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Investigating Items as Predictors for Application of Personalized Mathematics Learning Instrument among Pre-University Students in the Maldives: An Exploratory Factor Analysis

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Abstract

Personalized Mathematics Learning (PML) holds significant importance in mathematics education in the global learning environment. Accordingly, PML in any institution allows tailored instruction catering to students' individual learning needs and preferences. The study aims to investigate the items as predictors for PML instrument validation for pre-university students in Maldives through Exploratory Factor Analysis (EFA). A total of 120 pre-university students were randomly chosen for data collection at the Maldives National University using a structured questionnaire. The instrument consists of 52 items on the five-point Likert scale with eleven constructs of PML. EFA was conducted for each construct using IBM SPSS version 25.0. The results discovered one dimension in all the constructs; 11 items with factor loading < 0.60 were eliminated. 41 items determined a factor loading > 0.60 were retained to measure the PML construct. Bartlett's Test of Sphericity was < 0.05 for all the constructs, yielding a significant $p-$value < 0.05. Kaiser–Meyer–Olkin Measure of Sampling Adequacy was > 0.5 for all the constructs, signifying a sufficient sample size. The results indicate a greater internal consistency for individual and overall constructs. The instrument proved valid and reliable for predicting the application of the PML construct in mathematics education in the Maldives.

Keywords: personalized learning; instrument; reliability; exploratory factor analysis; Maldives National University.

1 Introduction

Personalized learning, a pedagogical strategy that tailors instruction to each student's specific requirements, has received significant attention in educational research. Recently, educators and researchers have been focussing on advancing and integrating personalized learning [19].

1.1 Importance of personalized learning

Well-developed and efficiently implemented personalized learning can significantly transform higher education [96]. Personalized learning has been adopted across various fields such as chemistry [47], biology [4], physics [70], business management [36], and medical sciences [86].

1.2 Personalized mathematics learning

PML has garnered substantial attention in mathematics education, providing tailored instructional approaches to meet the diverse needs of students. In particular, with the advancement of technological tools in the classroom teaching and learning of mathematics provoked effective ways to teach and boost student enjoyment [15]. For instance, augmented reality technology approaches with smart devices studied by [61] demonstrated benefits on students' conceptual and procedural knowledge of mathematical concepts. The Personalised System of Instruction (PSI) is an educational technique that tailors learning to each student's goals, interests, requirements, and abilities within the curriculum setting. It mainly promotes logical thinking skills, especially in science and mathematics.

1.3 Curriculum adaptation and benefits of PSI

PSI effectively evaluates students' responses, makes necessary adjustments, and identifies misconceptions, aiming to provide a personalized learning environment. Personalized learning involves students engaging in learning at various stations and settings with minimal teacher intervention [51]. This approach connects students' previous knowledge and experiences with training materials to enhance learning performance and engagement [43].

1.4 Transition to modern educational approaches

In the 21^{st} century, educators are transitioning from traditional classroom strategies to more modern approaches, enhancing the dynamics of learning environments. Personalized instruction customizes educational experiences to individual student characteristics and needs, employing adaptable teaching methods.

1.5 Role of personalization-focused teachers

Personalization-focused teachers help students create personalized learning plans, recognize cognitive strengths and weaknesses, adapt instruction to individual learner needs and interests, and build reflective learning experiences [78]. This approach can enhance student achievement across all subjects, including mathematics.

1.6 Conceptualizing personalized learning

This study conceptualizes personalized learning as a method that alters learning experiences to meet customized student needs, encompassing their preferences, and abilities [75]. Studies have shown that personalized learning strategies can improve students' subject mastery, cognitive and emotional involvement, and self-directed learning [2, 7].

1.7 Impact on learning success

Scholars in the Maldives have shown concern about integrating personalized learning into learning practices [56, 59]. Adam [3] reported that teachers' adapted learning experiences cannot be fully understood without considering their specific cultures' social and cultural patterns.

1.8 Challenges and efficacy of digitalization programs

Likewise, Mariyam and Saeed [53] evaluated the efficacy and explored the challenges of the digitalization program initiated by the Ministry of Education in Maldives. However, despite this research effort, there remains a noticeable gap in the literature regarding specific pertinent factors influencing the application of PML among pre-university students in Maldives. The existing studies have primarily focused on broader educational reforms and digital initiatives rather than delving into the intricacies of personalized learning methodologies tailored to mathematics education. Consequently, a comprehensive investigation into the adoption, implementation barriers, and effectiveness of PML in the Maldivian educational context is crucial to inform policy-making and educational practices.

1.9 Study contribution

This study investigates the factors influencing the application of PML among pre-university students in the Maldives. It focuses on the learner and instructional features such as performance expectancy, effort expectancy, social influence, hedonic motivation, learning value, habit, student commitment, intrinsic motivation, behavioral intention, and usage behavior through a Learning Management System (LMS), Moodle. Therefore, the study contributes to the body of literature by measuring the efficacy of the items for using the PML instrument through EFA. It also provides insights into the underlying mechanisms in discovering an appropriate measurement of PML construct among pre-university students.

