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Future is Digital: Digital Transformation Acceptance in Online Flexible Distance Learning Higher Education Institutions

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Abstract

This study aims to comprehensively assess the direct and indirect relationships among performance expectancy, effort expectancy, innovative work behavior, facilitating conditions, intention, and the acceptance of digital transformation within the context of online distance learning higher education institutions in Malaysia. We build upon existing theoretical frameworks and empirically validate the relevance of these constructs in this specific educational setting. Data for this research were collected through a carefully structured questionnaire distributed among employees within online flexible distance learning higher education institutions. Our analysis involved a rigorous examination of the associations between latent variables and acceptance, incorporating a range of statistical methods. We conducted regression analysis and hypothesis testing on data gathered from a diverse sample

of 387 participants. The statistical backbone of this study was the robust structural equation modelling (SEM) technique. Our findings supported most of the direct relationship hypotheses, except the direct links between performance expectancy and acceptance, and innovative work behavior and acceptance. However, all indirect relationship hypotheses were substantiated, highlighting the intricate dynamics of acceptance in the online distance learning context. The theoretical implications of this study extend the existing body of knowledge on acceptance theories. They shed light on the multifaceted nature of acceptance factors in online distance learning. Future research avenues include exploring additional variables, conducting longitudinal studies to understand the long-term impact of digital transformation, and investigating cultural and contextual factors that may influence acceptance dynamics. This research contributes to a better understanding of the evolving landscape of digital transformation within the realm of online education, offering insights that can inform practice and policy in higher education institutions.
Keywords: Performance Expectancy, Effort Expectancy, Innovative Work Behaviour, Facilitating Conditions, Intention, Acceptance

Introduction

Digital transformation is the process of using digital technologies to change the way an organization works. This can include many changes, such as the use of new technologies, the renewal of business processes, and the creation of new products and services (Bond et al., 2018). Digital transformation is using digital technologies to change how organizations work and create value for customers. In the context of distance education in online universities, digital transformation can be used to improve student learning, expand the reach of institutions, and lower the price (Ellis & Goodyear, 2016). For example, technology can be used to provide 24/7 access to course materials and resources, deliver live lectures and facilitate discussion, online and group work as needed, and provide individual advice and support from instructors. Digital transformation can also be used to expand the reach of higher education institutions, enabling students to learn anywhere in the world (Gafurov et al., 2020). This is especially beneficial for students who live in rural areas or have other limitations that always make it difficult for them to access physical higher education institutions (Jackson, 2019). Finally, digital transformation can reduce costs by eliminating the need for physical classrooms and other infrastructure. This allows higher education institutions to offer lower tuition fees and reach a wider student population (Udovita, 2020). Digital transformation in Malaysia is driven by many factors, including the greater availability of high-speed internet, the proliferation of mobile devices, and the growing demand for online services. As a result, the number of online universities in higher education in Malaysia has increased (Rahim et al., 2022). Online distance higher education institutions have many advantages over real-world higher education institutions. They are more flexible, cheaper, and accessible to students nationwide (Raju et al., 2007). , 2021). Therefore, they are popular with students looking for an easier and cheaper higher education (Nguyen et al., 2025). The development of digital transformation has had a huge impact on higher education in Malaysia. Online distance learning institutions have now played an important role in ensuring Malaysian students' access to quality higher education (Kamil et al., 2022). A virtual learning environment (VLE) is an online platform that allows students to access course materials, communicate with teachers and classmates, and submit assignments (Kebah et al., 2019). VLEs are important tools for online distance learning as they provide a central location for all activities (Ahmad et al., 2023). E-learning modules are individual courses that can be accessed online. E-learning modules are a popular option for online distance learning as they allow students to learn at their own pace and time (Kebah et al., 2019). Online assessment is used to measure a student's progress in an online distance learning course. Online assessments can be tests, quizzes, or assignments. Digital transformation is still a new phenomenon in Malaysia, but it is having a huge impact on higher education (Toh et al., 2023). Online distance learning institutions have now played an important role in providing Malaysian students with access to quality higher education. The rapid development of technology has also led to changes in the university profession (Aloussef, 2023). Online Distance Learning (ODL) is growing in popularity because it gives students the flexibility to study independently anywhere in the world. However, employees of ODL organizations in Malaysia have been slow to adopt digital technology. This is due to many factors, such as lack of education and support, fear of change, and security and privacy concerns (Ismail et al., 2023). This research has great significance in today's educational environment. As technology continues to transform education, it is important to understand the factors that influence employee acceptance of digital transformation. Online distance learning institutions rely on digital tools and platforms to support teaching, learning, and administration. This study examines employees' acceptance of digital transformation and sheds light on factors such as attitudes, attitudes, and readiness to embrace technological change. The findings can provide intervention and support by helping organizations identify issues and challenges employees may face as they embrace digital transformation. In addition, this research helps develop effective strategies and training programs to develop employee skills and promote good leadership. The staff of online distance learning institutions has successfully implemented digital transformation for enhanced learning, productivity, and the ability to adapt to future technologies. This study aims to assess the direct and indirect relationship among performance expectancy, effort expectancy, innovative work behavior, facilitating conditions, intention, and acceptance of digital transformation among employees in online distance learning higher education institutions in Malaysia.

