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Digital Natives' Mobile Learning Adoption in terms of UTAUT-2 Model: a Structural Equation Model

Adopción del aprendizaje móvil por parte de los nativos digitales en términos del modelo UTAUT-2: un modelo de ecuaciones estructurales

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ABSTRACT
This research investigates university students' intentions and behaviors regarding the adoption of mobile learning tools in higher education, with a focus on the Unified Theory of Acceptance and Use of Technology (UTAUT-2) model. A sample of 541 university students from a state university in the Southeastern Anatolia Region of Turkey participated in this study. Structural equation modeling was employed to assess students' mobile learning adoption levels, and statistical analyses were conducted accordingly. The findings indicate a moderate level of mobile learning adoption among the students. The study reveals that students employ various strategies while using mobile tools for learning. Notably, among digital natives, intention to use mobile devices is significantly influenced by habit, hedonic motivation and effort expectancy. Additionally, the study identifies a significant relationship between the use behavior variable and facilitating conditions. The research also examines regulatory effects within the model, demonstrating that age moderates the relationship between habit and use behavior. Furthermore, gender has a moderating effect on the relationship between facilitating conditions and behavioral intention, as well as between hedonic motivation and behavioral intention. Finally, experience moderates the relationship between habit and use behavior, as well as between behavioral intention and use behavior.

KEYWORDS Mobile Learning Adoption; Unified Theory of Acceptance and Use of Technology 2; UTAUT2; Structural Equation Model; Digital Natives.

RESUMEN

Este estudio investiga las intenciones y comportamientos de los estudiantes universitarios respecto a la adopción de herramientas de aprendizaje móvil en la educación superior, con enfoque en el modelo de la Teoría Unificada de Aceptación y Uso de la Tecnología (UTAUT-2). En este estudio participó una muestra de 541 estudiantes de una universidad estatal de la región sudoriental de Anatolia en Turquía. Se empleó un modelo de ecuaciones estructurales para evaluar los niveles de adopción del aprendizaje móvil de los estudiantes y se realizaron análisis estadísticos en consecuencia. Los hallazgos indican un nivel moderado de adopción del aprendizaje móvil entre los estudiantes. El estudio revela que los estudiantes emplean diversas estrategias mientras utilizan herramientas móviles para aprender. En particular, entre los nativos digitales, la intención de utilizar dispositivos móviles está significativamente influenciada por el hábito, la motivación hedónica y la expectativa de esfuerzo. Además, el estudio identifica una relación significativa entre la variable conducta de uso y las condiciones facilitadoras. La investigación también examina los efectos regulatorios dentro del modelo, demostrando que la edad modera la relación entre el hábito y el comportamiento de uso. Además, el género tiene un efecto moderador sobre la relación entre las condiciones facilitadoras y la intención conductual, así como entre la motivación hedónica y la intención conductual. Finalmente, la experiencia modera la relación entre hábito y conducta de uso, así como entre intención conductual y conducta de uso.

PALABRAS CLAVE Adopción del aprendizaje móvil; Teoría unificada de aceptación y uso de la tecnología 2; UTAUT2; Modelo de ecuaciones estructurales; Nativos digitales.

1. INTRODUCTION

Mobile learning (m-learning) literally denotes the utilization of mobile devices in learning environments. M-learning, which provides equal opportunities in education, is a form of learning that provides access to content independent of time and place, and allows to communicate with other learners (Bozkurt, 2015; Talan, 2020). This concept has become more important in recent years, especially with the prevalence of smart phones and tablets, and it has brought many opportunities in teaching. M-learning is the advanced form of e-learning, which is a form of utilizing information and communication technologies (Talan, 2020). M-learning is effective in enabling students to learn without being tied to time and place, and in making learning more interesting (Yuliani, 2010). M-learning, which takes place through mobile technologies or mobile environments, offers unlimited opportunities in terms of time as well as providing easy access to content (Yosiana et al., 2021). M-learning is a type of learning that allows users to interact with social interaction and content with the help of personal electronic devices with its versatile structure (Crompton, 2013). M-learning is a result of mobile technologies. Therefore, each new technology should be examined separately. With the development of technology day by day, user decisions are important in integrating technology into users' lives. In the relevant literature, it has been pointed out that the effective and successful use of m-learning in the teaching-learning process largely depends on the level of acceptance and adoption of m-learning (Açıkgül, & Diri, 2020). Thus, it is also imperative to scrutinize the acceptance of m-learning tools. In this respect, the technology acceptance model (TAM) has been included in many studies in order to reveal the reasons for the acceptance or rejection of a new technology by its users. TAM, whose foundations are based on the theory of reasoned action and theory of planned behavior, plays a key role in understanding the behavior of users to embrace or reject technology (Marangunić, & Granić, 2015).

There are various studies in the literature on technology acceptance of m-learning. For instance, the use and adoption of m-learning technologies in Saudi Arabia were examined, and as a result of the research, it was found that effort expectancy, learning expectancy and social effects were among the predictors of students' intention to use m-learning technologies (Alasmari, & Zhang, 2019). On the other hand, Sánchez-Prieto et al. (2015) examined students' behavioral intentions regarding mobile technology use within the framework of TAM. In another study on m-learning, it was aimed to reveal the main factors affecting university students' behavioral intentions towards m-learning and their actual use of m-learning in education. In this study based on TAM, it was revealed that perceived mobile value, academic relevance, and m-learning self-management were predictors of students' acceptance of m-learning (Al-Rahmi et al., 2022). Therefore, it is important to adopt m-learning for users to use it.

The effectiveness of m-learning also depends on student acceptance. In a study on this subject, variables on university students' behavioral intentions towards m-learning were analyzed using structural equation modeling. As a result of this study, which was based on TAM and the theory of planned behavior, it was seen that subjective norm and perceived behavioral control were effective on m-learning (Afacan Adanır, & Muhametjanova, 2021).

With the rapid developments in mobile technologies and the increasing functionality of mobile devices, the importance of mobile learning in educational settings has grown (Altunçekiç, 2020). Mobile learning tools allow students to access learning materials and participate in learning activities anytime and anywhere, providing them with independence, personalized learning, and freedom (Yağan, 2023). In the context of Turkey, there are various studies related to the concept of mobile learning. Research indicates that students' attitudes toward mobile learning should be taken into consideration in the design of mobile learning environments (Sirakaya, & Sirakaya, 2017). In the context of mobile learning, digital natives are considered an important concept. Digital natives are individuals who have grown up in the digital age and are familiar with digital technologies (Cañete Estigarribia et al., 2022; Onursoy, 2018). Kirk et al. (2015) define digital natives as a generation that accesses information especially through the use of mobile devices. Therefore, it is important to examine mobile learning from the perspective of digital natives.