1.10 Significance of the study

The study contributes to the corpus of literature by analyzing the effectiveness of the items utilizing the PML instrument with EFA. The findings provide valuable knowledge for educators, policymakers, and researchers regarding the principal determinants of student behavior within personalized learning environments. Ultimately, this contribution aims to improve practices in mathematics education, fostering continual improvement and innovation in educational strategies.

Recently, the development of education technology has resulted in the broad adoption of personalized learning [57]. Personalization, in general, refers to the act of developing something that suits individual needs [22]. In the educational setting, personalized learning is a method that tries to give a tailored learning process on learners' specific requirements and skills using emerging instructional technologies [75, 79]. The review of personalized learning by Cheung et al. [22] emphasizes students' learning preferences and flexibility (pace, time) and encourages their accountability for their learning. Additionally, a personalized learning instructional approach supports learners' intrinsic motivation in inspiring them to acquire knowledge and skills [9].

Personalized learning involves various techniques to analyze individual learner characteristics, needs [40, 52], and learners' knowledge levels and learning styles [11]. Research has shown that personalized learning contributes to improved learning outcomes [45, 65], boosts motivation [9, 74], develops metacognitive skills [12] and general learning experiences [84].

The study context's personalized learning concept accounts for the integration of technology through LMS, which paved the way for learner preferences and learner characteristics to optimize their learning experiences. However, several factors depend on the successful adoption and utilization of LMS for personalized learning. Tiippana [83] stated that performance expectancy, effort expectancy, social influence, facilitating conditions, and intrinsic value factors as dimensions of PL. Panjaburee et al. [66] identified perceived ease of use, usefulness, attitude, and intention to use as underlying factors of PL. In addition to these factors, Utami et al. [85] mentioned attitude toward the system, perceived interaction, self-efficacy, user interface design, and course design. Thus, an in-depth understanding of multidimensional constructs involved in PML is prominent for educators, administrators, and developers to improve the efficiency of LMS in creating a full potential PML approach.

2 Dimensions of Personalized Mathematics Learning

2.1 Performance expectancy

Performance Expectancy (PE) relates to PML success by determining the degree to which students believe using the system will enhance their learning performance in mathematics. Extensive research in financial technology has established performance expectations as the key drive of technology acceptance [23, 68]. While studies on social networking platforms have underscored the significance of perceived benefits in motivating users persistently to utilize the technology [23] and incorporate it to enhance learning performance and students' behavioral intentions [62]. Several studies indicated performance expectancy's significant effect on learners' behavioral intention to use LMS [10, 71], system adaptation of personalized learning [83].

2.2 Effort expectancy

Effort Expectancy (EE) impacts PML success by evaluating how easy students find the system to use, which influences their willingness to engage with the personalized learning tools. The ease of using technology and effort expectancy are crucial factors in determining users' adoption and previous studies have supported this notion [29, 82]. The perception of users in using the technology requires minimal effort, it drives users to continue using it in the long term [35, 63]. Several studies have demonstrated effort expectancy affects users' behavioral intentions on the use of Moodle [1, 6], e-learning adoption [21], and teachers' usage behavior towards GeoGebra software [93].

2.3 Social influence

Social Influence (SI) affects PML success by assessing the extent to which students perceive that important others (peers, family, instructors) believe they should use the personalized learning system. Social Influence (SI), is a vital determinant of a learner's decision to adopt a particular system or approach, particularly in education [43]. García et al. [32], SI represents the extent to which an individual's perception (including colleagues, school principals, or educational consultants) or belief that they should employ a modern system or a new approach to learning. This perception is instrumental in shaping learners' behavioral intentions toward adopting a system, as evidenced by multiple studies [16, 67].

2.4 Facilitating condition

Facilitating Conditions (FC) contribute to PML success by ensuring that students have the necessary resources and support to effectively use the personalized learning system. Facilitating Conditions (FC) refers to how people perceive the accessibility of resources and help when utilizing technology. Abbad [1] describes FC as learners' comprehension of the organizational and technological infrastructure, as well as the tools essential to facilitate the use of a system. Previous studies showed a significant effect of FC on users' behavioral intention toward LMS [1, 5], on positive usage behavior of adopting a technology [20, 93], and on system adaptation of personalized learning [41].

2.5 Motivational factors

2.5.1 Hedonic motivation

Hedonic Motivation (HM) enhances PML success by capturing the enjoyment or pleasure students derive from using the personalized learning system, thereby increasing their engagement. Hedonic Motivation (HM) is a synonym for perceived enjoyment, and studies have shown its effect on technology uptake [62, 97]. Hedonic Motivation (HM) refers to the intrinsic desire of individuals to engage in activities that provide them with enjoyment from technology use. Research by [92] suggests that HM act as a considerable role in manipulating students' engagement and persistence in learning tasks, markedly in technology-mediated environments. Research has revealed a substantial effect of HM on users' behavioral intention to adopt technology [69, 88].

