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Research Article

Analysis Of Quality Of Mobile Learning (QML) And Its Sustainable Use: Task Technology Fit & Expectation Confirmation Approach

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ABSTRACT

The purpose of the study was to analyze the quality of mobile learning from the perspective of the students studying in higher educational institutions. The sustainable use of mobile learning and satisfaction of students were analyzed using task-technology fit, expectation-confirmation model and input output model. The study was confirmatory in nature and cross-sectional research design was used. 321 students were selected using convenience sampling method from seven different higher educational institutions of Gujarat (India). The structured questionnaire was used to collect the data. Two multiple linear regression models were used to identify the predictors of satisfaction and sustainable use of mobile learning. SPSS was used to analyze the data. The results indicate that satisfaction of the students from mobile learning is more influenced by process part while sustainable use of mobile learning is influenced by resource part of mobile learning.

Keywords: m-learning, sustainable use, task technology fit, expectation confirmation, higher education institutions.

1. Introduction

Mobile is considered as key enabler of sustainable economic growth and value driver in terms of satisfying United Nations' 17 Sustainable Development Goals (SDGs) (Granryd, 2018; Kim, 2020). Post COVID-19 pandemic, institutions globally have migrated from traditional face-to-face (F2F) learning to online learning to achieve the objectives of Sustainable Development Goal Four (SDG4) (Adarkwah & Huang, 2023). The study of Maketo et al. (2023) shows that mobile technologies can facilitate the achievement of SDG4. The global corporate e-learning market size is estimated to increase by USD 44,908.64 million from 2022 to 2027 with a CAGR of 12.19% (Yahoo Finance, 2022). The sustainability of mobile learning refers to its ability to address current educational needs and intent, possibility of high adoption, scope for its progress and its adaptability for improvement (Setirek & Tanrikulu, 2015). In July 2020, the Government of India came up with National Education Policy (NEP) to transform educational system and provide quality education to all. It was found that almost 50 per cent of Indian students lack the required infrastructure as they live in areas with low digital penetration (Singh, 2023). To bridge this gap, National Digital Education Architecture (NDEAR) was launched as key enabler of NEP2020 with a vision to create unifying national digital infrastructure to energize and catalyze the education ecosystem. Mobile learning is found dominant amongst Indian students when it comes to online learning. According to India Lockdown Learning Report, 79 percent of students in India used smartphone as medium of online learning, 17 percent used laptops while 4 percent resort to tablets (Ahaskar, 2020). The area of sustainable use of technology in education has not been explored in depth and requires research efforts (Moya & Camacho, 2023). Further, there is a dearth of studies that address the issue of sustainable use of mobile learning and its quality from the perspectives of students in higher education. The present study addressed this research gap and aimed to analyze quality of mobile learning factors combining task technology fit, expectation-confirmation model and input out model.

2. Literature Review

2.1 Mobile Learning

There is a lack of consensus on definition of mobile learning (Brantes Ferreira et al., 2013) also known as m-learning. However, it can be understood as use of mobile technologies to facilitate learning (Hwang & Tsai, 2011). According to Peng et al. (2009), the literature on mobile learning emphasized on different aspects like functionality, mobility and ubiquity. These features are analyzed while discussing the concept of m-learning. There are several studies that have been carried out to analyze components of mobile learning. Alfalah (2023) analysed university students' behavioural intention towards mobile learning management systems using UTAUT model and other external variables. M. Almaiah et al. (2022) proposed a framework technical quality requirement for mobile learning apps. The framework comprised of six dimensions interactivity, functionality, Interface design, accessibility, learning content quality, content design quality. Ng & Nicholas (2013) have proposed a person-centred sustainable model for mobile learning using dimensions like economic sustainability, social sustainability, political sustainability, technological sustainability, pedagogical sustainability. Motiwalla (2007) provided m learning application framework using mobile connectivity and e learning. Koole (2006) considered (a) usability (b) learner (c) social aspects and provided the Framework for the Rational Analysis of Mobile Education (FRAME) model to assess mobile learning.

2.2 Theories and Models

2.2.1 Task Technology Fit (TTF)

Task Technology Fit (TTF) model originally developed by Goodhue and Thompson (1995) is also used widely in information system literature. The model assumes that there should be an alignment (task technology fit) between specific task of a user (task characteristics) and the capability of technology (technology characteristics) (Figure 1).