In conclusion, mobile learning has transformed the delivery of education and instruction by utilizing mobile devices to provide learning materials and activities. It has gained significance in educational environments, and research has focused on various aspects such as students' attitudes toward mobile learning, the concept of digital natives, technology acceptance, and usage. Understanding these aspects can contribute to the design of effective mobile learning environments and the promotion of the integration of mobile learning into education. Additionally, while there are studies that examine mobile learning from the perspective of technology acceptance and adoption, this study attempts to explain the acceptance and adoption of mobile learning technologies in relation to the characteristics of digital natives.

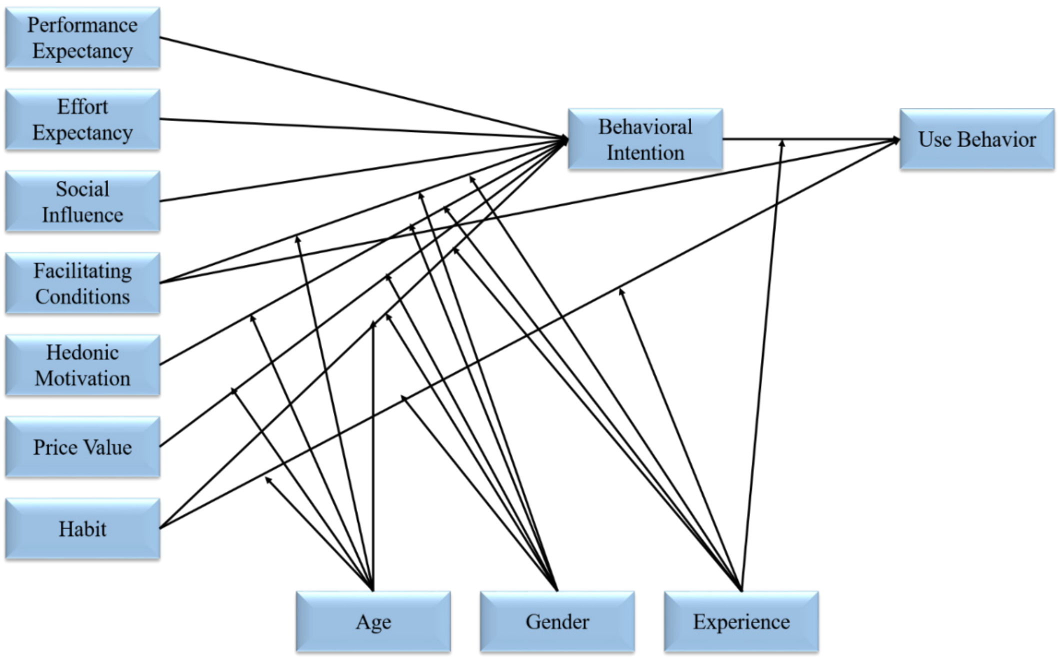
1.1. Literature review

1.1.1. The UTAUT2 Model

There are many models that explain technology acceptance. One of these models is the Unified Theory of Acceptance and Use of Technology (UTAUT). The UTAUT model consists of Theory of Reasoned Action (TRA), the Technology Acceptance Model (TAM), Motivational Model, the Theory of Planned Behaviour (TPB), the model of Personal Computer Utilization, the Innovation Diffusion Theory and the Social Cognitive Theory

(Venkatesh et al., 2003). The UTAUT model uses the behavioral intention variable to explain technology usage behavior (Thomas et al., 2013). Although the UTAUT model is widely accepted (Venkatesh et al., 2012), it has been expanded with new components added to it. The UTAUT-2 model seen in Figure 1 explains behavioral intention by 74%, while the UTAUT model explains behavioral intention by 56%. Similarly, the UTAUT-2 model explains the technology use by 52%, whereas the UTAUT model explains 40% (Chang, 2012).

FIGURE 1. The UTAUT-2 Model.



The UTAUT-2 model consists of some components as seen in Figure 1. The description of these components is as follows:

- Performance Expectancy (PE): This component denotes how much impact this technology has on the user's performance when the user uses the technology. It purports how much the user benefits when he uses the technology. In other words, this refers to the degree to which a student believes that using mobile learning will help them to achieve their learning goals. Students' beliefs about the usefulness of mobile learning for their learning needs can significantly influence their adoption of this technology. For example, students who perceive that using mobile learning will enhance their academic performance are more likely to adopt it.
- Effort Expectancy (EE): This component of the model represents how much effort the user puts into using the relevant technology. This component refers to the degree of convenience of the technology used. In other words, this construct relates to the degree of ease or difficulty a student perceives when using mobile learning. It reflects the extent to which the student believes that using mobile learning is easy or cumbersome. Students' perception of the ease of use of mobile learning can significantly

affect their adoption. For example, students who perceive that using mobile learning is simple and user-friendly are more likely to adopt it.

- Social Influence (SI): This component refers to the relevance of the individual's use of the technology in question to their social environment. It can be expressed as an attitude of care to the use of this technology by the people that the individual considers important, his/her close environment, and the social friend environment. In other words, this construct relates to the degree to which a student perceives that significant others (such as peers, instructors, or family members) will influence their adoption of mobile learning. Students' beliefs about the attitudes of others towards mobile learning can significantly impact their adoption. For example, students who perceive that their peers and instructors have positive attitudes towards mobile learning are more likely to adopt it.
- Facilitating Conditions (FC): It is the support that the user using the technology receives to perform a behavior. The technical support and infrastructure factor that the user receives while using the relevant technology is represented by this component. In other words, this construct relates to the degree to which a student perceives that the necessary resources (such as technological infrastructure, access to the internet, and technical support) are available to support their use of mobile learning. Students' perception of the availability of necessary resources can significantly affect their adoption. For example, students who perceive that the required technological infrastructure is in place, and technical support is available, are more likely to adopt mobile learning.
- Hedonic Motivation (HM): This component in the model expresses the pleasure and delight that the individual gets while using the related technology.
- Price Value (PV): It is based on the relationship between the price the user pays for using the technology and the benefit obtained. In other words, this component means that the cost of technology affects the use of technology.
- Habit (HT): It refers to the behavior of the user automatically. It is a habit that an individual acquires based on previous learning.
- Behavioural Intention (BI): This component, which is also affected by other variables, is the tendency of the individual to perform a behavior.

