



Article

FACTORS INFLUENCING BEHAVIOURAL INTENTION TO USE THE INNOVATIVE OPEN AND DISTANCE LEARNING SYSTEMS WITH THE ROLE OF CONTINUANCE INTENTION

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ABSTRACT

Educational institutions have extensively used the groundbreaking features of Open and Distance Learning (ODL) programs to manage Continuous Professional Development (CPD) for teachers over the last few decades. Despite the importance of educational technology, most research has concentrated on initial adoption, with few attempts made to examine factors affecting teachers' continued intention to use the new functions of ODL systems. This research enhances the scholarly direction by presenting a combined model encompassing UTAUT (Unified Theory of Acceptance and Use of Technology), ECM (Expectation Confirmation Model), and TTF (Task Technology Fit). Statistical data gathered from 393 secondary school educators in Bangladesh who engage with ODL systems was used to validate the suggested model. The validation process employed the PLS-SEM technique. Based on the results of this study, performance expectancy, teacher satisfaction, and social influence emerge as key drivers that positively impact continuous intention. This continuous intention influences the behavioural intention to explore fresh features within the ODL tools. Moreover, Continuous Intention, Performance Expectancy, and Effort Expectancy indirectly Behavioural Intention. The study also reveals that facilitating conditions do not play a role in shaping behavioural intention. Task technology fit does not affect continuity intention. The potential implications and constraints of this research are further elaborated.

KEYWORDS

Behavioural Intention, Continuance Intention, ECM, UTAUT, TTF;

INTRODUCTION

There is a pressing need for skilled teachers to ensure universal, quality education and ongoing learning opportunities, with CPD (Continuous Professional Development) being an essential component of teacher training. Edge (2000) suggests that the value of Continuing Professional Development (CPD) is as widely recognised and uncontested as universally beloved concepts such as motherhood and apple pie, implying a lack of significant opposition (p.45). It is posited that individuals can truly consider themselves professionals only when they actively engage in learning and adhere to professional standards. CPD encapsulates all the structured and unstructured learning experiences a teacher goes through from their initial training until they retire, as highlighted by Fullan (2007). However, Baron et al. (2019) suggest a noticeable shortage of comprehensive research on professional teacher development. This indicates that it is challenging for educators and decision-makers to craft impactful programs without enough high-grade studies on the subject, as presented in CPD modules. Recently, there has been a noticeable uptick in the focus and integration of tech tools in education. The professional development scope has broadened to encompass tech-driven aids facilitating teacher progress. This expansion has led to a consensus that merely holding an undergraduate degree might not fulfil the demands of modern teaching.

Martins et al. (2019) highlight the effectiveness of Open and Distance Learning (ODL) in enhancing teachers' professional development, especially through modern features like MOOCs (Massive Open Online Courses) and Learning Management Systems (LMS). Data from the Student Support Services (SSS) of Bangladesh Open University and the Bangladesh Bureau of Educational Information and Statistics (BANBEIS) in 2019 show that 3,951 secondary school teachers participated in professional development programs using traditional face-to-face methods. This indicates a substantial reliance on conventional training methods, suggesting a significant potential for ODL systems to revolutionise teacher training by offering more flexible and accessible learning opportunities. In contrast, the ODL approach witnessed an enrolment of 7,364 teachers in the same year (BANBEIS, 2019; BOU, 2020). Diving deeper into ODL-based CPD courses, 5,474 teachers opted for the B.Ed. Program and 1,890 chose the M.Ed. course in 2018. This is a significant increase from 2012, when only 3,168 and 685 teachers enrolled for the B.Ed. and M.Ed. programs, respectively. Nevertheless, secondary education teachers are not fully leveraging the advanced features of ODL, as observed by Naidu and Laxman (2019). The World Bank (2019) acknowledges that Bangladesh has made commendable progress in terms of enrolment, completion rates, and gender balance at the secondary education level. However, there remains a pressing need to improve the quality of education. With the steady increase in users of Open and Distance Learning (ODL) systems, it is crucial for educational stakeholders to encourage the sustained adoption of these platforms and to motivate users to explore and utilise their full range of features. Emphasising the potential of ODL can help bridge the gap in educational quality by providing more diverse and effective learning resources.

This study seeks to explore the factors influencing the adoption and continued use of Open and Distance Learning (ODL) systems among educators. Specifically, the research aims to address several key questions: How do facilitating conditions impact users' behavioural intention to use the ODL system? To what extent does performance expectancy influence users' behavioural and continuance intentions? What is the relationship between task-technology fit and users' continuance intention to utilise the ODL platform? How does teacher satisfaction affect their continuance intention to engage with the ODL system? Additionally, this study examines the impact of effort expectancy on both behavioural and continuance intentions and the role of social influence in shaping users' behavioural intention to adopt the ODL system. Finally, it investigates how continuance intention affects users' behavioural intention to use the ODL platform consistently.

LITERATURE REVIEW

In modern times, ODL integrates various other concepts, among them "online learning", "web-based learning", and "e-learning". Kennedy (1999) delineated these by specifying that "online learning" is a subset of distance education. It entails accessing instructional and supplementary resources through a computer via local storage mediums like CD-ROMs, DVDs, or the Internet. On

the other hand, web-based learning broadly pertains to utilising Internet technologies for interaction and collaboration in an educational context. Based on the employed technology. Based on the used technology, distance learning methodologies can be divided into synchronous and asynchronous states (Hrastinski, 2008). The synchronous format involves real-time engagement, where participants interact simultaneously, necessitating a set schedule. Examples include web conferencing and other real-time technologies such as VoIP over the web, telephonic communication, videoconferencing, satellite broadcasts, and live streaming via Internet radio. In contrast, asynchronous learning offers flexibility by allowing participants to access materials at their convenience without requiring the simultaneous presence of both student and instructor. Technologies supporting this mode include audiocassettes, online discussion boards, emails, printed resources, voicemail/fax, and video materials on cassettes or DVDs. Various forms of distance education can be structured based on the technology used or a combination of multiple technologies. These include (a) mail-based correspondence courses, (b) online courses, both synchronous and asynchronous, (c) broadcast telecourses delivered via radio or TV, (d) interactive content on CD-ROMs, and (e) mobile learning through content on mobile or telecommunication devices (Hrastinski, 2008). Additionally, "integrated distance learning" combines live group interaction or instruction with a remote learning curriculum, providing a hybrid approach that can enhance the learning experience by blending face-to-face and online elements.