Literature Review

Underpinning Theory

The Unified Theory of Technology Acceptance and Use (UTAUT) provides a broad framework for understanding how people accept and use new technologies. It is widely used in many contexts, including digital transformation (Ventakesh et al., 2003). UTAUT has four main components: facilitating conditions, social norms, performance expectancy, and effort expectancy, which reflect people's belief that new technology will improve their job performance, while effort expectancy reflects their belief that technology will improve their performance. The technology will be simple and easy. Social influence captures the influence of peers who use and approve of technology, and support includes the individual's belief that he or she has the necessary resources and support to use good technology (Wang & Liao, 2014). These trends play an important role in creating people's willingness to adopt new technologies in the context of digital transformation. For example, people who believe that technology will improve their job performance are more likely to adopt it, while those who want it to be easier and more convenient will find it acceptable. UTAUT has proven its reliability and validity as a theory for predicting technology acceptance and has been widely used in many studies. In the world of digital transformation, UTAUT is an essential tool for understanding the factors that influence people's readiness to adopt new technologies to improve business processes and achieve corporate goals (Yu et al., 2017).

Relationship between Performance Expectancy, Intention & Acceptance

Many studies support the relationship between performance expectations and acceptance of digital transformation. In the context of online distance learning, employees who believe that digital tools will have a positive impact on their job performance are more likely to accept and adopt them. For example, a study by Venkatesh and Davis (2000) found that students' perceptions of the value of online learning affect their acceptance of technology. Similarly, a study by Sair and Danish (2018) showed that teachers' perceptions of e-learning's potential to increase effectiveness influence their recognition and adoption (Li et al., 2020). Many studies consistently show that there is a positive relationship between performance expectations and the willingness to use digital transformation technologies (Mohamad & Osman, 2025). When employees believe that the use of digital technology will increase their work performance and productivity, they will be willing to use this technology. For example, a study by Pangaribuan and Wulandar (2019) found that it has a positive effect on employee willingness to use crowdfunding platforms. In addition, Nikolopoulou et al. (2021) pointed out that employees' perception of knowledge management's ability to improve performance affects their willingness to use these systems. Previous studies have supported the hypothesis that performance expectations influence acceptance through emotional mediation. When employees see that the use of digital tools will improve their job performance, they increase their willingness to accept and use these technologies, resulting in increased satisfaction. For example, Raza et al. (2021) found that performance expectations affect employees' willingness to use technology, which affects their acceptance and user behavior. Also, Fedorkp et al. (2021) showed that employee opinions regulate the relationship between their approval (a measure of expected performance) and acceptance of the e-learning machine.

Relationship between Effort Expectancy, Intention & Acceptance

Previous studies have shown a positive relationship between effort expectancy and acceptance of digital transformation. Davis's (1989) Technology Acceptance (TAM) study found that perceived ease of use is one of the key expectations that influence people's acceptance of technology. Employees who see digital tools as user-friendly, intuitive, and less demanding will accept and embrace them. For example, a study by Walrave et al. (2021) found that contact tracing technology is easy to use and understand, and they are more likely to accept and use the machine (Osman et al., 2018). The data support a positive relationship between effort and willingness to use digital transformation technologies. When employees see that tools are easy to use, require little effort, and are compatible with their existing skills and abilities, they are willing to adopt and use digital tools. For example, a study by Venkatesh and Bala (2008) found that perceived ease of use positively affects employees' willingness to use business technology. Similarly, Muangmee et al. (2021) show that perceived ease of use affects employees' willingness to use team support techniques. Altalhi (2021) work provides evidence for the mediating role of emotion on motivational expectations and acceptance. His research focuses on the acceptance of MOOCs by universities. The results of the research show that employees' perception of expected effort can affect their willingness to use language skills, which in turn affects their acceptance and use of behavior. Similarly, Shiferaw et al. (2021) examined the acceptance of a training website and found that employees' perception of expected effort had a positive effect on their intention to use the system. Research shows that employees who find the courses easy to use and require less effort are more likely to adopt the courses, leading to greater acceptance. In addition, van der Shaikh et al. (2021) evaluated that doctors accept mobile phone information. This study shows that employees' perceptions of job expectations significantly affect their willingness to use mobile technology, which in turn affects their acceptance, knowledge, and behavior use. The findings show that employees who see mobile phone systems as more efficient and easier to use will have a positive attitude towards them and be more accepted.