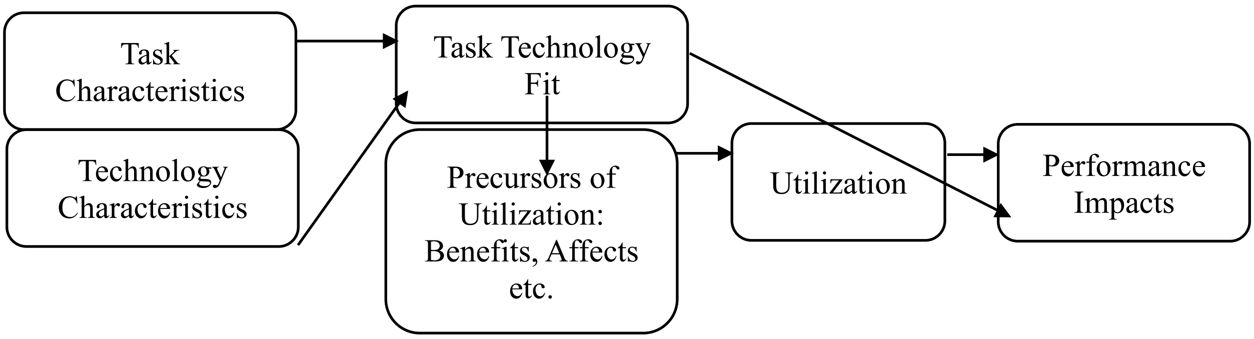


Figure 1 Task Technology Fit (Source: Goodhue and Thompson, 1995)

Utilization is the behaviour of employing the technology in completing tasks while performance impact refers to the accomplishment of a portfolio of tasks by an individual (Goodhue and Thompson, 1995). With reference to mobile learning, task technology fit refers to the alignment between capacity of mobile technology (technology characteristics) and students' learning abilities and their tasks (task characteristics) that may include learning from quality content, learning from peers or attempting quizzes etc.

2.2.2 Expectation Confirmation Model

Expectation Confirmation Model was proposed by Bhattacherjee (2001) and it is based on the expectation confirmation theory (ECT) which was introduced by Oliver (1980) (Cheng, 2021). Accordingly, a customer before purchasing product or service has an expectation regarding its performance. Post consumption, he or she will confirm the extent to which the expectation is fulfilled and level of satisfaction derived. If customer is satisfied; he or she will continue its usage or consumption in future (Figure 2).
In information system literature, expectation-confirmation refers to users' perception of the congruence between expectation of technology use and its actual performance (Bhattacherjee, 2001; Davis, 1989; as cited in Joo et al., 2016).

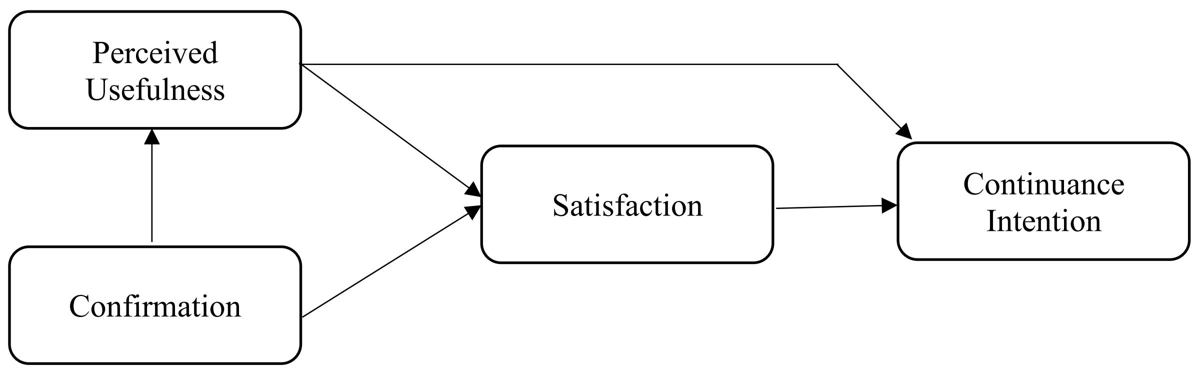


Figure: 2 Expectation Confirmation Model (Source: Bhattacherjee 2001)

In case of mobile learning, if students are satisfied, they would use mobile technology on a continuous basis. Therefore, several studies have used expectation confirmation model to analyze users' continuous intention. Alshurideh et al. (2020) used Technology Acceptance Model (TAM) and Expectation Confirmation Model (ECM) to study the continuance intention and actual usage of mobile learning system with reference to higher education setting in UAE.

