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Conflict of Interest
The author (s) declared no conflict of interest and have not received any funds for the project.

Antecedents to Intention to Adopt Mobile Learning: A Moderating Model

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Abstract

Due to the availability of technology, most of the population worldwide has mobile access. Most mobile users use it for making calls or sending messages to friends and family members and are reluctant to use other advanced features such as accessing web pages and social forums. This study has extended the UTAT model to examine the factors (i.e., performance expectancy, effort expectancy, and social influence) that affect attitudes toward mobile learning. Also, the study examines the moderating roles of perceived risk. The study collected 355 responses from SMEs' employees in Karachi using a self-administered questionnaire. We used Smart PLS for data analysis and found that "performance expectancy, effort expectancy, and social expectancy significantly affect mobile learning." However, the effect of effort expectancy is negative. Also, the study results support the moderating roles of perceived risk. Based on the results, we suggest that SMEs must motivate employees to make more efforts to use mobile for learning. Many consumers are still concerned about the risk elements of using mobile for learning. Policymakers and managers must counsel employees that the risk factors have reduced considerably due to technological advancements. However, they may not share their information with non-reputable web pages and unknown numbers.

Keywords: *Performance expectancy, efforts expectancy, social influence, mobile learning, and UTAT model.*

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Introduction

The diffusion of telecommunication technology has changed the lifestyles of consumers. Banks, health, and other sectors extensively use it to communicate with consumers (Loorbach et al., 2020). Due to its availability and affordable price, mobile usage has increased significantly in this era of technology (Pantano & Vannucci, 2019; Woo & Magee, 2022). Many researchers believe mobile learning is an effective tool for learning and educational purposes (Bernacki, Greene, & Crompton, 2020; Almaiah et al., 2022). UNESCO strongly recommends that countries adopt new technology and make it available to majority of the population at affordable prices (Crompton & Burke, 2018).

Many studies have documented that despite the popularity and usage of mobile learning, it is below expectations (Granić & Marangunić, 2019; Lutfi et al., 2022). Thus this study examines critical antecedents that affect m-learning in SMEs. The effectiveness of both the information technology (IT) and information system (IS) depends on users' acceptance (Hu, Ding, Li, Chen, & Yang, 2019; Alsharida, Hammood, & Al-Emran, 2021). Many past studies have used different theoretical models to predict and explain user acceptance of IT or IS (Wang et al., 2020). Most studies have used the technological acceptance model (TAM) to understand consumers' attitudes and behavior toward adopting technology (Chao, 2019). At the same time, many researchers believe that the TAM model has several limitations (Zaineldeen, Hongbo, Koffi, & Hassan, 2020; Martín-García, Redolat, & Pinazo-Hernandis, 2022). For example, it does not provide adequate insight into the attitudes and behaviors of consumers.

Given its limitation, Venkatesh et al. (2003) developed a complete model by taking the core elements of eight models and theories and named it a Unified Theory of Acceptance and Use of Technology (UTAUT) Model. Since its introduction, various researchers have used it in diversified domains (Hoque & Sorwar, 2017; Czerwinska, 2020; Martín-García, Redolat, & Pinazo-Hernandis, 2022). The newly developed framework helps understand the acceptance of IT and IS and the actual usage of technologies. Given the versatility of the UTAUT model, this study has used it to examine the effect of technology-related factors on m-learning. Besides its versatility, many researchers believe the UTAUT model does not adequately explain individual attitudes and behavior toward technology acceptance (Patil, Tamilmani, Rana, & Raghavan, 2020; Hassan et al., 2022). Researchers can increase studies' predicting power by incorporating external variables in the model. Some researchers assert that incorporating variables such as "self-efficacy, trust, habits, satisfaction, and perceived risk" can increase its predictive power (Kabra, Ramesh, Akhtar, & Dash, 2017; Almaiah et al., 2022). This study has extended the UTAUT model and developed a conceptual framework with three antecedents, one moderator, and one dependent variable. Figure 1 depicts the developed conceptual framework.