Relationship between Innovative Work Behavior, Intention, & Acceptance
Many studies have shown that there is a positive relationship between adopting new business behaviors and accepting digital transformation. Employees with a positive attitude towards innovation and who are open to new ideas and technologies are more likely to adopt and participate in digital transformation projects. For example, a study by Zhang et al. (2021) found that employees with higher levels of innovation perform better in knowledge management. In addition, Kurniawan et al. (2021) reported that employees' innovative work attitudes positively affect their acceptance of information technology. The research supports that there is a positive relationship between innovative work behaviors and the desire to use digital transformation technologies. Employees who are more open to new work behaviors will be more willing to adopt and use digital tools. For example, a study by Hsiao and Chen (2016) revealed that employees' innovative work behaviors affect their willingness to use mobile technology in the office. Also, Khan et al. (2022) pointed out that innovative work behaviors of employees have a positive effect on their willingness to adopt a business investment plan. The data support the hypothesis that new job attitudes affect acceptance through emotional adjustment. Employees who are more eager for new work behaviors will be more willing to use digital transformation technologies, which will lead to greater acceptance. For example, the work by Hu et al. (2019) found that new work behaviours have an impact on employees' willingness to use their mobile phones, which in turn affects their acceptance and use behaviours. In addition, research by Kwahk and Kim (2017) shows that there is a positive relationship between the new work behaviors of employees and the acceptance of social media platforms.

Relationship between Facilitating Conditions & Acceptance
Previous studies consistently support a positive relationship between productivity and acceptance of digital transformation. The program refers to the availability of resources, educational support, training, and institutional guidelines that support and use digital tools (Giua et al., 2022). The findings highlight the role of a supportive environment in motivating online distance education workers in higher education institutions. Ifinedo's (2017) study investigated the acceptance of e-learning systems and found that convenience affects employee acceptance. This study shows that employees who receive technical support and training are more likely to adopt and effectively use e-learning systems. In addition, Hairul et al. (2020) evaluated universities adopting digital transformation initiatives and found that support, including access to technology and administrative support, was effective and good for admission. Also, a study by Al-Musharafi and Yusuf (2017) explores employee acceptance of cloud computing and shows the role of work in the situation. This study shows that employees who have access to adequate resources, such as sufficient bandwidth and storage capacity, are more willing to accept and use technology using AI.

Given the above hypotheses' development, the following hypotheses were proposed for this study:

H1: There is a relationship between effort expectancy and acceptance of digital transformation among employees in online flexible distance learning higher educationinstitutions.
H2: There is a relationship between performance expectancy and acceptance of digital Transformation among employees in online flexible distance learning higher education institutions.
H3: There is a relationship between facilitating conditions and acceptance of digital Transformation among employees in online flexible distance learning higher education institutions.
H4: There is a relationship between *i*nnovative work behavior and acceptance of digital transformation among employees in online flexible distance learning higher education institutions.
H5: There is a relationship between Intention and acceptance of digital transformation among employees in online flexible distance learning higher education institutions.
H6: There is a relationship between effort expectancy and intention on the acceptance of digital transformation among employees in online flexible distance learning higher education institutions.
H7: There is a relationship between performance expectancy and the intention of the acceptance of digital transformation among employees in online flexible distance learning in higher education institutions.
H8: There is a relationship between Innovative work behavior and the intention of the acceptance of digital transformation among employees in online flexible distance learning in higher education institutions.
H9: There is a mediating effect of intention on the relationship between effort expectancy and acceptance of digital transformation among employees in online flexible distance learning in higher education institutions.
H10: There is a mediating effect of intention on the relationship between performance expectancy and acceptance of digital transformation among employees in online flexible distance learning in higher education institutions.
H11: There is a mediating effect of intention on the relationship between innovative work behaviour and acceptance of digital transformation among employees in online flexible distance learning in higher education institutions.

