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iJIM International Journal of Interactive Mobile Technologies

iJIM | eISSN: 1865-7923 | Vol. 19 No. 5 (2025) | OPEN ACCESS

https://doi.org/10.3991/ijim.v19i05.52039

PAPER

Exploring the Impact of Interactive Technologies on Student Engagement in Blended Learning Environments at Higher Education Institutions

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ABSTRACT

Adopting new technologies in higher education is essential for enhancing students' skills and knowledge. Blended learning, an innovative approach integrating traditional classroom instruction with online components, has emerged as an effective educational solution. Incorporating online elements into blended learning models has shown great promise in enriching the learning experience. This study employs a structural equation model to investigate the key factors influencing students' adoption of blended learning in higher educational institutions. The study identifies significant relationships among various factors, highlighting their roles in shaping student experiences and intentions. These findings provide practical recommendations for educators and institutions aiming to optimize blended learning environments, ultimately fostering active student participation and satisfaction. This study contributes to the continuous improvement of educational practices and student outcomes within blended learning models, particularly with the integration of massive open online courses (MOOCs).

KEYWORDS

blended learning, higher education, massive open online courses (MOOCs), student's intention, technology acceptance

1 INTRODUCTION

Higher educational institutions increasingly recognize the importance of incorporating new technologies to enhance students' skills and knowledge. These institutions aim to revolutionize the learning experience by embracing technological advancements and creating a more effective and engaging educational environment. Integrating technology in higher education offers numerous benefits, such as facilitating learning material accessibility, overcoming geographical limitations,

Ghai, A.S., Altinay, Z., Altinay, F., Jasola, S., Dagli, G., Yikici, B. (2025). Exploring the Impact of Interactive Technologies on Student Engagement in Blended Learning Environments at Higher Education Institutions. *International Journal of Interactive Mobile Technologies (iJIM)*, 19(5), pp. 233–257. https://doi.org/10.3991/ijim.v19i05.52039

Article submitted 2024-09-02. Revision uploaded 2024-12-01. Final acceptance 2024-12-01.

and catering to diverse student needs. Technology promotes collaboration and communication between students, faculty, and other educational stakeholders. One significant advantage is increased accessibility, as technology breaks down geographical barriers, providing students access to learning materials from anywhere [1]. This flexibility accommodates diverse needs, allowing individuals with scheduling conflicts to pursue education remotely. Technology also fosters collaboration and communication among students, faculty, and stakeholders, with online platforms enabling teamwork, idea exchange, and critical thinking, preparing students for the modern workforce.

The assessment process has been revolutionized by introducing efficient tools such as automated grading and online quizzes, which provide immediate feedback, allowing students to track their progress and make timely improvements [2]. Multimedia elements enhance engagement, and personalized feedback helps students focus on areas for growth. Overall, technology integration improves convenience and efficiency, positively impacting academic achievement and effective knowledge transfer by educators.

With the rise of online learning platforms, higher education institutions can offer flexible learning options, implement interactive teaching methods, streamline administrative processes, and facilitate research and collaboration. These advancements make education more personalized, engaging, and adaptable to the diverse needs of students. As technology evolves, higher education institutions will continue to leverage its potential to shape and transform the learning experience. By embracing technologies such as online learning, massive open online courses (MOOCs), virtual classrooms, and mobile learning, institutions can provide innovative and accessible education to a broader audience. This evolution in higher education benefits students and empowers educators to deliver knowledge effectively in an ever-changing digital landscape [3]. However, despite the widespread adoption of technological tools in education, there remains a gap in understanding the specific impacts of these technologies on various aspects of learning outcomes and student engagement. This study aims to address this gap by examining the effectiveness of MOOCs in blended learning environments for enhancing academic performance and fostering collaborative learning experiences. By focusing on recent advancements and practical implementations, this research provides valuable insights into how higher education institutions can effectively leverage technology to improve education quality and meet the evolving needs of learners.

1.1 MOOCs and blended learning

MOOCs have emerged as a significant development in online education. MOOCs are free, web-based courses that accommodate many participants from diverse backgrounds. They appeared in the early 2000s to respond to the need for accessible and affordable education. Popularized in 2011 by Stanford University's free online courses, MOOCs gained widespread attention and have since revolutionized the education landscape [4]. Their significance lies in providing accessible education to people from diverse backgrounds and regions, breaking down geographical barriers, and reaching millions of learners worldwide. MOOCs offer flexibility and convenience, allowing students to study at their own pace, especially when working. These courses foster lifelong learning, as learners can access high-quality educational content anytime, anywhere, promoting continuous personal and professional development [5].

The global reach of MOOCs has also enriched the learning experience by bringing together a diverse and international community of learners, facilitating the exchange of ideas and perspectives. MOOCs' concept and potential to connect learners globally, facilitate knowledge sharing, and promote self-directed learning. The demographics and motivations of MOOC participants were examined, underscoring the importance of MOOCs in enhancing access to education and fostering lifelong learning [6]. The impact of MOOCs on learners' institutions was discussed, and the potential of MOOCs was discussed, such as addressing educational inequalities, promoting lifelong learning, and supporting professional development [7]. These approaches hold transformative potential in improving learning outcomes, expanding access to education, and promoting lifelong learning. They provide access to high-quality educational content, often delivered by renowned instructors and prestigious institutions. MOOCs typically employ multimedia resources such as videos, quizzes, and discussion forums to engage learners in self-paced learning experiences [8].

The Learning Innovation and Networked Knowledge (LINK) Research Lab [9] at the University of Texas reported that MOOCs are a new form of online learning that brings education to the masses and encourages lifelong learning. They allow open access to educational resources and foster a global community of learners. MOOCs have the potential to revolutionize education by making high-quality courses accessible to anyone, anywhere, and at any time. They offer a flexible learning experience and promote collaboration among learners from diverse backgrounds [10].

Blended learning and MOOCs have gained attention in educational settings due to their potential to address various challenges in traditional education. Personalized learning becomes more achievable by enabling students to navigate materials according to their needs and preferences. Integrating MOOCs and blended learning environments fosters active learning and collaborative engagement through interactive elements and online discussion forums. This approach holds significant promise for enhancing the overall student learning experience [11].

Educators can create a more comprehensive and dynamic learning environment by combining face-to-face instruction with online resources. This approach offers the benefits of in-person interaction and instructor guidance while leveraging MOOC platforms' vast resources and diverse perspectives, enhancing the learning experience. Understanding the background and significance of blended learning and MOOCs is essential for educators, administrators, and policymakers seeking to implement effective instructional strategies. By harnessing the potential of these approaches, educational institutions can address learners' evolving needs, promoting student engagement and satisfaction. Exploring the benefits and challenges associated with blended learning and MOOC integration can inform decision-making processes and shape policies related to educational technology integration and online learning initiatives, emphasizing the importance of blended learning [12]. The significance of blended learning lies in its ability to create a more dynamic and convenient learning environment that caters to diverse learning needs. By integrating both online and traditional instruction, blended learning fosters deeper learning by allowing students to engage with content in multiple ways—through interactive online modules, in-class discussions, and collaborative projects.