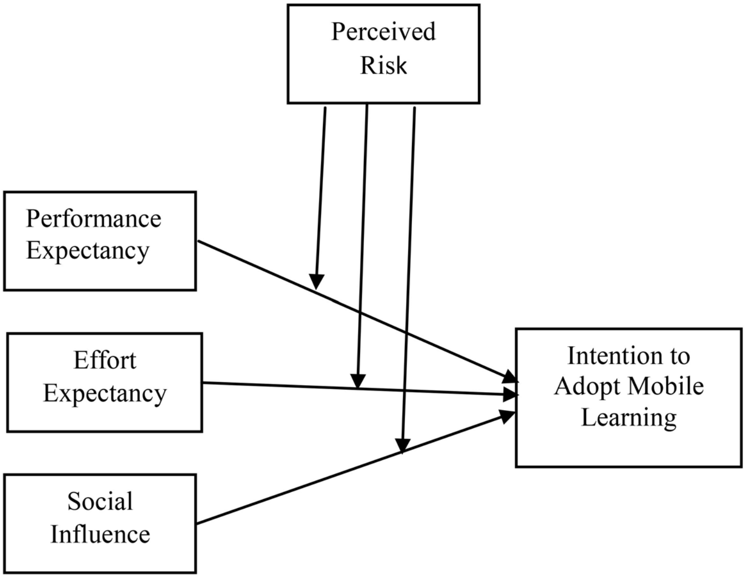

Figure 1: Conceptual Framework

Literature Review and Hypotheses Development

M-Learning

Due to mobile and wireless technology availability, individuals worldwide have started using mobile for learning and education purposes. Consequently, new terms such as "e-learning and m-learning" have emerged. Initially, the focus was on programmed instruction, followed by computer-assisted learning, internet-connected learning, and mobile learning. In the last few years use of IT has increased. Due to the usage and efficiency of mobile learning, many researchers have extensively studied it from different perspectives (Crompton & Burke, 2018; Hamidi & Jahanshaheefard, 2019; Pagé et al., 2022). M-learning is important compared to other devices as it allows one to learn anytime and anywhere. Despite its importance, researchers have conceptualized m-learning differently. Many researchers assert that m-learning promotes an environment that allows students to learn and interact (Hamidi & Chavoshi, 2018; Criollo et al., 2021). Sophonhiranrak (2021) argues that m-learning is effective if learners access information all the time and in all places through mobile technologies. The availability of such an environment motivates learners to participate in learning actively. Researchers assert that m-learning is a process with no constraint of fixed location and learning materials are accessible through mobile devices (Papadakis, 2021). Apart from other methods, mobile learning has many advantages, including learning materials, affordable and quick access to information, no restriction on location, and two-way communication (Hamidi & Jahanshaheefard, 2019; Al-Rahmi et al., 2021).

Performance Expectancy and Intention to Use Mobile

The effect of performance expectancy on m-learning is not linear, as it varies from one consumer to another. Researchers have examined its effectiveness in different domains (Nikolopoulou et al., 2021; Milošević et al., 2022). For example, Shin (2009) examined consumers' behavioral intentions in m-data services. The study has extended Technology Acceptance Model by incorporating perceived innovations and perceived cost to examine their effects on the behavior intention of m-learning. The study found that the usage rate of 3G technology is low. Studies document personal innovativeness stimulates the usage of 3G mobile technology. Perceived usefulness of m-learning increases with the ease of use resulting in a positive attitude towards m- learning (Yang, Song, Cheung, & Guan, 2022). Yu (2012) extended the UTAUT theory to examine the determinants of m-learning in the banking sector. Based on a sample of 441 drawn from the banking sector, the study found that "social influence and performance expectancy" significantly predict "mobile learning." These findings align with Tai and Ku (2013), who examined the attitude toward m-learning in Taiwan. Based on the dataset of 329 stock investors, the study concluded that performance expectancy is a significant factor that stimulates a positive attitude towards mobile learning. Extant literature also suggests that consumers adopt m-learning if they perceive the new technology could be helpful and useful (Lee, Xu, & Porterfield, 2022).

Performance expectancy is the consumer perception that mobile usage will enhance learning (Lui et al., 2021; Sabri et al., 2022). Extant literature suggests inconclusive results regarding the perceived usefulness and behavioral intention of adopting m-learning. For example, Liébana-Cabanillas et al. (2017) found that perceived usefulness stimulates consumer intention towards mobile learning. On the contrary, Zhang et al. (2012) reported an insignificant association.

