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Moodle-based Blended Learning: Factors Influencing the Behavioral Intention of Undergraduate Students

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Abstract

The demand for blended learning by higher education has increased since COVID-19. Blended learning combines the advantages of both face-to-face and online learning. Many HEIs in developing countries have started to depend on Moodle to offer blended courses to their students, as it is freely available and open source. The current study aims to explore the factors that influence the intentions to use Moodle-based Blended Learning (MBBL) by higher education students in a public university in Jordan, a developing country. For this purpose, we used a modified version of the UTAUT2 model. Data were gathered through a survey that targeted undergraduate students. The study used 319 valid response samples and analyzed the data using SmartPLS 4 software that implements PLS-SEM analysis. The data analysis results show that the factors that influence the students' behavioral intention to use MBBL are performance expectancy ($\beta = .18$), effort expectancy ($\beta = .21$), social influence ($\beta = .16$), and habit ($\beta = .25$). However, the results indicate that facilitating conditions and hedonic motivation factors do not have a significant influence. In addition, the results reveal that result demonstrability has significant effect on both performance expectancy ($\beta = .58$) and effort expectancy ($\beta = .52$). Also, effort expectancy is found to influence performance expectancy ($\beta = .17$). Among the influential factors, habit is identified as the strongest predictor of intentions followed by effort expectancy, whereas social influence is the weakest predictor. The proposed model was able to explain 50% of variance in students' intentions to use MBBL. The current study provides HEIs with valuable insights needed to improve the MBBL process and enhance the performance of students. It also suggests future research directions that build on this study to reach more generalized and stable results.

Keywords: UTAUT2; Blended Learning; Moodle; Behavioral Intention; Developing Country

1. Introduction

With the vast and fast progress in information technologies in the recent years, especially web technologies, many Higher Educational Institutions (HEIs) have started to adopt new web-based and remote teaching methods to deliver education to students [1]. Some HEIs, in Jordan for example, started to introduce online or blended courses, side by side with on-campus courses.

Since the COVID-19 pandemic, HEIs have limited on-campus teaching and shifted to e-learning [2], [3]. Each HEI adopted one or more e-learning platforms to maintain the education process during the worldwide lockdowns. For example, some HEIs used social media apps like YouTube, WhatsApp, and Facebook, and others used Google classrooms, while others used online meeting apps like Zoom. However, for the purpose of maintaining the education process during the pandemic, many HEIs chose to depend on Learning Management Systems (LMSs), whether free or paid, like Moodle, Canvas, and Blackboard (recently became Anthology). After the pandemic period, HEIs switched back to traditional education settings, but many continued to offer some courses in either fully or partially e-learning settings armed with the e-learning experiences gained during the governmental enforced closure. Thus, they continued introducing online or blended courses side by side with traditional on-campus courses.

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In 2021, The Jordanian government issued a regulation for e-learning integration in HEIs (i.e., institutions that provide higher education, including universities, colleges, community colleges, or others). The legislation asked HEIs to mandatory re-evaluate their academic programs to integrate e-learning materials. It stated that courses must be delivered in one of these three categories: online, blended, or face-to-face. First, the percentage of online courses must constitute 10% to 20% of the total program credits. Second, the percentage of blended courses must constitute 40% to 60% for humanities and social sciences programs, and 30% to 50% for scientific, technical, health, and environmental disciplines. The remaining percentage of a program's credits is allocated for face-to-face courses, such that it does not fall below 20% for humanities and social sciences and 30% for scientific, technical, health, and environmental disciplines.

Some higher education institutes in Jordan have started to encourage faculty members to use LMSs in their courses. More even, many have already adopted Moodle as the primary LMS for delivering online and blended education. Moodle is an open-source LMS which is available at no cost, and it supports creating personalized learning environments for educators, administrators, and learners [4]. It is mainly used to deliver online and blended learning [5]. Blended Learning (BL) is an educational approach that merges face-to-face and online learning [6]. It gained significant attention by many HEIs all over the world, including developing countries like Jordan, especially in the middle of the pandemic and after. Thus, Moodle-Based Blended Learning (MBBL) has emerged as a new approach for delivering education by most HEIs in Jordan to enforce e-learning integration legislation.

However, faculty members at HEIs have noticed that a high percentage of students do not visit the pages of their blended learning course in Moodle regularly or at all, which probably leads to a decrease in students' educational outcomes. Thus, it is very necessary for HEIs in developing countries to aim to enhance educational outcomes of students who participate in MBBL courses by understanding the key factors that influence the behavioral intentions of students to use or accept MBBL.

To the best of our knowledge, there are few or no previous studies specifically related to the behavioral intention's influencing factors to use MBBL by students. The only study we could find was conducted by Ustun et al. [7] which investigated the variables that indirectly influence the engagement and sense of community of students that are mediated by MBBL acceptance. UTAUT2 has been frequently used by researchers to assess technology acceptance in diverse contexts, including education. So, we decided to use UTAUT2 in the current study to explore the key factors that influence undergraduate students to use MBBL. Al al-Bayt University is a large public university with more than twenty thousand students from various disciplines, regions and demographics, strictly applied the Jordanian government policies on blended learning mentioned above. Therefore, we chose it as the target of this study.

The remaining of this paper is organized as follows: Section 2 reviews prior studies. Following that, Section 3 presents the research model and hypotheses. Next, Section 4 introduces the research methodology. The assessment results of the measurement and structural models are detailed in Section 5. Lastly, Section 6 discusses the results, draws conclusions, explores the research implications, lists the limitations, and suggests further research.

2. Literature Review

2.1. Moodle

Moodle is a widely used LMS by educational institutes and mainly within Science, Technology, Engineering, and Mathematics (STEM) disciplines for delivering online and BL [5]. Moodle has gained a massive popularity amid COVID-19 over the globe. Just in the period from March 2020 to May 2020, 50k new Moodle sites were registered [8]. This number only includes sites that have decided to make their information available to the public. In addition, the number of Moodle users has increased enormously. It increased from 190m users in 2020 to 300m users in April 2022 [9]. It also continued this dramatic increase until it reached 432m by January 2025 [10]. Even though Moodle is increasingly used to offer online educational settings and there evidences that it enhances the learning process, but it cannot be a complete alternative for traditional classroom settings [11].

2.2. Blended Learning

BL is a newly emerged educational paradigm that integrates both traditional (i.e., on-campus) and online learning approaches [1], [6]. It aims to improve the student learning by leveraging the strengths of both these approaches [12]. Various research studies have shown that deploying BL in academic programs at HEIs will provide significant advantages over face-to-face or online teaching methods. Next, we provide the findings of some of these research papers as examples.

