INTERNATIONAL JOURNAL OF ACADEMIC RESEARCH IN BUSINESS & SOCIAL SCIENCES
Vol 14, Issue 2, (2024) E-ISSN: 2222-6990

Unveiling the Catalysts of Digital Transformation Acceptance: Insights from Employees in Online Distance Learning Higher Education Institutions

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To Link this Article: http://dx.doi.org/10.6007/IJARBSS/v14-i2/20676 DOI:10.6007/IJARBSS/v14-i2/20676

Published Date: 28 February 2024

Abstract
Online distance learning in higher education institutions is experiencing significant growth and is increasingly adopting digital transformation. However, employee acceptance and adoption of these changes present a major challenge. This study investigates the factors influencing employee acceptance of digital transformation in online distance learning institutions. It examines the influence of latent variables, such as effort expectancy, performance expectancy, self-efficacy, and intention, on the acceptance of digital transformation. It also expands on existing theoretical frameworks and provides empirical evidence of their importance. Data was collected from 387 employees using a structured questionnaire, and statistical analysis, including regression and PLS structural equation modelling, was used to assess the relationships between variables. The findings revealed that effort expectancy, performance expectancy, self-efficacy, and intention significantly influenced employee acceptance of digital transformation. The indirect relationship hypotheses are also supported. Several practical implications and strategies such as user-friendly technologies, effective communications, professional development opportunities and involvement in decision-making processes are identified as key strategies to enhance employee acceptance. The study contributes to the existing knowledge of acceptance theories and suggests avenues for future research including exploring additional variables such as culture and contextual factors and conducting longitudinal studies to understand the long-term effects of digital transformation.
Keywords: Effort Expectancy, Performance Expectancy, Self-Efficacy, Intention, Acceptance, Online Distance Learning

Introduction
Online distance learning has emerged as a prominent mode of education, especially in the context of higher education institutions (Grosseck et al., 2020). With advancements in

technology and the increasing demand for flexible learning opportunities, many institutions have adopted digital transformation initiatives to enhance the learning experience and improve educational outcomes (Grosseck et al., 2020). However, the successful implementation of digital transformation heavily relies on the acceptance and adoption of these initiatives by employees within higher education institutions (Giang et al., 2021). In the Malaysian context, online distance learning higher education institutions have witnessed rapid growth in recent years. These institutions are actively embracing digital transformation to cater to the diverse needs of students and to overcome the challenges posed by traditional classroom-based education (Lazim et al., 2021). However, the acceptance and adoption of digital transformation by employees in these institutions pose a significant challenge. Factors such as unfamiliarity with digital tools, resistance to change, and a lack of necessary skills and competencies can hinder the successful implementation of digital initiatives. Therefore, it is crucial to understand the factors that influence employee acceptance of digital transformation in online distance-learning higher education institutions in Malaysia (Othman et al., 2021). Organizations need to invest in comprehensive training programs, develop a supportive culture, and address technological challenges to enhance employee acceptance and engagement in digital transformation initiatives effectively (Lu & Wang, 2023). There is a need to establish clear communication channels, provide adequate resources and support, and address concerns related to workload and job security to ensure smooth acceptance and implementation of digital transformation in these institutions (Rof et al., 2022). Online distance learning institutions in Malaysia can benefit from the findings of this study. They can gain insights into the factors that influence employee acceptance and utilize this knowledge to design targeted strategies and interventions (Raju et al., 2021). By promoting acceptance and successful implementation of digital transformation initiatives, institutions can enhance their teaching and learning practices, improve student outcomes, and increase institutional effectiveness. Employees within these institutions will benefit from the study (Al-Kumaim et al., 2021). Understanding the key factors that influence acceptance can help employees navigate and embrace digital tools more effectively, leading to increased job satisfaction, productivity, and professional growth. The study's emphasis on fostering self-efficacy and providing continuous professional development opportunities can empower employees to enhance their digital skills and competencies (Abad-Segura et al., 2020). Students enrolled in online distance learning programs will benefit from the study's implications. The successful implementation of digital transformation initiatives can result in an improved learning experience, enhanced access to resources and support, and greater engagement with educational content (Benavides et al., 2020). Given the potential benefits of digital transformation, this study aims to assess the direct and indirect relationships between effort expectancy, performance expectancy, self-efficacy, intention, and acceptance of digital transformation among employees in online distance learning higher education institutions in Malaysia.