2.5.2 Intrinsic motivation

Intrinsic Motivation (IM) supports PML success by focusing on the internal drive of students to engage in learning activities for personal satisfaction rather than external rewards. According to Fishbach and Woolley [30], Intrinsic motivation (IM) is the key to persistence at work. IM refers to enrolling in an activity for intrinsic gratification instead of external rewards [26]. Further, Deci and Ryan [26] indicated a person with advanced levels of intrinsic motivation tends to demonstrate more remarkable persistence and performance. This concept has been extensively studied in the literature with increased engagement in learning activities and academic achievement [81, 90], higher retention rates, and greater overall well-being among students [44]. Moreover, studies have indicated that learners appreciate platforms like Moodle to enhance their understanding of course material, session plans, and assignment submissions and facilitate improved learning experiences that contribute to improved learning outcomes [46]. Recognizing intrinsic motivation adds depth to understanding students' self-directed learning behaviors [73]. Research has supported intrinsic motivational factors for behavioral intention to use n application for $m-$learning [77] and intrinsic value factors as a significant outcome indicator for behavioral intention to use a system adaptation in Personalised [41].

2.5.3 Learning value

Learning Value (LV) relates to PML success by reflecting the students' perception of the worthiness of investing time and effort into personalized learning to achieve better outcomes. LV refers to the learners's view of the worthiness of investing additional time and effort in acquiring knowledge through personalized mathematics learning. It is the time and effort learners use when engaged in personalized learning platforms for their learning needs [57] to improve their learning outcomes [60]. As Solari et al. [78] highlighted, understanding this dynamic is crucial for comprehending the motivational factors that drive students' interactions with personalized learning platforms. Studies have demonstrated the impact of LV directly on learners' behavioral intention to use LMS [5] and actual use of adopting technology acceptance [95].

2.6 Behavioral factors

2.6.1 Habit

Habit (HT) influences PML success by establishing consistent patterns of behavior in using the personalized learning system, which can lead to sustained usage and learning improvements. Habit encompasses repetitive behaviors that stem from the learning process. Initially, users rely on a strategy to grasp technology usage and, upon successful adaptation, consider the technology to be user-friendly [39]. This perception fosters habitual use, leading to the continued utilization of the technology. Study habits provide academic stability and are necessary for academic success [17]. These behaviors can be enhanced through different training and practices [89]. Many studies have reported the factors that influence study habits [28]. Previous literature have corroborated the significance of habit as a determinant of user intention in technology adoption among students [8, 49].

2.6.2 Student commitment

Student Commitment (SC) is crucial for PML success as it represents the dedication and sustained effort students put into their personalized learning activities. Student commitment has comparable phrases to describe, such as "student involvement" and "student engagement" [38, 48]. The commitment denotes a persistent engagement that sustains the student's involvement over time [50]. Students' commitment represents the student's unwavering dedication to engaging in learning [18, 54]. Understanding what drives students to stay committed is pivotal. Kim et al. [42] specified that course design factors greatly influence learners' commitment as a result of deficient learner-instructor involvement in the online setup. Batista-Toledo and Gavilan [18] examined how commitment affects satisfaction with BL, resulting in a significant relationship. Lu et al. [50] indicated cognitive engagement being the direct factor of continuous usage intention. Correspondingly, Goh and Yang [34] proved a positive continuance effect of e-engagement on e-learning systems. Several studies have examined the effect of student commitment or continuance of engagement in learning through LMS [18, 31].

3 Research Methodology

The overall objective of this study is to investigate the factors predicting the successful application of PML among pre-university students in the Maldives.

3.1 Research design

A correlational research design was employed to establish reliable measures for PML construct among pre-university students of the Maldives National University (MNU) in Male City. A correlational research design was chosen to investigate these factors because it allows us to measure the degree of association between multiple variables and their interrelationships. This design is particularly suitable for understanding how various factors, such as performance expectancy, effort expectancy, social influence, facilitating conditions, and motivational aspects, relate to student outcomes in PML. By using a correlational design, the researcher can identify patterns and relationships between these factors, providing an important understanding of how the factors collectively influence the effectiveness of personalized mathematics learning and student engagement, satisfaction, and performance. This approach to research design was deemed suitable for the study as it enabled the investigation to measure the degree of associations between two or more variables and their interrelationships [25]. A quantitative approach was employed, and data from 120 pre-university students were collected utilizing a self-administered Google Forms questionnaire link. The sample was chosen from a cohort of 559 students registered in 2023 Term II in the Centre for Foundation Studies Certificate Level 4 at MNU. Based on Hair et al. [37], the minimal base sample size for EFA is 100 when considering a model with five or fewer constructs, each consisting of three or more items. However, we chose to include 120 participants to ensure a more robust analysis and to increase the reliability and validity of the results. This larger sample size helps to better capture the diversity of student responses and increases the generalizability of the findings to the broader population of pre-university students in the Maldives.

To identify and modify the items measuring the PML construct, a thorough review was undertaken. Initially, a comprehensive literature review was conducted to gather existing instruments and items related to personalized learning and its constructs. Relevant sources such as Venkatesh et al. [88] and Ain et al. [5] were examined to extract items that align with the PML context. These items were then carefully reviewed and modified to fit the specific needs and context of pre-university students in the Maldives. Modifications included rewording items for clarity, ensuring cultural relevance, and aligning them with the specific goals of the PML framework. Also, the preliminary items were evaluated by a panel of experts, including two internal validators from Universiti Putra Malaysia (UPM) and three external validators from the MNU, whose feedback was incorporated to refine the items further, ensuring their validity and reliability for measuring the PML construct. The adopted items were modified to fit the needs of the research. The EFA technique used IBM-SPSS version 25.0.