This multimodal approach enhances critical thinking by encouraging students to analyze and apply knowledge in varied contexts. It promotes learner autonomy, as students are empowered to take control of their learning pace and style. Through these methods, blended learning deepens understanding and prepares students for lifelong learning by cultivating essential abilities such as problem-solving, self-regulation, and independent thinking.

Blended learning has become the norm, leveraging emerging technologies to create flexible and interactive educational environments. Studies [13, 14] have shown that blending online and traditional classroom instruction positively affects student learning and performance. This approach benefits from contemporary information communication technologies, making learning more accessible and engaging for students. Recent research also emphasizes the importance of cognitive presence in blended learning classes. This involves creating meaningful interactions between students and instructors and fostering a deeper understanding of the subject.

Additionally, flipped classrooms, where students engage with MOOCs as a part of their coursework, have been identified as an effective strategy for integrating online learning with traditional teaching methods. The global reach of MOOCs has expanded further, connecting a diverse and international community of learners. This facilitates the exchange of ideas and perspectives, enriching the learning experience. By promoting lifelong learning and offering high-quality educational content, MOOCs continue to break down geographical barriers and provide education to a broader audience.

Higher education institutions can offer more personalized, engaging, and flexible learning options as they embrace these trends. This evolution in blended learning and MOOCs is shaping the future of education, ensuring that it meets the diverse needs of students in an ever-changing digital landscape. Despite the widespread adoption of MOOCs in blended learning environments, limited research specifically examines their impact on student engagement and academic performance in higher education. This study aims to address this gap by exploring how the integration of MOOCs in blended learning influences these critical educational outcomes.

2 LITERATURE REVIEW

The successful implementation of blended learning using MOOCs relies on students' acceptance of the approach. Researchers have explored various factors influencing this acceptance, including social interactions, psychological attitudes, and cultural norms [15]. A positive classroom atmosphere and support from peers and teachers enhance students' acceptance of the learning environment. When students feel valued and supported, they are more engaged and motivated. Peer support fosters collaboration and community, while teacher encouragement and feedback further boost students' enthusiasm and participation. These factors create a more effective and welcoming learning experience [16]. Students' readiness for blended learning is influenced by their attitudes toward technology, self-efficacy in using digital tools, and past experiences with online learning. Positive attitudes and confidence in technology can facilitate smoother adaptation to blended environments, while prior online learning experiences can either ease the transition or pose challenges based on their nature [17]. Cultural acceptance of technology use also influences students' attitudes toward this innovative approach. Understanding and addressing these factors are crucial for effectively integrating blended learning into the curriculum. Numerous studies have identified critical factors influencing learner satisfaction and the intention to use blended learning [18]. Key aspects such as the adaptability of e-learning platforms, perceived usefulness, ease of use, and timely instructor feedback play a significant role in enhancing learner satisfaction with blended learning environments. Factors such as expected outcomes, available support conditions, and social influences (SIs) have positively affected students' intentions to engage with blended learning [19]. Students' readiness for blended learning was positively correlated with their attitudes toward online learning, ability to manage studies effectively, engagement in online interactions, and perceptions of learning flexibility [20]. Computer self-efficacy and perceived usefulness are crucial to acceptance in blended learning environments. High computer self-efficacy enables students to effectively utilize technological tools while recognizing the benefits of blended learning, which increases their engagement and motivation. These factors significantly enhance students' readiness and success in educational settings [21].

Several other factors also influence students' satisfaction with blended learning. Key factors encompass the learning environment, perceived enjoyment, effectiveness of the service system, social interactions, content relevance, and performance expectations [22]. Among these, perceived usefulness, ease of use, system functions, content characteristics, interaction, and the overall learning atmosphere are critical for student satisfaction [23]. In e-learning, the essential factors influencing student adoption include perceived usefulness, ease of use, SI, and perceived playfulness [24]. Additionally, perceived usefulness, ease of use, and self-efficacy significantly shape students' intentions to adopt mobile learning within higher education settings [25].

2.1 Blended learning models

The research consolidates and organizes the key blended learning models, providing a comparative analysis of their unique features and contributions. This synthesis offers a clear understanding of how different theoretical frameworks and practical applications can impact the success of blended learning initiatives. Table 1 summarizes these models, highlighting their definitions, contributing factors, advantages, limitations, and practical examples. By presenting a structured comparison, the table enables educators and researchers to decide which models best suit specific educational contexts. This comparative approach is essential for tailoring blended learning strategies to meet the needs of diverse learning environments, ensuring that the strengths of each model are maximized while potential limitations are addressed. The significance of Table 1 lies in its ability to provide a comprehensive overview of various models, facilitating a clearer understanding of the theoretical underpinnings that guide blended learning adoption. By summarizing critical factors such as perceived usefulness, SI, and learner engagement, the table supports the development of more effective strategies for integrating blended learning into higher education. This structured comparison assists educators and researchers in identifying best practices, potential challenges, and areas for customization, thereby enhancing the overall effectiveness of blended learning initiatives.

Table 1. Summarizes the key blended learning models

Model Name	Definition	Author(s)	Factors	Advantages and Limitations	Examples of Use
Diffusion of Innovations (DoI)	Explains the spread of new ideas and technologies through a population	Rogers (1962)	Innovation characteristics, communication channels, social system, time	It helps understand how the adoption of blended learning innovations spreads among students and focuses on the collective behavior of a group, not individual intentions	Studying the acceptance of a new blended learning program among students in various departments of a university
Technology Acceptance Model (TAM)	Predicts user acceptance of information technology systems	Davis (1989), Venkatesh and Davis (2000)	Perceived usefulness, perceived ease of use, attitude toward using technology, behavioral intention	It helps identify factors influencing students' acceptance of blended learning and focuses on individual beliefs, not external or contextual factors	Assessing students' intention to use a new blended learning platform in a university setting
Community of Inquiry (CoI) Framework	Analyzes the process of learning in online and blended learning environments	Garrison, Anderson, and Archer (2000)	Cognitive presence, social presence, teaching presence	Provides a structured framework to facilitate practical online discussions in blended learning settings; Requires active facilitation and moderation by instructors	Enhancing student engagement and interaction in blended learning courses for a specific subject or topic
Unified Theory of Acceptance and Use of Technology (UTAUT)	Explains technology acceptance and use by individuals	Venkatesh et al. (2003), Venkatesh and Bala (2008)	Performance expectancy, effort expectancy, social influence, facilitating conditions	Provides a comprehensive view of factors influencing technology acceptance among students in higher education; May be complex to apply for some researchers and educators	Investigating students' intention to use a blended learning approach for science courses in a university
Experiential Learning Theory	Proposes learning through concrete experience	Kolb (1984)	Concrete experience, reflective observation, abstract conceptualization, active experimentation	Enhances students' learning experiences by engaging them in concrete, hands-on activities; May require careful design and scaffolding to ensure effective learning outcomes	Designing blended learning activities that promote experiential learning in a college course
ARCS Model of Motivational Design	Enhances learner motivation in instructional settings	Keller (1987)	Attention, relevance, confidence, satisfaction	Addresses learners' motivational needs, increasing their interest and engagement in the learning process; Requires careful application to consider individual learner preferences and needs	Developing a blended learning course that fosters learners' motivation and engagement
4C-ID Model (Four-Component Instructional Design)	Fosters complex cognitive skills	van Merriënboer and Kirschner (2007)	Learning tasks, supportive information, procedural information, part-task practice	Provides a systematic approach to designing blended learning experiences that support the development of complex skills; May require careful alignment of instructional components to achieve desired learning outcomes	Designing a blended learning program to enhance students' complex problem-solving abilities