Literature Review

Digital Transformation and Acceptance of Digital Transformation

Digital transformation is a concept that has gained significant attention in both academic and business circles in recent years. It refers to the integration of digital technology into all aspects of an organization, fundamentally changing how it operates and delivers value to its customers (Fernandez-Vidal et al., 2022). Digital transformation has emerged in many organisations across the economy, from manufacturing to organisations operating in areas such as healthcare and education (Bozintan et al., 2023). Digitalization has changed our way of life in many aspects and the transformation rate was amplified by the wrath of the Covid-19 pandemic that struck the world almost 2 years ago. One never heard of the terms working from home, Google Classroom, e-wallet, online shopping, and ride-hailing to name a few which currently become the norm. As people around the globe continue to embrace digitalization in running their daily tasks, and the borderless market opportunities, higher education institutions also must do the same in meeting the expectations or risk being left out and being replaced by more adaptable competitors. Many higher education institutions today are currently undergoing digital transformation simply because it brings benefits to organisations and society at large. Acceptance of digital transformation is a critical factor in its successful implementation, as it involves not only technological change but also cultural and organizational shifts.

Digital transformation requires a considerable amount of funding, manpower equipped with a set of skills or knowledge in Information and Communication Technology (ICT) and strong supporting ecosystems that have a common interest in digitalization. Universities are facing a lot more challenges and would require support for them to be on board the digital transformation journey. The challenges were well studied in many past literatures from a technological, organization and environment such as ICT infrastructure and expertise, Top management and government support, financial resources, regulatory environment, business model and stakeholders' collaboration were investigated on the impact of adoption of digital transformation (Mujahed et al., 2021). Any changes to process workflow or new technology would face two potential responses from the targeted group which are either acceptance or skepticism.

The acceptance of digital transformation is a multifaceted and dynamic process that involves a combination of individual, organizational, and technological factors. Research in this field underscores the need for a holistic approach, combining technological innovation with a focus on people, culture, and leadership support to achieve successful digital transformation outcomes (Bozintan et al., 2023). As technology continues to evolve, so too will the research on its acceptance, providing insights for organizations striving to thrive in an increasingly digital field.

Theories of Technology Acceptance

Most of the existing studies regarding 'acceptance' were conducted by using previous acceptance theories such as the Theory of Reasoned Action -TRA Ajzen (1975); Theory of Planned Behavior Ajzen (1991) technology Acceptance Model – TAM (Davis, 1989; Davis et al., 1992). TAM is an extension of the Theory of Reason Action (TRA) which according to this theory, objectives and attitudes of people shape their behaviors (Kinis & Tanova, 2022). TRA is a broad theory, and it is not limited to a specific belief that may only apply to a particular situation. It mainly aims to explain the relationship between an individual's belief or perception and behavioural intention (Moslehpour et al., 2020). This theory discusses that behavioural intention is a concept that leads to the adoption of technology and is influenced by attitude, which is the general impression of technology (Zamani, 2022). According to TRA, beliefs influence attitudes and attitudes will influence behavior. The formation of belief depends on a person's experience, information, knowledge, and social norms that were exposed to them and how they perceived it. TRA is widely applied in marketing research to study consumer purchase intention. TAM is widely used in technology acceptance research, however, despite its robustness, it has some limitations. It is too simple to keep up with the pace and development and changes in IT-related industries. To address this limitation, new TAM2 and TAM3 models were introduced and a Unified Theory of Acceptance and Use of Technology (UTAUT) was also introduced. The UTAUT, which was established by Venkatesh et al. (2003) has integrated eight well-established theories – TRA, TPB, TAM, TAM 2, TAM 3, motivational model, innovation diffusion theory and social cognitive theory. The UTAUT theory has integrated 32 concepts explaining behavioural intention, including four constructs namely performance expectancy, effort expectancy, social influence and facilitating conditions. These constructs shape consumer behaviour to adopt technology. The construct performance expectancy is near the concepts of 'relative advantage' and 'perceived usefulness'. Effort expectancy is near the concept of 'perceived ease of use'. These two constructs are being studied in the current study, treated as independent variables.

Performance Expectancy (PE)

Performance Expectancy is the degree to which one believes job performance will improve using innovative technologies (Venkatesh et. al. 2003). The concept of 'perceived usefulness' in the TAM models is consistent with 'performance expectancy' in UTAUT. In other studies such as Jambulingam, (2013), performance expectancy is defined as 'an individual's perception that the usage of the system will improve the performance.