When the components of the model are examined, it is seen that the behavioral intention variable is affected by the variables of habit, price value, hedonic motivation, facilitating conditions, social influence, effort expectancy and performance expectancy. Besides, usage behavior is affected by behavioral intention, habit, facilitating conditions variables. In the model, the effect of age on the interaction of facilitating conditions and behavioral intention, the interaction of hedonic motivation and behavioral intention, the interaction of price value and behavioral intention, the interaction of habit and behavioral intention, and the interaction of habit and use behavior were also investigated. Gender is affected by the interactions of habit and use behavior, habit and behavioral intention, price value and behavioral intention, hedonic motivation and behavioral intention, facilitating conditions and behavioral intention. Experience, another moderator in the model, is affected by the interactions of habit behavioral intention, facilitating conditions behavioral intention, hedonic motivation behavioral intention, behavioral intention use behavior and habit use behavior interactions.

1.1.2. Previous Studies

M-learning tools have entered our lives more and more with the development of technology. With the use of m-learning tools, it has become important to understand how effective these tools are in education. In this context, since m-learning tools are also technologies, these technologies should be examined within the scope of the diffusion of technology. By using the UTAUT-2 model, which is a model that prioritizes the diffusion of technology, it can be fully understood whether m-learning technologies are adopted by students. Therefore, in this study, it is aimed to investigate m-learning in the context of the components included in the UTAUT-2 model.

When the studies on UTAUT-2 are examined, it is clear that the use of various technologies for educational purposes is scrutinized. For instance, in a study, students' intention to use online learning during the COVID-19 period was examined within the scope of UTAUT-2. As a result of the study conducted with university students, it was revealed that the variables of self-efficacy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and price value positively affect behavioral intention (Xu et al., 2022). The adoption and use of each new technology used in education changes the effects of technology on education. Massively open online courses (MOOCs) are widely accepted as a unified platform to reduce the digital divide and make education accessible to all (Cabero Almenara, & Romero Tena, 2020).

Despite these benefits of MOOCs, their adoption and completion rates are remarkable. In a study, the main factors affecting behavioral intention to use MOOCs among university students were examined. As a result of the study, performance expectation, hedonic motivation and habit are positively effective on behavioral intention, while hedonic motivation is effective on behavioral intention in favor of men, moderated by gender effect (Mohan et al., 2020). Blended learning, which includes face-to-face and online learning, is a heterogeneous type of learning. With COVID-19 and developments in technology, the blended learning approach has come to the fore in universities. In this context, the UTAUT-2 model was used in a study to examine the acceptance and usage levels of students in blended learning at universities. As a result, it was revealed that performance expectation, effort expectancy, social influence, facilitating conditions and hedonic motivation, which are the components of the UTAUT-2 model, positively affect the behavioral intentions of university students to accept blended learning (Rudhumbu, 2022). With the increasing prevalence of technology and the internet, the way education is delivered has changed rapidly in different environments. In this respect, mobile technologies are also widely used in education. In a study on this subject, the acceptance and adoption of mobile technologies by academicians in higher education was examined. In this study, in which the UTAUT-2 model was used, it was revealed that the most important factors affecting the behavioral intentions and usage behaviors of academicians are performance expectation, facilitating conditions, hedonic motivation and habit, and gender, age, experience and discipline have moderator effects (Hu et al., 2020).

In another study on m-learning, the technology acceptance levels of university students were examined within the scope of the UTAUT-2 model. As a result of the study, it was revealed that the most important variable affecting the acceptance of mobile technologies by students is habits (Moorthy et al., 2019). Mobile technologies are attractive learning devices for education. In another study, the acceptance and use of mobile technologies by undergraduate students were examined within the scope of UTAUT-2. As a result of the study, it was seen that the variables of performance expectation, effort expectancy, social influence, facilitating situation, hedonistic motivation, price and habit, which are the components of the model, affect behavioral intention (Ahmed, & Kabir, 2018). Online learning, which has come to the fore due to the pandemic, is carried out with various tools (Kalinkara, & Talan, 2022). One of the tools used in online learning through internet-based learning management systems is Google Classroom. In a study, students' intention to use Google Classroom was examined. In this study, in which the UTAUT-2 model was used, students' intentions to use Google Classroom were examined. According to the results obtained, it was revealed that while facilitating conditions were associated with effort expectancy, habit, and social influence, facilitating conditions were not significantly related to behavioral intention (Bervell et al., 2022).

Factors affecting the use of mobile technologies for academic purposes, which are known to facilitate communication and information sharing among students, are important in education. In a study on this subject, the factors affecting the use of smartphones were discussed. In this study, which was based on the UTAUT-2 model, it was seen that effort expectancy, facilitating conditions and social influence had a significant effect on hedonic motivation and perceived usefulness. Habit and price value, which are the components of the model, showed that hedonic motivation and perceived usefulness have a significant effect on behavioral intention and usage behavior (Gyamfi, 2021).

1.1.3. The Present Research

Investments and breakthroughs in the use of mobile technologies in education have gained momentum in recent years. However, evaluations regarding the adoption of m-learning by both educators and students have become of secondary importance. On the other hand, when a new technology or service is offered to users, some factors affect their decisions about how and when to use it (Šumak et al., 2010). The UTAUT model stands out among the theories developed to evaluate such factors and to determine the acceptance levels of technological tools (Guillén-Gámez et al., 2024). When we look at the studies in which m-learning is examined in terms of technology acceptance, it is discernible that the technology acceptance model is generally used, while a limited number of studies have examined m-learning with the UTAUT-2 model. The UTAUT-2 model, which was put forward by Venkatesh et al. (2012) regarding students' technology acceptance and use, reveals which variables are highly dependent on students' behavioral intentions. Thus, despite the use of many models for technology acceptance and adoption, we decided to use UTAUT-2 as a powerful model, in which the elements of eight models were cross-integrated. Therefore, in this study, it is aimed to explain the behaviors and intentions of higher education students to use m-learning tools with the UTAUT-2 model.