(Continued)

Table 1. Summarizes the key blended learning models *(Continued)*

Model Name	Definition	Author(s)	Factors	Advantages and Limitations	Examples of Use
Constructivist Learning Design	Focuses on learner-centered, active learning	Duffy and Jonassen (1992)	Authentic learning tasks, collaboration, reflection, scaffolding	Promotes active engagement and knowledge construction through authentic and collaborative learning experiences; Requires skilled facilitators to guide learners through the constructivist learning process	Implementing a blended learning environment that fosters constructivist learning in a college course
Hexagonal E-Learning Assessment Model (HELAM)	Evaluates e-learning program quality	Siklander, Savolainen, and Mäkinen (2018)	Learning effectiveness, content quality, interaction quality, technology quality, learner satisfaction, and pedagogical quality	Provides a systematic approach to evaluating the quality and effectiveness of e-learning programs; Requires careful selection and definition of assessment criteria to ensure valid and reliable evaluations	Assessing the quality and effectiveness of a blended learning program in an online university course
UTAUT2 (Unified Theory of Acceptance and Use of Technology 2)	Explains tech adoption behavior	Venkatesh et al. (2012), Dakduk et al. (2018)	Gender, age, experience, voluntariness of use, job relevance, output quality, result demonstrability, image, facilitating conditions, effort expectancy, social influence, performance expectancy, hedonic motivation, price value, habit, self-efficacy	Offers an extended model that accounts for various factors influencing tech adoption and use. The comprehensive model may be complex in some research and educational settings	Investigating students' intention to use a new blended learning platform incorporating MOOCs in a university course

2.2 Blended learning and MOOCs

Recent studies have explored the integration of technology in higher education, emphasizing its role in enhancing learning accessibility, student satisfaction, and engagement. Research on blended learning, particularly incorporating MOOCs, has shown promising results in improving flexibility and access to diverse learning materials. However, much of the existing literature focuses on generalized outcomes, such as increased accessibility and convenience, without delving into the specific effects on academic performance and long-term student engagement. Furthermore, while frameworks such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) have been applied to assess user acceptance of e-learning platforms, limited attention has been given to understanding how these factors interact within blended learning environments that include MOOCs. Moreover, the role of cognitive engagement, motivation, and the perceived value of such learning environments has not been adequately examined in higher education settings. These gaps underscore the need for targeted research that assesses the nuanced effects of MOOCs on student performance and engagement in blended learning, providing a more comprehensive understanding of optimizing these technologies for improved educational outcomes.

Table 2 consolidates recent research on blended learning and MOOCs, summarizing key studies that contribute to understanding their impact on higher education. Each study's title, author(s), key findings, and identified research gaps are outlined. This table is an essential resource for researchers and educators, helping them recognize underexplored areas and prioritize future studies. By offering a concise overview of the existing literature, the table highlights the ongoing need to investigate the specific effects of MOOCs on academic performance, cognitive engagement, and student satisfaction in blended learning environments. It also underscores the significance of addressing these gaps to create more effective, evidence-based educational strategies.

Table 2. Key studies on MOOCs and blended learning

Author(s)	Year	Title of Paper	Summary	Research Gap
Cao-Tuong, D., & Phuong, H.-Y.	2024	MOOC learners' perspectives on the effects of self-regulated learning strategy intervention on their self-regulation and speaking performance	Investigate the impact of self-regulated learning strategies on MOOC learners' self-regulation and speaking performance	Limited empirical studies on the impact of self-regulated learning interventions in MOOCs
Liu, Y., Ma, S., & Chen, Y.	2024	The impacts of learning motivation, emotional engagement, and psychological capital on academic performance in a blended learning university course	Explores the relationships among psychological capital, learning motivation, emotional engagement, and academic performance	Need for more research on the interplay of psychological factors in blended learning environments
Das, P. P.	2023	MOOCs in India – Evolution, Innovation, Impact, and Roadmap	Reviews the evolution and impact of MOOCs in India, focusing on localized content and emerging technologies	Need for research on MOOCs' impact in diverse educational contexts
Jiang, X., & Iosif, E.	2021	Enhancing Online Education Resources During the COVID-19 Pandemic	Discusses the enhancement of online education resources during the pandemic	Need for updated research on online education enhancements during the pandemic
Zhu, M., Sari, A. R., & Lee, M. M.	2019	A comprehensive systematic review of MOOC research: Research techniques, topics, and trends from 2009 to 2019	Reviews research methods, topics, and trends in MOOC studies from 2009 to 2019	Need for more recent reviews covering the latest trends in MOOC research

3 THEORETICAL BACKGROUND OF THE FRAMEWORK

The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), as the theoretical framework for this study, is based on several critical considerations derived from the extensive literature review and the specific research objectives. UTAUT2 was chosen due to its comprehensive nature, encompassing a wide range of factors influencing technology acceptance and use, making it highly suitable for studying students' intention to use blended learning. Firstly, UTAUT2 extends the original UTAUT model by incorporating additional constructs that capture the user experience more holistically. These constructs include hedonic motivation (HM), price value, and habit, which are particularly relevant in blended learning environments. Including these factors allows for a more nuanced understanding of students' acceptance of blended learning, addressing both utilitarian and hedonic aspects of technology use. Secondly, UTAUT2 has been empirically validated in various contexts, including education, making it a robust and reliable model for this study. The model's ability to explain significant variance in behavioral intention (BI) and usage behavior further supports its applicability. Studies have shown that UTAUT2 can account for up to seventy percent of the variance in behavioral intention, highlighting its predictive power and relevance [26]. The constructs of UTAUT2 align closely with the factors identified in the literature review, which is critical to making it an ideal framework for this study, which aims to explore blended learning in higher educational institutes in India.

The adaptability of UTAUT2 to different technological contexts and its ability to incorporate cultural and contextual factors flexibility allows for the inclusion of specific variables relevant to the local context, ensuring a more accurate and comprehensive analysis. UTAUT2 was selected for this study due to its extensive coverage of relevant factors, empirical validation, alignment with the literature, and adaptability to different contexts. This framework provides a solid foundation for investigating the multifaceted influences on students' intention to use blended learning, facilitating a deeper understanding of the dynamics at play in higher educational institutes.