2.2.3 Input Output Model & Quality of Mobile Learning

With reference to quality of mobile learning (QBL), M. Almaiah et al. (2022) have categorized past studies emphasizing quality into software quality, information system quality and service quality models. Isaac et al. (2019) analyzed overall quality of online education as second order construct using service, system, and information qualities. Further, they combined Task Technology Fit (TTF) and found significant influence on performance impact. Further, Esfijani (2018) carried out a meta synthesis review of quality of online education and prepared a list of indicators to assess quality of online education using input output model. The list included procedural dimensions and composed of various aspects like inputs, resources, processes, and outcomes/outputs.

2.3 Research Hypotheses

The objective of the study is to analyze quality of mobile learning using task technology fit, expectation confirmation model and input out model. Therefore, the following constructs were identified and hypotheses were developed.

2.3.1 Task Technology Fit

TTF measures how well a technology helps an individual complete their portfolio of tasks; tasks are roughly defined as the actions people do to transform inputs into outputs, while technologies are seen as the tools people use to complete their duties (Cheng, 2019). If students understand that using technology would help them carry out their daily chores properly, they will adopt it without a doubt (Alyoussef, 2021). Lin (2012) integrated information system continuance theory with task technology fit to analyze perceived fit and satisfaction for Virtual Learning System (VLS) and found the significance impact of task technology fit on satisfaction from VLS. Further, other studies on internet usage (Isaac et al., 2017) and smartwatch (El-Masri et al., 2022) also found significant impact of TTF on satisfaction.
Therefore, we propose following hypotheses;
H1 (a): Task-technology fit will positively affect satisfaction from mobile learning.
H1 (b): Task-technology fit will positively affect sustainable use of mobile learning.

2.3.2 Self Directed Learning

Self-directed learning is described as learning on one's initiative, with the learner taking major responsibility for the design, implementation, and evaluation of the effort (Salah Dogham et al., 2022). According to Kim et al. (2014) when a course adopts a personalized and collaborative learning approach that enables students to be more proactive in planning, organizing, and monitoring their course activities, students' SDL skills can increase. The literature on self-directed learning supported its relationship with satisfaction (Brockett, 1985; Schweder & Raufelder, 2021; Zhu et al., 2023).
Hence, we can hypothesize that;
H2 (a): Self-directed learning will positively affect satisfaction from mobile learning.
H2 (b): Self-directed learning will positively affect sustainable use of mobile learning.

2.3.3 Computer Self Efficacy

Computer self-efficacy refers to an individual's belief in his or her ability to use a computer effectively. (Compeau & Higgins, 1995; Marakas et al., 1998; Simmering et al., 2009). As students' confidence improves, they will be more comfortable using e-learning resources as a source of additional knowledge during lectures. Lim (2001) found that learners with high computer self-efficacy are more satisfied in web-based distance education courses. Shen et al. (2013) carried out a survey of 406 students of online courses to analyze the multiple dimensions of online self-efficacy. They found four dimensions of self-efficacy viz. complete online course, socially interactions with classmates, interactions with instructors and interaction with classmates for academic purpose as significant predictors of learning satisfaction.
Therefore, we propose following hypothesis;
H3 (a): Computer self-efficacy will positively affect satisfaction from mobile learning.
H3 (b): Computer self-efficacy will positively affect sustainable use of mobile learning.

2.3.4 Learning Content Quality

The learning content quality refers to suitability of the content for users in terms of reliability, currentness, and appropriateness (Rieh, 2002; Almaiah et al., 2016). Further, it should be in alignment with learners' needs. Young & Norgard (2006) carried out a survey to assess quality of online courses from the students' perspective. They considered online course design, online course interaction, online course content (content quality), online course support and online vs. face-to-face courses as important constructs to analyze the quality. They found 94 percent of the students have agreed that content quality of course is important for their course discussions. Further, studies on online service quality confirmed content quality of website to be an important determinant of its continuous usage that leads to satisfaction (Udo et al., 2011; Faisal et al., 2020). Accordingly, it is hypothesized that
H4 (a): Learning content quality will positively affect satisfaction from mobile learning.
H4 (b): Learning content quality will positively affect sustainable use of mobile learning.