Many researchers have documented that performance expectancy significantly affects m-learning (Oliveira et al., 2016; Su & Chao, 2022; Milošević et al., 2020). Performance expectancy also measures relative advantage and extrinsic motivation. Therefore, researchers believe it is more important than perceived usefulness (Milošević et al., 2022). Thus the effect of performance on adopting m-learning would differ from the perceived usefulness (Wairiya, Sahu, & Tyagi, 2022). A study on the Jordanian banking sector extended the UTAUT model to examine the effect of performance expectancy, effort expectancy, and five other variables. Based on 343 respondents, the study concluded that all factors, including performance expectancy, social influence, and effort expectancy, motivate banking employees to adopt mobile for learning purposes.

H1: "Performance expectancy" positively affects "intention to adopt m-learning."

Effort Expectancy and Mobile Use

Effort expectancy explains how consumers perceive the technology as easy to use (Su & Chao, 2022). Adopting mobile technology for learning varies from one culture to another. A study on behavior intention in Singapore based on 264 responses found that "effort expectancy affects consumers' intention to adopt mobile learning." Contrary to the UTAUT model, the study found that age and gender moderate "effort expectancy and intention to adopt m-learning." Thus, the study concluded that the UTAUT model might give different results when applied to different cultures (Teo & Noyes, 2014). Researchers have documented that "effort expectancy is an important predictor of intention to adopt m-learning" only if consumers believe that the new technology is easy to use (Winata & Tjokrosaputro, 2022). Tan et al. (2012) also found that easy to use, a sub-determinant of effort expectancy, significantly affects attitude towards m-learning. The results of the discussed study are based on a sample size of 402 Malaysian consumers and multiple regression analysis. Researchers also believe young consumers are more motivated to adopt mobile for learning than old consumers, as the younger generation is well-versed in mobile-related technology (Bylok, 2022).

Another study based on the TAM model examined the moderating effect of individualism and collectivism on adopting m-learning. The study found that perceived usefulness and ease of use stimulate positive attitudes toward m-learning. The study also found that individualism and collectivism have a moderating effect on attitudes toward mobile learning. Also, another study in Jordan validated the association between effort expectancy and attitude toward m-learning. Contrarily, the extant literature found that "effort expectancy and intention to adopt m-learning" have an insignificant relationship (Oliveira et al., 2016). Many studies found an indirect association "between effort expectancy and intention to adopt mobile learning." These studies found that performance expectancy mediates "effort expectancy and intention to adopt m-learning" (Orosa-Duarte et al., 2021; Sair & Danish, 2018).

Another study in Tawain extended the UTAUT model and Hofstede's cultural dimensions for understanding consumers' attitudes toward m-learning. Based on 435 responses, the study concluded that "effort expectation, performance expectation," and other variables promote positive attitudes toward mobile learning. The study also found that power distance moderates "the intention to adopt mobile learning" (Hwang et al., 2021).

H2: "Effort expectancy" positively affects "intention to adopt m-learning."

Perceived Risk and Intention to Adopt M-Learning

Bauer (1960) coined the concept of perceived risk. Perceived risk refers to consumer uncertainty about whether the goods purchased deliver what they expect and what the seller promised. Perceived risk is a multi-dimension construct including "financial risk, physical risk, social risk, time loss risk, and psychological risk" (Qalati et al., 2021; Bangkit, Tumbuan, & Tielung, 2022). Perceived risk varies from one product category to another. Generally, it is higher in technology, and internet-related transactions as consumers are unsure whether their data will remain secure. Many studies have documented that consumers negatively perceive mobile services and online banking (Noreen et al., 2021; Sharma, Singh, & Pratt, 2022).

While adopting mobile technology, consumers are concerned about many risk factors, including "privacy problems, system errors, losing passwords, incompatibility of mobile operating systems and security" (Jain, Bhaskar, & Jain, 2022). Due to these risk perceptions, consumers are reluctant to adopt mobile technology for learning purposes. The association of risk factors varies from one age group to another. It is low in the low age group and high in higher age strata. Similarly, in terms of gender, the studies have documented females have a negative perception of perceived risk and an intention to adopt mobile technology for teaching (Noreen et al., 2021).