Another purpose of the research is to analyze the acceptance level of students in terms of gender, age and experience of using mobile technologies. To this end, the effect of performance expectation, effort expectancy, social influence, and facilitating conditions were examined in order to understand students' intentions to adopt m-learning. In addition, the moderator effects of these factors, such as gender, on behavioral intention to adopt m-learning were investigated. In addition, researchers want to see the results by making additions to the UTAUT-2 model while examining the acceptance and use of certain technologies by the user. For example, Osei et al. (2022) used a synthesis of UTAUT 2, Self Determination Theory and Core Self-Evaluation Theory in their study to determine students' adoption of e-learning. In another study, the UTAUT-2 model was extended with self-efficacy, motivation to use, and mobile literacy to predict users' behavioral intentions to use a mobile health education website (Yu et al., 2021). In a study examining students' use of social networks for educational purposes, the UTAUT-2 model was expanded by adding instructor support and student variables (Gharrah, & Aljaafreh, 2021). The present study tried to reveal the acceptance and use of m-learning by the UTAUT-2 model.

The purpose of this research is also to examine the technology usage habits of digital natives within the scope of UTAUT-2. Studies related to digital natives indicate that this new generation, having been born in the digital age, demonstrates a positive attitude towards technology. However, this intense use of technology can weaken deep learning and productive work abilities, while becoming a distracting factor (Bauerlein, 2008). Studies conducted on university students show that there is a complex relationship between technology usage and learning among digital natives (Thompson, 2013).

Digital natives represent a generation that is naturally proficient in technology, whereas digital immigrants refer to a generation that encountered technology and digital tools later in life (Wang et al., 2013). Kirk et al. (2015) define digital natives as individuals who have grown up in highly interactive digital networks and particularly access information using mobile devices. The general consensus is that digital natives are more advanced in digital technologies. However, the concept of digital natives is not solely limited to age; it is also associated with technology access, education level, and interaction and engagement with technology (Misci Kip, & Umul Ünsal, 2020).

It is believed that the natural inclination of digital natives towards digital technologies could challenge theories like the technology acceptance model. These theories suggest that digital immigrants tend to resist new technologies or systems, while assuming that digital natives are more open to these technologies (Wang et al., 2013). However, there are studies that indicate variations in skill levels within the digital native term (Brown, & Czerniewicz, 2010). Digital natives can exhibit different approaches to technology; some may keep technology to a minimum, while others are not hesitant to fully utilize the opportunities that technology provides (Zenios, & Ioannou, 2018).

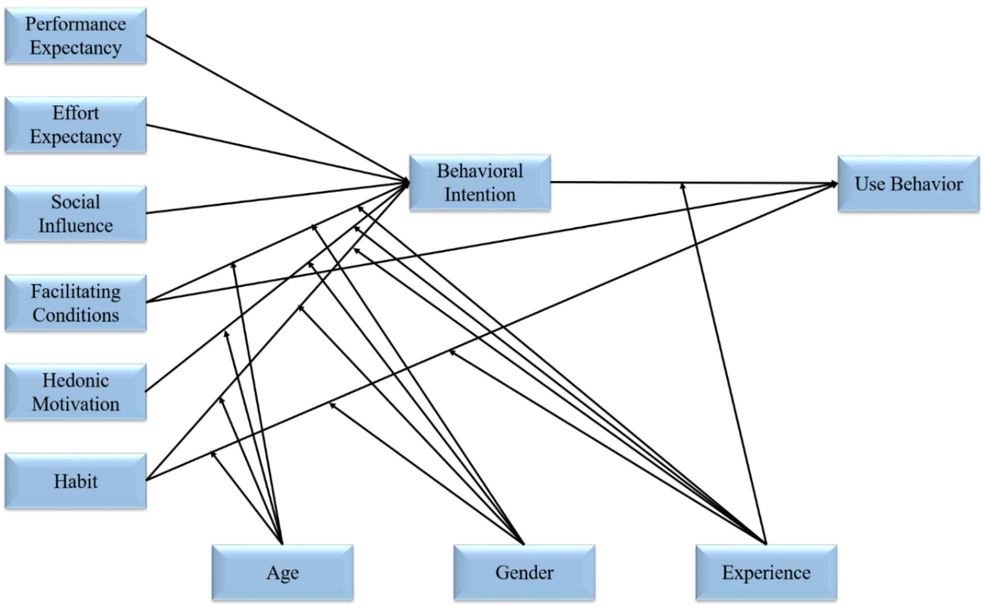
Digital natives have different characteristics compared to digital immigrants. Online technologies are central to the lives of digital natives, and they prefer to do their work mostly through online technologies. Mobile phones and instant messaging applications dominate a significant portion of the lives of digital natives (Bilgiç et al., 2011). In terms of learning habits, digital natives are not reliant on printed materials, and their information processing methods differ. Digital natives, as described by Prensky (2001) as "21st-century learners," approach learning from a different perspective. For these reasons, this research has been conducted with the aim of better understanding the perspective of digital natives towards mobile learning tools and predicting the level of usage and acceptance of these tools. This study will assist us in gaining a better understanding of the mobile learning habits of digital natives.

2. METHODOLOGY

In this part of the study, the preferred model, the hypotheses and the participants were given to examine the technology acceptance status of the students. In addition, in this section, data collection process, data collection tools and data analysis are mentioned.

2.1. Research Model and Hypotheses

FIGURE 2. The Purposed Model.



The model in Figure 2 was used within the scope of the research. This study was conducted at a state university in the Southeastern Anatolia region of Turkey. Although different results were obtained in the studies in the literature on UTAUT-2, the model in Figure 2 was tested with this study. All variables were examined with age, gender and experience moderators. The hypotheses included in the research are shown below:

- H1: Performance Expectancy is positively related to Behavioral Intention.
- H2: Effort Expectancy is positively related to Behavioral Intention.
- H3: Social Influence is positively related to Behavioral Intention.
- H4: Facilitating Conditions are positively related to Behavioral Intention.
- H5: Facilitating Conditions are positively related to Use Behavior.
- H6: Hedonic Motivation is positively related to Behavioral Intention.
- H7: Habit is positively related to Behavioral Intention.
- H8: Habit is positively related to Use Behavior.
- H9: Behavioral Intention is positively related to Use Behavior.
- H10: There is a moderating role of age in the relationship between the Habit variable and the Behavioral Intention variable.
- H11: There is a moderating role of age in the relationship between the Habit variable and the User Behavior variable.