Venkatesh initially developed the UTAUT2 model which is an extension and improvement of the UTAUT model introduced by Venkatesh, explicitly focusing on assessing users' behavioral intentions (BI) to accept technology. According to the UTAUT model, an individual's intention to use technology is influenced by four primary constructs: performance expectancy (PE), effort expectancy (EE), SI, and facilitating conditions (FC) [27]. The UTAUT2 model incorporates three additional constructs: HM, Price Value, and Habit. These additions aim to provide a more comprehensive understanding of users' BI in accepting technology [28].

The UTAUT2 model was modified in this study to better align with the specific objectives of investigating technology acceptance behaviors within blended learning environments that incorporate MOOCs. While the original UTAUT2 model offers a comprehensive framework for analyzing general technology acceptance, it does not fully address the unique dynamics and challenges of blended learning, particularly when MOOCs are involved. Blended learning presents distinct factors, such as the interaction between online and face-to-face components, course structure, and the specific nature of MOOCs, which the standard UTAUT2 model does not fully capture [29]. Therefore, the modifications were made to incorporate these context-specific elements, ensuring the research model more effectively examines the factors influencing students' intention to use technology in this blended learning setting. These adjustments allow for a more precise investigation of how MOOCs impact the acceptance and use of blended learning in higher education. The following are the factors that are adopted and modified:

- **i)** **PE** refers to an individual's belief that using a system (here refers to blended learning using MOOCs) will improve performance. Several studies have demonstrated the effect on students' BI to use blended learning but do not cover MOOCs.
- **ii)** **EE:** In the UTAUT2 model, EE is one of the core constructs influencing users' BI and technology usage. When users perceive the technology as easy to use, they are more likely to develop positive attitudes toward adopting it, leading to increased intention to use it and higher levels of actual technology usage.
- **iii)** **PE:** The PE of use is associated with adopting and utilizing the technology, defined as the perception of the system's simplicity and ease of use.
- **iv)** **SI:** SI of others, such as colleagues, supervisors, or friends, on an individual's decision to use the technology. Individuals' belief in their peers and faculty members supporting blended learning has significantly influenced students' BI to adopt new learning systems, such as blended learning.
- **v)** **FC:** It refers to the degree to which an individual perceives the availability of necessary resources and support to use technology effectively. It represents learners' perspectives on the presence of technological and organizational support for utilizing the system. It has been found to influence both BI and method use significantly.
- **vi)** **Hedonic motivation:** A novel construct in the UTAUT2 model, refers to the pleasure users derive from using a system. It has been identified as an essential factor in predicting students' intention to use blended learning [30].
- **vii)** **Price value (PV),** defined as learners' consideration of the perceived benefits of adopting blended learning compared to the monetary costs, is positively related to students' acceptance of it.

viii) **Perceived assessment (PA)** refers to an individual's subjective perception of the methods used, such as in education or performance evaluation. It significantly influences attitudes, motivation, and engagement during assessments. Positive perceptions increase confidence and willingness to participate, while negative perceptions result in anxiety and reluctance. Educators and policymakers consider individuals' PA experiences to create fair and effective assessment strategies tailored to learners' needs, ultimately fostering a positive learning environment.

ix) **Student's personal development (SP):** In academics, it encompasses various growth aspects, including cognitive, emotional, and social development. Benjamin Bloom, who developed Bloom's Taxonomy, provided valuable insights into effective educational strategies and support systems to enhance students' learning experiences and academic success [31].

x) **BI:** It is a crucial determinant of students' likelihood to use blended learning. It directly affects the adoption of blended learning as a mode of instruction. BI represents students' intentions or willingness to engage in the behavior of using blended learning. Positive choices lead to increased participation and engagement in blended learning. Emphasize. The significance of BI in the successful adoption and acceptance of blended learning. Educators and policymakers should consider students' BI when implementing blended learning strategies to foster positive perceptions and attitudes toward this approach. Figure 1 shows the factors used in UTAUT2.

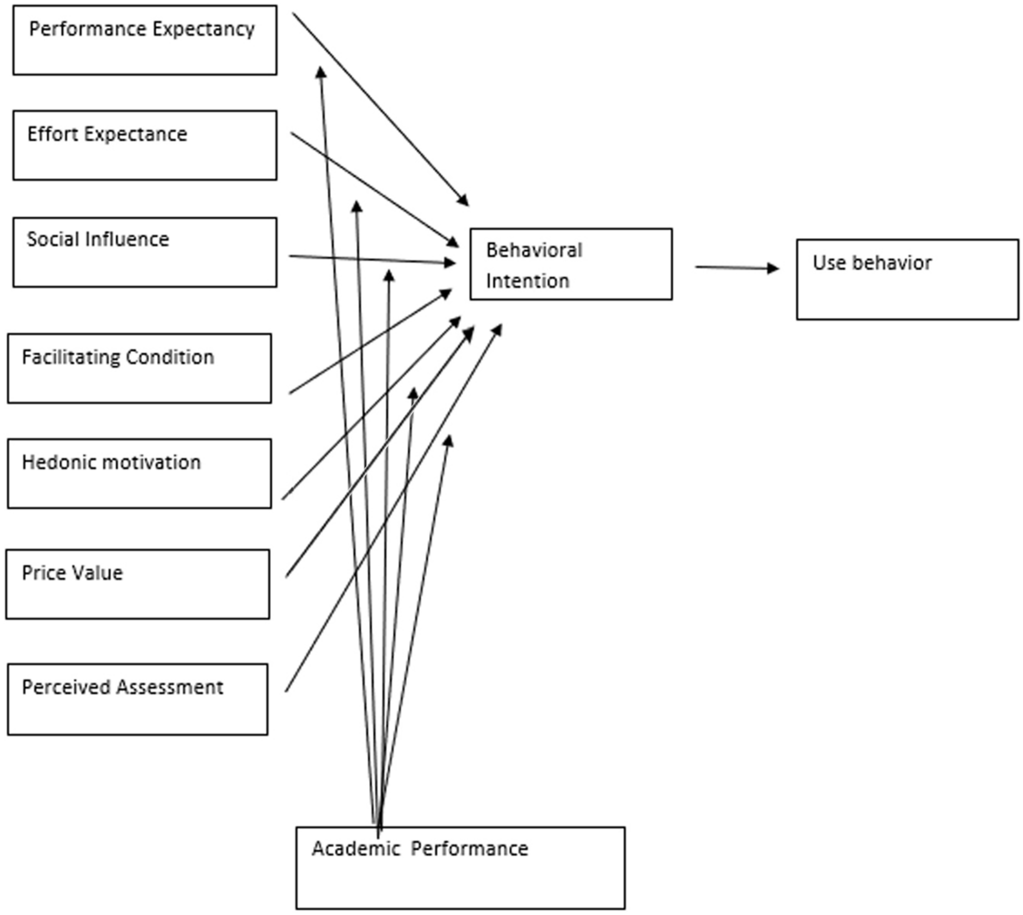

Fig. 1. Factors used in UTAUT2

In this study, the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model is adapted to analyze students' intention to use blended learning with MOOCs in higher education. While UTAUT2 includes core constructs such as PE, EE, SI, and FC, this study extends the model by incorporating additional factors relevant to the context of MOOCs and blended learning environments. Specifically, HM, PV, and Habit (HT) are included to capture learners' intrinsic enjoyment of the learning process and perceptions of the cost-benefit. Constructs such as PA and Student Personal Development (SP) are introduced to address the unique aspects of evaluating performance and personal growth in an online-blended setting. These modifications ensure that the model better reflect MOOCs' specific challenges and dynamics within blended learning environments in higher educational institutes.