3.2 Research instrument

The study utilized a structured questionnaire with 52 items on Likert's 5-point scale, consisting of two primary sections: Section A for demographic data and Section B for items with response choices ranging from "strongly agree" to "strongly disagree" measuring PML among pre-university students at the Maldives National University. Table 1 indicates the number of items and sources utilized in the investigation to measure the eleven variables (constructs).

Table 1: Component of the questionnaire.

Section A		Section B	
Constructs		**No. of items**	**Sources**
Demographic information (10 items)	Performance Expectancy (PE)	5	[88] & [5]
	Effort Expectancy (EE)	5	[88] & [87]
	Social Influence (SI)	5	[88] & [87]
	Facilitating Conditions (FC)	5	[88] & [87]
	Hedonic Motivation (HM)	5	[88]
	Learning Value (LV)	5	[5]
	Habit (HT)	4	[62]
	Student Commitment (SC)	5	[91]
	Intrinsic Motivation (IM)	5	[72] & [94]
	Behavioral Intention (BI)	4	[62]
	Usage Behavior (UB)	5	[62] & [5]
Total		**52**	

3.3 Content expert review and validation

The previous literature review aided in developing preliminary items by adjusting them to fit the present study. Based on Shkeer and Awang [76], validating a modified instrument must be performed if the standardized instrument relies on a culture and industry different from the present study. Therefore, the instrument's items were thoroughly evaluated for validity and reliability. A panel of experts, two internal validators from UPM and three external validators from the MNU analyzed the validation process. The experts made insightful remarks on the need to shorten some questions and avoid the double-barrel questions. The content validity and face validity of the instrument were established after refining the items based on input collected from experts. Subsequently, the instrument was approved for investigation by the Research Development Office (RDO) ethics committee at MNU.

4 Results and Discussion

4.1 Demographic description

Descriptive statistical analyses were used to assess the participants' demographic characteristics. Random sampling was utilized to select a sample size of 120 students from a university in the Maldives, consisting of 18 males and 102 females. The sample includes 49 students from semester one and 71 from semester two, 2023, term 2. Table 2 displays the demographic characteristics of participants. It indicates that most participants were female, accounting for 85% of the sample, with males making up 15%.

In terms of age distribution, most participants (90%) were under the age of 20, followed by 8.33% between the ages of 21 and 25, and only 1.66% beyond the age of 26. 77.5% of the participants in the study were from the science stream, while business and humanities had a more miniature representation. All participants reported having access to devices such as Moodle.

Table 2: Demographic characteristics of participants.

Descriptive Statistics		
	Number (n)	**Percent(%)**
Gender		
Male	18	15
Female	102	85
Age group (years)		
Under 20	108	90
21 − 25	10	8.33
26 and above	2	1.66
Program of study		
Science	93	77.5
Business	14	11.6
Humanities	13	10.83
Semester		
One	49	40.83
Two	71	59.17
Gadgets availability		
Yes	120	100
No	0	0
Moddle access		
Yes	120	100
No	0	0

4.2 Exploratory factor analysis

The data was analyzed with IBM SPSS version 25.0 software and the instrument construct validity was assessed using EFA. All 52 instrument items were used in the EFA with orthogonal rotation (varimax). EFA is essential for determining the fundamental structure of the analysis, with variables representing latent constructs that cannot be directly measured. The EFA approach is utilized when uncertainty arises toward the number of potential factors of a set of variables, as suggested by previous studies [27, 76].

5 Sampling Adequacy for Exploratory Factor Analysis

5.1 Normality test for the study variables

The data was evaluated for normality using skewness and kurtosis values, including the minimums and maximums, standard deviations, and means of the eleven proposed elements of the student's PML instrument. Kurtosis details a distribution's peakiness, while skewness indicates symmetry [64]. The results display the mean value for every component ranged from 3.317 to 4.078 for all the factors presented in Table 3. The minimum values range between 1 and 2, while the maximum values were identical in all the constructs. Furthermore, the results show variable degrees of skewness and kurtosis, indicating different distributions across the dataset. The data confirmed normal distribution for all variables based on the skewness and kurtosis. According to Hair et al. [37] and Garson [33], the distribution is normal if the skewness ranges from -2 to $+2$ and kurtosis from -7 to $+7$. Table 3 showed that the kurtosis and skewness values were less than 2.0. Therefore, it can be settled that the mean distribution for all variables in this study was normally distributed.

Table 3: Descriptive statistics of each variable of the MPL instrument.