- H12: There is a moderating role of age in the relationship between the Hedonic Motivation variable and the Behavioral Intention variable.
- H13: There is a moderating role of age in the relationship between the Facilitating Conditions variable and the Behavioral Intention variable.
- H14: There is a moderating role of gender in the relationship between the Habit variable and the Behavioral Intention variable.
- H15: The gender has a moderating role in the relationship between the Habit variable and the user behavior variable.
- H16: Gender plays a moderating role in the relationship between the Hedonic Motivation variable and the Behavioral Intention variable.
- H17: Gender plays a moderating role in the relationship between the Facilitating Conditions variable and the Behavioral Intention variable.
- H18: Experience plays a moderating role in the relationship between the Habit variable and the Behavioral Intention variable.
- H19: Experience plays a moderating role in the relationship between the Habit variable and the User Behavior variable.
- H20: Experience plays a moderating role in the relationship between the Hedonic Motivation variable and the Behavioral Intention variable.
- H21: Experience plays a moderating role in the relationship between the Facilitating Conditions variable and the Behavioral Intention variable.
- H22: Experience plays a moderating role in the relationship between the Behavioral Intention variable and the User Behavior variable.

2.2. Research Design

In this study, which aims to determine the intentions and behaviors of university students towards adopting m-learning in higher education, the correlational survey model, which is among the general survey model types, was used. This model can be expressed as describing and analyzing the relationships between two or more variables (Karasar, 2009). Structural equation modeling with latent variables was used to analyze the obtained data. Structural equation modeling, which is used as a combination of confirmatory factor analysis and path analysis, has been used in the use of relationships between UTAUT-2 model components (Thomas et al., 2013).

2.3. Participants

This study was carried out in the fall semester of the 2022-2023 academic year. In order to test the research hypotheses, the necessary data were obtained from students studying at a state university in the Southeastern Anatolia region of Turkey by using convenience sampling method. Convenience sampling is a sampling method that is conducted with sample elements that the researcher can easily access. (Yener, & Abdülkadir, 2007). The data of the research was collected by online questionnaire and offline schedules. In this study, structural equation modeling was used with the partial least squares method. In such studies, when calculating the minimum sample size, it is sufficient to have at least 10 times the number of structural paths directed towards a specific structure in the structural model (Hair et al., 2017). The structural equation model successfully used with small sample groups can also be preferred for large sample groups (e.g., 250 and above) using the partial least squares method (Hair et al., 2017). Since there are 8 structural paths in the model used, it is sufficient to have a minimum of 80 samples. A total of 541 students were reached within the scope of the study. Information about the participants is as in Table 1.

TABLE 1. **Demographic Data.**

Variable	Category	Frequency (f)	Percentage (%)
Gender	Female	251	46.4
	Male	290	53.6
Age	≤18	107	19.8
	≥19, ≤21	328	60.6
	≥22	106	19.6
Total		**541**	**100**

In Table 1, more than half (53.6%) of the university students participating in the research are men and 46.4% are women. Again, there is an unequal distribution according to age in the study. It was observed that the participant students were generally between the ages of 19 and 21 (60.6%). In addition to the demographic characteristics of the students, the research also includes questions about the average daily phone usage time and how many years they have been using mobile phones. In addition, it was also asked in the form whether the participants used mobile communication tools for educational purposes, and if so, which mobile content types/tools they used and how often. Findings related to this are given in Table 2.

TABLE 2. **Information on students' mobile phone usage.**

Variable	Category	Frequency (f)	Percentage (%)
Average phone usage time per day	<1h	8	1.5
	≥1, ≤2h	87	16.1
	≥3, ≤5h	259	47.9
	≥6h	187	34.6
How many years have you been using a mobile phone?	<1y	21	3.9
	≥2, ≤4y	151	27.9
	≥5, ≤7y	260	48.1
	≥8y	109	20.1
Do you use mobile communication tools for educational purposes?	Yes	507	93.7
	No	34	6.3

According to the data in Table 2, a significant part of the participants (82.5%) use their mobile phones for 3 hours or more per day. Again, about half of the students (48.1%) who participated in the research stated that they used mobile phones for 5-7 years. However, it was observed that 21 (3.9 %) of the students used mobile phones for less than 1 year. On the other hand, it was concluded that a high percentage of students (93.7%) use mobile communication tools for educational purposes.

2.4. Data Collection Instrument

A questionnaire consisting of three parts was prepared in order to test the students' intentions and behaviors towards adopting m-learning. In the first part, there are six questions in accordance with the sub-objectives of the research and these questions are about the demographic information of the participants and their mobile phone usage status. In the second part, there are UTAUT-2 scale questions

2.5. UTAUT-2 Scale

This scale was developed by Venkatesh et al (2012). The Turkish adaptation of the scale was conducted by Baraz et al (2021). The scale consists of 8 factors and 30 items. The factors are performance expectancy (4), effort expectancy (4), social influence (3), facilitating conditions (4), hedonic motivation (3), habit (4), and behavioral intention (3). The scale is a likert-type seven-point scale. Items are rated from "Strongly Disagree (1)" to "Strongly Agree (7)". The Cronbach alpha internal consistency coefficient calculated for the entire scale was calculated as .91. Therefore, it was concluded that the scale was reliable.

2.6. Data Analysis

IBM SPSS Statistics v20.0 and Smart PLS 4.0.9 programs were used to analyze the data collected in the study. The SPSS Program was used to learn the descriptive statistical analyses, normality test, Cronbach Alpha and correlation status between the variables of the participants. The AMOS program, on the other hand, was used to evaluate the validity and reliability of the structural equation model to be created in the research, based on model fit index values, and to conduct hypothesis tests. Structural Equation Model (SEM) was tested for the suitability of the proposed model in the analysis of the data. SEM is a comprehensive statistical technique used to analyze the theoretical model proposed by the researcher, as well as to reveal the relationships between observed variables and latent variables (Schumacker, & Lomax, 2004).

3. FINDINGS

IBM SPSS Statistics 22 and Smart PLS 4.0.9 were used in the analysis of the data obtained as a result of the study. Within the scope of the study, data obtained from the scale were used to test the model as well as demographic data. In testing the model, the structural equation model partial least squares method was preferred.

3.1. Validity and Reliability Analyses of the Scale

Before conducting the analysis of the research model, validity and reliability studies of the constructs in the study were performed. Within the scope of validity and reliability studies, internal consistency reliability, convergent validity, and discriminant validity were assessed. Cronbach's Alpha and composite reliability (CR) coefficients were examined for internal consistency reliability. In determining convergent validity, the values of factor loadings and the average variance extracted (AVE) were used. It is expected that factor loadings should be ≥0.70, Cronbach's Alpha and composite reliability coefficients should be ≥0.70, and the AVE should be ≥0.50 (Fornell & Larcker, 1981; Hair et al., 2006; Hair et al., 2017). To ensure internal consistency reliability, achieve convergent validity, and establish discriminant validity, necessary modifications were made, and indicators affecting reliability and validity were removed from the model. Table 3 below presents the results of internal consistency reliability and convergent validity for the constructs included in the study.