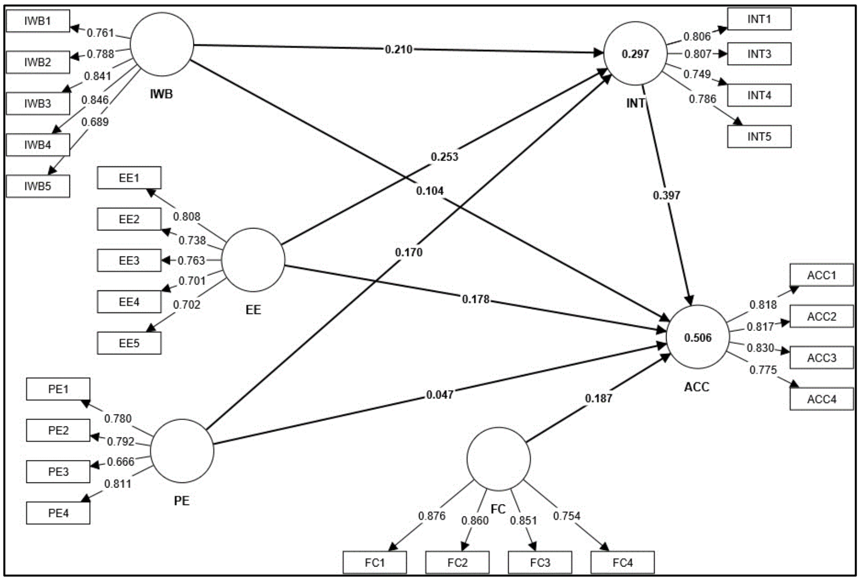

Figure 1: Research Model
Note: IWB=Innovative Work Behavior EE=Effort Expectancy PE=Performance Expectancy FC=Facilitating Conditions INT=Intention ACC=Acceptance

Methodology

Using a quantitative research method, this study explores the impact of various factors on the acceptance of digital transformation among employees of online distance-learning universities in Malaysia. This approach allows the collection of numerical data that can be analyzed using statistical methods. The sample of this study consisted of employees working at online distance education institutions in Malaysia. Online distance education institution employees were selected based on their suitability and willingness to participate in the research. Using a purposive sampling technique, individuals who met the inclusion criteria were contacted and invited to participate in the study. The model of this study consisted of 5 latent variables and 22 observed variables. The independent variables in this study include self-efficacy, effort expectancy, performance expectancy, intention, and acceptance. Self-efficacy was measured using a scale developed by Sherer et al. (1982), while effort expectancy and performance expectancy were measured using Venkatesh et al. (2003). Intention was measured using a scale developed by Davis et al. (1992), and acceptance was measured using Brock et al. (1998). The items in the questionnaire were measured with a 5-point Likert scale. On a scale of 1 (disagree) to 5 (agree), ask participants whether they agree with each statement. A total of 448 questionnaires were distributed to a selected sample of employees. Of these, 391 questionnaires were returned, and the return rate was 87.27%. After data filtering, cleaning, and removal of outliers, a database of 387 valid responses was subjected to further analysis. The structural equation modeling (SEM) technique was used in this study to analyze the collected data. SEM allows for the analysis of sample size (measurement) and sample size (measurement of the relationship between variables). The use of SEM helps measure relationships and better understand research patterns. In this study, Smart-PLS 4 software was used to analyze statistical and structural models. Smart-PLS 4 is a software tool widely used in equation modeling, providing powerful data and performance analysis Ringle et al., 2022). Table 1 shows the respondents' profiles in this study.

Table 1
Respondents' Profiles

		N	%
Gender	Male	225	58
	Female	162	42
Age	<30 Years Old	77	20
	31-40 Years Old	138	36
	41-50 Years Old	112	29
	51-60 Years Old	40	10
	>60 Years Old	20	5
Years of Service	<5 Years	21	5
	6-10 Years	127	33
	11-15 Years	132	34
	16-20 Years	79	20
	21-25 Years	18	5
	26-30 Years	7	2
	>30 Years	3	1
Job Category	Academician	337	87
	Non-Academician	50	13
Education	Doctorate	97	25
	Master	124	32
	Degree	92	24
	Diploma	45	12
	Certificate	19	5
	Others	10	3
Recommend	Yes	381	98
	No	6	2

Data Analysis
Common Method Bias
In the field of business management research, scholars often encounter a recurring challenge known as "common method bias." This refers to a situation where the observed fluctuations in data do not accurately represent the variables being studied but rather reflect the measurement technique used in that specific domain. As a result, this can distort or amplify the relationships between variables, potentially undermining the credibility of research findings. To address this issue directly, the researchers in this study have employed a reliable method called Harman's single-factor test. After conducting this test to assess common method bias, the results showed that the primary factor accounted for only 38.6% of the variation. This indicates that the impact of common method bias is not a significant concern in this study. This finding aligns with the advice given by Podsakoff and Organ (1986), who suggest that when the primary factor explains less than 50% of the variability, the influence of common method bias on the results is unlikely to be substantial.