Effort Expectancy (EE)

Another variable that is found in UTAUT is 'effort expectancy' which is defined as 'how an individual feels that he/she easily uses technology and how much strength is there in the usage of technology. The construct of Effort Expectancy is consistent with the construct of 'perceived ease of use' as in TAM.

Behavioural Intention

The concept of Behavioural Intention plays a major role in both theories of TAM (Davis, 1989) and UTAUT (Venkatesh et al., 2003) Based on these theories, Performance Expectancy and Effort Expectancy are the factors that influence Behavioral Intention, and the effect is assumed to be positive. The current study is to explore the individual's behavioural intention of digital transformation acceptance rather than to investigate the actual use of digital technology

Self-Efficacy

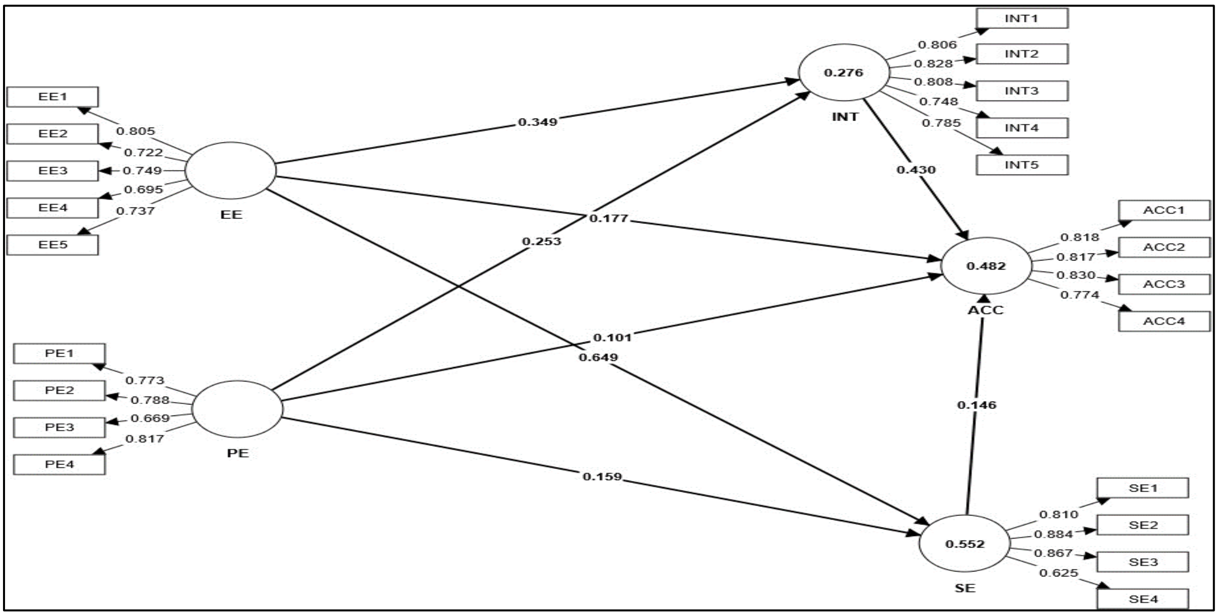
The present study examined the role of self-efficacy in predicting their acceptance of digital transformation. We defined self-efficacy as an individual's judgement of their ability to accept digital transformation. Self-efficacy is considered an internal motivational factor behind new technology adoption. In a study by Yuxin et al (2021), self-efficacy was found to have a mediating effect on the relationship between organisational culture and employee performance. This study analyses the mediating role of self-efficacy in the relationship between performance expectation and acceptance of digital transformation and the relationship between Effort Expectancy and Acceptance of digital transformation

Acceptance of Digital Transformation

Digital transformation refers to the integration of digital technologies into all aspects of an organization's operations, fundamentally reshaping how it delivers value to customers, optimizes processes, and maintains competitiveness. Central to the success of digital transformation efforts is the concept of "acceptance," which pertains to the willingness of individuals, teams, and organizations to embrace and leverage digital technologies.