Literature Review

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Users' Behavioural Intention to Adopt the ODL System

Finding the best-suited models or strategies for this query requires a review of prior theories and previously pinpointed factors affecting ODL adoption in the sector. Numerous studies have ingeniously combined different models or approaches to understand better the motivating factors behind the intention to embrace ODL. Table 1 presents a comprehensive summary, depicting these research efforts, the prominent constructs in each, and their corresponding countries of investigation (See Table 1).

Table 1: Studies on Users' Behavioural Intention of the Open and Distance Learning Systems

Author(s)	Theory/Model	Significant Constructs	Country
Lakhal et al. (2013)	Unified Theory of Acceptance and Use of Technology (UTAUT)	Performance Expectancy, Facilitating Conditions, Social Influence	Canada
Alharbi and Drew (2014)	Technology Acceptance Model (TAM)	Perceived Ease of Use, Perceived Usefulness, Attitude towards Usage	Saudi Arabia
Chang and Tung (2008)	Innovation Diffusion Theory (IDT) and TAM	Compatibility, Perceived Usefulness, Perceived Ease of Use, Perceived System Quality	Taiwan
Jambulingam (2013)	UTAUT	Performance Expectancy, Affordability	Malaysia
Muhideen et al. (2019)	Theory of Planned Behaviour (TPB)	Attitude, Subjective Norms, Perceived Behavioural Control, Enabling Environment	Africa
Mtebe and Raisamo (2014)	UTAUT	Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions	East Africa
Abu-Al-Aish and Love (2013)	UTAUT	Performance Expectancy, Effort Expectancy, Influence of Lectures, Quality of Service	England
Park et al. (2012)	TAM	Attitude, Subjective Norms	South Korea
Binyamin et al. (2019)	TAM	Perceived Usefulness, Perceived Ease of Use	Saudi Arabia
Venter et al. (2012)	TAM and TAM2	Perceived Usefulness	South Africa
Almarashdeh et al. (2010)	TAM	User Satisfaction	Malaysia

ODL Continuance Intention

Despite the wealth of studies focusing on initial adoption in the literature, there is a scarcity of research addressing the sustained intention towards Open and Distance Learning systems (Dai et al., 2020). Bhattacharjee's (2001) ECM (Expectation Confirmation Model) stands out in this field, distinguishing between initial user acceptance of Information Systems (IS) and ongoing usage behaviours. The ECM provides a theoretical framework for scholars to explore the prolonged use of IS. Various academics have harnessed this model to scrutinise the persistent use of ODL tools, as seen in Table 2, covering areas such as MOOCs (Dai et al., 2020; Ouyang et al., 2017), E-learning (Amin et al., 2016; Zhou, 2017), and LMS (Sultana, 2020; Binyamin et al., 2019). Table 2 also encapsulates the primary theories employed in researching continuance intention, along with their pivotal constructs and research locations.

Table 2: Studies on Users' Continuance Intention of the Open and Distance Learning Systems

Author(s)	Theory/Model	Significant Constructs	Country
Dai et al. (2020)	Expectation Confirmation Model (ECM)	Confirmation, Satisfaction, Attitude	China
Karim et al. (2018)	UTAUT	Effort Expectancy, Facilitating Conditions	Bangladesh
Mohamad and Irwan (2018)	Self-developed model	Usefulness, Enjoyment, Interactivity, Openness	Malaysia
Islam et al (2013)	TAM, UTAUT	Perceived Compatibility, Satisfaction,	Finland
Sultana (2020)	UTAUT	Perceived Usefulness, Performance Expectancy, Effort Expectancy, Self-management Learning	UK
Tseng et al. (2019)	UTAUT2	Performance Expectancy, Social Influence, Facilitating Conditions, Price Value	Taiwan
Ouyang et al. (2017)	ECM, Task-Technology Fit (TTF)	Perceived Usefulness, Satisfaction, Task-Technology Fit	China
Zhou (2017)	ECM	Satisfaction, Confirmation, Perceived Usefulness	China

Expectation Confirmation Model (ECM)

Bhattacharjee (2001) introduced the PAM (Post-Acceptance Model) or ECM (Expectation Confirmation Model) after reviewing prior research concerning the sustained use of Information Systems (IS). The study revealed that perceived usefulness and user satisfaction play a role in determining a user's intent to persist. User satisfaction arises from their validated expectations from previous interactions with the information system's perceived utility. Furthermore, the extent to which these expectations are confirmed also impacts perceived usefulness. Moreover, the ECM suggests that users' preliminary expectations transform following actual system use, leading to a post-adoption expectation grounded in perceived benefits.

The Unified Theory of Acceptance and Use of Technology (UTAUT)

The UTAUT model, introduced by Venkatesh et al. (2003), combines various theories to explain technology adoption. It highlights four primary determinants: Facilitating Conditions (FC), Social Influence (SI), Effort Expectancy (EE), and Performance Expectancy (PE) that influence behavioural intentions and actions, further impacted by user factors like age and past experiences. This comprehensive model is a fusion of prominent theories like SCT, IDT, TPB, and TAM, which have been influential in research across fields such as marketing and information systems.

Task-technology Fit (TTF)

The UTAUT model provides insight into human perceptions of technology. Zhou et al. (2010) and Afshan and Sharif (2016) expanded UTAUT using the Task-technology Fit (TTF) model from Goodhue and Thompson (1995). Integrating UTAUT with TTF offers a deeper understanding of

ODL system usage by considering technological perceptions and task alignment. Combining UTAUT, ECM, and TTF can further enhance this explanatory depth (Goodhue & Thompson, 1995).