Measurement Model
The assessment of construct validity and reliability in this study utilized the PLS-SEM algorithm, following the guidelines put forth by Hair et al. (2022). Two crucial dimensions

within PLS-SEM, namely the outer goodness model's and reliability and validity, were thoroughly examined. The research model, depicted in Figure 1, yielded satisfactory outcomes, with all constructs surpassing the minimum threshold of 0.5 for average variance extracted (AVE). The AVE values, spanning from 0.553 to 0.700 (Table 2), affirm the establishment of convergent validity for all constructs. Furthermore, the composite reliability values, ranging from 0.848 to 0.903 (Table 2), exceeded the recommended threshold of 0.7, as advised by Hair et al. (2017). The reliability of the constructs was further supported by Cronbach's alpha coefficients, all of which exceeded 0.7, ranging from 0.760 to 0.856 (Table 2). To ensure discriminant validity, scrutiny of cross-loading measurement items was conducted, with all item loadings found to be higher than their respective cross-loadings (Table 2), confirming discriminant validity. The Heterotrait-Monotrait (HTMT) ratios analysis (Table 2) also supported discriminant validity, with all four construct ratios falling below the threshold of 0.9, as recommended by Henseler et al. (2015). In conclusion, this study successfully established the reliability and validity of all latent constructs, aligning with Hair et al.'s (2022) recommendations. The utilization of the PLS-SEM algorithm and the comprehensive assessment of measurement properties enhance the credibility and robustness of the study's findings.

Table 2
Construct Reliability & Validity & HTMT

					Hetrotrait-Monotrait(HTMT) Ratio				
Items	Loadings	CA	CR	AVE	ACC	EE	FC	INT	IWB
ACC1	0.818	0.826	0.884	0.656					
ACC2	0.817								
ACC3	0.830								
ACC4	0.775								
EE1	0.808	0.797	0.860	0.553	0.656				
EE2	0.738								
EE3	0.763								
EE4	0.701								
EE5	0.702								
FC1	0.876	0.856	0.903	0.700	0.552	0.510			
FC2	0.860								
FC3	0.851								
FC4	0.754								
INT1	0.806	0.855	0.896	0.633	0.733	0.574	0.421		
INT2	0.828								
INT3	0.807								
INT4	0.749								
INT5	0.786								
IWB1	0.761	0.846	0.890	0.620	0.608	0.808	0.478	0.561	
IWB2	0.788								
IWB3	0.841								
IWB4	0.846								
IWB5	0.689								
PE1	0.780	0.760	0.848	0.584	0.559	0.646	0.495	0.528	0.769
PE2	0.792								
PE3	0.666								
PE4	0.811								