Based on the above hypotheses' development, the following hypotheses were proposed for this study

H1: There is a positive relationship between effort expectancy and acceptance of digital transformation among employees in online distance-learning higher education institutions
H2: There is a positive relationship between performance expectancy and acceptance of digital transformation among employees in online distance-learning higher education institutions
H3: There is a positive relationship between intention and acceptance of digital transformation among employees in online distance-learning higher education institutions
H4: There is a positive relationship between self-efficacy and acceptance of digital transformation among employees in online distance-learning higher education institutions
H5: There is a positive relationship between effort expectancy and intention in digital transformation acceptance among employees in online distance-learning higher education institutions .
H6: There is a positive relationship between performance expectancy and intention in digital transformation acceptance among employees in online distance-learning higher education institutions
H7: There is a positive relationship between effort expectancy and self-efficacy in digital transformation acceptance among employees in online distance-learning higher education institutions
H8: There is a positive relationship between performance expectancy and self-efficacy in digital transformation acceptance among employees in online distance-learning higher education institutions
H9: There is a mediating effect of self-efficacy on the relationship between effort expectancy and digital transformation acceptance among employees in online distance-learning higher education institutions
H10: There is a mediating effect of self-efficacy on the relationship between performance expectancy and digital transformation acceptance among employees in online distance-learning higher education institutions
H11: There is a mediating effect of intention on the relationship between effort expectancy and digital transformation acceptance among employees in online distance-learning higher education institutions
H12: There is a mediating effect of intention on the relationship between performance expectancy and digital transformation acceptance among employees in online distance-learning higher education institutions



Note: EE=Effort Expectancy PE=Performance Expectancy SE=Self-Efficacy
INT=Intention ACC=Acceptance
Figure 1: Research Model

Methodology

This study focused on employees working in online distance learning higher education institutions in Malaysia as the target population. Primary data was collected using a survey instrument, specifically a survey questionnaire developed based on prior studies that had demonstrated strong reliability and validity. The questionnaire consisted of measurement items carefully selected to ensure suitability and frequent utilization in the field. To gather data, the survey questionnaires were distributed via email to the selected respondents. Due to the absence of a sample frame, non-probability purposive sampling was employed as the sampling technique. A total of 22 observed variables were included in the study, encompassing exogenous, mediating, and endogenous variables. The effort expectancy construct consisted of 5 measurement items Venkatesh et al (2003), performance expectancy consisted of 4 measurement items Venkatesh et al (2003), self-efficacy consisted of 4 measurement items Venkatesh et al (2003), intention consisted of 5 measurement items Davis & Warshaw (1992), and acceptance consisted of 4 measurement items (Brocks et al., 1998).

A five-point Likert scale ranging from strongly disagree to strongly agree was used to measure all the constructs' measurement items. Out of the 570 questionnaires sent out, a total of 426 questionnaires were returned, resulting in a response rate of 74.7%. This response rate was deemed adequate for data analysis using the structural equation modelling technique (SEM). After screening the data and removing outliers, 387 questionnaires were considered clean and suitable for analysis. In this study, component-based SEM, specifically partial least squares structural equation modelling (PLS-SEM), is employed to test the relationships in the proposed model (Hair et al., 2022). PLS-SEM allows for the analysis of the strength of a construct's influence on the target construct within the path model (Hair et al., 2022). It supports both explanatory and predictive goals in analyzing causal-predictive model relationships (Wold, 1982). To ensure compatibility with existing theory and to enable correlational explanation and predictive accuracy, the model must be compared with prior theoretical frameworks (Chin et al., 2020). This research methodology is particularly suitable for the development of new theories and the refinement of existing ones (Ritcher et al., 2016). Furthermore, PLS-SEM enables the estimation of reflective and formative measurement models, as well as complex structural models (Hair et al., 2022; Wold, 1982). Researchers from various fields within the social sciences, including human resource management (Ringle et al., 2020), higher education (Ghasemy et al., 2020), information systems Chin et al (2020), and particularly marketing Liu et al (2021); Chaouali et al (2021); Damberg (2021a), as well as corporate and organizational reputation Damberg (2021b); Schloderer et al (2014), have utilized the PLS-SEM method in empirical analyses to support the objectives of their studies. For the estimation and modelling of evaluation results, this study employs SmartPLS 4 (Ringle et al., 2022).