	N	Min	Max	Mean	Std. deviation	Skewness	Kurtosis
Performance Expectancy (PE)	120	2.00	5	3.780	0.662	0.067	−0.298
Effort Expectancy (EE)	120	1.80	5	3.705	0.655	−0.218	0.211
Social Influence (SI)	120	1.40	5	3.317	0.826	0.213	−0.244
Facilitating Conditions (FC)	120	1.60	5	4.078	0.579	−0.915	2.510
Hedonic Motivation (HM)	120	1.00	5	3.418	0.719	−0.520	0.803
Learning Value (LV)	120	1.00	5	3.731	0.787	−1.055	1.910
Habit (HT)	120	1.50	5	3.423	0.678	−0.176	0.139
Student Commitment (SC)	120	1.00	5	4.005	0.751	−0.893	1.565
Intrinsic Motivation (IM)	120	1.60	5	3.655	0.647	−0.582	1.320
Behavioral Intention (BI)	120	1.00	5	3.948	0.762	−0.878	2.026
Usage Behavior (UB)	120	1.80	5	3.667	0.629	−0.494	0.957
Valid N (listwise)	120						

5.2 Kaiser–Meyer–Olkin and Bartlett's test

The Kaiser–Meyer–Olkin (KMO) test and Bartlett's Test of Sphericity values for the eleven-factor structure verified the sampling adequacy for the analysis. Generally, the two tests are designed to determine the data index or the adequacy of the sample to adopt the factorability of the matrix [37]. Table 4. displays KMO values evaluation for each construct between range (KMO $= 0.701$ to KMO $= 0.844$), which is above 0.50, indicating the acceptance of the factorability dataset [37]. Likewise, Bartlett's Test of Sphericity shows significance ($p-$value < 0.05) for all the constructs, indicating the structure between the items is sufficiently significant for factor analysis [24, 37].

Table 4: Evaluation of constructs for EFA suitability.

No.	**Constructs**	**KMO** (> 0.50)	**Bartlett's test of sphericity** $P < 0.05$
1	Performance Expectancy (PE)	0.844	0.000
2	Effort Expectancy (EE)	0.784	0.000
3	Social Influence (SI)	0.706	0.000
4	Facilitating Conditions (FC)	0.722	0.000
5	Hedonic Motivation (HM)	0.817	0.000
6	Learning Value (LV)	0.746	0.000
7	Habit (HT)	0.673	0.000
8	Student Commitment (SC)	0.810	0.000
9	Intrinsic Motivation (IM)	0.709	0.000
10	Behavioral Intention (BI)	0.835	0.000
11	Usage Behavior (UB)	0.701	0.000

5.3 Principal component analysis

The principal component analysis (PCA) was used for the extraction method with varimax rotation to obtain eigenvalues, and total variance was explained for all the items under each construct, as shown in Table 5. The purpose is to determine item retention based on factor loadings, communalities, and conceptual relevance criteria. In PCA, eigenvalues are computed for each component, reflecting the variance captured by that specific component. The variance is represented by the initial eigenvalues before extraction in the EFA. The variance followed by extraction is indicated by the extraction sum of squared loadings. The results from the EFA procedure based on the Eigenvalue in Table 5 show eleven components having the Eighen value > 1.0. The eigenvalues ranged from 2.093 to 3.270.

Table 5: Components and total variance explained for PML.

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	3.161	79.025	79.025	3.161	79.025	79.025
2	3.137	74.421	74.421	3.137	78.421	78.421
3	2.383	79.440	79.440	2.383	79.440	79.440
4	2.093	69.758	69.758	2.093	69.758	69.758
5	3.270	81.754	81.754	3.270	81.754	81.754
6	2.662	66.553	66.553	2.662	66.553	66.553
7	2.403	80.090	80.090	2.403	80.090	80.090
8	2.937	73.423	73.423	2.937	73.423	73.423
9	2.895	72.372	72.372	2.895	72.372	72.372
10	3.080	77.004	77.004	3.08	77.004	77.004
11	2.703	67.563	67.563	2.703	67.563	67.563

Note: Extraction method: Principal component analysis.

The general rule of thumb from Streiner [80], for the total variance described, is at least 50%. The total variance explained is acceptable, as recommended by Awang [13] and Cohen et al. [24], if it surpasses the base 60%. Moreover, the cut-off mark of the items with factor loading below 0.6 was eliminated, indicating that the elements below 0.6 were insignificant [14, 58]. Table 6 represents the item retention results from EFA indicating the removal of eleven items with factor loading below 0.6. Therefore, the final questionnaire retained 41 items ensuring the most relevant and reliable items contribute to the measurement scales for each construct, enhancing the validity of the study findings.

Table 6: Results of item retention from EFA.

Constructs	Items before run EFA	Number of items dropped	Number of items retained after run EFA
Performance Expectancy (PE)	5	1	4
Effort Expectancy (EE)	5	1	4
Social Influence (SI)	5	2	3
Facilitating Conditions (FC)	5	2	3
Hedonic Motivation (HM)	5	1	4
Learning Value (LV)	4	0	4
Habit (HT)	4	1	3
Student Commitment (SC)	5	1	4
Intrinsic Motivation (IM)	5	1	4
Behavioral Intention (BI)	4	0	4
Usage Behavior (UB)	5	1	4
Total items	52	11	41

5.4 Rotation component matrix

The analysis for the division of components is indicated in Table 7 which displays only one component for the EFA technique on construction. According to Cohen et al. [24] and Awang [14] for the items above 0.6-factor loading, the latent factor values meet the condition. Therefore, as indicated in Table 7, eleven items have been removed in order to retain the 41 items over 0.6 following EFA.