Limitations of the UTAUT2 Model include its primary focus on individual technology acceptance, potentially overlooking contextual and external factors such as institutional support and cultural influences. To address these limitations, this study includes factors such as PA and SI, which account for the collective learning experience, and institutional factors that impact the acceptance and use of MOOCs. Additionally, while UTAUT2 emphasizes short-term technology use behavior, this study extends the model by assessing Student Personal Development, allowing for a more comprehensive analysis of long-term educational outcomes. These adaptations provide a more holistic view of the factors influencing the use of blended learning with MOOCs in higher education.

4 RESEARCH METHODOLOGY

4.1 Research question

What factors influence students' engagement with blended learning environments in higher educational institutes?

4.2 Research design and data analysis process

The research employs a quantitative design based on the UTAUT2 model to investigate the factors influencing students' intention to use blended learning with MOOCs. The process can be broken down into the following steps:

Step 1 Research Question Formulation: The study begins by formulating key research questions on how various factors (e.g., PE, EE, SI, etc.) affect students' engagement with blended learning and MOOCs.

Step 2 Theoretical Framework Adaptation (UTAUT2): The UTAUT2 model includes additional constructs such as HM, Price Value, Perceived Assessment, and Student Personal Development to reflect the specific context of blended learning in higher education.

Step 3 Questionnaire Design: A structured questionnaire is developed based on the constructs in UTAUT2. It includes multiple items per construct (e.g., PE, EE, SI) measured on a 7-point Likert scale to gauge students' intentions and attitudes toward MOOCs in a blended learning environment.

Step 4 Data Collection: Surveys are distributed to students from higher educational institutes, targeting those enrolled in blended learning programs involving MOOCs.

Step 5 Sampling Technique (Stratified Random Sampling): Stratified random sampling is used to ensure a representative sample across different academic disciplines, genders, and levels of study. This technique allows for the analysis of subgroups, ensuring diverse perspectives and reducing sampling bias.

Step 6 Data Analysis (Structural Equation Modeling – SEM): The collected data is analyzed using SEM, which tests the relationships between constructs (e.g., the impact of EE on BI). SEM allows for the examination of complex relationships and model fit assessment.

Step 7 Interpretation and Conclusion: The results are interpreted to identify significant factors influencing the acceptance of MOOCs in blended learning environments, leading to practical recommendations for educational institutions.

Figure 2 illustrates the sequential stages of a research process investigating factors influencing blended learning in higher education.

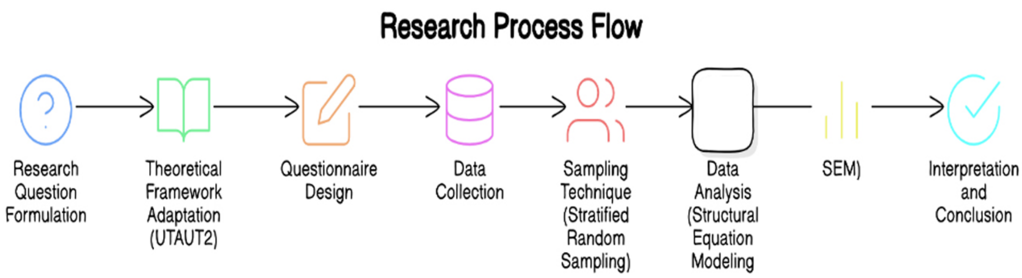

Fig. 2. Research process flow using UTAUT2 and SEM

Sampling technique and rationale. The study adopts stratified random sampling to ensure the sample represents the broader student population. This method divides the population into strata (e.g., based on academic disciplines, gender, age, and levels of study) and randomly selects participants from each stratum. The Stratified random sampling ensures that important subgroups are adequately represented, providing more accurate and reliable results. For instance, the study can compare students' experiences from different academic backgrounds or those at different stages of their education.

Reduced Sampling Bias: Ensuring each subgroup is proportionately represented helps mitigate the risk of over- or under-representing specific groups, improving the study's external validity.

Rationale for Sample Size: The sample size of 630 participants is selected based on several factors:

SEM Requirements: SEM requires a relatively large sample size to produce stable parameter estimates and achieve good model fit. A common rule of thumb for SEM is to estimate at least 10 participants per parameter, ensuring that the data appropriately supports the model's complexity. A larger sample increases the study's power to detect significant relationships between variables. With 630 participants, the study has adequate power to reveal even small-to-moderate effects between constructs such as EE and PE. The sample size was also chosen to ensure that findings can be generalized across different student populations in higher education, considering the diversity of academic disciplines and student demographics. This approach provides a solid foundation for robust data analysis and reliable findings.

5 ANALYSIS

The sample size ascertained from the study was 630 participants, with inclusion criteria revolving around students willing to participate during different semesters of the 2022–2023 academic year. The questionnaire consisted of (i) demographic information and MOOC-related questions and (ii) blended learning aspects based on MOOC items. The items in the questionnaire were developed with the guidance of the UTAUT2 framework. It had a total of 32 items categorized into the following constructs: perceived enjoyment (PE)-4 items, EE-4 items, SI-3 items, FC-4 items, HM-3 items, PV-3 items, BI-3 items, PA-6 items, and SP-2 items. All items were rated on a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree).

The validity of the finalized questionnaire, tested using the Content Validity Indices and Content Validity Ratio, turned out to be 0.87 and 0.84, respectively. The internal consistency was measured using Cronbach's alpha coefficient with a value of 0.943. Data analysis was done using SPSS, version 18.0, AMOS, version 23.0, and R tools through Python. Construct validity was checked in terms of both convergent and discriminant validity. Convergent validity was checked through composite reliability (CR) and average variance extracted (AVE), accepting above 0.70 for CR and above 0.50 for AVE. Discriminant validity has been checked through the correlation coefficients between constructs versus the square root of AVE, as presented in Table 3. The CR index has been calculated through the following expression: $CR = (\sum Fl)^2/[(\sum Fl)^2 + (\sum 1–Fl)^2]$ and the AVE index was calculated by $AVE = \sum (Fl^2)/n$. Data from this study were analyzed using Structural Equation Modeling regarding the research question, assuming the significance level of $P \leq 0.05$. The socio-demographic information of participants is summarized in Table 4, as per gender, and in Table 5, according to age group, graphically represented in Figures 3 and 4, respectively.