Hypotheses Development

The term "Facilitating Conditions" is understood as the extent to which an individual believes that there's adequate organisational and technological support to aid the system's use (Venkatesh et al., 2003). The potential and suitability of a system play pivotal roles in shaping FC. This dimension incorporates elements from the Theory of Planned Behaviour, specifically perceived behavioural control, and the Integrated Diffusion Theory's compatibility. The measure determines how users perceive a system or technology as enhancing their tasks. In this research, FC assesses the perception of ODL users regarding how the service has streamlined their experiences.

H1: Facilitating Condition (FC) has a significant impact on Behavioural Intention (BI)

Venkatesh et al. (2003) developed the Unified Theory of Acceptance and Use of Technology (UTAUT) model, which integrates multiple hypotheses to explain technology adoption. The model emphasizes four key variables that affect behavioural intentions and actions: Facilitating Conditions (FC), Social Influence (SI), Effort Expectancy (EE), and Performance Expectancy (PE). Additionally, the model considers factors such as age and previous experiences, which further influence these variables. This elaborate model combines well-known theories impacting marketing and information systems research, including SCT, IDT, TPB, and TAM.

H2: Performance Expectancy (PE) has a significant impact on Behavioural Intention (BI)

H3: Performance Expectancy (PE) has a significant impact on Continuance Intention (CI)

"Task-Technology Fit" (TTF) describes a task's functional alignment with a particular technology. Technology has a greater chance of improving the efficiency of job execution when there is a better alignment (Oliveira et al., 2014). Understanding "the qualities of the job in issue and how appropriate the technology is for achieving that task" is the foundation of this idea (Oliveira et al., 2014, p.113). The measurement seeks to determine if users' expectations of the technology in fulfilling their work demands and the technology's capabilities are compatible. TTF is used in this study to assess how effectively the ODL platform meets users' expectations in supporting them with their jobs.

H4: Task Technology Fit has a significant impact on the Continuance Intention (CI).

Analysing the mental states associated with a user is consuming experience compared to their expectations before consumption yields information about user satisfaction (Oliver, 1980). This measure compares pre-utilization expectations for a product, technology, or system with post-utilization psychological experiences to determine satisfaction levels. The TS (Teacher Satisfaction) measure used in this study assesses teachers' general psychological health after implementing the ODL service. This factor helps the researcher determine if the ODL platform meets the psychological demands of teachers and encourages good feelings in them.

H5: Teacher Satisfaction has a significant impact on the Continuance Intention (CI).

Effort Expectancy (EE), as opposed to the Technology Acceptance Model's (TAM) "Perceived Ease of Use," refers to the perceived simplicity associated with the usage of a system (Venkatesh et al., 2003). The "Perceived Ease of Use" from TAM, the "Complexity" from MPCU, and the "Ease of Use" from IDT are combined in EE. This measure evaluates how much work users put into implementing a technology or system. In the context of this study, EE assesses the effort and time used by EFL teachers in integrating the ODL platform.

H6: Effort Expectancy (EE) has a significant impact on Behavioural Intention (BI).

H7: Effort Expectancy (EE) has a significant impact on Continuance Intention (CI)

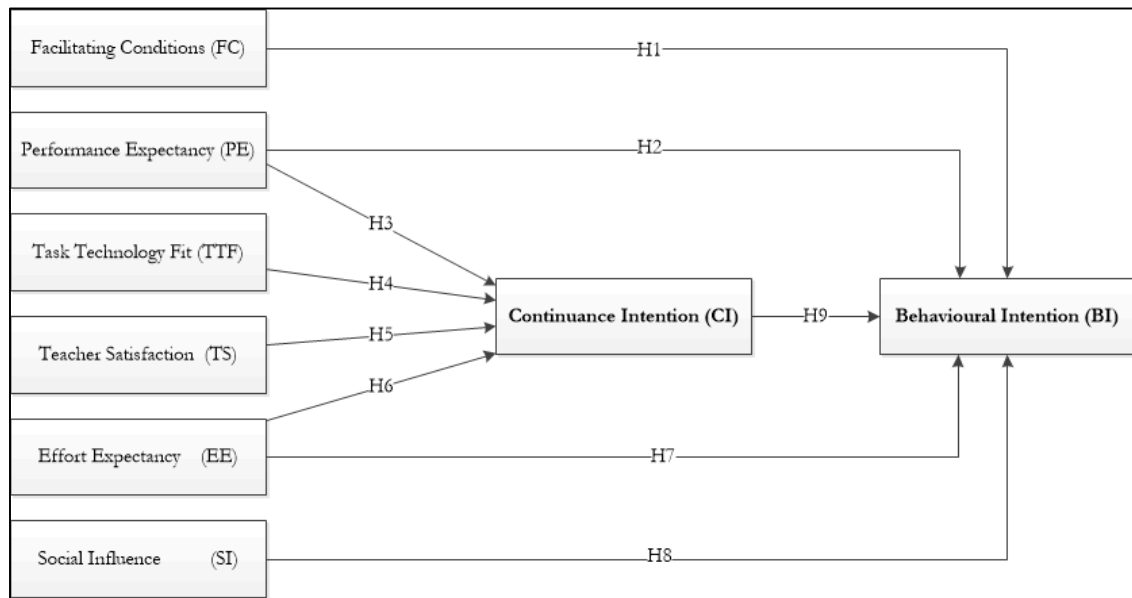
Social influence is "the degree to which a person feels that important individuals think they should embrace the new system" in the context of the UTAUT paradigm (Venkatesh et al., 2003). Social influence in UTAUT includes earlier components from TRA, MPCU, and IDT, as well as social norms, societal variables, and image. This indicator assesses how users' social networks influence their choices. Social Influence (SI) is primarily employed in this study to examine how ODL users' goals are influenced by their social connections and acquaintances.

H8: Social Influence (SI) has a significant impact on Behavioural Intention (BI).

The term "Continuance Intention" (CI) refers to a user's propensity to stick with a specific technology, item, or system (Bhattacharjee, 2001). It acts as a behavioural intention and continuous commitment indicator. In the context of this study, CI assesses the users' perceived propensity to use the ODL platform regularly. It specifically aims to comprehend the teachers' driving forces for utilising the ODL system after their first exposure.