2.3.5. Accessibility

Accessibility refers to the practice of making e-learning systems accessible to a wide range of people (Seale, 2014; Mikic et al., 2007). Past studies that were conducted during COVID-19 pandemic showed that accessibility of online courses had significant impact on satisfaction of the students from online learning (Ranadewa et al., 2021; Aboagye et al., 2020; Qazi et al., 2020; Kapasia et al., 2020). Ranadewa et al. (2021) in their concept paper hypothesized that accessibility is found to have relationship with satisfaction. Further, it is also considered as significant contributor for Education for Sustainable Development (ESD) that can further help in achieving Sustainable Development Goals (SDGs.) (Timbi-Sisalima et al., 2022).
Hence, it is hypothesized that;
H5 (a): Accessibility will positively affect satisfaction from mobile learning.
H5 (b): Accessibility will positively affect sustainable use of mobile learning.

2.3.6. Interactivity

Interactivity refers to the interactions between learners and instructors and among learners themselves, and the collaboration in learning that results from these interactions (Palloff and Pratt, 1999; Pituch and Lee, 2006; Cheng, 2012). Choi et al. (2007) observed that interaction plays an important role in online education. Interaction worked as feedback mechanism also. They found significant relationship between interaction and flow experience in case of web-based ERP training. If students perceive interactivity to be useful in their learning, they would be satisfied from learning and will continue to use mobile learning. Elshami et al. (2021) found significant correlation between the overall satisfaction of students and interactivity. Therefore, it is hypothesized that
H6 (a): Interactivity will positively affect satisfaction from mobile learning.
H6 (b): Interactivity will positively affect sustainable use of mobile learning.

2.3.7 Confirmation

Expectation confirmation (EC) also known as confirmation refers to users' perceptions of the congruence between the expectation of information system usage and its actual performance (Bhattacherjee 2001, Al-Emran et al., 2020). Ambalov (2018) conducted meta-analysis on expectation confirmation model with reference to IS continuance model using 51 studies published during 2001 to 2017. They found strongest relationship between confirmation and satisfaction. Similarly, Alshurideh et al. (2020) found positive influence of confirmation on satisfaction from use of mobile learning system. Further, Al-Sharafi et al. (2022) also supported this hypothesis and found satisfaction of using chatbot leading to its sustainable use. Accordingly, we proposed that
H7 (a): Interactivity will positively affect satisfaction from mobile learning.
H7 (b): Interactivity will positively affect sustainable use of mobile learning.

2.3.8 Satisfaction

In the online learning system context, user satisfaction can be described as the extent to which learners believe the online learning system meets their online learning needs (Alshare et al., 2011). Past studies showed several

predictors of students' satisfaction that include student interaction, social ability, reputation of university, computer self-efficacy, course content, self-regulation, task value, intrinsic goal value and perceived usefulness. (Landrum et al., 2021; Parahoo et al., 2016; Landrum et al., 2021). Al-Sharafi et al. (2022) observed satisfaction is the main driver of continuous usage intention (Zhang et al., 2022) that can lead to sustainable use. The following hypothesis, therefore, is proposed
H8: Satisfaction will positively affect sustainable use of mobile learning.