Similarly, studies have documented that the collective society has a negative perception of perceived risk, which makes it reluctant to adopt mobile technology. At the same time, individualist societies have fewer negative perceptions of perceived risk. Therefore they are more motivated to adopt mobile technology for learning purposes. Based on extant literature, we can conclude that if perceived risk perception is low, adopting new technology will be higher and vice versa (Al-Saedi et al., 2019).

H3: "Perceived risk " positively affects "intention to adopt m-learning."

Social Influence Peers and Intention to Mobile Learning

Organizational culture and social norms are factors of social influence in adopting new technology. Extant literature suggests that "social influence promotes positive attitudes toward new technology" (Lall et al., 2019; Chavoshi & Hamidi, 2019; Lutfi et al., 2022). When individuals see their peers and family using mobile technology for learning, it motivates them to adopt new technology. Subjective norms are also an important aspect of social influence. Social norms are the perceived pressure of friends and peers to perform or not perform a given behavior (Ajzen, 2011). Individuals with high subjective norms adapt to friends' behavior, including new technology. At the same time, individuals with low subjective norms do not adapt the behavior of their friends and peers (Alaba, Abass, & Igwe, 2022). Studies have documented that subjective norms influence the adoption of new technology (Rejón-Guardia et al., 2020; Buabeng-Andoh, 2021), but it varies with age group. It is higher in the low age group and lower in the high age strata (Mhlana et al., 2022). A study extended the TAM model and the UTAUT model to examine the effect of social influence and other factors on adopting new technology and found that social influence has an insignificant effect on adopting new technology (Naveed, Alam, & Tairan, 2020). Maniar, Bennett, Hand, and Allan (2008) extended the TAM model to understand consumers' attitudes toward adopting mobile for learning purposes. The study found that subjective norms significantly affect adopting technology. Many technology acceptance studies have empirically validated the association of social norms and attitudes toward adopting new technology for learning (Lucas Jr & Spitler, 2000; Wong et al., 2022; Yeoh et al., 2022).

H4: Social influence stimulates a positive attitude toward mobile technology.

Moderating Effect of Perceived Risk

While adopting new technology, perceived risk can increase or decrease the association between (i) "performance expectancy and intention to adopt m-learning" and (ii) "effort expectancy and intention to adopt m-learning." While adopting technology, mobile consumers are concerned about risk factors, including "privacy problems, system errors, losing passwords, incompatibility of mobile operating systems and security" (Jain, Bhaskar, & Jain, 2022). Extant literature documents that perceived risk is critical for adopting new technology. If the perceived risk is high, the adoption of new technology will be lower (Al-Saedi et al., 2019). Consumers will adopt the technology rapidly if they perceive it riskless. Researchers believe that perceived risk relates to potential loss while using e-services (Lafraxo, Hadri, Amhal, & Rossafi, 2018). Many past studies have used perceived risk as the UTAUT model's external variable (Mahardika & Giantari, 2020). Further, researchers believe that perceived risk can affect the association between performance expectancy and intention to adopt new technology. It also affects the association between effort expectancy and attitude toward new technology (Wei, Luh, Huang, & Chang, 2021). We only found one study that has used perceived risk as a moderator between (i) performance expectancy and intention to adopt new technology and (ii) effort expectancy and intention to adopt new technology. This study's contribution is that it has incorporated "perceived risk in UTAUT concerning m-learning." Many past studies support social influence significantly affects the intention to adopt new technology.

H5: Perceived risk moderates "performance expectancy and intention to adopt mobile learning."

H6: Perceived risk moderates "effort expectancy and intention to adopt mobile learning."

H7: Perceived risk moderates "social influence and intention to adopt mobile learning."

Research Design

This study is quantitative research and it has tested seven relationships empirically. We have collected the primary data from selected SMEs in Karachi. The approach used in the study is deductive because we have developed hypotheses based on the existing literature and relevant theories which we empirically tested by collecting the data from SMSs employees. The questionnaire was adapted from the previous studies which we have used for data collection.