H9: Continuance Intention (CI) has a significant impact on Behavioural Intention (BI).

Figure 1: The conceptual Framework of this study



METHOD

Sample and Data Collection

The survey, rated on a five-point Likert scale, targeted Bangladesh Open University (BOU) teacher-trainees. BOU, a leading institution in Bangladesh, offers blended learning to over 10,000 teacher-students, combining traditional and technology-enabled methods. Direct links to the survey and an introductory letter detailing the study's objectives and ensuring confidentiality were sent to secondary school teachers familiar with the ODL system to gather responses. Of 400 distributed surveys, 393 were valid, while seven were not. Based on guidelines from Barclay et al. (1995) for PLS path modelling, the study required a minimum of 90 samples, considering various criteria related to paths and constructs. The chosen sample size exceeded this to ensure reliable results.

Table 3: Overview of Respondent Characteristics

Category	Percentage of Respondents	
Gender	Male	39.8%
	Female	60.3%
Age	25 to 30 years	30.3%
	31 to 35 years	29.5%
	36 to 40 years	17.0%
	Over 40 years	23.3%

Measures

A survey tool based on published research was created to guarantee content validity and validate the suggested model. The scale items for the constructs were modified from the investigations of Zhou et al. (2010) and Oliveira et al. (2014) (Bhattacharjee, 2001).

FINDINGS

Data analysis was conducted using the Partial Least Squares (PLS) method via the SmartPLS 3 software. The research model, depicted in Figure 2, comprises the measurement and structural models constructed with PLS-SEM. The ensuing section presents results using a bifurcated approach. Initially, the focus is on evaluating the measurement model. Subsequently, the structural model undergoes examination through PLS path modelling. The measurement model in SmartPLS (encompassing item reliability and both convergent and discriminant validity) and the structural model (comprising path coefficients and R square values) are evaluated.