Two meta-analysis studies have shown that university students satisfied better academic achievement in BL classes than traditional classroom classes alone [13], [14]. In the same way, the study [15] concluded that incorporating BL in higher education courses has significantly improved the performance of students in comparison to face-to-face approach. In an experimental study conducted to assess the impacts of BL settings in higher education context, Ma and Lee [16] concluded that deploying BL approach in higher education has led to improvements in many aspects of students compared to online approach. Specifically, it enhances satisfaction, attention, and confidence. Moreover, the same study found that the BL approach greatly improves students' satisfaction in comparison to traditional face-to-face education.

A meta-analysis study by Porkodi et al. [17] stated that students' educational outcomes and learning experiences improved for courses delivered using BL approach. According to Salcedo [18], BL positively contributes to the forming of problem-solving and critical thinking skills among students. Vaughan [19] stated that the BL increases the interaction between students and educators which in turn leads to improving students' engagement and educators' teaching methods. Similarly, Lazarinis et al. [20] conducted a study that targeted faculty members. In this study, a BL course offered to faculty members to enhance teaching experiences. It concluded that the BL approach improves the engagement of faculty members and increases their commitment to finish the course. It also enhances the abilities of faculty members to deliver effective online teaching materials.

Castro [21] mentioned that when BL is deployed in higher education, it will make education accessible by more students, and it will provide them with self-paced and customized learning choices that takes into account each student's individual requirements. Also, Vaughan [19] stated that HEIs provides students with time flexible education through BL approach. In addition, Vaughan [19] mentioned that HEIs will cut the operating costs of their programs by delivering BL education.

Due to the various seen benefits of delivering BL education that align with the needs of both students and HEIs, the BL will be a valuable learning approach in higher education programs. The increasing interest and adoption of BL approach in HEIs has led to an annually increasing research papers on BL context as stated by Ishmuradova et al. [22]. However, most research in BL is coming from developed countries and there is a need for more research in BL from developing countries perspective [22].

2.3. Moodle-based Blended Learning (MBBL)

In BL approach, Moodle integrates online and face-to-face instructions to enhance educational outcomes. Numerous prior studies have indicated that MBBL enhances learning outcomes in various disciplines. In physics, Dari et al. [23] suggested that deploying MBBL has a significant positive effect on motivation and cognitive abilities among students in physics course. Also, in another physics course taught by MBBL, Yuniarti Suhendi et al. [24] reported an improvement in the critical thinking skills of participated students.

In medicine, the results of teaching a physiology of vision course in MBBL which stated by Goyal et al. [25] have shown an improvement in engagement and performance of students. Another study by Lebeaux et al. [26] observed that deploying MBBL in microbiology and infectious diseases classes increased the attendance and satisfaction of students in face-to-face lectures. Lastly, in a physiology course taught according to MBBL, Popović et al. [11] stated an increase in students' performance, attendance, and interest indicators. In addition, students provided positive feedback regarding Moodle easiness and its usefulness as a complementary tool to face-to-face teaching [11].

In engineering, the findings by Manasrah et al. [27] showed an improvement in the performance and engagement of students for MBBL courses. In computer science discipline, a C programming course was offered using MBBL approach, and the results stated that it improved teaching effects for both teachers and students [28]. In humanities, a controlled study conducted by El-Maghraby [29] in an EFL course found that the writing skills of university students who studied using MBBL were higher than that of their peers who studied using traditional methods. Also, in [30], it was found that MBBL led to an improvement in students' motivation, activeness, independence, and outcomes. In social sciences, the study [31] in social networks analysis course that was taught using MBBL showed that by adding only one online discussion activity in a mandatory basis, resulted in an increase in students' total activities, pass rates, and average grades. The results of this study were based on three years of Moodle data logs that were analyzed using machine learning techniques.

2.4. UTAUT and UTAUT2

The Unified Theory of Acceptance and Use of Technology (UTAUT) [32] is proposed as a synthesized model of the most eight prominent user acceptance models in the literature at that time. The UTAUT paper [32] took these eight models and compared them by conducting an empirical study. The main goal of the UTAUT paper was to find the best elements over all these models and combine them in a new unified model. The study then compared UTAUT against each of the eight individual models and it outperformed them. UTAUT is mostly tailored for studying user acceptance of IT in organizational context [32]. UTAUT2 [33] is an extension to UTAUT to make it mostly suited for predicting user acceptance of IT in consumer context. UTAUT2 has six predictor constructs: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit. These predictors are hypothesized to influence behavioral intention. In turn, behavioral intention acts as a predictor for actual use behavior. In addition, UTAUT2 has three moderating variables: gender, age, and experience. According to Venkatesh et al. [33], UTAUT2 enhances the explained variance for both behavioral intention and technology usage more effectively than UTAUT [33].

3. RESEARCH MODEL AND HYPOTHESES

3.1. Performance Expectancy

With reflection to the current study, PE denotes the degree level of university students' belief that deploying MBBL in educational activities will improve their learning outcomes and performance. Numerous prior research studies have found that PE is a key determinant in adoption of technology in various domains, including educational environments [31], [32], [33], [34]. Hence, we hypothesize that:

H_1*: PE has a significant positive effect on students' BI to use MBBL.*

3.2. Effort Expectancy

According to the current study, EE refers to the degree level to which university students believe that deploying MBBL in educational activities will be easy. Previous studies have shown that EE has a direct influence on behavioral intention to use technology [30], [33], [34], [35]. In TAM2, EE is hypothesized to have influence on BI directly or through PE [39]. In addition, the results of [36], [37] have shown that PE mediates the relationship between EE and BI. Also, a plenty of prior studies have shown a positive effect for EE on PE [35], [37], [38], [39]. When individuals find a technology user-friendly, they will probably view it as more beneficial, which subsequently increases their intentions to adopt the technology. Therefore, we come up with the following hypotheses:

H_2*: EE has a significant positive effect on students' BI to use MBBL.*

H_{2a}*: PE mediates the relationship between EE and BI.*

H_3*: EE has a significant positive effect on students' PE.*

3.3. Social Influence

Many studies have shown the direct influence of friends, peers, teachers, and co-workers on the BI to accept technologies [30], [32], [33], [37]. In addition, the influence of social networks on the BI is supported in educational context [31], [34], [35]. Regarding the domain of this study, SI is an estimate for degree level of the effect of university students' social networks on their BI to engage in MBBL. Hence, we propose that:

H_4*: SI has a significant positive effect on students' BI to use MBBL.*

3.4. Facilitating Conditions

Within the domain of MBBL, FC denotes the presence of necessary resources and technical infrastructure, and adequate support for university students to facilitate MBBL. Various previous research studies, for examples, [31], [32] have shown positive direct effect of FC on students' BI to use technologies in educational settings. Based on this, we suggest the following hypothesis:

***H*$_5$**: *FC has a significant positive effect on students' BI to use MBBL.*

3.5. Hedonic Motivation

The beneficial impact of HM on the behavioral intention of users toward technology usage is supported by various research studies [30], [33], [34]. When users have pleasure and entertaining experiences with a technology, they will probably consider to use it repeatedly. Regarding the current study, HM is an estimation for the degree of fun and enjoyment perceived by students while they engage with MBBL. Based on this, we hypothesize that:

***H*$_6$**: *HM has a significant positive effect on students' BI to use MBBL.*

3.6. Habit

With respect to our proposed study, H refers to the extent of automatic routine behaviors developed by students while learning and gaining more experience in MBBL environment. The positive influence of H on BI has been reported in numerous prior studies, for examples, in [30], [33], [34], [40]. Based on this, we hypothesize that:

***H*$_7$**: *H has a significant positive effect on students' BI to use MBBL.*

3.7. Result Demonstrability

Result Demonstrability (RD) is defined as the "tangibility of the results of using the innovation" [44]. In the context of MBBL, RD is the degree to which the outcome of using MBBL is observable and perceptible by students to the extent they can convey it to others easily. RD is hypothesized to influence PE directly and positively in TAM2 [39]. When users can effortlessly demonstrate the outcomes of using a technology, RD will increase, which in turn will likely boost the PE of users toward the technology. This hypothesis is found significant in the prior research studies [36], [42], [43]. In the same way, RD is identified as a significant predictor that influences EE in the prior study [47]. But we could not find any other studies that hypothesized this path. Therefore, we state the subsequent hypotheses:

***H*$_8$**: *RD has a significant positive effect on students' PE.*

***H*$_{8a}$**: *EE mediates the relationship between RD and PE.*

***H*$_9$**: *RD has a significant positive effect on students' EE.*

3.8. The Theoretical Model

Figure 1 is a pictorial representation of the proposed theoretical model. The constructs are represented with rectangle boxes. The relationships between the constructs and their directions are represented by arrows. An arrow links an individual independent construct to its dependent construct. The labels on the arrows indicate the proposed hypotheses. We did not include potential moderating variables such as gender, age, university year, or experience, in our developed theoretical model. The reason for this decision was based on the study's primary focus on revealing the key influencing factors from within the UTAUT2 framework. However, we acknowledge that anticipating their impact during the design phase would have strengthened the methodology.

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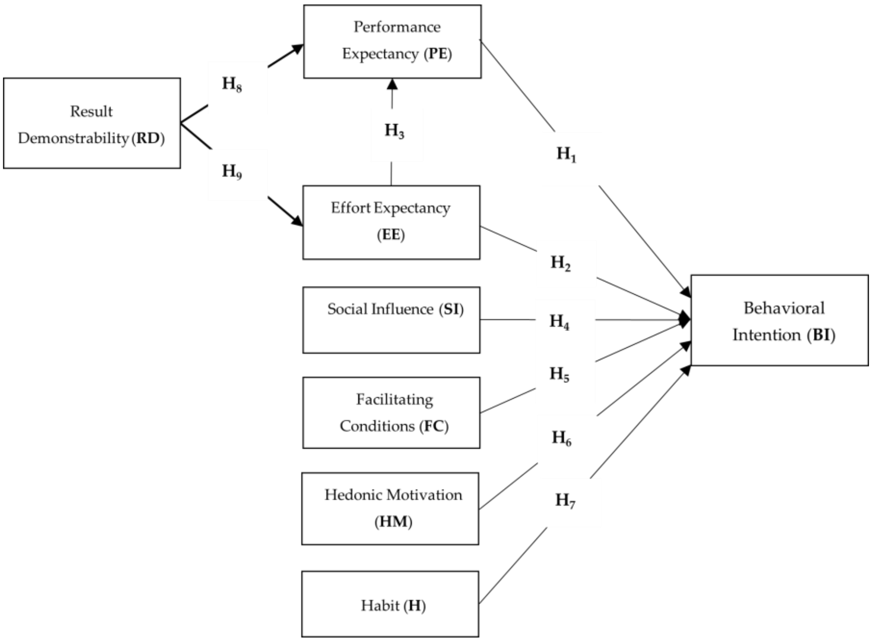

Figure 1. The Suggested Research Model

4. Research Methodology

4.1. Survey Design

We divided the survey into two sections. The first section contained questions about demographic variables. In the second section, we included 29 questions to assess students' perceptions of MBBL, as shown in table 1. Every question in the second section was evaluated using a 7-point Likert scale, where 1 represents strong disagreement and 7 represents strong agreement. The survey questions were selected based on widely recognized measures found in the literature. Nonetheless, these questions were adapted to fit the specific context of this study.

Table 1. Survey questions

Construct	Code	Item	Source
PE	PE1	Using Moodle helps me get better grades in my blended learning courses.	[39] [33] [32]
	PE2	Using Moodle enhances my learning efficiency in a blended learning environment.	
	PE3	Moodle contributes to improving my academic performance in blended courses.	
	PE4	Moodle contributes to my learning speed and comprehension in blended environments.	
EE	EE1	It is easy for me to become skillful at using Moodle for blended learning.	[39] [33] [32]
	EE2	Navigating through Moodle is straightforward for my blended course's topics and activities.	
	EE3	I can manage Moodle without needing much technical knowledge.	
	EE4	It is easy for me to access any information I need by using Moodle for my blended learning.	
SI	~~SI1~~	~~Students and friends who influence my behavior think I should use Moodle for blended learning.~~	[33] [32]
	SI2	The positive experience of others using Moodle for blended learning encourages me to use it.	
	SI3	In general, the university administration has supported using Moodle for blended learning.	
FC	FC1	I have the resources necessary to use Moodle for blended learning.	[39] [33] [32]
	FC2	I have the knowledge necessary to use Moodle for blended learning.	
	FC3	The technical infrastructure at my institution supports using Moodle for blended learning.	
	FC4	I get adequate support and help from others when I have difficulties using Moodle for blended learning.	
HM	HM1	Using Moodle for blended learning is enjoyable.	[33] [32]
	HM2	Using Moodle stimulates my interest in learning in a blended environment.	
	HM3	Using Moodle for blended learning is fun and engaging.	