Structural Model

In this research, we assessed the structural model by concurrently examining pathway coefficients (β) and coefficients of determination (R^2), following the methodology outlined by Hair et al. (2017). The assessment was conducted using the Partial Least Squares (PLS) method, incorporating 5000 subsamples to ascertain the significance of the path coefficients. Detailed results of the hypothesis tests, encompassing the path coefficients (beta), t-statistics, and p-values, can be found in Table 3. This comprehensive analysis provides valuable insights into the significance and robustness of the relationships among the variables within the structural model. *H1* posits that Effort Expectancy positively influences Acceptance. The analysis reveals robust support for this hypothesis. The positive beta value (0.178), coupled with a T-statistic of 2.955 and a low p-value of 0.003, firmly indicates a significant and positive relationship between individuals' perceptions of the effort required and their acceptance of a system or technology. Consequently, H1 is substantiated. *H2* suggests that Performance Expectancy influences Acceptance. However, the results of the analysis do not support this hypothesis. The low beta value (0.047) and the T-statistic of 0.871, combined with a high p-value of 0.384, indicate that there is no significant relationship between performance expectancy and acceptance. Therefore, H2 is not supported. *H3* proposes that Facilitating Conditions positively affect Acceptance. The analysis strongly supports this hypothesis. The positive beta value (0.187), along with a T-statistic of 3.675 and a very low p-value of 0.000, suggests a significant and positive relationship. Given that, H3 is supported. *H4* posits that Innovative Work Behavior influences Acceptance. Nevertheless, the outcomes of the analysis fail to offer substantial support for this hypothesis. The modest beta value (0.104), a T-statistic of 1.693, and a p-value of 0.090, surpassing the common significance threshold of 0.05, collectively suggest the absence of a significant connection between innovative work behaviour and acceptance. Consequently, H4 is not corroborated. Moving on to *H5*, which posits that intention positively impacts acceptance, the analysis robustly validates this hypothesis. A substantial beta value (0.397), accompanied by a T-statistic of 8.061 and an exceedingly low p-value of 0.000, firmly substantiates a noteworthy and favorable relationship between individuals' intentions and their acceptance of a system or technology. Thus, H5 is indeed supported. *H6* advances the proposition that effort expectancy positively influences intention, and the analysis vigorously endorses this hypothesis. The positive beta value (0.253), coupled with a T-statistic of 4.090 and an extremely low p-value of 0.000, signifies a significant and favorable relationship. Consequently, H6 garners support. Turning to *H7*, which suggests that performance expectancy impacts intention, the analysis results align with this hypothesis. The positive beta value (0.170), a T-statistic of 3.005, and a relatively low p-value of 0.003 collectively denote a substantial and positive relationship. Hence, H7 is substantiated. *H8* posits that innovative work behaviour positively affects intention, and the analysis findings uphold this hypothesis. The positive beta value (0.210), a T-statistic of 3.034, and a low p-value of 0.002 together indicate a significant and favorable relationship. Thus, H8 garners support. *H9* proposes an indirect relationship wherein effort expectancy influences intention, which, in turn, influences acceptance. The analysis robustly supports this hypothesis. The positive beta value (0.100), a T-statistic of 3.772, and an extremely low p-value of 0.000 provide compelling evidence of significant relationships among all three constructs. Therefore, H9 is affirmed. *H10* introduces an indirect relationship in which performance expectancy influences intention, subsequently impacting acceptance. The analysis results are consistent with this hypothesis, signifying that H10 is validated. Lastly, *H11* suggests an indirect relationship wherein innovative work behavior influences intention, which, in turn, affects acceptance. The analysis results endorse this hypothesis, revealing significant relationships within the proposed sequence. Consequently, H11 is substantiated.

Effect sizes(f^2) in this study (Table 3) were evaluated according to Cohen's criteria (1992) and categorized as small (0.020 to 0.150), medium (0.150 to 0.350), or large (0.350 or greater). The observed effect sizes spanned from small (0.003) to large (0.231). Notably, the acceptance level demonstrates a high amount of explained variance in endogenous constructs, with an R^2 value of 0.506 (as illustrated in Figure 1). Concerning the mediators, particularly intention, the model accounted for approximately 29.7% of the variance in the structural components, as indicated by an R^2 value of 0.297.

Table 3
Hypotheses Testing Results & f^2

Hypotheses	Beta	T statistics	P values	f^2	2.50%	97.50%	Decision
H1: EE -> ACC	0.178	2.955	0.003	0.032	0.058	0.295	*Supported*
H2: PE -> ACC	0.047	0.871	0.384	0.003	-0.053	0.158	*Not Supported*
H3: FC -> ACC	0.187	3.675	0.000	0.049	0.079	0.281	*Supported*
H4: IWB -> ACC	0.104	1.693	0.090	0.009	-0.021	0.224	*Not Supported*
H5: INT -> ACC	0.397	8.061	0.000	0.220	0.298	0.492	*Supported*
H6: EE -> INT	0.253	4.090	0.000	0.049	0.127	0.369	*Supported*
H7: PE -> INT	0.170	3.005	0.003	0.025	0.057	0.278	*Supported*
H8: IWB -> INT	0.210	3.034	0.002	0.028	0.067	0.339	*Supported*
H9: EE -> INT -> ACC	0.100	3.772	0.000		0.052	0.156	*Supported*
H10: PE -> INT -> ACC	0.068	2.662	0.008		0.021	0.12	*Supported*
H11: IWB -> INT -> ACC	0.084	2.805	0.005		0.027	0.144	*Supported*