Data Analysis

Respondents' Profile

Examination of the frequency table reveals several key insights about the participants in this study. First, in terms of gender distribution, it is clear that the majority of respondents identified as male (58%), and the remaining proportion identified as female (42%) If we refer to the age structure of the participants, it was found that the oldest age group was people aged 31-40 years old which made up 29% of the sample. Furthermore, participants under 30 years of age represented 20% of the total, reflecting the diverse age range in the study. Looking at the years of service of the participants, the data shows that most fell into the 6-10-year range, which made up 33% of the sample. This indicates that the distribution of individuals with moderate levels of work experience is balanced. Furthermore, the 11-15-year group made up 34% of the participants, confirming the importance of this mid-career distance in the study population The frequency table examining occupational classification variables shows that they were distributed among the majority of participants (87%) as administrative employees, while a small proportion (13%) are the administrators. Data on educational qualifications held by non-academic positions show that 25% have doctoral degrees, 32% with master's degrees, 24% have bachelor's degrees and 19% are school leavers.

Common Method Bias

In the field of business management research, one common challenge that researchers often encounter is the presence of something called "common method bias." This refers to a situation where the variation observed in data does not represent the intended variables being studied but instead reflects the measurement method used in that particular field. This can lead to distorted or inflated relationships between variables, ultimately compromising the validity of research findings. To tackle this issue head-on, the researchers in this study have employed a reliable method known as Harman's single-factor test. When conducted the common method bias test, it was found that the principal factor accounted for only 39.4% of the variance. This result indicates that common method bias is not a major concern in this study. It aligns with the guidance provided by Podsakoff and Organ (1986), who suggest that when a principal component explains less than 50% of the variance, it is unlikely that common method bias is significantly influencing the findings.

Measurement Model

The validity and reliability of the constructs in this study were evaluated using the PLS-SEM algorithm. Following the recommendations of Hair et al (2022), two crucial aspects of PLS-SEM were considered: the reliability and validity of the outer goodness model. The research model, as depicted in Figure 1, demonstrated satisfactory results, with all constructs surpassing the minimum threshold of 0.5 for average variance extracted (AVE). The AVE values ranged from 0.551 to 0.656 (Table 1), indicating the establishment of convergent validity for all constructs. Additionally, the composite reliability values for the constructs ranged from 0.848 to 0.896, surpassing the threshold of 0.7 as suggested by (Hair et al., 2017). The Cronbach's alpha coefficients for all constructs were also above 0.7, ranging from 0.760 to 0.855, further affirming their reliability. To ensure discriminant validity, the cross-loading measurement items were examined. As shown in Table 1, all item loadings were higher than their respective cross-loadings, confirming the discriminant validity of the constructs. The assessment of discriminant validity was further supported by the Heterotrait-Monotrait (HTMT) ratios analysis (Table 2), which revealed that all four construct ratios were below the threshold of 0.9, as proposed by (Henseler et al., 2015). Based on these findings, it can be concluded that this study successfully established the reliability and validity of all latent constructs, aligning with the recommendations of (Hair et al., 2022). The use of the PLS-SEM algorithm and the comprehensive assessment of the constructs' measurement properties contribute to the robustness and trustworthiness of the study's results.

Table 1
Construct Reliability, validity & Cross Loadings

Constructs	Items	ACC	CA	CR	AVE
Acceptance	ACC1	0.818	0.826	0.884	0.656
	ACC2	0.817			
	ACC3	0.830			
	ACC4	0.774			
Effort Expectancy	EE1	0.805	0.797	0.860	0.551
	EE2	0.722			
	EE3	0.749			
	EE4	0.695			
	EE5	0.737			
Intention	INT1	0.806	0.855	0.896	0.633
	INT2	0.828			
	INT3	0.808			
	INT4	0.748			
	INT5	0.785			
Performance Expectancy	PE1	0.773	0.760	0.848	0.584
	PE2	0.788			
	PE3	0.669			
	PE4	0.817			
Self-Efficacy	SE1	0.810	0.810	0.877	0.645
	SE2	0.884			
	SE3	0.867			
	SE4	0.625			