Figure 2: SmartPLS Screenshot of the measurement model and structural model

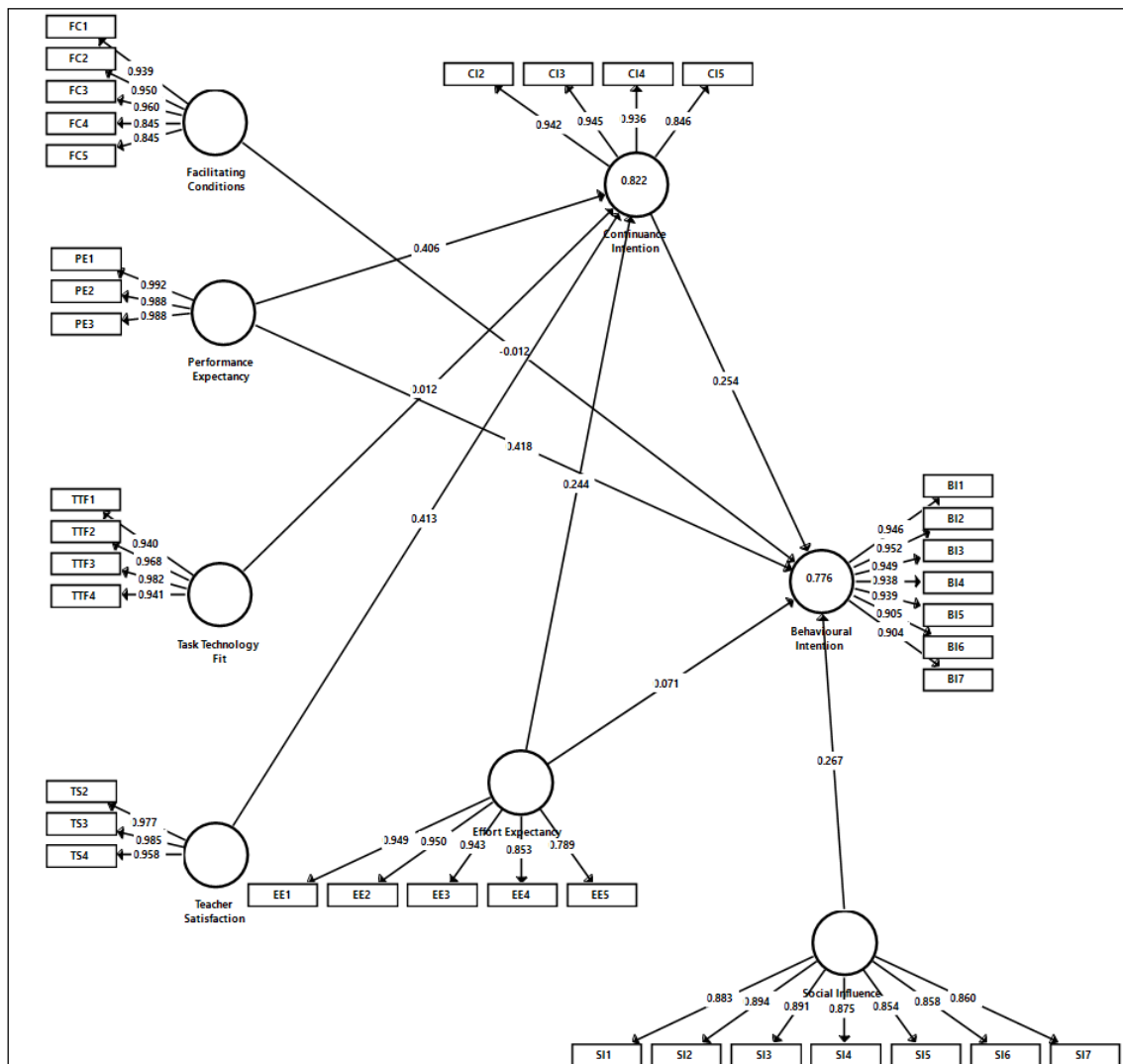


Table 3: Measurement Item Model: Cronbach's Alpha, Factor Loading, CR, and AVE

Item	Loading	rho_A	CR	Cronbach's α	AVE
BI1	0.946	0.919	0.931	0.975	0.659
BI2	0.952				
BI3	0.949				
BI4	0.938				
BI5	0.939				
BI6	0.905				
BI7	0.904				
CI2	0.942	0.924	0.949	0.937	0.862
CI3	0.945				
CI4	0.936				
CI5	0.846				
EE1	0.949	0.923	0.947	0.939	0.857
EE2	0.950				
EE3	0.943				
EE4	0.853				
EE5	0.789				
FC1	0.939	1.069	0.934	0.947	0.826
FC2	0.950				
FC3	0.960				
FC4	0.845				
FC5	0.845				
PE1	0.992	0.910	0.923	0.989	0.631
PE2	0.988				
PE3	0.988				
SI1	0.883	1.854	0.859	0.948	0.673
SI2	0.894				
SI3	0.891				
SI4	0.875				
SI5	0.854				
SI6	0.858				
SI7	0.860				
TS2	0.977	0.909	0.924	0.970	0.635
TS3	0.985				
TS4	0.958				
TTF1	0.940	0.921	0.946	0.972	0.855
TTF2	0.968				
TTF3	0.982				
TTF4	0.941				

Note: Due to the low loadings, the Items numbers CI1, CI6, CI7, EE6, EE7, FC6, FC7, TS1, TS5, TS6, TS7, TTF5, TTF6, TTF7 were deleted

Assessment of the Measurement Model

The internal consistency of the constructs was assessed using both Cronbach's alpha and the composite reliability metrics, which are expected to exceed 0.7. To guarantee convergent validity, each item's factor loadings should surpass 0.70, while the average variance extracted (AVE) should be greater than 0.50 (Hair et al., 2016). Table 4 showcases the concluding values for Cronbach's alpha, composite reliability, factor loadings, and AVE. All these figures surpass their respective threshold values.

Table 4: Fornell–Larcker criterion

	BI	CI	EE	FC	PE	SI	TTF	TS
BI	0.933							
CI	0.786	0.918						
EE	0.729	0.739	0.899					
FC	0.709	0.736	0.704	0.909				
PE	0.824	0.802	0.699	0.719	0.989			
SI	0.706	0.572	0.699	0.685	0.605	0.874		
TTF	0.686	0.512	0.664	0.607	0.624	0.751	0.958	
TS	0.483	0.750	0.491	0.632	0.528	0.365	0.205	0.973

To establish discriminant validity, the square root of the AVEs should be larger than the correlations with other variables (Fornell & Larcker, 1981). None of the correlations between the components were higher than the square root of AVE, as seen in Table 5. All AVEs (0.631-0.862) in Table 5 exceed the 0.5 criterion.

Table 5: Heterotrait- monotrait (HTMT)

	BI	CI	EE	FC	PE	SI	TTF	TS
BI								
CI	0.819							
EE	0.761	0.787						
FC	0.734	0.781	0.746					
PE	0.838	0.831	0.725	0.739				
SI	0.734	0.606	0.739	0.721	0.622			
TTF	0.704	0.535	0.695	0.630	0.637	0.781		
TS	0.496	0.787	0.517	0.663	0.539	0.384	0.211	

Correlations were also analysed using the Heterotrait-Monotrait (HTMT) ratio. HTMT is the average of the correlations between heterotraits and heteromethods (i.e., the correlations between indicators across constructs measuring distinct phenomena) relative to the correlations between monotraits and heteromethods (i.e., the correlations of indicators within the same construct). To distinguish between two factors, the HTMT should be significantly less than one (Henseler et al., 2016). According to the analysis results, all VIFs were less than five, indicating that the model does not suffer from multicollinearity (Hair et al., 2011). As a result, the model has the required discriminant validity.

Assessment of the Structural Model

If a suitable measurement model is provided, hypotheses may be tested by looking at the structural model. The SEM approach was combined with SmartPLS 3 to examine the predictive relevance (Q square), coefficient of determination (R square), modified R², and path coefficients. The blindfolding method (cross-validated redundancy) was used to calculate the route model's predictive relevance (Q square), which measures how effectively the path model can predict the first observed values (Hair Jr et al., 2016). The fact that every Q² value was much higher than 0 supports the model's high predictive significance. Henseler et al. (2016) assert that the redundant commonality of endogenous variables must be more significant than zero to be predictively relevant.