Table 3. Demographic details of the student's age

Age Group	Frequency	Percent
Upto 18	36	5.7
18–20	212	33.7
20–22	292	46.3
Above 22	90	14.3
Total	630	100.0

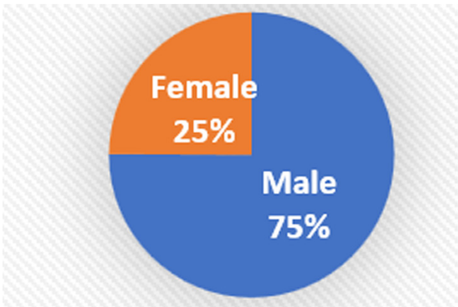

Fig. 3. Chart for age

Table 4. Demographic details of the student's age

Gender	Frequency	Percent
Male	473	75.1
Female	157	24.9
Total	630	100.0

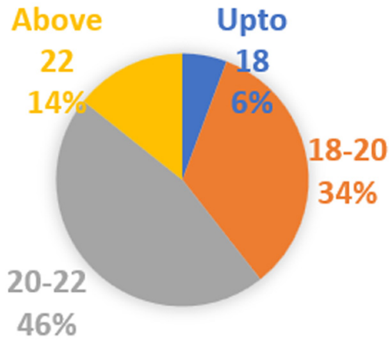

Fig. 4. Chart for gender

Table 5 displays the results for both convergent and discriminant validity. Convergent validity was confirmed as all composite reliability (CR) and AVE values exceeded the thresholds of 0.70 and 0.50, respectively, for each item. Additionally, the Cronbach's alpha (CA) reliability coefficients for all constructs were above 0.70, indicating high reliability.

To assess discriminant validity, we compared the square roots of the AVE with the correlation coefficients between factors. Discriminant validity is considered adequate if the square root of the AVE for each factor exceeds the correlation coefficients involving that factor. These results demonstrate that the questionnaire exhibits discriminant solid validity.

Table 5. Convergent validity result

Factors	CR	AVE	MSV	MaxR(H)	SI	PA	PE	FC	EE	PV	BI	HM	SP
SI	0.915	0.781	0.667	0.915	0.884								
PA	0.930	0.689	0.658	0.961	0.762	0.830							
PE	0.922	0.746	0.667	0.973	0.817	0.791	0.864						
FC	0.894	0.779	0.689	0.978	0.805	0.811	0.780	0.824					
EE	0.896	0.783	0.687	0.982	0.803	0.780	0.816	0.888	0.826				
PV	0.886	0.724	0.654	0.985	0.626	0.744	0.613	0.677	0.624	0.851			
BI	0.909	0.768	0.646	0.987	0.761	0.804	0.733	0.722	0.723	0.739	0.876		
HM	0.925	0.804	0.615	0.989	0.746	0.784	0.745	0.752	0.784	0.640	0.750	0.896	
SP	0.788	0.750	0.653	0.989	0.679	0.808	0.669	0.696	0.637	0.618	0.703	0.671	0.806

Table 6 shows regression weights from a regression or SEM. Each row represents an item or indicator, and the columns display the estimates, standard errors (SE), and critical ratios (CR) for the regression weights. The estimate column displays the regression weights or path coefficients for each indicator.

Table 6. Results of discriminant validity

Indicators	Factor Loading	Cronbach Alpha	CR	AVE
PE1	0.681	0.922	0.915	0.781
PE2	0.687			
PE3	0.698			
PE4	0.692			
EE1	0.623	0.896	0.93	0.689
EE2	0.662			
EE3	0.733			
EE4	0.715			
SI1	0.724	0.914	0.922	0.746
SI2	0.680			
SI3	0.689			
FC1	0.685	0.891	0.894	0.779
FC2	0.749			
FC3	0.749			
FC4	0.616			
HM1	0.663	0.923	0.896	0.783
HM2	0.664			
HM3	0.618			
PV1	0.696	0.882	0.886	0.804
PV2	0.817			
PV3	0.772			
BI1	0.734	0.908	0.909	0.768
BI2	0.715			
BI3	0.700			
PA1	0.660	0.929	0.925	0.804
PA2	0.702			
PA3	0.738			
PA4	0.720			
PA5	0.719			
PA6	0.772			
SP1	0.520	0.785	0.788	0.75
SP2	0.620			

These values represent the strength and direction of the relationship between the latent construct (e.g., PA – perceived assessment) and the observed indicator (e.g., PA1, PA2, etc.). For example, suppose the estimate is 0.788 for PA1. In that case, a one-unit increase in the latent construct PA is associated with an estimated increase of 0.788 units in the observed indicator PA1. The SE (standard error) column shows the estimate's standard error. It represents the level of uncertainty associated with the regression weight. Smaller standard errors indicate more precise estimates.

The CR (Critical Ratio) column provides the critical ratio, which is the ratio of the estimate to the standard error. It indicates the significance of the regression weight. Larger C.R. values indicate that the estimate is statistically significant (i.e., different from zero) at a certain confidence level, often a 95% confidence level (alpha = 0.05). All the CR values in this table are large, indicating significant relationships between the latent constructs and their indicators. The table seems to represent regression weights for multiple latent constructs, such as PA, PE, FC, EE, PV, and BI. (Behavioral Intention), HM, SI, and SP. Each construct comprises several indicators (e.g., PA1, PA2, etc.), and the regression weights tell us how much each indicator contributes to the overall construct. The CR values can help to identify which relationships are statistically significant. Table 7 represents the regression weights between the indicators. Figure 5 shows the confirmatory factor analysis. This analysis measured the associations between the latent variables and factors to support the subsequent structural model assessment. The structural model was then assessed, as the measurement model showed a good fit.

- PE <–> EE: 0.849
- EE <–> SI: 0.733
- SI <–> FC: 0.685
- FC <–> HM: 0.749
- HM <–> PV: 0.772
- PV <–> BI: 0.700
- BI <–> PA: 0.702
- PA <–> SP: 0.620

Table 7. Represents the regression weights between the indicator

Indicator	Estimate	SE	CR
PA1	0.788		
PA2	0.837	0.043	23.793
PA3	0.829	0.045	23.484
PA4	0.799	0.047	22.388
PA5	0.858	0.044	24.627
PA6	0.868	0.044	24.991
PE1	0.849		
PE2	0.861	0.037	27.793
PE3	0.875	0.038	28.578
PE4	0.87	0.038	28.288
FC1	0.806		
FC2	0.855	0.04	24.947
FC3	0.874	0.041	25.733
FC4	0.757	0.043	21.098
EE1	0.787		
EE2	0.832	0.044	23.139
EE3	0.842	0.043	23.496
EE4	0.843	0.045	23.567
PV1	0.759		
PV2	0.925	0.048	24.069
PV3	0.86	0.047	22.586

(Continued)

Table 7. Represents the regression weights between the indicator *(Continued)*

Indicator	Estimate	SE	CR
BI1	0.885		
BI2	0.872	0.03	30.134
BI3	0.872	0.031	30.141
HM1	0.909		
HM2	0.934	0.026	38.153
HM3	0.844	0.03	30.43
SI1	0.885		
SI2	0.887	0.031	31.529
SI3	0.88	0.031	31.026
SP1	0.757		
SP2	0.853	0.055	19.052