	H1	Using Moodle for blended learning has become a habit for me.	
H	H2	I frequently log into Moodle as part of my daily study routine for the blended courses.	[33]
	H3	Using Moodle-based blended learning has become natural to me.	
	BI1	I intend to use Moodle regularly in my upcoming semesters for blended courses.	
BI	BI2	I plan to use Moodle in blended learning more frequently in my academic studies.	[33]
	BI3	I will always try to use Moodle-based blended learning in my learning activities.	
	RD1	I have no difficulty telling others about the benefits of using Moodle in blended courses.	
	RD2	The results of using Moodle for blended learning are apparent to me immediately.	
RD	RD3	I believe I could communicate to others the consequences of using Moodle-based blended learning.	[39]
	RD4	Using Moodle makes it easier for me to understand the learning material in blended courses.	
	~~RD5~~	~~I would have difficulty explaining why Moodle-based blended learning may or may not be beneficial.~~	

Note: We dropped SI1 and RD5 items because their outer loadings were less than 0.70.

4.2. Population Samples

Samples were collected using Google Form from undergraduate students who were pursuing a undergraduate degrees at a public university in Jordan. The respondent students experienced MBBL for at least one year. The survey was administered during the second semester. Emails were sent to faculty members asking them to post the survey link for their students by adding announcements inside the Moodle's pages for the courses taught by them. They were also asked to give a few minutes of their next lectures to encourage students to voluntarily participate in the survey study. The survey link was open for students for about a week in the period from May 6 until May 14, 2024. At the end of the period, we collected 340 responses.

From those collected samples, we removed 21 responses that were straight lining answers. That is, all questions were answered as strongly agree or all questions were answered as strongly disagree. These types of answers are considered as outliers and do not help in the analysis process. Hence, the sample size used in data analysis is reduced to 319, which constitutes 93.8% of the total collected samples.

4.3. Demographic Characteristics

The demographic characteristics of the respondents are outlined in table 2. As shown in the table, most respondents were male (63.32%), while the remaining (36.68%) were female. With respect to the respondents' ages, most of them were between 20 and 22 years old (70.85%), as most of them were either in the second or third years of their academic study, while (17.24%) were younger than 20 years, and (11.91%) were older than 23 years. Because most respondents were 20, 21, or 22 years old, most of them were either sophomores (47.96%) or juniors (31.66%) in their bachelor's degrees, while only (5.96%) were freshmen, (10.66%) were seniors, and the remaining (3.76%) were in the fifth year or higher. Lastly, regarding the experience of respondents in MBBL, most respondents had intermediate experience (71.16%), while the remaining had beginner experience (23.82%) and advanced experiences (5.02%).

Table 2. Demographic characteristics of respondents (n = 319)

Variable	Category	Frequency	%
Gender	Male	202	63.32
	Female	117	36.68
Age	< 20	55	17.24
	20-22	226	70.85
	23+	38	11.91
Academic Year	1st Year	19	5.96
	2nd Year	153	47.96
	3rd Year	101	31.66
	4th Year	34	10.66
	5+	12	3.76
	Highly Experienced	16	5.02

MBBL Experience	Moderately Experienced Beginner	227 76	71.16 23.82

4.4. Data Analysis

We performed data analysis and tested the hypotheses through SmartPLS 4 software [48]. Nowadays, SmartPLS is one of the most popular software that supports the Partial Least Squares Structural Equation Modeling (PLS-SEM) method. It has a distinguished user-friendly GUI compared to other competitors. It can also work very well with small sample sizes and produce reliable results. It can also handle various types of data regardless of whether it is in normal or non-normal distribution. Its robust bootstrapping feature also produces more reliable statistical results by generating multiple subsamples from the original dataset. For these reasons, we used SmartPLS for analyzing the proposed model and extracting meaningful conclusions from the data.

5. Results

5.1. Measurement Model Assessment

For the assessment of the measurement model, we use the following metrics: convergent validity, internal consistency reliability, and discriminant validity.

Convergent validity measures how well the items of the same construct correlate with each other. It is usually evaluated using indicator reliability (i.e., outer loadings) and Average Variance Extracted (AVE) at the individual factor and at the individual construct, respectively [49]. For assessment of item reliability, it is recommended that the outer loading of the item must be 0.708 or higher [49]. The outer loading values for items SI1 and RD5 were less than the threshold of 0.708 but more than 0.40. Following the guidelines in [49] for this scenario, we decided to drop these two indicators from the analysis and regenerate the results of measurement model. Indicator reliability is satisfied, as shown in table 3, where all indicators of the proposed models have loading values above the recommended threshold. It is recommended that the AVE value be 0.50 or above [50]. All our constructs have AVE values that exceed the recommended threshold as shown in table 3. Thus, the convergent validity of our proposed model was established.

Table 3. Results of measurement model as extracted from SmartPLS

Construct	Item	Loadings	AVE	Cronbach's α	CR
Performance Expectancy (PE)	***PE1***	0.860	0.702	0.858	0.859
	PE2	0.842	-	-	-
	PE3	0.849	-	-	-
	PE4	0.798	-	-	-
Effort Expectancy (EE)	***EE1***	0.769	0.599	0.779	0.792
	EE2	0.784	-	-	-
	EE3	0.732	-	-	-
	EE4	0.808	-	-	-
Social Influence (SI)	***SI2***	0.903	0.778	0.717	0.730
	SI3	0.861	-	-	-
Facilitating Conditions (FC)	***FC1***	0.729	0.557	0.734	0.737
	FC2	0.791	-	-	-
	FC3	0.754	-	-	-
	FC4	0.708	-	-	-
Hedonic Motivation (HM)	***HM1***	0.889	0.781	0.860	0.861
	HM2	0.873	-	-	-

	HM3	0.888	-	-	-
Habit (H)	***H1***	0.796	0.646	0.726	0.749
	H2	0.731	-	-	-
	H3	0.878	-	-	-
Behavior Intention (BI)	***BI1***	0.848	0.673	0.758	0.760
	BI2	0.810	-	-	-
	BI3	0.803	-	-	-
Result Demonstrability (RD)	***RD1***	0.856	0.673	0.838	0.843
	RD2	0.812	-	-	-
	RD3	0.811	-	-	-
	RD4	0.801	-	-	-

Internal consistency reliability is usually assessed by Cronbach's Alpha (CA) and Composite Reliability (CR) measures. CA estimates the reliability of a construct based on the intercorrelations between its items. Because CA is considered a conservative estimate for a construct reliability (i.e., it reduces reliability values), while CR underestimates the reliability values, researchers most commonly report both estimates [49]. The recommended values for both CA and CR are between 0.7 and 0.90 [51]. Table 3 shows that all constructs in the proposed model achieved CR and CA values within the recommended range [0.70 - 0.90]. Thus, the internal consistency reliability of our proposed model was satisfied.