Table 7: Factor loading for each item.

	Statements	Items	Component 1
1	I find the use of Moodle, useful for my personalized mathematics learning studies.	PE1	0.841
2	By using Moodle, it helps me to accomplish tasks for my personalized mathematics learning more quickly.	PE2	0.916
3	Using Moodle increases my productivity for my personalized mathematics learning	PE3	0.905
4	The use of Moodle improves the chances of a better performance in my personalized mathematics mathematics	PE4	0.893
5	I find Moodle not as an effective platform for my personalized mathematics learning.	PE5	
6	Operating Moodle for my personalized mathematics learning is easy for me to use.	EE1	0.891
7	For the subject Mathematics when Moodle is personalised for learning, which is easy for me.	EE2	0.880
8	I find difficult to become skilful with Moodle's features and design for my personalized mathematics learning.	EE3	
9	My interaction with study materials on Moodle is clear for my personalized mathematics learning.	EE4	0.869
10	My interaction with study materials on Moodle is understandable for my personalized mathematics learning.	EE5	0.902
11	The Centre for Foundation Studies (CFS) agrees with the use of Moodle for my personalized mathematics learning.	SI1	
12	I prefer to use the Moodle in learning mathematics because peers who influences my behaviour think I should use it.	SI2	0.832
13	I prefer to use the Moodle for my personalized mathematics learning because my family think I should use it.	SI3	0.929
14	My role model lecturers' advices me to use Moodle for my personalized mathematics learning.	SI4	
15	I prefer to use the Moodle in learning mathematics because friends who influence my behaviour think I should use it.	SI5	0.909
16	The required information to use Moodle for my personalized mathematics learning is provided through student guide and videos.	FC1	
17	I get the support when technical difficulties arise in the use of Moodle for my personalized mathematics learning.	FC2	
18	MNU provides free internet at CFS premises to be accessed to use Moodle for my personalized mathematics learning.	FC3	0.839
19	I have the knowledge to use Moodle for my personalized mathematics learning.	FC4	0.811
20	Moodle access is compatible on technological gadgets like i-pad/tablet, mobile phone, laptop, smart TV's apart from computer desktop.	FC5	0.855
21	The use of Moodle enhances my satisfaction to learn the course materials in personalized mathematics learning.	HM1	0.897

22	The experience of using Moodle features adds enjoyment to my personalized mathematics learning.	HM2	0.905
23	Moodle is not an entertaining platform for my personalized mathematics learning.	HM3	
24	The interactive activities on Moodle motivates into my personalized mathematics learning.	HM4	0.839
25	The use of Moodle increases joy in task completion in personalized mathematics learning.	HM5	0.899
26	I feel that using Moodle for my personalized mathematics learning is worth more than the time and effort given to it.	LV1	0.754
27	In less time, for my personalized mathematics learning, Moodle allows me to quickly and easily share my knowledge with others (chat session, forums, messages etc.)	LV2	0.833
28	Moodle gives me the opportunity to decide about the pace of my own personalized mathematics learning.	LV3	0.839
29	Moodle for my mathematics personalised learning gives me the opportunity to increase my knowledge (e.g., via quizzes and assignments/assessments, etc).	LV4	0.805
30	The used of Moodle for learning mathematics is something I do automatically without thinking.	HT1	0.879
31	Learning mathematics through Moodle has become a habit for my personalized mathematics learning.	HT2	0.942
32	I find it difficult to use Moodle consistently for my personalized mathematics learning.	HT3	
33	I have developed a routine of using Moodle when studying mathematics for my personalized mathematics learning.	HT4	0.861
34	I complete all mathematics tasks (tutorial/ assignment/ quizzes) assigned on the Moodle for my personalised learning on time to meet the deadline.	SC1	
35	I consistently use Moodle for my personalized mathematics learning to read the mathematics tasks recommended by math lecturer/tutor.	SC2	0.808
36	I spend sufficient time on Moodle for personalized learning to achieve the best of my ability in learning mathematics.	SC3	0.919
37	I always use Moodle for my personalized mathematics learning in preparing myself for mathematics exams (Moodle practice quizzes/ Moodle lessons).	SC4	0.810
38	I consistently use Moodle for my personalized mathematics learning to do the additional tasks recommended by math lecturer/tutor.	SC5	0.885
39	I want to understand well all the tasks (tutorials/activities) for my personalized mathematics learning through Moodle.	IM1	0.859
40	I want to develop in mastering mathematic skills by using the Moodle tasks for my personalized mathematics learning.	IM2	0.903
41	I rarely feel to learn/study mathematics by using Moodle tasks for my personalized mathematics learning.	IM3	
42	I prefer to learn challenging concepts of mathematics through Moodle activities for my personalized mathematics learning so I can learn new things.	IM4	0.855
43	I prefer to learn math concepts for my personalized mathematics learning that arouse my curiosity even if they are difficult to learn.	IM5	0.781
44	I intend to continue my personalized mathematics learning in the future.	BI1	0.878
45	I will always try to use Moodle in my studies for my personalized mathematics learning.	BI2	0.892
46	I plan to use Moodle for my personalized mathematics learning	BI3	0.895