Table 6: Construct Cross-validated Redundancy

	SSO	SSE	Q ² (=1-SSE/SSO)
Behavioural Intention	2751.000	905.328	0.671

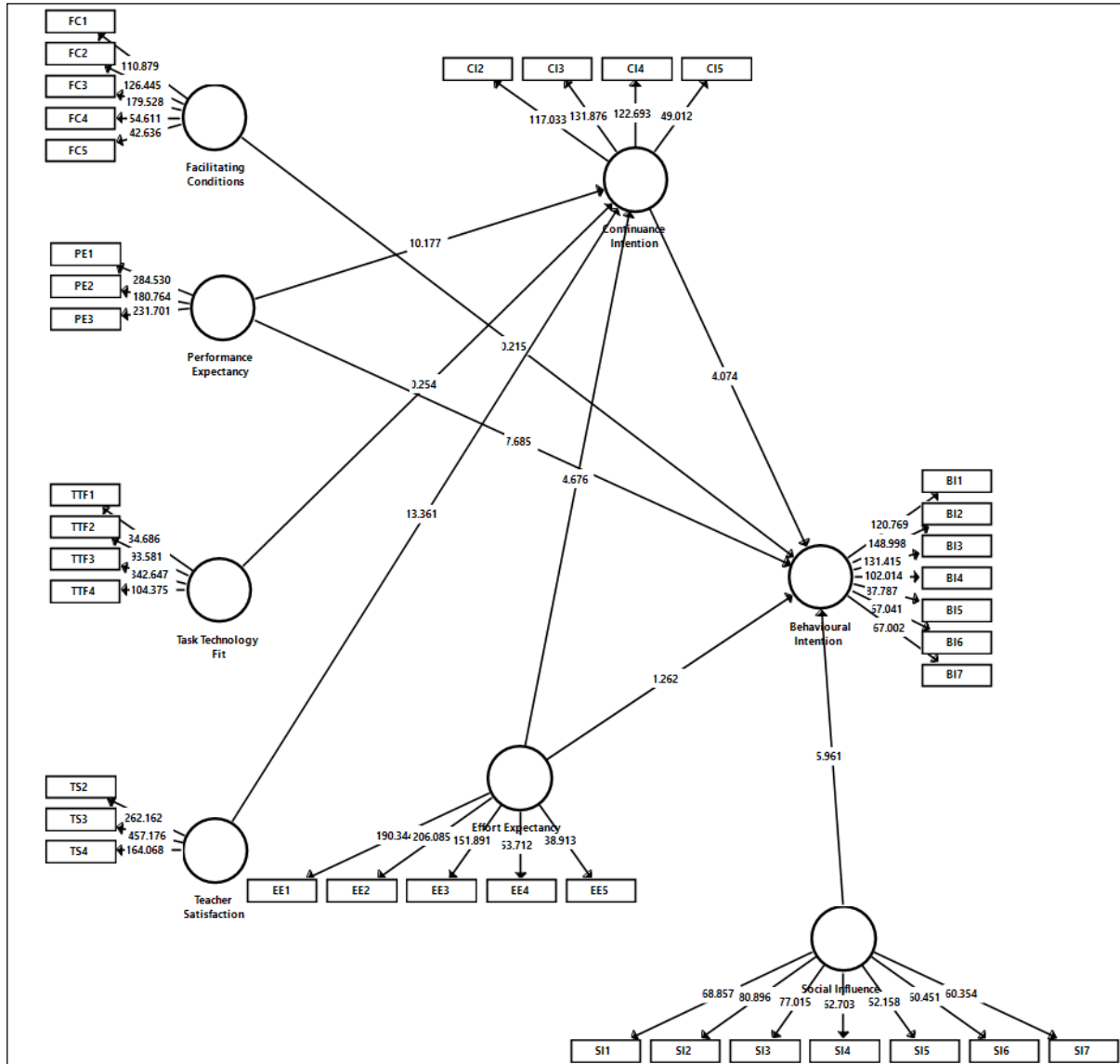


Figure 3: The PLS Analysis Results

Table 7: R Square Summary

	R Square	R Square Adjusted
Behavioural Intention (BI)	0.776	0.773
Continuance Intention (CI)	0.822	0.820

Tables 8 and 9 demonstrate that six of the nine presented hypotheses have significance relationship. According to the results, PE, TS, and EE significantly and favourably impacted participants' Continuous Intention (CI) for ODL systems. Nevertheless, the results showed that TTF did not affect Continuous Intention (CI) toward ODL systems. Additionally, the behavioural intention (BI) to try novel ODL tasks is significantly and favourably impacted by PE, EE, SI, and CI. The empirical data analysis results show FC and EE have not significantly affected behavioural intention (BI).

Table 8: Path Coefficient Assessment (N=393)

Relationship		Beta	Standard Deviation	T Statistics	P Values	Results
H1	FC -> BI	-0.017	0.055	0.215	0.830	Not Supported
H2	PE -> BI	0.416	0.054	7.685	0.000	Supported
H3	PE -> CI	0.404	0.040	10.177	0.000	Supported
H4	TTF -> CI	0.013	0.045	0.254	0.800	Not Supported
H5	TS -> CI	0.413	0.031	13.361	0.000	Supported
H6	EE -> CI	0.246	0.052	4.676	0.000	Supported
H7	EE -> BI	0.073	0.057	1.262	0.207	Not Supported
H8	SI -> BI	0.268	0.045	5.961	0.000	Supported
H9	CI -> BI	0.257	0.062	4.074	0.000	Supported

Mediation Model

According to the results (Table 10), continuation intention acts as a mediator between performance expectancy (PE) and behavioural intention (BI), causing an indirect impact. Similarly, effort expectation (EE) indirectly influences behavioural intention (BI) through the mediating effect of continuation intention (CI).

Table 9: Indirect Effect

Path	Beta	Standard Deviation	T Statistics	P Values
PE -> CI -> BI	0.104	0.028	3.632	0.000
EE -> CI -> BI	0.062	0.017	3.715	0.000

DISCUSSION

"Facilitating Conditions" refers to various software and hardware setups needed to utilise the most recent ODL apps. A previous study shows that these circumstances significantly impact behavioural intention or behaviour. In contrast to previous conclusions, this research suggests that enabling environments had little effect on behavioural intention. In the context of information systems research, Afshan and Sharif (2016) found that among the core four factors in the UTAUT model, only facilitating conditions significantly affect behavioural intention. In contrast, Baptista and Oliveira (2015) argued that favourable environments do not significantly influence behavioural choice or user adoption in Africa. Given this conflicting information, this study investigates how enabling factors affect individuals' intentions within Bangladesh's Open Distance Learning (ODL) networks. The results indicate that facilitating conditions do not greatly influence a person's desire to explore novel aspects. However, users in Bangladesh are more likely to explore new features if they receive technical support and have access to essential resources, and they may seek help from others while testing out new features. This suggests that the perception of inadequate institutional support contributes to the low regard for ODL services in Bangladesh, highlighting the need for better resource allocation and support systems to enhance user engagement.

This research also determined that performance expectancy dramatically enhances users' desire to continue using the ODL system. This finding introduces the context of Information System (IS) continuity to the Unified Theory of Acceptance and Use of Technology (UTAUT) framework. Performance expectancy has been previously identified as a pivotal precursor to behavioural

intention in the UTAUT model (Venkatesh et al., 2003). Past research has shown a strong positive correlation between users' performance expectations and their adoption of ODL (Wan et al., 2020). However, there is limited research examining the role of performance expectancy in the continuity of information systems. This research confirms that in Bangladesh, the users' intentions to persist with ODL systems are driven positively by performance expectations. The users are hopeful about the benefits of the ODL system in Bangladesh, believing it can enhance their proficiency in professional endeavours. A study in Qatar shows a positive relationship between behavioural intentions and e-learning system performance expectations (El-Masri & Tarhini, 2017). This research indicates a significant direct influence of performance expectations (PE) on behavioural intention. In this context, behavioural intention pertains to exploring new features rather than adopting ODL systems. The study uncovers a unique association between performance expectancy and the behavioural intent to explore new capabilities by broadening the scope from adopting ODL systems to trying new features.