Discriminant validity ensures that each individual construct is distinct from other constructs. A construct must uniquely capture a concept that is not completely or partially captured by another construct [49]. In other words, the relationships between the construct and its underlying indicators must be stronger than the relationships between its factors and other constructs. The commonly used measures to evaluate the discriminant validity are cross loadings, Fornell-Larcker criterion, and Heterotrait-Monotrait Ratio (HTMT). Cross loadings are used to evaluate the discriminant validity at an item-level while Fornell-Larcker criterion and HTMT are used to evaluate the discriminant validity at a construct-level.

Discriminant validity at the item level is achieved when the outer loading of each item exceeds its correlations with other constructs [49]. As indicated in table 4, each item has a stronger loading on its own construct than its cross-loadings with other constructs. Consequently, our proposed model demonstrated adequate discriminant validity at the item level.

Table 4. Cross loadings

Items/Construct	BI	EE	FC	H	HM	PE	RD	SI
BI1	0.848	0.417	0.430	0.493	0.439	0.440	0.503	0.480
BI2	0.810	0.416	0.319	0.457	0.395	0.380	0.404	0.420
BI3	0.803	0.458	0.384	0.454	0.475	0.488	0.600	0.429
EE1	0.410	0.769	0.455	0.334	0.320	0.394	0.400	0.327
EE2	0.400	0.784	0.482	0.339	0.246	0.273	0.413	0.378
EE3	0.322	0.732	0.430	0.324	0.170	0.296	0.279	0.226
EE4	0.467	0.808	0.496	0.348	0.437	0.449	0.471	0.374
FC1	0.326	0.499	0.729	0.361	0.245	0.329	0.397	0.228
FC2	0.379	0.572	0.791	0.358	0.359	0.403	0.400	0.367
FC3	0.308	0.401	0.754	0.279	0.326	0.372	0.408	0.350
FC4	0.360	0.320	0.708	0.339	0.318	0.347	0.377	0.263

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H1	0.475	0.337	0.370	0.796	0.553	0.377	0.499	0.421
H2	0.367	0.277	0.312	0.731	0.300	0.260	0.367	0.429
H3	0.518	0.418	0.397	0.878	0.477	0.367	0.506	0.466
HM1	0.466	0.346	0.395	0.467	0.889	0.529	0.602	0.495
HM2	0.498	0.414	0.403	0.533	0.873	0.511	0.599	0.547
HM3	0.447	0.284	0.311	0.490	0.888	0.521	0.551	0.505
PE1	0.468	0.366	0.407	0.364	0.494	0.860	0.586	0.418
PE2	0.469	0.445	0.461	0.394	0.470	0.842	0.549	0.386
PE3	0.427	0.354	0.371	0.327	0.485	0.849	0.544	0.394
PE4	0.421	0.396	0.391	0.325	0.526	0.798	0.553	0.415
RD1	0.559	0.450	0.492	0.505	0.597	0.610	0.856	0.512
RD2	0.494	0.441	0.498	0.491	0.502	0.464	0.812	0.392
RD3	0.441	0.367	0.321	0.463	0.545	0.526	0.811	0.353
RD4	0.519	0.431	0.421	0.431	0.524	0.575	0.801	0.403
SI2	0.514	0.378	0.334	0.497	0.554	0.469	0.499	0.903
SI3	0.435	0.381	0.388	0.460	0.472	0.374	0.394	0.861

The Fornell-Larcker criterion ensures that the square root of the AVE value of each construct is greater than all its correlation values among other constructs [50]. The bolded diagonal values under columns (PE-BI) in table 5 represent the square root of constructs' AVE values, while the values underneath represent the correlation values among constructs. As shown in the table, we can say that according to the Fornell-Larcker criterion, our proposed model possesses sufficient discriminant validity at the construct level.

Table 5. Evaluation of discriminant validity by Fornell-Larcker criterion as derived from SmartPLS 4

Construct	AVE	PE	EE	SI	FC	HM	H	RD	BI
PE	0.702	0.838	-	-	-	-	-	-	-
EE	0.599	0.467	0.774	-	-	-	-	-	-
SI	0.778	0.482	0.429	0.882	-	-	-	-	-
FC	0.557	0.488	0.603	0.406	0.746	-	-	-	-
HM	0.781	0.589	0.397	0.585	0.421	0.884		-	-
H	0.646	0.422	0.434	0.544	0.450	0.563	0.804	-	-
RD	0.673	0.667	0.516	0.510	0.530	0.662	0.576	0.820	
BI	0.673	0.534	0.525	0.541	0.463	0.533	0.571	0.617	0.821

Note: Square roots of the AVE are the bolded diagonal values and the nondiagonal ones are the factor correlation coefficients.

Although cross-loadings and Fornell-Larcker are the most common criteria for discriminant validity assessment, Henseler et al. [52] introduced HTMT as a new criterion for establishing discriminant validity that is more reliable compared to cross-loadings and Fornell-Larcker criterion. An HTMT value of two different constructs that is very close or equal to 1, means that the two constructs are not distinct and thus they lack discriminant validity [52]. The suggested HTMT threshold for constructs that are conceptually very similar is 0.95, whereas it is 0.85 for those that are conceptually more different [48], [50]. It is clearly shown in table 6 that all HTMT values among constructs remarkably fall below the 0.85 threshold, which implies that according to the HTMT criterion, the proposed measurement model demonstrates sufficient discriminant validity.

In summary for this section, the assessment criteria results for the measurement model demonstrate that the model's measures have satisfied the reliability and validity conditions.

Table 6. Evaluation of discriminant validity by HTMT criterion as derived from SmartPLS 4

Construct	PE	EE	SI	FC	HM	H	RD	BI
PE	-							
EE	0.556	-						
SI	0.609	0.564	-					
FC	0.612	0.790	0.562	-				
HM	0.686	0.459	0.739	0.524	-			
H	0.526	0.567	0.754	0.610	0.697	-		
RD	0.764	0.622	0.647	0.673	0.777	0.730	-	
BI	0.658	0.671	0.729	0.613	0.657	0.760	0.764	-

5.2. Structural Model Assessment

In the previous subsection, we assessed the measurement model against validity and reliability metrics and there were no issues with the evaluation process. Next, we evaluate the structural model by using the bootstrapping procedure of the PLS. The outputs of the bootstrapping procedure are the results of the structural model that will be used in the assessment process. Researchers usually consider the following criteria for assessment of the structural model: collinearity assessment, path coefficients, R^2, Q^2, and f^2. The results of the structural model generated by the SmartPLS 4 are shown in table 7, table 8, and tabel 9. In addition, a pictorial representation of the structural model results is shown in figure 2.