PLSpredicts & Cross-Validated Predictive Ability Test

Importantly, we turn our attention to the model's out-of-sample predictive capabilities, which are essential for drawing conclusions and offering managerial recommendations. To assess this aspect, we employed the PLSpredict procedure to evaluate business performance, following the approach outlined by Shmueli et al. (2016, 2019). We utilized Q^2, where a value greater than 0 signifies that the PLS-SEM predictions surpass the standard outcomes predicted by a naïve mean value (as detailed in Table 4). Additionally, the root mean square error (RMSE) of the PLS-SEM predictions was consistently smaller than that of the linear model (LM) prediction benchmark in all cases, substantiating the model's predictive power (as shown in Table 4). Furthermore, in line with Hair et al.'s (2022) suggestion, we incorporated the Cross-Validated Predictive Ability Test (CVPAT) to assess the predictive performance of the PLS-SEM model, as conducted by Liengaard et al. (2021) alongside the PLSpredict analysis. The CVPAT employed an out-of-sample prediction method to quantify the model's prediction error and compute the average loss value. Two benchmarks were used for comparison: the average loss value based on predictions using indicator averages (IA) as a straightforward benchmark and the average loss value of a linear model (LM) forecast as a more conservative benchmark. To establish the superiority of the model's predictive capabilities over these benchmarks, it was crucial to observe a lower average loss value for PLS-SEM, resulting in a negative difference in the average loss values. The CVPAT aimed to ascertain whether this difference in average loss values between PLS-SEM and the benchmarks was significantly below zero. A significantly negative difference would indicate the model's enhanced predictive abilities. The results of the CVPAT, presented in Table 5, unequivocally confirm that the average loss value of PLS-SEM was indeed lower than that of the benchmarks. This is substantiated by the negative difference in the average loss values, providing robust evidence of the model's superior predictive capabilities.

Table 4
PLSpredicts

	Q^2	PLS_RMSE	LM_RMSE	PLS-LM
ACC1	0.329	0.624	0.628	-0.004
ACC2	0.232	0.624	0.635	-0.011
ACC3	0.252	0.673	0.697	-0.024
ACC4	0.157	0.723	0.727	-0.004
INT1	0.227	0.619	0.625	-0.006
INT2	0.191	0.625	0.645	-0.020
INT3	0.144	0.678	0.688	-0.010
INT4	0.136	0.689	0.707	-0.018
INT5	0.177	0.623	0.639	-0.016

Table 5
Cross-Validated Predictive Ability (CVPAT)

	Average loss difference	t-value	p-value
ACC	-0.139	6.509	0.000
INT	-0.088	4.808	0.000
Overall	-0.111	6.668	0.000

Importance-Performance Map Analysis (IPMA)

The Importance Performance Analysis (IPMA) by Ringle and Sarstedt (2016) and Hair et al. (2018) is a recommended approach for assessing the significance and effectiveness of latent variables in explaining acceptance, as outlined in Table 6. In assessing their overall impact, it was discovered that intention exerted the most substantial influence on acceptance (with a coefficient of 0.397), followed by effort expectancy (0.279), innovative work behavior (0.188), facilitating conditions (0.187), and performance expectancy (0.115). These coefficients provide insights into the relative importance of each latent variable within the adoption context. In terms of performance scores, it's noteworthy that effort expectancy achieved the highest score (67.427), while intention garnered the lowest score (60.929) on a scale ranging from 0 to 100. This implies that effort expectancy performed relatively well, whereas intention exhibited the lowest level of performance. It's worth highlighting that, despite being the most critical factor for adoption, intention exhibited the lowest performance level. Consequently, based on these findings, it is advisable for top management within OFDL higher education institutions to prioritize and place greater emphasis on activities aimed at enhancing employees' intentions. By directing efforts toward improving intention, it becomes possible to enhance overall acceptance levels as well.

Table 6
Importance-Performance Map Analysis (IPMA)

	Total Effect	Performance
EE	0.279	67.427
FC	0.187	67.039
INT	0.397	60.929
IWB	0.188	66.639
PE	0.115	66.790