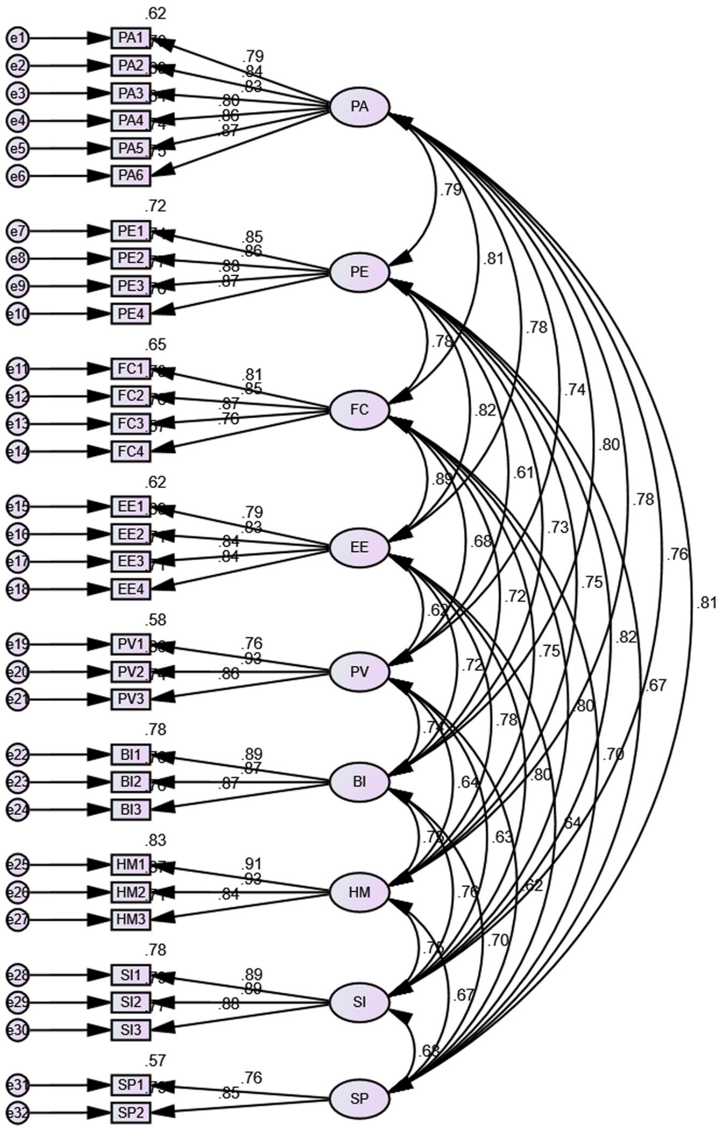

Fig. 5. Measurement model

6 RESULTS

The SEM exhibited a strong fit with the data, supported by several fit indices. These results indicate that the model represents the observed variables well.

i) **PE –> EE:** The analysis revealed a significant and robust positive relationship between PE in the context of blended learning with MOOCs and EE. This relationship is characterized by a substantial standardized coefficient (β = 0.849) and a p-value less than 0.001. These findings indicate that when learners perceive improved performance outcomes from engaging with MOOCs within their blended learning environment, they are more likely to view the associated efforts as manageable and less demanding. In essence, as the perceived educational benefits increase, the perceived effort required decreases.

ii) **EE –> SI:** Analysis demonstrates a noteworthy and statistically significant positive effect of EE on SI within the context of blended learning with MOOCs. This is reflected by a substantial standardized coefficient (β = 0.733) and a p-value below 0.001. This finding underscores the pivotal role of enhanced EE in positively contributing to the influence of social factors on learning. In other words, when learners find engaging with MOOCs less effortful in their blended learning setting, they are more inclined to be influenced by their peers, instructors, or the learning community.

iii) **SI –> FC:** Observation shows a significant and positive relationship between SI related to blended learning through MOOCs and FC. This is evidenced by a standardized coefficient of 0.685 and a p-value less than 0.001. This finding implies that a more robust perception of SI can alleviate perceived barriers or FCs in the blended learning environment. When learners feel more influenced by their learning community and instructors, they tend to perceive fewer hindrances or challenges in navigating the conditions for successful blended learning with MOOCs.

iv) **FC –> HM:** Analysis reveals that FC positively influence HM as a mediating factor within the context of blended learning with MOOCs. This is supported by a substantial standardized coefficient (β = 0.749) and a p-value below 0.001. This suggests that improved conditions facilitating blended learning, such as access to resources and supportive technology, favor learners' intrinsic motivation for engaging with MOOCs. In practical terms, a conducive environment enhances learners' enjoyment and inspiration for blended learning.

v) **HM –> PV:** HM is found to have a significant and positive influence on PV within the context of blended learning through MOOCs, as indicated by a β coefficient of 0.772 and a p-value less than 0.001. This implies that effective HM, driven by the pleasure and enjoyment of the learning experience, aligns with a higher perception of value. In other words, when learners are intrinsically motivated and find the blended learning experience enjoyable, they are likelier to perceive more excellent value in the knowledge and skills acquired through MOOCs.

vi) **PV –> BI:** PV exhibits a notable and positive impact on BI in the context of blended learning using MOOCs, with a standardized coefficient of 0.700 and a p-value less than 0.001. This finding suggests that the PV of the learning experience significantly influences learners' intentions to engage further in blended learning activities. When learners perceive a higher value in the knowledge and skills acquired through MOOCs within their blended learning journey, they are more inclined to express intentions to participate and apply what they have learned actively.

vii) **BI –> PA:** The latent variable BI maintains a substantial and positive relationship with PA within the context of blended learning using MOOCs. This relationship is characterized by a β coefficient of 0.702 and a p-value less than 0.001. This underscores the robust connection between learners' intentions to apply their acquired knowledge and their perceptions of the assessments associated with their blended learning experience. When learners firmly intend to utilize what they have learned from MOOCs within their blended learning setting, their perceptions of the quality and effectiveness of those assessments align accordingly.

viii) **PA –> SP:** The relationship between PA and SP within the framework of blended learning through MOOCs is characterized by a coefficient of 0.620. This signifies a positive association between learners' perceptions of the assessment they encounter within the blended learning environment and their personal development initiatives. In practical terms, as learners perceive the assessments associated with MOOC-based blended learning positively, they are more likely to actively engage in activities that contribute to their personal growth and development.

The latent variable PE displayed substantial variability, indicated by a significant variance of 0.372 ($p < 0.001$). This underscores its critical significance within the framework of blended learning with MOOCs. In essence, the wide range of performance expectations among learners participating in MOOC-based blended learning emphasizes the importance of PE as a critical factor influencing their educational experiences. Research sheds light on the complex relationships among latent variables. Notably, factors such as learners' perceptions of the digital learning environment, PE and EE play critical roles. These factors influence various aspects of the blended learning experience, including SI, FC, HM, and PV intentions to engage in learning activities and subsequent actions. Our study emphasizes the multifaceted impact of PE and EE on the holistic learning journey within MOOC-based blended learning.