5.2.1. Collinearity Assessment

We use Variance Inflation Factor (VIF) to check for multicollinearity problems. As stated in literature, a predictor construct with a VIF values above the threshold five may have collinearity issues [49]. All VIF values of predictors in our proposed model are remarkably below the threshold of five, as shown in table 7, which confirms that the structural model has no collinearity issues. Thus, we move to the next step of assessing the structural model.

5.2.2. Path Coefficients

To be considered significant, the path coefficient must have a p-value below the 0.05 threshold [48], [51]. We can also confirm that the path is significant by using the 95% Confidence Interval (CI), such that it is significant if the upper and lower limits of the CI do not include zero [48], [51]. As shown in table 7, the path coefficients of our proposed hypotheses except for H_5 and H_6 are significant. All significant path coefficients have p-values less than 0.05 and do not include zero between lower and upper limits of the CI, while the path coefficients for both H_5 and H_6 are not significant because their p-values are more than 0.05 and zero is included between lower and upper limits of the CI.

Table 7. Hypothesis findings generated from SmartPLS 4

H	Paths	β	t	p	R^2	Q^2	f^2	VIF	SD	Support	CI	
											5%	*95%*
H_1	PE→BI	0.183**	2.575	0.005	0.501	0.444	0.038	1.797	0.071	Yes	0.060	0.292
H_2	EE→BI	0.205**	3.030	0.001	-	-	0.048	1.757	0.068	Yes	0.085	0.308
H_3	EE→PE	0.167***	3.466	0.000	0.465	0.437	0.038	1.362	0.048	Yes	0.087	0.245
H_4	SI →BI	0.160**	2.362	0.009	-	-	0.029	1.789	0.068	Yes	0.054	0.275
H_5	FC→BI	0.032	0.485	0.314	-	-	0.001	1.795	0.065	No	-0.076	0.140

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H_6	HM⟶BI	0.097	1.493	0.068	-	-	0.009	2.059	0.065	No	-0.005	0.209
H_7	H⟶BI	0.249***	3.719	0.000	-	-	0.071	1.747	0.067	Yes	0.147	0.367
H_8	RD⟶PE	0.581***	11.422	0.000	-	-	0.462	1.362	0.051	Yes	0.496	0.663
H_9	RD⟶EE	0.516***	10.526	0.000	0.266	0.259	0.362	1.000	0.049	Yes	0.435	0.594

Notes: Significance at p < *: 0.05, **: 0.01, ***: 0.001. CL: Confidence Intervals; LL: 5%, UL: 95%. f^2: 0.02: small, 0.15: medium, 0.35: large. 10,000 bootstrap samples.

5.2.3. Coefficient of Determination

The coefficient of determination (R^2) is used to determine the explanatory power of the structural model. The R^2 value indicates how much of the variance in the dependent construct is explained by all predictor constructs that have relationships with it [49]. The value of R^2 falls in the range [0,1], such that a model with a value that is close to one means a better explanatory power than another with less R^2 value [55]. There is no agreement on the acceptable R^2 values among researchers, as it may depend on the research field and the complexity of the model. However, many researchers consider R^2 values 0.25 and below as weak, 0.26 to 0.74 as moderate, and above 0.74 as substantial [46] [51]. Others consider (019, 0.33, and 067) as weak, moderate, and substantial, respectively [56]. In our example, as shown inside the blue circles in figure 2, the endogenous constructs BI, PE, and EE achieved moderate R^2 values (0.501, 0.465, 0.266). Since the explanatory power of the model is acceptable, we confirm that the model has a good fit. It is known that the explanatory power of the structural model can be increased by including the moderator variables, like gender and experience, but we decided to ignore them from the current study.

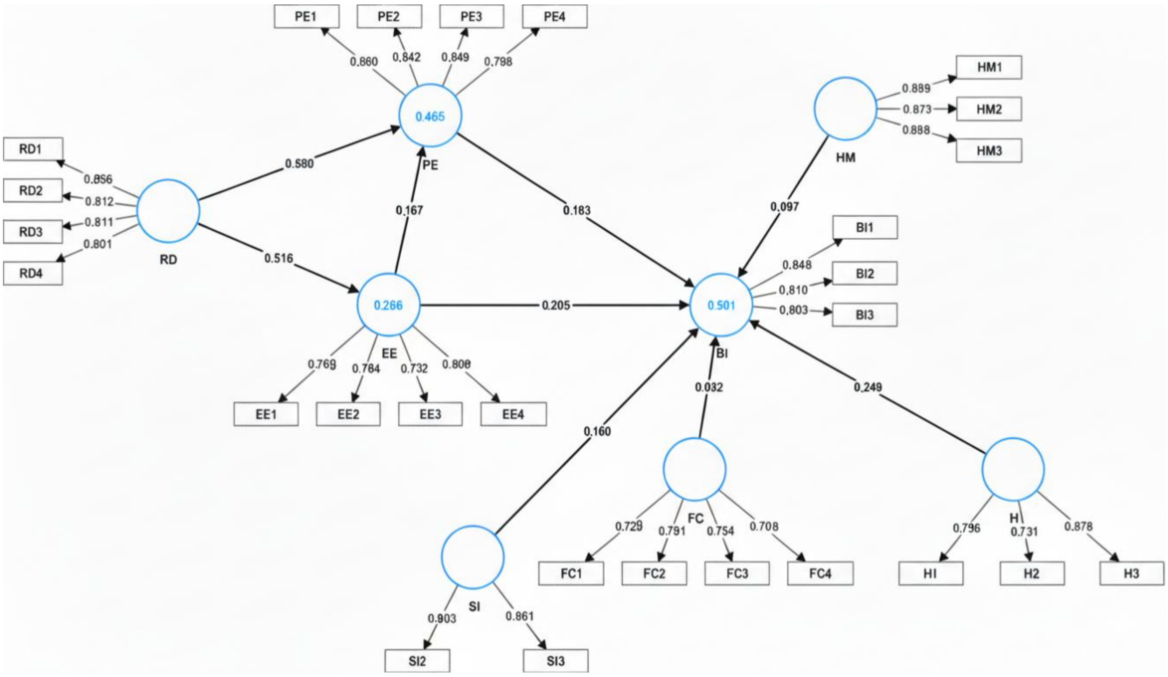

Figure 2. An illustration of the structural model results (showing outer loadings, path coefficients and R^2 values) as generated from the PLS-SEM algorithm of SmartPLS 4.