Discussion & Conclusion

Discussion

This study focuses on the direct and indirect impact of effort expectancy, performance expectancy, facilitating conditions, innovative work behavior, and their influence through intention on digital transformation acceptance among employees in online flexible distance learning higher education institutions. Based on the research findings, to ensure an effective direct and indirect impact of key factors, including effort expectancy, performance expectancy, facilitating conditions, innovative work behavior, and their influence through intention on Digital Transformation Acceptance among Employees in Online Flexible Distance Learning Higher Education Institutions, several strategic approaches can be employed. Firstly, comprehensive training programs should be implemented, focusing on enhancing technical skills while emphasizing the ease of use (effort expectancy) and practical benefits (performance expectancy) of digital tools, alongside addressing facilitating conditions by providing necessary resources and support. Secondly, a user-centric design approach should be adopted to develop and continuously improve digital tools and systems, making them intuitive, minimizing complexity, and aligning with employees' needs and preferences. Thirdly, engaging top management and leadership as champions of digital transformation initiatives can positively influence employees' intention to use the technology. Fourthly, fostering a culture of innovation within the organization, encouraging and rewarding innovative work behavior, promotes a mindset of continuous improvement and experimentation. Fifthly, effective change management strategies should be implemented to address resistance and communicate the benefits of digital transformation. Sixthly, feedback mechanisms should be established to allow employees to provide input on the digital tools they use, promoting a sense of ownership and facilitating refinements based on user suggestions. Seventhly, clear performance metrics and KPIs tied to the use of digital tools should be defined, with regular assessments to communicate the impact on job performance, reinforcing the link between performance expectancy and acceptance. Eighthly, recognizing and rewarding employees who actively engage with digital tools and contribute innovative ideas can boost motivation and intention to use the technology effectively. Lastly, continuous evaluation of the impact of these strategies and adjustments as needed will ensure their effectiveness in driving digital transformation acceptance within the organization.

Theoretical Implications

The theoretical implications derived from the strategies outlined for enhancing Digital Transformation Acceptance among Employees in Online Flexible Distance Learning Higher Education Institutions are significant. Firstly, these strategies underscore the relevance of established theories such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) in the context of higher education. They reaffirm that factors like effort expectancy, performance expectancy, and intention continue to play pivotal roles in predicting technology adoption, with facilitating conditions and innovative work behavior adding nuanced dimensions to the model. Secondly, the emphasis on user-centric design and innovation cultivation aligns with the Human-Centered Design theory, emphasizing the importance of tailoring technology to user needs and promoting a culture of innovation within organizations. Thirdly, the incorporation of change management principles underscores the significance of theories related to organizational change and transformation. These strategies highlight that successful digital transformation in higher education requires a multifaceted approach that draws upon a range of established theoretical frameworks to address the complex interplay of factors influencing technology acceptance and implementation.

Practical Implications

The practical implications stemming from the strategies outlined for enhancing Digital Transformation Acceptance among Employees in Online Flexible Distance Learning Higher Education Institutions are highly actionable. Firstly, institutions should prioritize investing in comprehensive training programs that not only build technical skills but also emphasize the user-friendliness and real-world benefits of digital tools. Secondly, organizations must adopt a user-centric design approach, involving end-users in the development and refinement of technology solutions to ensure they align with their needs and preferences. Thirdly, securing leadership buy-in and support is crucial, as it sets the tone for the entire organization. Leaders should actively champion digital transformation initiatives to inspire employee confidence and intention to engage with new technologies. Fourthly, cultivating a culture of innovation through recognition and rewards for innovative work behavior can stimulate employees to contribute creative solutions and adapt to technological changes more readily. Fifthly, effective change management strategies should be employed to address resistance and encourage acceptance, including clear communication of benefits and constant feedback mechanisms. Lastly, organizations must establish clear performance metrics tied to technology use to measure their impact on job performance, providing data-driven insights into their effectiveness. These practical implications offer a roadmap for higher education institutions to navigate the complex terrain of digital transformation and foster a culture of technology acceptance and innovation among their employees.

Suggestions for Future Studies

Future research directions within the domain of Digital Transformation Acceptance among Employees in Online Flexible Distance Learning Higher Education Institutions offer several promising avenues for exploration. Firstly, longitudinal studies can provide valuable insights into the sustained impact and evolving dynamics of technology acceptance over time, shedding light on how attitudes and behaviours change or stabilize. Secondly, cross-cultural investigations hold the potential to uncover cultural influences on technology adoption, examining how diverse cultural contexts shape acceptance patterns within higher education. Thirdly, research efforts could be directed towards assessing the transformative potential of emerging technologies, such as AI and virtual reality, in enhancing the online learning experience. Moreover, future studies might explore the interplay of emotional intelligence and psychological factors in influencing digital acceptance. Lastly, an investigation into the external factors, including regulatory frameworks and market forces, can offer a comprehensive view of the ecosystem in which technology adoption occurs, providing deeper insights into its complexities.

Conclusion

The notion of transformation acceptance among employees in online flexible distance learning higher education institutions is of paramount importance, carrying profound theoretical and practical implications. Grounded in well-established theories, it underscores the pivotal role of various factors in shaping the adoption of technology, including effort expectancy, performance expectancy, and innovation. By delving into these elements, institutions can craft a pragmatic roadmap for promoting technology acceptance among their staff. This approach not only aligns with user needs but also fosters a dynamic culture of innovation that is indispensable in the ever-evolving landscape of online education.

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