in similar contexts: the intention to adopt is most pronounced when students find the value of learning evident, are ready to commit to it, and establish a repeated usage pattern that becomes a habit. In this respect, PML supported by Moodle is effective not just because of its presence, but also because of the experience gained through students' normal learning activities. For MNU and similar Maldives higher education contexts, the most practical next step is to pilot implementation strategies that strengthen routine use, visible learning value, and sustained commitment, while monitoring student engagement over short and medium time frames to determine which actions most effectively support continued adoption.

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Conflict of Interest

All authors declare no competing interests or potential conflicts of interest that could compromise the integrity of the research.

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