Population and Sample

There are various opinions on the sample size for primary data collection. Sekaran and Bougie (2016) suggest selecting 30 samples for each variable in a study. Hair Jr et al. (2017) suggest 5 to 30 samples for each indicator variable. We distributed 400 questionnaires and received 375 responses. After dropping incomplete cases, we had 355 valid cases.

Instrumentation

The instrument developed for our research has five latent and 18 indicator variables. The study measured the responses on a five-point Likert Scale. "One suggests strongly disagree, and five suggests strongly agree." Table 1 depicts the summary of the instrument used in the study.

Table 1: Scales and Measures

Construct	Sources	Items	Reliability in Past studies
Performance Expectancy	Lowenthal (2010a)	4	0.829 to 0.720
Effort Expectancy	Lowenthal (2010b)	3	0.822 to 0.855
Social Influence	Olaleye and Sanusi (2019)	3	0.748 to 0.852
Perceived Risk	Wei et al. (2021)	5	0.728 to 0.764
Intention to Adopt M Learning	Lowenthal (2010a)	3	0.882 to 0.874

Statistical Analysis

The study examined the predictive power of the measurement model and fit indices. The analysis includes descriptive, "internal consistency and validity". The software we used in the study is Smart PLS version 4.

Results and Findings

Profile the Respondents

In this study, we received 355 responses and respondents profile is presented in Table 2.

Table 2: Demographics of the Respondents Surveyed in this Study

Variables	Frequency	Percentage
Gender		
Male	245	69%
Female	110	31%
Age		
Less than 20 years	0	0%
21 - 30 years	174	49%
31 - 40 years	156	44%
41 - 50 years	14	4
51 and above	11	3
Qualifications		
Matriculation/O-Levels or below	43	12%
Intermediate/A-Levels	110	31%
Diploma	53	15%
Bachelors	78	22%
Masters and above	71	20%
Income Level		
PKR 50,000 or below	75	21%
PKR 50,001 - 100,000	216	61%
PKR 100,001 - 150,000	42	12%
PKR 150,001 - 200,000	4	1%
PKR 200,001 and above	18	5%
No. of Employees		
100 or below	18	5%
101 – 200	07	2%
201 – 300	36	10%
301 – 400	131	37%
401 and above	163	46%

Descriptive Statistics

Table 3 depicts results related to the internal consistency and the shapes of Skewness and Kurtosis.

Table 3: Descriptive Results

	Cronbach's Alpha	Mean	Std. Dev.	Skewness	Kurtosis
Performance Expectancy	0.801	3.980	1.380	2.740	-2.650
Effort Expectancy	0.753	3.910	1.580	-2.430	-2.850
Social Influence	0.880	3.840	2.410	-1.990	1.970
Perceived Risk	0.716	3.960	1.990	2.310	2.890
Intention to Adopt Mobile Learning	0.844	3.570	1.730	2.090	-1.880

The results show that the Skewness and Kurtosis values ranged between ±3.50, suggesting the constructs have univariate normality. "Cronbach's values are greater than 0.70, suggesting the constructs have acceptable internal consistency."

Convergent and Discriminant Validity

Table 4 presents the results relating to "convergent and discriminant validities" .

Table 4: Convergent and Discriminant Validity

	Composite Reliability	(AVE)	PE	EF	SI	PR	IAML
Performance Expectancy	0.869	0.625	0.791				
Effort Expectancy	0.842	0.675	0.728	0.759			
Social Influence	0.926	0.807	0.688	0.732	0.898		
Perceived Risk	0.837	0.633	0.669	0.539	0.534	0.795	
Intention to Adopt Mobile Learning	0.891	0.671	0.779	0.558	0.564	0.713	0.819

The results show that all the composite reliability values are greater than 0.70 and AVE values greater than 0.60, suggesting the constructs do not deviate from the requirements of convergent validity. The results also "suggest that the constructs used in the study are unique and distinct since all AVE square route values are greater than Pearson correlation values."

Common Method Bias

Common method bias can adversely affect the results. Therefore, the study used Harman's single-factor with five and 19 indicator variables. The statistical results indicate that no single factor emerged as the first factor. It also accounted for 48.78% of the variance, which is less than the cut-off value of 50%, suggesting the data is not infected with common method bias (Harman, 1967).