TABLE 3. Information on students' mobile phone usage.

Variable	Expression	Factor Load	Cronbach Alpha	CR	AVE
Performance Expectancy	PE1	0,873	0,947	0,948	0,820
	PE2	0,996			
	PE3	0,824			
	PE4	0,920			
Effort Expectancy	EE1	1,000	-	-	-
Social Influence	SI1	1,000	-	-	-
Facilitating Conditions	FC1	0,940	0,904	0,908	0,769
	FC2	0,928			
	FC3	0,749			
Hedonic Motivation	HM1	0,966	0,952	0,952	0,908
	HM2	0,939			
Habit	H1	1,000	-	-	-
Behavior Intention	BI1	1,000	-	-	-
Use Behavior	UB1	0,780	0,708	0,710	0,551
	UB2	0,703			

Due to the Cronbach's Alpha coefficients of the constructs ranging from 0.708 to 0.952 and CR coefficients ranging from 0.710 to 0.952, it can be concluded that internal consistency reliability has been achieved. Upon examination of the values in the table, it can be noted that the factor loadings are between 0.703 and 1.000, and the AVE values range from 0.551 to 0.908, indicating that convergent validity has been established.

Various methods exist for assessing discriminant validity. One such method is the Fornell and Larcker (1981) criterion. However, the Fornell and Larcker criterion fails to reliably identify issues related to discriminant validity (Radomir, & Moisescu, 2019). As a better alternative for assessing discriminant validity, the Heterotrait-Monotrait Ratio (HTMT) (Henseler et al., 2015) is recommended (Hair et al., 2021). Therefore, in this study, only HTMT coefficients have been reported.

For the determination of discriminant validity, cross-loadings were assessed using the HTMT criterion proposed by Henseler et al. (2015). Following the modifications made, the PLS algorithm was rerun, and cross-loadings, and HTMT coefficients were rechecked. The control results revealed that there was no substantial overlap among the items measuring the research constructs. The outcomes HTMT coefficients are displayed in Table 4.

TABLE 4. Results of Discriminant Validity (HTMT Coefficients)*.

	Behavioral Intention	Effort Expectancy	Facilitating Conditions	Habit	Hedonic Motivation	Performance Expectancy	Social Influence	Use Behavior
Behavioral Intention								
Effort Expectancy	0,728							
Facilitating Conditions	0,689	0,712						
Habit	0,816	0,754	0,718					
Hedonic Motivation	0,716	0,730	0,869	0,745				
Performance Expectancy	0,662	0,780	0,800	0,719	0,833			
Social Influence	0,672	0,843	0,765	0,747	0,743	0,819		
Use Behavior	0,424	0,494	0,554	0,465	0,547	0,556	0,481	

According to the criteria set by Henseler et al. (2015), the HTMT ratio expresses the ratio of the average correlations among the items belonging to different variables to the geometric mean of the correlations among the items of the same variable. The authors have stated that theoretically, the HTMT value should be below 0.90 for closely related concepts and below 0.85 for distant concepts. It can be observed in Table 3 that the HTMT values are below the threshold. Given that there is no substantial overlap among the indicators measuring the variables in the research and HTMT coefficients have been achieved within the desired limits, it can be concluded that discriminant validity has been established.

3.2. Testing of the Research Model and Results

The results of the structural equation model created to test the hypotheses of the study are presented below. Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed for analyzing the research model. The data were analyzed using the SmartPLS 4.0.9.6 statistical software (Ringle et al., 2015). To assess linearity, path coefficients, R-squared (R2), and effect sizes (f2) related to the research model, the PLS algorithm was used, and Blindfolding analysis was conducted to calculate predictive power (Q2). To evaluate the significance of PLS path coefficients, t-values were calculated by resampling (bootstrapping) 5000 subsamples from the dataset. The research results, including VIF, R2, f2, and Q2 values, are presented in Table 5, and the coefficients of the research model are presented in Table 6.

When examining the Variance Inflation Factor (VIF) values between variables, it can be observed that the values are below the threshold of 5, indicating that there is no multicollinearity issue among the variables (Hair et al., 2021). Upon reviewing the obtained R-squared (R2) values for the model, it was found that the Behavioral Intention variable is explained to the extent of 71%, while the Use Behavior variable is explained to the extent of 21%.

TABLE 5. Results of the Research Model.

Variables		VIF	R^2	f^2	Q^2
Performance Expectancy	Behavioral Intention	4,807	0,711	0,003	0,700
Effort Expectancy		4,131		0,058	
Social Influence		4,936		0,007	
Facilitating Conditions		4,816		0,008	
Hedonic Motivation		4,541		0,014	
Habit		2,975		0,357	
Behavioral Intention	Use Behavior	3,203	0,315	0,000	0,207
Facilitating Conditions		2,195		0,135	
Habit		3,457		0,010	

The coefficient of effect size (f2) is considered low if it is 0.02 or higher, moderate if it is 0.15 or higher, and high if it is 0.35 or higher (Cohen, 1988). According to Sarstedt et al. (2017), it has been stated that it is not possible to talk about an effect when the coefficient is below 0.02. When examining the effect size coefficients (f2), it can be seen that the Habit variable has a high level of effect size on the Behavioral Intention variable. According to Sarstedt et al. (2017), Performance Expectancy, Social Influence, Facilitating Conditions, and Hedonic Motivation variables have low effect size on Behavioral Intention, and Behavioral Intention and Habit variables have low effect size on the Use Behavior variable.

The calculated predictive power coefficients (Q2) for the endogenous variables being greater than zero indicate that the research model has predictive power for the endogenous variables (Hair et al., 2017). Due to the Q2 values in the table being greater than zero, it can be stated that the research model has predictive power on the Behavioral Intention and Use Behavior variables.

TABLE 6. Coefficients of the Research Model.