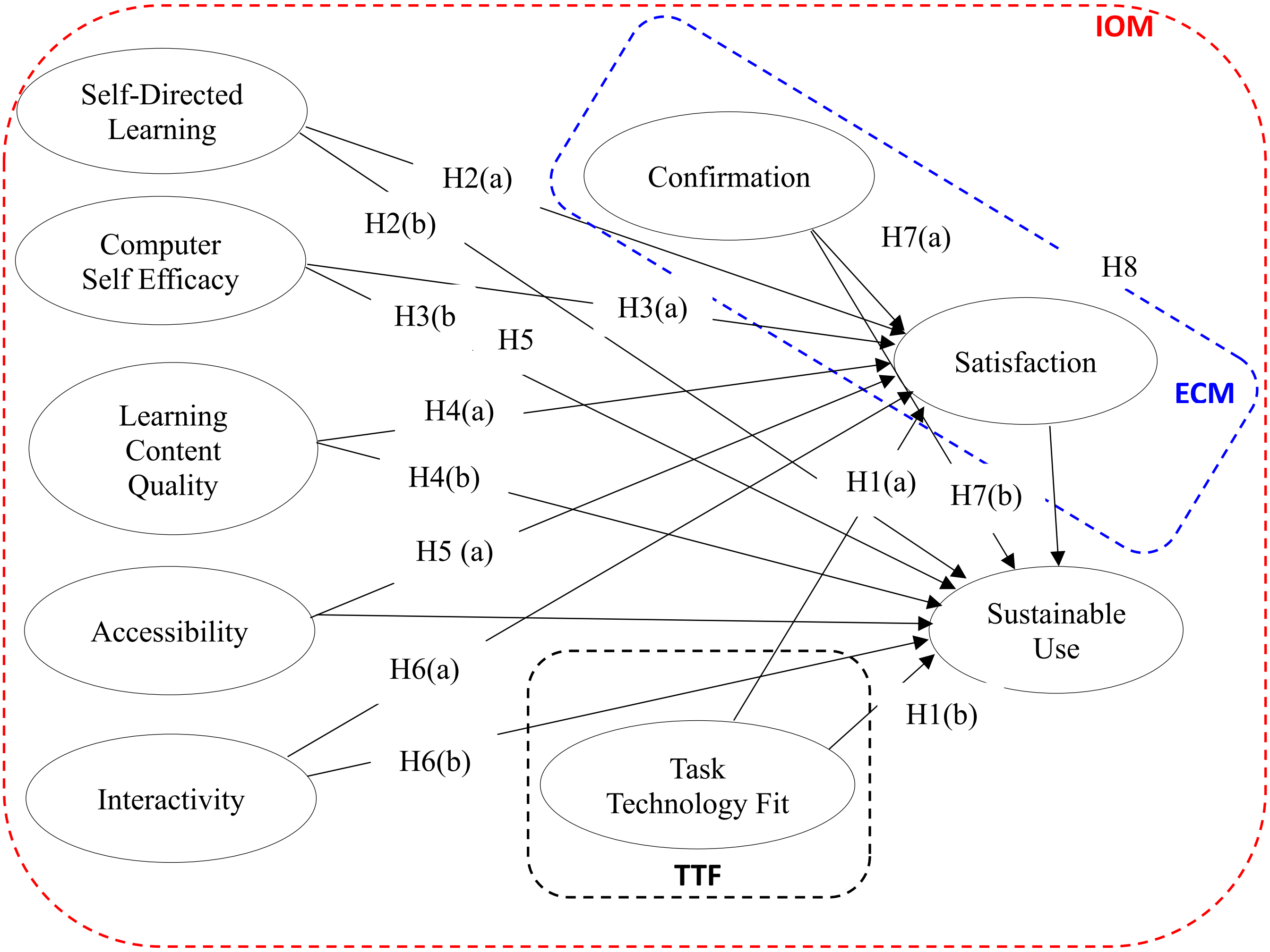
3. Methods

3.1 Research Questions

This research work attempts to answer the following questions:
RQ1: Which quality factors affect satisfaction of the students from mobile learning studying in higher educational institutions?
RQ2: Which quality factors affect sustainable use of mobile learning by the students studying in higher educational institutions?

3.2 Research Model

To answer these questions, the present study proposed the following research model (Figure 3) that was developed based combination of task technology fit (TTF), expectation confirmation model (ECM) and input output model (IOM).



Note: IOM: Input Output Model, ECM: Expectation Confirmation Model & TTF: Task

Technology Fit Model

Figure 3 Proposed Research Model (Source: Prepared by authors based on literature)
The input output model comprised of four dimensions that were inputs, resources, process and output. Further, each dimension was comprised of two sub-dimensions or constructs. The input category includes self-directed learning and computer self-efficacy; resources category includes learning content quality and accessibility, process part includes interactivity and confirmation and finally output category includes satisfaction and sustainable use of mobile learning.

3.3 Research Design

The present research work used deductive approach to analyze quality of mobile learning and its sustainable use by the students studying in higher educational institutions of Gujarat. The study was conducted using cross-sectional research design.