Measurement Model's Predictive Power

The R square values presented in Table 5 show they are higher than 0.20 and all the Q square values presented in Table 6 are greater than 0, suggesting adequate predictive relevance of the model.

Table 5: R-Square Values

	R Square	R Square Adjusted
Effort Expectancy	0.291	0.290
Intention to Adopt Mobile Learning	0.685	0.683
Performance _Expectancy	0.448	0.447
Social Influence	0.285	0.284

Table 6: Q Square Values

	SSO	SSE	Q^2 (1-SSE/SSO)
Effort Expectancy	4792	4014.637	0.162
Intention to Adopt Mobile Learning	4792	2610.565	0.455
Performance Expectancy	4792	3464.91	0.277
Social Influence	3594	2778.365	0.227

Fit Indices

Table 7 shows that the "SRMR values are less than 0.08 and the NFI value are greater than 0.800." Given these results, we have inferred the measurement model fits adequately.

Table 7: Fit Indices

	Saturated Model	Estimated Model
SRMR	0.075	0.078
d_ULS	1.231	4.283
d_G	0.526	0.743
Chi-Square	3559.291	4491.144
NFI	0.834	0.890

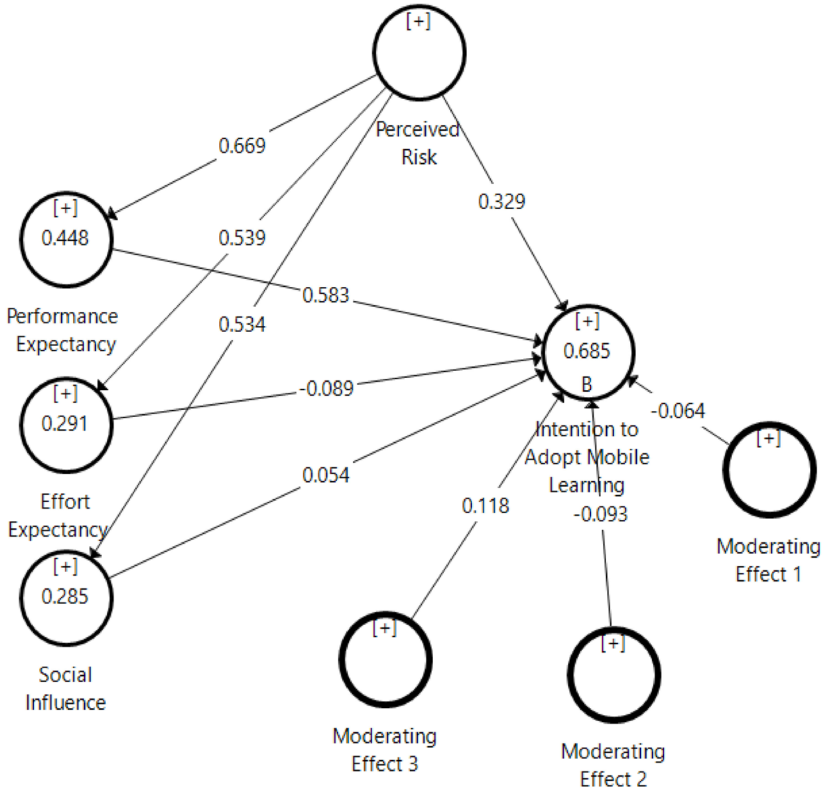

Figure 2: Measurement Model

Hypothesis Results

The study has tested four direct and three moderating relationships based on bootstrapping. The summarized results are presented in Table 8, and structural model in Figure 3.

Table 8: Hypotheses Testing Results

	Beta	T-value	P value	Results
Per. Expectancy -> Inten. to Adopt Mobile Learning (H1)	0.583	15.513	0.000	Accepted
Effort Expectancy -> Inten. to Adopt Mobile Learning (H2)	-0.089	3.274	0.001	Rejected
Perceived Risk -> Intention to Adopt Mobile Learning (H3)	0.329	11.650	0.001	Accepted
Social Influence -> Inten. to Adopt Mobile Learning (H4)	0.054	2.07	0.039	Accepted
Moderating Effect 1 -> Intent. to Adopt Mobile Learning(H5)	-0.064	3.205	0.001	Accepted
Moderating Effect 2 -> Inten. to Adopt Mobile Learning (H6)	-0.093	3.455	0.001	Accepted
Moderating Effect 3 -> Inten. to Adopt Mobile Learning (H7)	0.118	5.814	0.000	Accepted

We did not find support for hypothesis 2, stating, "effort expectancy positively affects intention to adopt mobile learning." However, our results support all three moderating hypotheses.