	frequently, as part of my learning experience.		
47	I plan to use Moodle for my personalized mathematics learning on a regular basis, as part of my learning experience.	BI4	0.805
48	I regularly use Moodle for my personalized mathematics learning during the academic period.	UB1	0.821
49	I want to develop in mastering I want to spend a significant amount of time on Moodle for my personalized mathematics learning.	UB2	0.830
50	I utilize various functions of Moodle (e.g., upload assignment/tutorial, download course content lecture PPTs.,) for mathematics learning experience.	UB3	0.792
51	Moodle usage always has supportive tools for my personalized mathematics learning experience.	UB4	0.844
52	I find it challenging to navigate through Moodle for my personalized mathematics learning.	UB5	

5.5 Reliability test

The study seeks to assess the applicability of components for EFA and their reliability using Cronbach's alpha. Cronbach's alpha was applied to test the internal consistency of the study since it is one of the most broadly utilized techniques of reliability, and the estimation of 0.7 or above generally demonstrates adequate internal consistency reliability [55]. Internal reliability or internal consistency shows how solid the specific items were when estimating the respective construct.

According to Table 8, the reliability of each construct was more significant than 0.7, indicating the instrument's reliability. These findings suggest that the items used to test these dimensions consistently reflected participants' intentions and actual behaviors in the PML setting. Thus, the reliability analysis results indicate that the measurement scales used to assess various constructs related to students' behavioral intentions and usage behavior in the context of personalized learning in mathematics were reliable and internally consistent. These findings enhance the confidence in the validity of the study's results and conclusions. The results indicate a greater internal consistency for both individual and overall constructs, (41 items retained) with Cronbach's alpha values exceeding the widely accepted threshold of 0.7 [37].

Table 8: Cronbach's alpha for each construct.

Constructs	**Cronbach's alpha coefficient** (α) $(n = 120)$	**Number of items**	**Status**
Performance Expectancy (PE)	0.911	4	Excellent
Effort Expectancy (EE)	0.908	4	Excellent
Social Influence (SI)	0871	3	Good
Facilitating Conditions (FC)	0.785	3	Acceptable
Hedonic Motivation (HM)	0.924	4	Excellent
Learning Value (LV)	0.831	4	Good
Habit (HT)	0.874	3	Good
Student Commitment (SC)	0.878	4	Good
Intrinsic Motivation (IM)	0.867	4	Good
Behavioral Intention (BI)	0.900	4	Excellent
Usage Behavior (UB)	0.837	1	Good
Total (11 constructs)	0.916	41	Excellent

6 Key Findings

6.1 Data suitability

Normality: The data confirmed normal distribution for all variables based on skewness and kurtosis, with values indicating acceptable distributional characteristics (skewness ranging from -2 to $+2$ and kurtosis from -7 to $+7$) as displayed in Table 3.

KMO test: The KMO values for the eleven-factor structure ranged between 0.701 and 0.844, indicating sampling adequacy for factor analysis as all values were above the threshold of 0.50 as shown in Table 3.

Bartlett's test of sphericity: This test showed significant results ($p-$value < 0.05) for all constructs, confirming that the correlations between items were sufficiently significant for factor analysis as presented in Table 4.

6.2 Instrument reliability

Cronbach's alpha (α)**:** The reliability of each construct was more significant than 0.7, indicating high internal consistency as shown in Table 8. The Cronbach's alpha values for the constructs ranged from 0.785 to 0.924, as demonstrated in Table 8.

These findings indicate the robustness of the study's methodology, offering important insights into the factors influencing students' behavior intentions and usage behavior in PML.

7 Discussions

In the present study, varying kurtosis values suggest diverse shapes of the distributions across the dataset, with most variables falling within an acceptable range of kurtosis, indicating their suitability for analysis. The analysis reveals that the dataset is suitable for factor analysis, with all constructs exhibiting KMO values above 0.50 and Bartlett's Test of Sphericity $p-$values below 0.05, indicating significant correlations between variables. Constructs like Performance Expectancy demonstrate the highest KMO values, suggesting the most reliable measure. Also, all constructs significantly impact students' usage behavior and behavioral intentions in personalized mathematics learning. Notably, behavioral intention, performance expectation, and effort Expectation emerge as the most influential factors. These findings underscore the multifaceted nature of factors influencing students' behavior and intentions in personalized mathematics learning, offering valuable insights for developing effective educational strategies tailored to individual student needs and preferences.

Few constructs retained original items, like learning value and behavioral intention, out of the 52 initial items eleven items were removed, resulting 41 relevant and reliable items contributed to constructing measurement scales, enhancing study validity. Among all the constructs, Performance Expectancy, Effort Expectancy, Hedonic Motivation and Behavioral Intention demonstrated excellent reliability ($\alpha = 0.911, \alpha = 0.908, \alpha = 0.924$ and $\alpha = 0.900$), indicating consistent measurement. Facilitating Conditions exhibited acceptable reliability ($\alpha = 0.785$) and the remaining constructs showed good reliability ranging ($\alpha = 0.831$ to $\alpha = 0.878$), respectively. Thus, overall reliability analysis shows high internal consistency for all the constructs, boosting confidence in study validity.