Variables		Standardize β	Standart Sapma	t-değeri	p
Performance Expectancy	Behavioral Intention	-0,065	0,050	1,296	0,195
Effort Expectancy		0,262	0,046	5,721	0,000
Social Influence		-0,103	0,059	1,753	0,080
Facilitating Conditions		0,104	0,059	1,756	0,079
Hedonic Motivation		0,151	0,066	2,291	0,022
Habit		0,554	0,067	8,245	0,000
Behavioral Intention	Use Behavior	-0,010	0,073	0,139	0,889
Facilitating Conditions		0,451	0,070	6,423	0,000
Habit		0,151	0,086	1,753	0,080

When examining the values in Table 6, it can be understood that there are significant effects on the Behavioral Intention variable from the Effort Expectancy variable ($\beta=0.262$; $p<0.05$), Hedonic Motivation variable ($\beta=0.151$; $p<0.05$), and Habit variable ($\beta=0.554$; $p<0.05$). On the Use Behavior variable, the Facilitating Conditions variable ($\beta=0.451$; $p<0.05$) has a significant effect. It was observed that the effects of

Performance Expectancy, Social Influence, and Facilitating Conditions variables on Behavioral Intention, as well as the effects of Behavioral Intention and Habit variables on the Use Behavior variable, are statistically insignificant. In light of these findings, it has been concluded that hypotheses numbered 2, 5, 6, and 7 are supported, while hypotheses numbered 1, 3, 4, 8, and 9 are not supported.

The moderating role of age in the relationship between Facilitating Conditions and the Behavioral Intention variable, the relationship between Hedonic Motivation and the Behavioral Intention variable, the relationship between Habit and the Behavioral Intention variable, and the relationship between Habit and the Use Behavior variable were tested through Multi-Group Analysis. The analysis results are shown in Table 7.

TABLE 7. Results of Multi-Group Analysis (Age).

Variables		Differences in Path Coefficients	p
Facilitating Conditions	Behavioral Intention	-0,056	0,339
Hedonic motivation		-0,933	0,256
Habit		0,414	0,241
Habit	Use Behavior	0,214	0,000

When examining the analysis results, it is observed that there is a moderating effect of age in the relationship between Habit and the Use Behavior variable ($\beta=0.214$; $p<0.05$). The other moderating effects in the pathways are statistically insignificant. Therefore, hypotheses numbered 10, 12, and 13 have been rejected. Hypothesis number 11, on the other hand, has been supported. Findings related to the moderating role of gender are presented in Table 8.

TABLE 8. Results of Multi-Group Analysis (Gender).

Variables		Differences in Path Coefficients	p
Facilitating Conditions	Behavioral Intention	0,078	0,015
Hedonic motivation		-0,305	0,010
Habit		-0,114	0,303
Habit	Use Behavior	0,084	0,501

When examining the analysis results, it is observed that there is a moderating effect of gender in the relationship between Facilitating Conditions and the Behavioral Intention variable ($\beta=0.078$; $p<0.05$), as well as in the relationship between Hedonic Motivation and the Behavioral Intention variable ($\beta=-0.305$; $p<0.05$). The other moderating effects in the pathways are statistically insignificant. Based on these results, hypotheses numbered 14 and 16 are supported in relation to the moderating effect of gender, while hypotheses numbered 15 and 17 have been rejected.

TABLE 9. Results of Multi-Group Analysis (Experience).

Variables		Differences in Path Coefficients	p
Facilitating Conditions	Behavioral Intention	-0,639	0,563
Hedonic motivation	Behavioral Intention	0,549	0,399
Habit	Behavioral Intention	-0,209	0,247
Habit	Use Behavior	-1,229	0,000
Behavioral Intention	Use Behavior	0,894	0,000

In Table 9, the results of the multi-group analysis related to experience are provided. According to this, there is a moderating effect of the experience variable in the relationship between Habit and the Use Behavior variable (β=-0.588; p<0.05), as well as in the relationship between Behavioral Intention and the Use Behavior variable (β=0.894; p<0.05). The other moderating effects in the pathways are statistically insignificant. In light of these results, hypotheses numbered 18 and 19 are supported, while hypotheses numbered 20, 21, and 22 are not supported.

4. DISCUSSION AND CONCLUSION

Digital natives are individuals who are born in an environment where all kinds of technological possibilities exist and can use these technological opportunities effectively (Prensky, 2001). These individuals, who do almost all of their daily work with technology, accept technology as one of the musts of life, not as a necessity. Especially the internet, computers, instant messaging, social networks, e-mail and mobile phones, which are increasingly used, are completely integrated with the daily lives of digital natives. The one-to-one interactions of digital natives with these technologies not only affect their daily activities, but also greatly affect their learning characteristics. On the other hand, in order to meet the needs and expectations of digital natives, the level of acceptance and adoption of these technologies is gaining importance day by day.

While digital media tools are so ingrained in the lives of the new generation of digital native students, not taking into account the adoption of these technological tools by digital natives while designing learning environments may render these environments ineffective in the eyes of users. In this study, it is aimed to determine and examine the factors affecting the behavioral intention of university students who are accepted as digital natives to adopt mobile learning. Performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation and habit, behavioral intention and usage factors, which are the variables affecting behavioral intention of the UTAUT-2 theory, which constitutes the basic model of the study, were included in the model. The moderator effect of gender, age and experience were also investigated in the study.

As a result of the relations established with the structural equation modeling method, many results were reached and this shows how complex the formation of students' intention is at the point of adopting mobile learning. The results of the study will help institutions and practitioners to understand the factors that influence students' intention to adopt mobile learning. Therefore, it is thought that the results will guide institutions in creating and implementing appropriate policies in terms of providing a better quality and effective learning environment. In this study, the acceptance and adoption of mobile learning tools by digital natives was examined using structural equation modeling, accompanied by the UTAUT-2 model. As a result of the research, it was confirmed that the UTAUT-2 model was statistically significant in the adoption of mobile learning. This result shows that students' usage behaviors, perceptions and intentions about mobile learning affect their adoption.

In this study, some of the proposed hypotheses have been confirmed, while others have been rejected H2 hypothesis has been supported. It has been observed that there is a significant relationship between the Effort Expectancy variable and the Behavioral Intention variable. Students believe that the less effort they put into using mobile technology, the more beneficial it will be, and they think that this type of usage also affects their academic achievements. There is a significant relationship between the facilitating conditions variable, which is our H5 hypothesis, and the use behavior variable. Accordingly, students exhibit more usage behavior in the presence of conditions that facilitate the use of the relevant technology. According to our H6 hypothesis, there is a significant positive relationship between the Hedonic Motivation variable and the Behavioral Intention variable. This indicates that students' enjoyment and pleasure when using mobile technologies affect their behavioral intentions. According to our H7 hypothesis, when students make using a mobile technology a habit, they are more inclined to turn it into a behavioral intention. H7 hypothesis has been confirmed.