3.4 Survey Instrument & Sample

To assess the research model, a structured questionnaire was used to collect the data. Based on past studies, nine constructs were identified and measured using five-point Likert Scale ranging from strongly disagree (1) to strongly agree (5). The details about all constructs and scale items are provided in appendix A.
The target population of present study comprised of students studying in different higher educational institutions of Gujarat who have experience of mobile learning. Seven higher educational management institutions were selected from Gujarat. The questionnaire was forwarded to students studying in graduate, post graduate and PhD programs and the data were collected from 321 students using convenience sampling method.

3.5 Statistical test and software

The proposed model was analyzed using multiple linear regression through Statistical Package for Social Sciences (SPSS) version 25.

4. Results

The respondent's demographic profile is illustrated in Table 1. 45.2 percent of the respondents were male and remaining 54.8 percent were female students. The sample was dominated by the students who were in the age group of 21-24 years (67.3 percent). All students were found to have mobile phone (100 percent) and half of respondents were using mobile phone for more than 5 years (53.3 percent). 31.5 percent of students were found to have internet usage of 2-3 hours a day followed by 3-4 hours (24 percent) and more than 4 hours (24 percent).

Table 1: Profile of Respondents (n=321)

Attribute	Frequency	Percent
Gender		
Male	145	45.2
Female	176	54.8
Age		
18-20 Years	36	11.2
21-24	216	67.3
Greater than 25 Years	69	21.5
Education		
Undergraduate	75	23.4
Post Graduate	225	70.1
PhD Student	21	6.5
Marital Status		
Single	289	90.0
Married	32	10.0
Have Mobile Phone		
Yes	321	100.0
No	0	0.0
Use of Mobile Phone (Years)		
0-2 years	23	7.2
3-5 years	127	39.6
More than 5 years	171	53.3
Average daily internet usage (in hours)		
Less than 1 hour a day	5	1.6
1-2 hours	61	19.0

2-3 hours	101	31.5
3-4 hours	77	24.0
More than 4 hours a day	77	24.0

Source: SPSS Output

4.1 Descriptive Statistics

Table 2 present the descriptive statistics, univariate normality of individual items and reliability of constructs. The mean score of items were more than 3 and indicated low spread around the mean score.

Table 2: Descriptive Statistics, Normality & Reliability

Constructs	Items	Mean	Std. Deviation	Skewness	Kurtosis	Cronbach's alpha
Task Technology Fit	TTF1	4.01	0.912	-0.934	0.712	0.708
	TTF2	4.16	0.807	-1.153	2.157	
	TTF3	4.05	0.912	-0.802	0.248	
Self-Directed Learning	SDL1	3.99	0.818	-0.610	0.356	0.709
	SDL2	3.97	0.788	-0.490	0.121	
	SDL3	3.76	0.960	-0.711	0.304	
	SDL4	3.97	0.855	-0.908	1.093	
	SDL5	4.03	0.885	-1.061	1.577	
Computer/ Internet Self Efficacy	CSE1	4.27	0.692	-0.589	-0.105	0.726
	CSE2	4.01	0.754	-0.593	0.575	
	CSE3	4.37	0.726	-1.043	1.136	
Learning Content Quality	LCQ1	3.94	0.857	-0.582	-0.044	0.786
	LCQ2	3.91	0.872	-0.586	0.186	
	LCQ3	4.09	0.791	-0.809	1.156	
	LCQ4	3.88	0.913	-0.761	0.476	
Accessibility	ACC1	4.21	0.714	-0.588	0.046	0.773
	ACC2	4.14	0.783	-0.718	0.434	
	ACC3	4.10	0.851	-0.858	0.746	
	ACC4	4.04	0.862	-0.780	0.414	
Interactivity	INT1	3.96	0.934	-0.861	0.521	0.801
	INT2	3.98	0.873	-0.945	1.158	
	INT3	4.08	0.804	-0.758	0.718	
	INT4	4.05	0.833	-0.740	0.492	
Confirmation	CON1	4.00	0.791	-0.535	0.167	0.730
	CON2	3.84	0.802	-0.469	0.302	
	CON3	3.86	0.791	-0.439	0.115	
Satisfaction	SAT1	4.01	0.773	-0.630	0.748	0.798
	SAT2	3.97	0.840	-0.706	0.608	
	SAT3	3.92	0.806	-0.644	0.767	
Sustainability	SS1	3.93	0.868	-0.667	0.485	0.780
	SS2	3.76	0.860	-0.437	-0.071	
	SS3	3.84	0.813	-0.397	0.108	

Source: SPSS Output

The univariate approach using skewness and kurtosis was adopted to test the normality of scale items (Byrne, 2010). The values of skewness were less than 2 (between –2 and +2) and a value of kurtosis less than 7 (between –7 and +7), which met the assumption for normality (Curran et al., 1996). The Cronbach's alpha value of all constructs were higher than minimum threshold value of 0.70 indicating acceptable level of reliability (Hair et al., 2010).