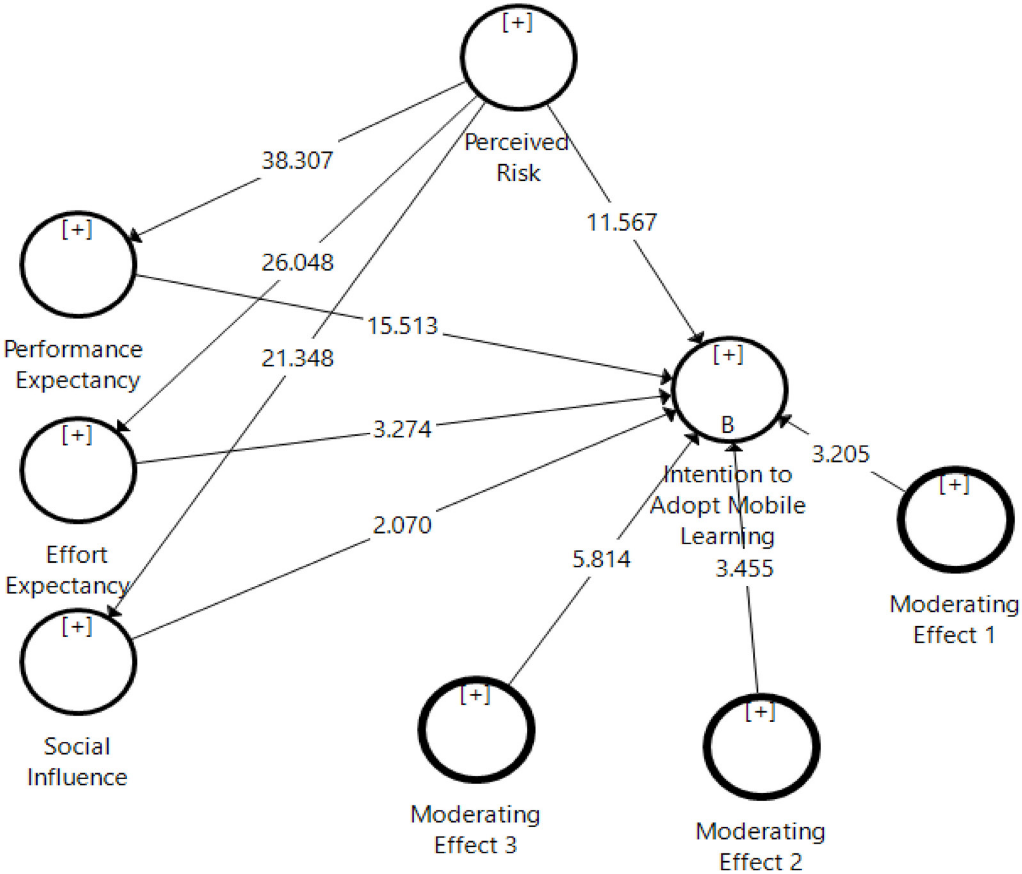

Figure 2: Structural Model of the Study Depicting Results

Discussion and Conclusion

Discussion

This study examined antecedents of the "intention to adopt mobile learning" in SMEs in Karachi. The developed model is unique as it has integrated "performance expectancy, effort expectancy, and perceived risk" into the UTAUT model to understand how these factors affect the intention to adopt mobile learning. This model also examines the moderating roles of "perceived risk on the intention to adopt mobile learning." The results of a cross-sectional survey found that important antecedents of mobile learning in order of relevance are performance expectancy, perceived risk, and social influence.

Effort expectancy, though, has an inverse impact.