7 CONCLUSION

The study delves into the intricate factors influencing students' intention to adopt blended learning in higher education, particularly when incorporating MOOCs. By implementing a SEM, the study has unveiled a series of significant and interrelated relationships among various factors, elucidating their pivotal roles in shaping students' experiences and intentions within a blended learning framework. The findings of this study hold practical implications for educational practitioners and institutions striving to enhance the implementation of blended learning models. Understanding and optimizing the identified factors can create more effective and engaging blended learning environments, ultimately fostering students' active participation and personal development [32]. The study also underscores the significance of considering the PV associated with the learning experience. It directly and indirectly influences students' assessments and intentions, emphasizing the importance of offering cost-effective, high-value blended learning experiences that maximize student satisfaction. This research provides valuable insights into the multifaceted factors that drive the acceptance and adoption of blended learning with MOOCs in higher education. It contributes to the continuous improvement of educational practices and the enhancement of student outcomes.

7.1 Recommendations for educators and policymakers

Based on the study's findings, several recommendations can be made for educators and policymakers to improve the adoption of blended learning in higher education. First, optimizing FCs and providing the required technological settings, resources, and support allow students to learn more stimulatingly and can contribute to strengthening HM. Third, perceived value plays an important role in students' BI and overall satisfaction. Thus, it requires offering cost-effective but quality blended learning experiences focusing on the value of education in return for the student's investment. Blended learning may involve flexible learning opportunities and personalized content, with students' needs and motivation for learning being considered. Additionally, PE will be improved while reducing perceived efforts; this, too, enhances SI and facilitates conditions. Thus, encouraging active student participation in the blended learning experience will be more appealing and effective.

8 SUMMARY

This study examines the factors influencing students' readiness to adopt blended learning in higher education, focusing on integrating MOOCs. It explores how perceived benefits, ease of technology use, and SIs shape students' attitudes and intentions. The study identifies key relationships among these factors using a SEM. PE reduces perceived effort, which enhances SI and facilitates conditions, creating a supportive environment that boosts intrinsic motivation. The findings highlight the interconnectedness of these factors and emphasize the importance of intrinsic motivation and value perception in promoting the adoption of blended learning.

9 LIMITATIONS

The study's findings are based on a specific sample size, and the generalizability of the results to a broader population of students may be limited. The data used in the study relies on self-reported information from the participants. This may introduce response bias and not accurately reflect participants' behaviors and perceptions. While the study identifies significant relationships between factors, it does not establish causality. Other unexamined variables may influence the observed relationships. The study does not consider potential changes in factors over time. Students' perceptions and intentions may evolve as they progress through a blended learning program, which is not addressed. The findings may be context-specific and not universally applicable to all higher educational settings. The effectiveness of blended learning with MOOCs may vary across institutions and disciplines. The study does not account for potential technological changes or the scholarly landscape that could impact students' perceptions and experiences of blended learning. Acknowledging these limitations is essential for comprehensively interpreting the study's results and their practical implications in higher education.

The study's reliance on self-reported data introduces the potential for response bias, as students may overestimate or misrepresent their engagement or intentions due to social desirability or lack of reflection. To mitigate this, the questionnaire was carefully designed using validated scales and a 7-point Likert scale, which offers a nuanced understanding of attitudes and reduces the extremity of responses. Another limitation is the cross-sectional nature of the data, capturing student perceptions at a single point in time, which may not account for changes in attitudes over time. To address the future, studies could employ longitudinal methods to track changes in perceptions as students engage more with MOOCs. Lastly, while stratified random sampling was used to ensure diversity across academic disciplines, the sample may still under-represent certain subgroups, such as students with limited access to technology, which could introduce selection bias. Expanding the sample to include a broader range of institutions and student demographics in future research would further enhance generalizability.

10 FUTURE DIRECTION

Future research should expand on the current study by exploring additional factors influencing students' acceptance of blended learning, such as personal motivation, institutional policies, and technological resources. Longitudinal studies could investigate how attitudes and behaviors toward blended learning evolve. Cross-cultural comparisons would provide insights into universal and culturally specific factors affecting blended learning adoption. Employing qualitative methods like interviews and focus groups could offer a more profound, nuanced understanding of student experiences. Additionally, evaluating the effectiveness of specific blended learning models and strategies through experimental or case studies would help identify best practices, ultimately enhancing the implementation and outcomes of blended learning programs in diverse educational contexts. Future research could build on this study by exploring additional factors that may influence students' adoption of blended learning, such as cultural differences or discipline-specific challenges. Longitudinal studies would be valuable to assess how students' perceptions and intentions evolve in response to blended learning models. Additionally, investigating the impact of different MOOCs on students' BI and PA could offer more nuanced insights into how course design and delivery methods affect student engagement. Lastly, expanding the research to include a comparative analysis of blended learning across various educational levels or institutions could help generalize the findings and provide broader recommendations for implementing blended learning on a larger scale.

10.1 Integration of additional factors in future models

Future research on integrating MOOCs and blended learning could benefit from additional factors, such as personal motivation and institutional policies, which are critical in influencing students' engagement and success. Personal motivation, which encompasses intrinsic and extrinsic drivers, is pivotal in students' willingness to engage with online learning platforms. While HM captures some of these intrinsic aspects, a more granular exploration of personal goals, such as career advancement, self-improvement, or acquiring specific skills, could offer a deeper understanding of student behavior. Similarly, institutional policies, including the availability of technological infrastructure, support systems, and clear guidelines on integrating MOOCs into curricula, can significantly impact the overall learning experience. Institutions that promote flexible learning policies, provide adequate resources, and incentivize using MOOCs through credit systems or professional development opportunities may see higher adoption rates. By incorporating these elements into future models, researchers can create a more holistic framework that addresses individual and organizational dynamics, improving the predictive accuracy and relevance of the model for blended learning environments.

10.2 Potential scalability of the model

The adapted UTAUT2 model in this study demonstrates significant potential for scalability across different institutions and educational contexts. Its core constructs, such as PE, EE, SI, and FC, are applicable across a wide range of educational environments, making it versatile for use in both developed and developing educational settings. However, when scaling the model, it is essential to account for institutional diversity, such as the level of technological infrastructure, administrative support, and the cultural context of learning. For instance, institutions with limited technological resources may emphasize FCs more, whereas those in highly developed settings might focus more on HM or PV as key drivers of student adoption. Furthermore, the model's ability to integrate new variables, such as institutional policies or personal motivation, makes it adaptable to varying educational goals and learner demographics. In contexts with different pedagogical approaches or regulatory frameworks, the model could be refined to include factors such as policy incentives or regulatory support for online learning, enhancing its relevance and scalability. This flexibility positions the model as a valuable tool for institutions globally, enabling them to assess and optimize their blended learning strategies while accommodating local educational conditions and objectives.

11 CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

12 FUNDING INFORMATION

No funding was received from any source for this study.

13 COMPETING INTERESTS

No competing interests are associated with this manuscript.

14 DATA AVAILABILITY STATEMENT

The datasets generated during and analyzed during the current study are available from the corresponding author upon reasonable request.

15 ETHICAL STATEMENT

This study contains no studies with human or animal subjects performed by any authors.

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