4.2 Multiple Regression Analysis

To satisfy the objectives of research, two multiple linear regression models were used. The first model treated satisfaction from mobile learning as dependent variable and analyzed the relationship between quality of mobile learning factors and satisfaction. The second regression model treated sustainable use of mobile learning as dependent variable and analyzed the relationship between quality of mobile learning factors and sustainable use. Table 3 indicates output of multiple linear regression for satisfaction from mobile learning.

Table 3 Multiple Linear Regression Model: Satisfaction

	Co-efficient β	t stats	Sig.	Tolerance	VIF	Decision
Task Technology Fit	0.171	3.559	0.000	0.636	1.573	Supported
Self-Directed Learning	-0.047	-1.038	0.300	0.715	1.398	Not Supported
Computer Self Efficacy	0.039	0.825	0.410	0.671	1.491	Not Supported
Learning Content Quality	0.109	2.057	0.041	0.527	1.899	Supported
Accessibility	-0.021	-0.422	0.674	0.567	1.764	Not Supported
Interactivity	0.190	3.657	0.000	0.546	1.832	Supported
Confirmation	0.447	8.576	0.000	0.540	1.853	Supported
R	0.735					
R^2	0.540					
F stats	52.548					
Sig	0.000					

Source: SPSS Output

The results of first regression model (satisfaction) indicated that quality of mobile learning factors (Task technology fit, self-directed learning, computer self-efficacy, learning content quality, accessibility, interactivity and confirmation) explained 54% of the variance (F=52.55; $p<0.05$). The test results of co-efficients indicates that task technology fit ($\beta = 0.171$, $p < 0.05$), Learning Content Quality ($\beta = 0.109$, $p < 0.05$), Interactivity ($\beta = 0.190$, $p < 0.05$) and Confirmation ($\beta = 0.447$, $p < 0.05$) were significantly positively associated with satisfaction of mobile learning.
Table 4 indicates output of multiple linear regression for sustainable use of mobile learning. The results of second regression model indicated that quality of mobile learning factors (Task technology fit, self-directed learning, computer self-efficacy, learning content quality, accessibility, interactivity, confirmation and satisfaction) explained 48% of the variance (F=35.49; $p<0.05$).

Table 4 Multiple Linear Regression Model: Sustainable Use

	Co-efficient β	t stats	Sig.	Tolerance	VIF	Decision
Task Technology Fit	0.061	1.157	0.248	0.611	1.637	Not Supported
Self-Directed Learning	0.040	0.819	0.414	0.713	1.403	Not Supported
Computer Self Efficacy	-0.120	-2.395	0.017	0.669	1.495	Supported
Learning Content Quality	0.179	3.153	0.002	0.520	1.925	Supported
Accessibility	0.115	2.121	0.035	0.567	1.765	Supported
Interactivity	0.014	0.247	0.805	0.523	1.910	Not Supported
Confirmation	0.065	1.048	0.295	0.437	2.289	Not Supported
Satisfaction	0.458	7.576	0.000	0.460	2.175	Supported
R	0.690					
R^2	0.476					
F stats	35.495					
Sig	0.000					

Source: SPSS Output

The test results of co-efficients indicates that Learning Content Quality ($\beta = 0.179$, $p < 0.05$), Accessibility ($\beta = 0.115$, $p < 0.05$) and Satisfaction ($\beta = 0.458$, $p < 0.05$) were significantly positively associated with sustainable use of mobile learning. However, computer self-efficacy ($\beta = -0.120$, $p < 0.05$) was significantly negatively associated with sustainable use of mobile learning. Further, the values of VIF were less than 10 while values of tolerance were higher than 0.10 for both regression models suggesting absence of multicollinearity (Pallant, 2000).