While previous research has highlighted the synergy of TTF with other models like UTAUT and TAM in the early stages of information system adoption, there has been limited focus on incorporating TTF in long-term intention studies. This study explores the synergy of TTF and ECM in the context of ODL systems in Bangladesh, finding a limited direct effect of task-technology fit on sustained intent. This outcome aligns in some ways and deviates from previous studies in others. For instance, TTF is pivotal in students' decisions to persist with MOOCs (Ouyang et al., 2017). Additionally, Lin and Wang (2012) argue that there's a positive relationship between perceived fit and the ongoing intent to use VLSs. However, this research suggests that in the context of Bangladesh, task-technology fit doesn't have a direct bearing on the continuous goal in ODL systems. This difference could be attributed to the distinction between VLS and ODL systems and the factors affecting ongoing use intentions across different tech platforms.

The findings reveal that the level of satisfaction with instructors significantly predicts users' intent to persist, aligning with Bhattacharjee's ECM conclusions that highlight the relationship between satisfaction and continuation intentions (Bhattacharjee, 2001). The ECM model posits that user satisfaction and perceived utility are the prime determinants of users' inclination to use IS, with satisfaction being the primary driver (Bhattacharjee, 2001). Satisfaction is a pivotal metric in technology adoption studies to gauge consumer behaviour. Ensuring ongoing use of IS and maintaining user satisfaction is critical. Brown, Craig, and Harris (2008) argue that post-adoption satisfaction is paramount in IT. This research corroborates that perspective.

This study suggests that elements from the UTAUT model, which typically guides Information Systems (IS) adoption, can also be applied to scenarios of IS continuation. While prior research indicated a positive influence of effort expectations on users' behavioural intentions (El-Masri & Tarhini, 2017; Venkatesh et al., 2012), there is limited exploration of its implications in the domain of IS continuation (Wan et al., 2020). For instance, a study in the USA found that effort expectations did not affect users' intentions toward e-learning systems (El-Masri & Tarhini, 2017). In contrast, this study highlights that effort expectations significantly influence users' decisions to continue using ODL systems in Bangladesh. Thus, ensuring that ODL systems are user-friendly could be a strategic move to encourage users to continue availing of their services. Furthermore, providing continuous training and support can enhance user confidence and satisfaction, fostering long-term engagement with ODL platforms.

The current research interprets users' behavioural intention as the willingness to experiment with new features rather than merely adopting ODL systems. It found no direct significant impact of effort expectancy on user behaviour, consistent with previous studies. This study contributes to the existing knowledge by highlighting the minor influence of effort expectancy on behavioural intention in technology-supported open and distance education. It shifts the focus from the general use of ODL services to the exploration of new features. The findings suggest that the usability of new ODL features rarely influences user decisions, indicating that other factors may be more critical in driving user engagement with new functionalities. Over time, as users become familiar with novel ODL tools, they tend to overlook their complexity. Therefore, even if improvements are made to the existing system, users might not be keen to use them. In the context of ODL systems and the UTAUT model, Wan et al. (2020) established that social influence

affects MOOC adoption. Moreover, Wu and Chen (2017) maintain that when it comes to using MOOCs, social influence doesn't have a significant effect on behaviour.

The recent research confirms the positive link between social influence and behavioural intention, echoing the conclusions of Wan et al. (2020). This study also enhances past research on the strong connection between behavioural intention and social influence by broadening the definition of behavioural intention to incorporate the intention to explore new features. Thus, it is recommended that educational organisations integrate feedback from initial users regarding new features in their promotional strategies. This is because these early users' views can lead to positive word-of-mouth, influencing the adoption habits of others. In simpler terms, integrating positive feedback from early users and obtaining celebrity endorsements can boost the usage of new features among existing ODL system users.

The study indicates that continuation intention, a previously unexplored aspect, considerably affects a user's inclination to try new functionalities. Earlier research highlighted the importance of identifying factors that drive behavioural intentions in ODL systems (M. Cheng & Yuen, 2018; Ifinedo, 2018; Mohamad, Kamarul, & Rahim, 2018; Wan et al., 2020; Wu & Chen, 2017). However, the behavioural objectives of emerging ODL applications have been under-researched. This current study identifies predictors of the intention to use new features in ODL systems. The findings suggest that users inclined to use ODL system services in the future are also likely to explore new features.

Performance and effort expectations considerably impact behavioural intention claimed Venkatesh et al. (2003). Unlike effort expectancy, this study shows that performance expectancy significantly influences behavioural intention. This study explores in further detail the causes of this insignificant effect. This is because effort expectation indirectly affects users' behavioural intentions through the mediating influence of continuation intention rather than directly impacting behaviour. This study contends that continuation intention mediates effort expectation and behavioural intention. In the "PE-CI-BI" pathway identified in this research, users tend to have a higher continuation intention with the ODL system when they perceive it to be advantageous. This heightened continuation intention motivates them to explore newer features. Similarly, the uncovered "EE-CI-BI" pathway suggests that when the ODL system is seen as user-friendly, individuals are more inclined to persist in its usage. As a result, these users are more likely to delve into the system's novel functionalities. This study's findings enrich the understanding of continuation and behavioural intentions within the ODL framework.

Implications for Research and Practice

In this research, there are significant theoretical advancements. While numerous studies have explored users' initial acceptance of ODL systems (El-Masri & Tarhini, 2017; Martins et al., 2019; Kayali & Gates, 2020), limited research has been conducted on the elements that impact users' intentions to continue using these systems (Ashrafi et al., 2020) or their inclination to experiment with new ODL features. Notably, the latter remains largely unexplored, as indicated by this research. The sustainability and efficacy of an information system are grounded more in users' sustained use rather than just initial adoption (Bhattacharjee, 2001). This study aims to bridge the understanding gap concerning the persistent utilisation of an information system by evaluating what drives users' intentions to remain engaged with the ODL system and their motivation to try out its new features. Furthermore, while prior studies (El-Masri & Tarhini, 2017; Kayali & Gates, 2020) have delved into the factors influencing ODL system adoption, they have not addressed users' motivations to experiment with new ODL capabilities.