In this study, the moderating effects of age, gender, and experience on the relationships have also been examined. Accordingly, there is a moderating effect of age on the relationship between habit and use behavior variables. There is a moderating effect of gender on the relationship between hedonic motivation and behavioral intention variables, as well as between facilitating conditions and behavioral intention variables. When examining the mediating effect of experience, it has been determined that there is a moderating effect of experience on the relationship between the habit variable and use behavior variable, as well as on the relationship between behavioral intention and use behavior variables.

Within the scope of this research, it was also revealed that which variable was explained and to what extent. According to the obtained results, the behavioral intention variable can be explained by other variables to the extent of 71%, while the use behavior variable can be explained by other variables to the extent of 32%.

When reviewing the literature, it is observed that there are similar studies. In our study, it was observed that the effort expectancy variable is a significant predictor of the behavioral intention variable. In studies conducted with university students by Al-Adwan et al. (2018a) and Al-Adwan et al. (2018b), it has been demonstrated that effort expectancy has a significant impact on mobile learning. Similarly, in a study conducted in Saudi Arabia, Alasmari and Zhang (2019) found that the effort expectancy variable predicts behavioral intention. In another study examining the acceptance of mobile technologies in mathematics education, Açıkgül and Şad (2021) also observed a significant effect of effort expectancy on behavioral intention. According to Açıkgül and Şad (2021), when mobile technologies have features that require less effort, behavioral intention is higher. On the other hand, Alowayr (2022), who focused on the acceptance of mobile learning in higher education, found that effort expectancy did not have a significant impact on behavioral intention.

In our study, it was also found that facilitating conditions significantly predict behavioral intention. Alowayr (2022), in a study based on the UTAUT model, concluded that facilitating conditions do not have a significant impact on the acceptance of learning. However, in the study conducted by Açıkgül and Şad

(2021), facilitating conditions were found to have a significant effect on behavioral intention. Açıkgül and Şad (2021) explain this by the increase in behavioral intention when students have the necessary knowledge, skills, and resources.

This study also demonstrates that hedonic motivation significantly predicts behavioral intention. Açıkgül and Şad (2021) have reached similar conclusions. This suggests that students' enjoyment while using mobile technologies for instructional purposes, both in mathematics education and other subjects, increases their behavioral intention.

The use of mobile technologies for educational purposes is related to habit. In our study, it was found that the habit variable significantly predicts behavioral intention. Similarly, Açıkgül and Şad (2021) concluded that the transformation of using a mobile technology for educational purposes into a habit affects behavioral intention.

In studies conducted using both the UTAUT and UTAUT2 models, the extent to which external variables explain internal variables has been examined. Our study indicates that the behavioral intention variable is explained by other variables to the extent of 71%, while the use behavior variable is explained by other variables to the extent of 32%. In Açıkgül and Şad's (2021) study, these percentages are 76% and 13%, respectively. In the study by Al-Adwan et al. (2018b), it is observed that behavioral intention is explained to the extent of 68%, while in Al-Adwan et al. (2018a), behavioral intention is explained to the extent of 64.8%.

This study has examined the moderating effects of age, gender, and experience within its scope, and similar studies can be found in the literature. Al-Adwan et al. (2018a) have shown that gender has a moderating effect on the relationship between certain components. Gender has been found to have a moderating effect on the relationship between the hedonic motivation variable and the behavioral intention variable, as well as between the facilitating conditions and the behavioral intention variable. However, in a study by Alasmari and Zhang (2019), gender does not have a moderating effect among the components of the UTAUT model.

When examining the moderating effect of age in our study, it was found that age has a moderating effect on the relationship between habit and use behavior variables. However, in Al-Adwan's (2018b) study, it was concluded that age does not have a moderating effect. Alasmari and Zhang (2019) also found that age does not have a moderating effect. Similarly, Alasmari and Zhang (2019) concluded that experience does not have a moderating effect. In our study, on the other hand, experience was found to have a moderating effect on the relationship between the habit variable and the use behavior variable, as well as on the relationship between behavioral intention and use behavior variables.

In light of this information, the use and acceptance of mobile technologies by digital natives can be examined based on the characteristics of digital natives. In this study, the sample group is referred to as digital natives according to the definition made by Joiner et al. (2013). Prensky (2001) described digital natives as being tech-savvy, inclined to acquire information quickly, prone to multitasking, and inclined toward active learning rather than passive learning. Digital natives, also known as Generation Y (Qingyang et al., 2018), have grown up with digital communication and use their smartphones for purposes such as connecting with the world (Smith, 2019). Digital natives create digital experiences by interacting with digital environments or technologies.

When examining the characteristics of digital natives within the scope of the UTAUT2 model, it is seen that the relationship between technology use and learning is complex for digital natives (Thompson, 2013). Therefore, this study serves as a guide to understanding digital natives' approach to mobile technology. Digital natives, although representing a generation born during a specific period, are not considered to be homogenous within themselves. This aspect is closely related to the usage behavior and intention of digital natives concerning mobile technologies. According to Wang et al. (2013), the natural inclination of digital natives toward digital technologies challenges technology acceptance models. Additionally, the most significant distinction between digital natives and digital immigrants is the resistance of digital immigrants to technology (Wang et al., 2013). However, this assumption does not necessarily mean that digital natives do not exhibit resistance to technology. The diversity of characteristics within digital natives raises questions about whether all digital natives have the same level of acceptance and usage of mobile technologies. As a result of this study, it was observed that the relationships of the sample group classified as digital natives with technology acceptance were not equally affected by the moderating effects of age, gender, and experience. Additionally, it was found that digital natives are more likely to convert behavioral intention when they habituate to mobile technologies. Moreover, the importance of social influence in converting mobile technologies into behavioral intention was found to be less significant, which suggests a need to reevaluate the characteristics of digital natives. According to this study, being inclined to use technologies like mobile technologies does not guarantee that digital natives will have high adoption behaviors and intentions when it comes to using them for learning purposes.

4.1. Research Limitations

This study has certain limitations. The original version of the UTAUT-2 model was used in the study. Additionally, the effects of more variables on the adoption and usage of mobile learning have not been explored. The research is limited to the components of the used model. Furthermore, this study is also limited to the design features of mobile technologies and tools. Since the data was obtained from a specific sample group, it has its own limitations. Therefore, caution should be exercised when making generalizations about the acceptance and usage of mobile learning tools by digital natives.

4.2. Future Work

In future studies, the research can be replicated with different sample groups to obtain diverse results. Accessing a larger sample size may lead to different findings. Additionally, the UTAUT-2 model used in this study can be retested by incorporating various additional variables. The results obtained from this study can serve as guidance for researchers in future studies.

5. DATA AVAILABILITY

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

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