5. Discussion and Conclusion

5.1 Quality of Mobile Learning (QML) Factors & Satisfaction

We have considered seven quality factors and analyzed its relationship with satisfaction of the students using multiple regression. The seven quality factors include task technology fit, self-directed learning, computer self-efficacy, learning content quality, acessibility, interactivity and confirmation. From the results, confirmation was the strongest predictor of satisfaction followed by interactivity, task technology fit and learning content quality. The relationship of expectation-confirmation and satisfaction is also found significant in past studies (Al-Emran et al., 2020; Alshurideh et al., 2020; Cheng, 2021). Therefore, the results are in line with the literature with reference to expectation confirmation model.
The second important determinant of students' satisfaction was interactivity. The literature on information system and online learning categorized interactivity as one of the determinants of system quality and it is also included as a construct in the updated DeLone and McLean model. In present study, expectation-confirmation and interactivity are considered under the process part of input output model. The linkage between interactivity

and satisfaction is also supported by the literature (Elshami et al., 2021). However, based on input output model, it is found that process part affects output (satisfaction) significantly as compared to inputs and resources. The third important predictor of students' satisfaction was task technology fit. Alyoussef (2021) found task technology fit (TTF) having largest impact on students' satisfaction while analyzing e-learning acceptance and sustainable higher education. Finally, learning content quality was found to be a predictor of students' satisfaction which is considered as a part of resources in case of input output model.

5.2 Quality of Mobile Learning (QML) Factors & Sustainable use

With reference to sustainable use of mobile learning, we have considered eight quality factors by including satisfaction as additional independent variable. Learning content quality was the primary determinant of sustainable use of mobile learning. The learning content is considered as one of the important constructs of e-service quality and found to have significant impact on students' perception of e-learning quality (Uppal et al., 2018). Calisir et al. (2014) have found significant effect of content quality on perceived usefulness of web-based learning system.

The second predictor of sustainable use was computer self-efficacy. It was found to have negative relationship with sustainable use of mobile learning that seems puzzling. The result was similar to the study of Compeau & Higgins (1995) wherein they found negative relationship between organizational support and computer self-efficacy. Therefore, future research is required in this direction. However, it could be assumed that the help and support required by the students from other may work as an obstacle in sustainable use of mobile learning.

The third and last important predictor of sustainable use of mobile learning was accessibility. Hebiri Madani et al. (2013) have emphasized on accessibility of mobile learning for learners with disabilities. Accordingly, it is found that for sustainable use of mobile learning it has to be accessible and personalized based on users' needs and learning preferences.

Finally, learning content quality and accessibility are significant predictors of sustainable use of mobile learning. Based on input output model, learning content quality and accessibility are part of resources. Therefore, in case of sustainable use of mobile learning, resources affect output (sustainable use) as compared to inputs and processes.

5.3 Theoretical Implications

The literature on mobile learning studies includes application of adoption models (like TAM, UTAUT) quality models (like e-service quality, system quality, software quality) and other IS models. The present study included systematic input-resources-process-output model along with ECM and TTF to analyze quality factors of mobile learning. There is no study that has analyzed quality of mobile learning using these models. It would provide new insights in analysis of quality of mobile learning in future also.

5.4 Managerial Implications

The higher education institutions can focus on process and resources part of mobile learning that include expectation-confirmation, interactivity and learning content quality to satisfy the students' needs of mobile learning. Further, the technology fit should be ensured while providing mobile learning facility.

However, for sustainable use of mobile learning it is required that institutions and teachers should focus on resources of mobile learning especially designing content of courses and ensuring accessibility of mobile learning to all students at their preferred timing and location.

5.5 Limitations & Future Research

The study has several limitations. First, the students have responded to questionnaire that include self-reported bias. Second, the results of the study cannot be generalized due to limited sample size. Finally, the convenience sampling method may be considered as one of the limitations of the study. The linkage between satisfaction and sustainable use of mobile learning should be further tested. The proposed model can be tested through Structural Equation Modeling (SEM).

5.6 Conclusion

The purpose of this study was to analyze quality of mobile learning using three models from the perspective of the students regarding its sustainable usage. Students' satisfaction from mobile learning and its sustainable use were considered as final outcomes. These outcomes were significantly predicted by processes and resources of mobile learning system respectively. The sustainable use of mobile learning required quality resources in the form of content and accessibility.

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