Firstly, the current literature seldom combines behavioural intention and continuation intention in one model. However, regular users of ODL services might likely be inclined to explore its new features. This research bridges this knowledge gap by incorporating both intentions in its proposed model, shedding light on users' willingness to delve into new ODL features. Findings reveal that satisfaction, performance expectancy, and effort expectancy predominantly drive continuation intention. Moreover, the desire to try new features is shaped by continuation intention and the influence of peers. This enhanced model is valuable for scholars exploring user intent in adopting new technological systems or functionalities.

Secondly, task-technology fit, a critical aspect, is often overlooked in ODL system adoption literature, which typically centres on users' technological perceptions (Ashrafi et al., 2020). Adopting information systems isn't just influenced by technical perceptions and the congruence between tasks and technology (Zhou et al., 2010). This research offers a dual-perspective analysis of continuation and behavioural intentions by amalgamating key elements from UTAUT, TTF, and ECM models. Hence, it enriches the existing literature, primarily focusing on user perspectives like performance and effort expectancy.

Thirdly, no prior effort has been made to fuse the theoretical frameworks (i.e., UTAUT, TTF, and ECM) that shape this research model, aiming to understand post-adoption behaviours of information system users, including ODL systems. Notably, this study boasts an 82.2% explanatory power for continuance intention, surpassing 65.0% by Cheng (2019) and 77.6% for behavioural intention, eclipsing 36.7% by Kayali and Gates (2020). The synthesis of these models in the ODL context reaffirms the success of the integrative approach. This study extends their applicability in persistent IS usage literature by incorporating and broadening the UTAUT, TTF, and ECM. Furthermore, this study innovatively probes the mediating role of continuation intention, assessing its indirect impact on performance and effort expectancy's influence on users' behavioural intent. Specifically, it shows the moderating role of continuation intention on the relationship between performance and effort expectancy with behavioural goals. Hence, "PE-CI-BI" and "EE-CI-BI" are the two groundbreaking pathways this research introduces. These novel mediation effects enhance our comprehension of behavioural and continuation intentions in IS continuance studies.

In Bangladesh, among secondary school educators with a history of ODL service utilisation, there's a growing preference for open and distant learning systems and tech-driven education. Although this mode of education is prevalent in Bangladesh (BANBEIS, 2019; Bou, 2020), many users typically resort to it for mandatory educational courses, like the Bachelor of Education (B.Ed.), leveraging more traditional ODL delivery methods, such as Correspondence and Multimedia models. However, many secondary teachers haven't fully embraced the latest ODL features (Naidu & Laxman, 2019). The World Bank (2019) notes that despite commendable strides in enrollment, completion rates, and gender balance in secondary education, there's still an evident quality education gap in Bangladesh. Educational institutions can tap into their escalating user base by emphasising the sustained usage of ODL systems and nudging users to explore newer features. Consequently, this research offers invaluable insights into the holistic management and operation of ODL institutions. It also bears significance for decision-makers at open universities, their marketing and IT wings, and other key players, including corporate software developers and service providers.

Limitations and Future Research Directions

Bangladesh is a developing nation with a collectivist culture, and the current study is framed within that cultural background. When applied to people from different cultural backgrounds, the findings may be less accurate and generalisable but can still apply to environments with similar cultures. The attitudes, opinions, and responses of other ODL service users might differ from those of the study's participants. It is advised that researchers use care when extrapolating research results to users in various places. In countries where ODL adoption is similarly high, the insights from this research may be suitably applied, provided the ODL services are comparably advanced. The cross-sectional data used in this research might not capture potential fluctuations caused by users' responses at different intervals. Given user behaviours' evolving and fluid nature, cross-sectional data may not comprehensively represent users' perspectives and reactions towards ODL systems.

Future studies can assess the applicability of this research's findings in diverse settings. Future researchers should utilise this framework to conduct similar investigations in different countries. Conducting a cross-cultural analysis regarding users' sustained and behavioural intentions towards the ODL system will bridge the current gaps in the literature, offering richer insights for scholars and ODL service providers. Future studies might benefit from adopting a longitudinal approach to better understand users' ongoing engagement with the ODL system or other related

services. This would address the constraints presented by the cross-sectional design, offering a deeper insight into users' behaviours over an extended period.

CONCLUSION

This study provides a comprehensive understanding of the factors influencing both the behavioural intention and continuance intention to use Open and Distance Learning (ODL) systems among secondary school teachers in Bangladesh. By integrating three theoretical frameworks—UTAUT, TTF, and ECM—the research offers a nuanced perspective on user motivation and technology acceptance beyond initial adoption. The findings highlight that performance expectancy, effort expectancy, teacher satisfaction, and social influence significantly shape users' intentions, while task-technology fit surprisingly shows no direct impact on continuance intention in the studied context. Notably, continuance intention emerged as a key mediator, strengthening the link between perceived usefulness and behavioural intention. These insights underscore the importance of designing ODL platforms that are not only effective and user-friendly but also capable of maintaining user engagement over time. Practical implications suggest that institutional stakeholders should prioritize ongoing technical support, user satisfaction, and peer influence to foster deeper engagement with advanced ODL features. Furthermore, this research contributes to the theoretical literature by demonstrating the utility of an integrative model in examining post-adoption behaviors in educational technology. Given the cultural and infrastructural specificity of the Bangladeshi context, future studies are encouraged to apply this model in cross-cultural settings and adopt longitudinal designs to better capture the dynamics of user engagement over time. Ultimately, the study reinforces the critical role of sustained usage and feature exploration in realizing the full potential of ODL systems in transforming teacher professional development and educational quality in emerging economies.

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