The study results show that the data is suitable for analysis, as evidenced by KMO values greater than 0.5 and significant Bartlett's Test of Sphericity $p-$values. Multivariate normality is observed across constructs, with skewness and kurtosis values indicating acceptable distributional characteristics. Reliability analysis reveals strong internal consistency for individual and overall constructs with Cronbach's alpha coefficients exceeding the widely accepted threshold of 0.7. Furthermore, EFA promotes item retention, ensuring the validity of assessment scales. These comprehensive analyses underscore the robustness of the study's methodology and provide valuable insights into the factors that influence students' usage behavior in the context of personalized learning in mathematics.

8 Contribution to knowledge

This study contributes significantly to mathematics education and the broader educational landscape in the Maldives by identifying key factors influencing the application of PML among pre-university students. The findings have practical implications for educators and policymakers, highlighting the importance of targeted strategies to enhance personalized learning experiences.

Students believe that using personalized learning tools will enhance their mathematics performance (Performance Expectancy, PE), indicating that educators should showcase the tangible benefits of personalized learning systems, incorporating data-driven evidence to demonstrate improvements in student performance. The ease of use of personalized learning tools is crucial for student adoption (Effort Expectancy, EE), suggesting that policymakers must ensure these systems are user-friendly and provide comprehensive training for both students and educators. Simplifying the user interface and presenting an intuitive design can facilitate smoother integration and usage.

Students are influenced by peers, family, and instructors in their use of personalized learning tools (Social Influence, SI). Leveraging social influence, educators and policymakers can create a supportive community around personalized learning. Programs that involve parents, peer mentors, and influential educators can drive higher adoption rates. Necessary resources and support are essential for the effective use of personalized learning systems (Facilitating Conditions, FC). Investment in infrastructure and ongoing technical support is essential. Policymakers should allocate resources to ensure all students have access to the required technology and support services.

Enjoyment and pleasure from using personalized learning tools enhance student engagement (Hedonic Motivation, HM). Incorporating engaging, interactive elements and gamification into personalized learning systems can make learning more enjoyable, thus increasing student participation and retention. Students perceive the worthiness of investing time and effort into personalized learning (Learning Value, LV). Highlighting long-term benefits, such as improved learning outcomes and future academic and career readiness, can motivate students to invest more effort into personalized learning activities.

Consistent use of personalized learning tools leads to sustained usage and improved outcomes (Habit, HT). Educators should integrate personalized learning into regular curriculum activities, encouraging habitual use through routine assignments and continuous engagement. Dedication and sustained effort are critical for personalized learning success (Student Commitment, SC). Schools should foster a culture of commitment and responsibility among students, advancing consistent use of personalized learning tools through structured and supportive learning environments.

Students' internal drive to engage in learning activities for personal satisfaction is significant (Intrinsic Motivation, IM). Personalized learning experiences should align with students' interests and intrinsic motivations, encouraging self-directed learning by offering choices that cater to individual preferences. Strong intentions among students to continue employing personalized learning tools (Behavioral Intention, BI) imply that sustaining and enhancing students' intentions to use personalized learning can be achieved through continuous innovation and improvements in learning systems, ensuring they remain relevant and effective. The actual usage behavior of personalized learning tools is influenced by perceived ease and value (Usage Behavior, UB). Implementing continuous monitoring and feedback mechanisms can help educators understand and improve how students use personalized learning tools, adapting strategies to meet their needs efficiently.

By uncovering these factors and their practical implications, this study provides educators and policymakers with actionable insights to enhance the implementation of PML. The findings support the development of tailored instructional methods and resources that better meet students' diverse needs, thereby improving engagement and proficiency in mathematics. Moreover, this research aligns with global trends in education towards student-centered approaches, contributing to the ongoing discourse on educational innovation and reform. Implementing these insights can lead to more effective and inclusive instructional strategies, fostering a culture of lifelong learning and innovation in the Maldives and beyond.

9 Conclusion

The study findings proved the validity and reliability of the adapted and modified instrument for PML constructs. It provides a valuable contribution for developing an effective instrument to measure the PML components of the target study cohort. All 52 items applied to the EFA were retained with 41 items evaluating the suitability for the eleven constructs/variables, exhibiting $p-$values < 0.05, resulting in a significant correlation within the items in the latent constructs.

The Cronbach's alpha coefficients confirmed a high internal consistency for all the eleven constructs exceeding the widely accepted threshold of 0.7, which produced appropriate KMO scores (> 0.6), met the criteria of the Bartlett test (significant), and had factor loadings above the required minimum of 0.6. Therefore, retention items were appropriate for this study.

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Conflicts of Interest The authors declare no conflict of interest with publishing this article. The greatest level of academic integrity and transparency was adhered to in the research process, encompassing all the stages of data collection, analysis, and interpretation. The study's results and conclusions are the sole outcome of unbiased, independent scientific work free from extraneous influences.

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