5.2.4. Effect Size

Effect size (f^2) criterion is used to evaluate the impact of each independent variable on the dependent variable that has a relationship with it. f^2 determines the change in R^2 of a dependent variable due to the removal of a particular dependent variable from the structural model, which is used to evaluate the amount of impact the removed variable has on the dependent variable's explanatory power [57]. In other words, f^2 estimates the strength of the effect of a specified predictor on the dependent construct. The values of f^2 can be interpreted as the following. An f^2 value of 0.02 or less means the effect size is negligible, greater than 0.02 and equals to 0.15 means the effect size is small, greater than 0.15 and equals to 0.35 means the effect is medium, and greater than 0.35 means the effect size is large [57]. Table 7 shows

f^2 values for all model's paths. PE, EE, SI, and HI achieved small effects on BI. In the same way, EE achieved a small effect on PE. However, the effects of RD on both PE and EE were large.

5.2.5. Predictive Relevance

Predictive relevance (Q^2) criterion assesses the predictive accuracy or relevance of the structural model for new data points that were not previously used in the model estimation [49]. Q^2 is used to evaluate the R^2's predictive accuracy of an endogenous construct. An endogenous construct with a Q^2 less than zero means it lacks predictive relevance while it has a meaningful predictive relevance when Q^2 is above zero [56]. As shown in table 7, the Q^2 values of all endogenous constructs (namely, BI, PE, and EE) were considerably above zero. More precisely, BI had the highest Q^2 value (0.444), followed by PE (0.437), and finally EE (0.259). In addition, Q^2 value indicates the strong predictive power of the structural model, such that a value above 0, 0.25 and 0.50 means small, medium and large predictive power [51]. Hence, we conclude that the structural model has acceptable predictive power.

5.2.6. Hypotheses Testing

We present the results of the proposed hypotheses in table 7. Only two of the nine relationships between the constructs of the proposed model are not significant, as shown in table 7, namely, FC→BI and HM→BI. Figure 2 gives a pictorial representation of the model's results. In addition, the figure shows the R^2 values of the endogenous variables within circles. In table 8 and table 9, we show the results of the mediated and indirect effects. The proposed model moderately explained 50% of the variance. We provide more details on hypotheses testing in the next section.

Table 8. The mediated effects of PE on EE-BI and EE on RD-PE as derived from SmartPLS 4

H	Paths	Effect			t	p	SD	Support	CI	
		β_{direct}	$\beta_{indirect}$	β_{total}					*5%*	*95%*
H_2	EE→BI	0.205**			3.030	0.001	0.068	Yes	0.085	0.308
H_{2a}	EE→PE→BI		0.031*		2.022	0.022	0.015	Yes	0.008	0.057
	EE→BI			**0.236**				Yes	0.111	0.341
H_8	RD→PE	0.581***			11.422	0.000	0.051	Yes	0.496	0.663
H_{8a}	RD→EE→PE		0.086**		3.174	0.001	0.027	Yes	0.044	0.133
	RD→PE			**0.667**				Yes	0.600	0.729

Table 9. The indirect effects of RD on BI through PE and EE as derived from SmartPLS 4

Paths	β	t	P	SD	Supported?	5%	95%
RD→BI	**0.228*** **	3.486	0.000	0.065	Yes	0.113	0.329
RD→PE→BI	0.106**	2.461	0.007	0.043	Yes	0.034	0.175
RD→EE→BI	0.106**	2.910	0.002	0.036	Yes	0.044	0.163
RD→EE→PE→BI	0.016*	1.955	0.025	0.008	Yes	0.004	0.030

6. DISCUSSION AND CONCLUSIONS

6.1. Discussion of Results

The primary aim of the current study is to explore the factors that affect the behavioral intention to use MBBL by the students of higher education institutes in Jordan. The study extended UTAUT2 model by adding result demonstrability predictor. The results obtained indicate that the explanatory powers of endogenous variables are good. Meanwhile, the extended model explained 50% of the variance in behavioral intention to use MBBL. We discuss below in detail the results of the proposed hypotheses.

The statistical results shown in table 7 indicate that the path from PE to BI is positively significant (H_1: β=0.183, p<0.01). This finding aligns with [30], [31], [32], [33], [34], [35], [37], [55] that concluded the positive impact of PE on BI. An explanation for this might be that students are more willing to use MBBL if they perceive that it will be beneficial to their academic performance. Thus, to encourage students to adopt MBBL, HEIs must explain to students the expected benefits of using MBBL in the education process. Examples on these benefits include improving students' outcomes, learning efficiency, comprehension, and speeding up learning process.

In addition, the results demonstrated that the path from EE to BI is significant (H_2: β=0.205, p<0.01). This suggests that the intention of students to use MBBL increases when they realize that it is effortless and user-friendly. This finding is consistent with the previous studies [30], [31], [32], [34], [37], [55]. Thus, to promote the adoption of MBBL, HEIs need to make efforts to customize their Moodle sites in ways that make the navigation of students much easier, besides simplifying the GUI to make it appealing for students. The results also indicate that the path from EE to PE is significant (H_3: β=0.167, p<0.001). This result aligns with previous findings in the studies [35], [37], [38], [56]. Additionally, it is shown in table 8 that PE partially mediates the influence of EE on BI (H_{2a}: β=0.031, p<0.05). This finding aligns with the prior studies [35], [37].

Moving forward, the results demonstrated that the path from SI to BI is significant (H_4: β=0.160, p<0.01). Even though MBBL was mandatory for the surveyed sample of students, however, the positive experiences of other students using Moodle for blended learning and the support and help given by instructors and e-Learning directorate reinforced the intention of students to use MBBL [60]. This finding is supported by the prior studies [30], [31], [32], [34], [35], [37].

In addition, the results indicate that the path from H to BI is significant (H_7: β=0.249, p<0.001). This outcome is consistent with the prior studies [30], [34]. Next, the results showed that the path from RD to PE is significant (H_8: β=0.581, p<0.001). The prior studies [36], [42] support this finding. In addition, the results concluded that the path from RD to EE is also significant (H_9: β=0.516, p<0.001). We could not find any previous studies that support this finding.