The study also found the negative moderating role of perceived risk on (i) "performance expectancy and intention to adopt m-learning" and (ii) "Effort expectancy and intention to adopt m-learning." The empirical results and their interpretation are as follows. "Performance expectancy" strongly affects the "intention to adopt mobile learning," followed by "perceived risk and social influence." Our "performance expectancy and social influence" results are consistent with earlier studies' findings (Kabra et al., 2017; Fedorko, Bačik, & Gavurova, 2021; Kofoworola & Ojo, 2022). However, contrary to past studies, we found a "negative association between effort expectancy and intention to adopt m-learning." Thus performance expectancy and social influence are critical factors in motivating employees to adopt m-learning. In the context of SMEs in Pakistan, the young population is already well-versed in using technology, and it would be easier for policymakers to adopt mobile learning to increase their competitiveness. However, the old generation has mobile access but is reluctant to use mobiles for learning purposes. Since the internet is still evolving, young people learn through face-to-face teaching and m-learning.

Many employees in SMEs understand the importance of e-learning and m-learning as they realize such learning has no time and space constraints. In the case of Pakistan, most of the employees have mobile access. Therefore, motivating them to use mobile for learning purposes would not be challenging for SMEs' management. Thus the SMEs in Pakistan must provide an environment where they can share and communicate what they have learned. In the process, the reluctant employees to use mobile for learning would adopt the process, especially considering that social influence significantly affects using mobile for learning purposes. In this study, we used perceived risk as moderator to intention to adopt mobile learning. We found that perceived risk significantly moderates (i) "Performance expectancy and intention to adopt mobile learning," (ii) "Effort expectancy and intention to adopt mobile learning," and (iii) "Social influence and intention to adopt mobile learning." But the moderating effect of perceived risk is negative for the two associations. Thus, while promoting mobile learning, SMEs must educate employees that the perceived risk elements have decreased significantly due to new technology development.

Conclusion

We developed a new integrative model to understand SMEs "employees' intention to adopt mobile learning." Based on the UTAUT model, this study has incorporated four variables in the new model: "performance expectancy, effort expectancy, social expectancy, and perceived risk." The study collected 355 cases from SMEs employees in

Karachi. The fit indices, R square and Q square values were within the prescribed limits suggesting adequate predictive power. The study found that performance and social influence positively affect “intention to adopt mobile learning, and effort expectancy negatively affects intention to adopt mobile learning.” Perceived risk negatively moderates (i) “performance expectancy and intention to adopt mobile learning and (ii) effort expectancy and intention to adopt mobile learning”. Whereas perceived risk has a “positive moderating effect on social influence and intention to adopt mobile learning.”

Limitations and Future Research

We found several limitations that other researchers can address in their studies. This study has focused on SMEs in Karachi, and other studies can focus on other sectors, including large-scale manufacturing and service. Our study has a cross-sectional design. SME employees’ perception changes over a while. Therefore, future studies can adopt a longitudinal research design. This study has used perceived risk as a moderator. Future researchers may use factors such as trust, literacy, gender, and cultural as moderating variables. Also, unlike this study, other researchers can extend this study model to other cities and comparative studies.

Annexure 1

Constructs and Items used in the Questionnaire
Performance Expectancy
PE1. I would find m-learning useful in my learning.
PE2. Using m-learning would enable me to accomplish learning activities more quickly.
PE3. Using m-learning would increase my learning productivity.
PE4. If I use m-learning, I will increase my chances of getting a better grade in class.
Effort Expectancy
EE1. It would be easy for me to become skillful at using m-learning.
EE2. I would find m-learning easy to use.
EE3. The electronic invoicing system would be flexible to implement and utilized.
Social Influence
SI1. Business partners think my firm should be use m-learning.
SI2. In general, the business communities think my firm should use m-learning.
SI3. People who are important to me think our firm should use m-learning.
Perceived Risk
PRI. Adoption of m-learning by my firm is financially risky.
PR2. Using a consultant to implement m-learning in my firm is financially risky.
PR3. Using m-learning may encounter unreasonable charges..
PR4. My firm is concerned about data security and privacy on the internet.
PR5. My firm considers that online transactions are not sufficiently protected by the laws.
Intention to Adopt Mobile Learning
BI1. I intend to use m-learning in the future.
BI2. I predict I will use m-learning in the future.
BI3. If available, I plan to use m-learning in the future.

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