However, the analysis found that both FC and HM variables have no effect on students' behavioral intentions to adopt MBBL. According to the results, the path from FC to BI is insignificant (H_5: β=0.032, p>0.05), which is consistent with the prior studies [33], [34], [35], [57], [58] but contradicts the previous findings [30], [32], [55]. The insignificant effect of FC may be related to the context of this study, where students had adequate institutional and technical support. Thus, they may perceive FC as less influential in their MBBL. In the same way, the path from HM to BI is insignificant (H_6: β=0.097, p>0.05), which differs from previous findings [30], [33], [34] but aligns with the prior studies [57], [59]. This finding can be explained due to the academic context of MBBL rather than enjoyment purposes [60]. Thus, the role of HM on influencing the students' intention is reduced.

According to the mediation effect analysis results shown in table 8 which is generated from SmartPLS 4, PE partially mediates the relationship between EE and BI (H_{2a}: β=0.031, p<0.05). Similarly, EE partially mediates the relationship between RD and PE (H_{8a}: β=0.086, p<0.01). Thus, both proposed hypotheses H_{2a} and H_{8a} are supported by the analysis results, albeit the mediation effects are weak. Table 9 shows the indirect effect between RD and BI through PE and EE. The results indicate a significant total mediation between RD and BI through PE and EE (β=0.228, p<0.001).

6.2. Conclusions

Most HEIs started to integrate blended learning in their educational curriculums after COVID-19 era. This integration will make the transition process from traditional to partially or fully inline educational settings much smoother in response to emergent situations. The limited budgets of HEIs in developing countries, like Jordan, make Moodle a favored LMS for delivering blended learning as it is free and open-source software. A plenty of HEIs in Jordan adopted Moodle to introduce blended learning to their students in response to the e-learning integration regulation issued by the Jordanian government, which requires HEIs to integrate inline and blended learning side by side with traditional classroom settings. We chose a public university in Jordan to unveil the influential factors on the intentions of undergraduate students to use MBBL. A model based on UTAUT2 with result demonstrability was developed, and the data were collected and analyzed using the PLS-SEM by SmartPLS 4.

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The results of the analysis show that the influential factors which have a positive significant effect on behavioral intentions of students to use MBBL ordered from the strongest to the weakest significant effect are H (.25), EE (.21), PE (.18), and SI (.16). Thus, the study reports that the most significant relationship path that influences the students' intentions is H→BI and the least significant relationship path is SI→BI. In addition, the results reveal that RD has a positive significant effect on both PE (.58) and EE (.52). Also, EE is found to positively influence PE (.17). However, the results demonstrate that the FC and HM factors do not influence BI.

The analysis results also reveal that PE positively mediates the relationship path EE→BI (.03, partial mediation) and EE positively mediates the relationship path RD→PE (.09, partial mediation). Thus, the total direct and indirect effects of PE on EE→BI is (β=0.24), and the total direct and indirect effects of EE on RD→PE is (β=0.67). In addition, the results unveil a positive indirect effect of both PE and EE on the indirect path between RD and BI with a total indirect effect of (β=0.23).

These findings provide educators and administrators with useful insights that may help them in designing and implementing robust blended learning environments. By highlighting the key factors that influence students' behavioral intention, this study can help the decision makers in HEIs to improve the educational settings.

6.3. Implications

The current study provides HEIs with valuable insights about the key factors that boost the intentions of students to use MBBL. For successful integration of MBBL in higher education, HEIs need to foster students' perceptions of these factors. When HEIs are aware of the factors that influence the intentions of students to use MBBL by higher education students, they can improve the learning process and may help enhancing the angagement and performance of students within HEIs. These improvements support the development of more flexible and effective educational environments. The decision makers and faculty members in HEIs when aware of the influencing factors of students' intentions to use MBBL, they can have a clear picture about the expectations of their students from MBBL. Hence, decision makers in HEIs can effectively deploy MBBL in their academic programs. In addition, educators can enhance their teaching methods by aligning with these factors, which will absolutely increase the intentions of students to use MBBL.

6.4. Limitations and Future Research

Generally, studies are not completely perfect and comprehensive, and this also applies to the current study. We mention some of the limitations that may guide researchers to conduct future research based on this study to get generalizable and stable results.

First, we collected our samples only from one public university in the northern region of Jordan. Therefore, the findings of this study may not be generalized to other public and private universities that have different educational values, and that expand different geographical locations in the north, south, and middle of the country. In addition, the findings may not be applicable to other HEIs located in different parts of the world. One direction for future research is to collect samples from different HEIs that represent all regions of Jordan. Even more, the collected samples may expand to represent other regions across the world.

Second, students come from different regions and have different cultural values. A limitation of this study is that the effects of students' cultural values, gender, experience, and faculty are not considered as possible moderators for the proposed model's relationships. Another future research direction is to incorporate these variables into the structural model and assess whether they influence the intention of students toward continuous use of MBBL.

Third, the current research did not take in consideration other external factors that could enhance the students' intentions toward using MBBL. Further research direction could explore new factors that may influence the intentions of students. For example, researchers may extend the current model by adding new contextual factors related to Moodle and blended learning elements and assessing whether they increase the explanatory power of the model.

Fourth, another limitation of this study is that it only measures the perception of learners toward the use of MBBL. Hence, future research direction could extend this study by also assessing the perception of educators to continue using MBBL. Thus, we can have a more thorough insight into the stakeholders' experiences toward the implementation of MBBL.

By considering these future studies, the research community of educational technology acceptance can conclude more generalized and stable results. This will help administrators of HEIs to create effective procedures to enhance the delivery of MBBL to their students which will lead to enhancing the students' outcomes.

7. Declarations

7.1. Author Contributions

Conceptualization, F.K., S.A.A., A.M., and T.A.; Methodology, F.K.; Software, F.K.; Validation, F.K., S.A.A., A.M., and T.A.; Formal Analysis, F.K.; Investigation, F.K., S.A.A., A.M., and T.A.; Resources, F.K., S.A.A., A.M., and T.A.; Data Curation, F.K., S.A.A., A.M., and T.A.; Writing Original Draft Preparation, F.K.; Writing Review and Editing, F.K., S.A.A., A.M., and T.A.; Visualization, F.K., S.A.A. and A.M.; Project Administration, F.K. and T.A. All authors have read and agreed to the published version of the manuscript.

7.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

7.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

7.4. Institutional Review Board Statement

This study did not require approval from an IRB, as it does not involve human or animal subjects.

7.5. Informed Consent Statement

Not applicable.

7.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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