Table 2
Hetrotrait-Monotrait (HTMT) Ratio

	ACC	EE	INT	PE
EE	0.656			
INT	0.733	0.574		
PE	0.559	0.646	0.528	
SE	0.622	0.884	0.524	0.617

Structural Model

In this study, the evaluation of the structural model was conducted by simultaneously assessing pathway coefficients (β) and coefficients of determination (R2) using a methodology outlined by (Hair et al., 2017). The evaluation employed the Partial Least Squares (PLS) method, utilizing 5000 subsamples to determine the significance level of the path coefficients. The findings of the hypothesis tests, including the path coefficients (beta), t-statistics, and p-values, are presented in Table 3. This thorough analysis offers valuable insights into the significance and strength of the relationships among the variables within the structural model. Effect sizes in this study were assessed using 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 ranged from small (0.003) to large (0.231). The statistical analysis reveals that H1 is supported. There is a statistically significant positive relationship between Effort Expectancy (EE) and Acceptance (ACC), as indicated by the beta coefficient of 0.177 ($p < 0.05$). The effect size (f^2) of 0.025 suggests a small but meaningful impact of EE on ACC. The statistical analysis confirms the support for H2. There is a significant positive relationship between Performance Expectancy (PE) and Acceptance (ACC), as indicated by the beta coefficient of 0.101 ($p < 0.05$). The effect size (f^2) of 0.013 indicates a small effect size. H3 is supported based on the statistical analysis. There is a significant positive relationship between Intention (INT) and Acceptance (ACC), with a beta coefficient of 0.430 ($p < 0.001$). The effect size (f^2) of 0.256 suggests a moderate effect of INT on ACC. The statistical analysis provides support for H4. There is a statistically significant positive relationship between Self-Efficacy (SE) and Acceptance (ACC), with a beta coefficient of 0.253 ($p < 0.001$). The effect size (f^2) of 0.018 indicates a small effect size. The statistical analysis supports H5, indicating a significant positive relationship between Effort Expectancy (EE) and Intention (INT). The beta coefficient of 0.125 ($p < 0.05$) suggests that EE has a moderate impact on INT. The effect size (f^2) of 0.125 indicates a moderate effect size. H6 is supported by the statistical analysis, indicating a significant positive relationship between Performance Expectancy (PE) and Intention (INT). The beta coefficient of 0.065 ($p < 0.05$) suggests a small but meaningful impact of PE on INT. The effect size (f^2) of 0.065 indicates a small effect size. The statistical analysis confirms the support for H7, indicating a significant positive relationship between Effort Expectancy (EE) and Self-Efficacy (SE). The beta coefficient of 0.696 ($p < 0.001$) suggests a strong impact of EE on SE. The effect size (f^2) of 0.696 indicates a large effect size. H8 is supported based on the statistical analysis. There is a statistically significant positive relationship between Performance Expectancy (PE) and Self-Efficacy (SE), as indicated by the beta coefficient of 0.042 ($p < 0.05$). The effect size (f^2) of 0.042 suggests a small effect size. The statistical analysis supports Hypothesis H9, indicating that SE mediates the relationships between EE and ACC. The beta coefficient was 0.095 ($p < 0.05$), hence confirms H9 is supported. For hypothesis H10, the statistical data analysis results show that SE mediates the relationships between PE and ACC. The beta coefficient was 0.023 ($p < 0.05$), which also confirms H10 is supported. For hypothesis H11 the statistical data analysis results show that INT mediates the relationships between PE and ACC. The beta coefficient was 0.150 ($p < 0.05$), hence confirms H10 is supported. For hypothesis H11, the statistical data analysis results revealed that INT mediates the relationships between EE and ACC. The beta coefficient was 0.150 ($p < 0.05$), therefore confirms H11 is supported. For hypothesis H12, the statistical data analysis results show that INT mediates the relationships between PE and ACC. The beta coefficient was 0.108 ($p < 0.05$), which also confirms H12 is supported.

The inner value inflation factors (VIFs) are all below the more liberal threshold of 5 with the highest value being 2.396 (Table 4). Collinearity at this level permits to comparison and interpretation of the structural model coefficient size. The acceptance demonstrates the high level of endogenous constructs' amount of explained variance with an R^2 of 0.482 (Figure 1). Regarding the mediators, intention, and self-efficacy, the model accounted for approximately 27.6% and 55.2% respectively of the variance in the structure, indicated by an R^2 value of 0.276 and 0.552 respectively. More importantly, the model's out-of-sample predictive power is to draw conclusions and give managerial recommendations. For this assessment, the PLSpredict procedure is used on business performance (Shmueli et al., 2016, 2019). Q^2 predict greater than 0 shows the PLS-SEM predictions are greater than the naïve mean value prediction standard outcomes (Table 5). In addition to that, the root mean square error (RMSE) value of the PLS-SEM predictions is ten of twelve cases smaller than the RMSE value of the linear model (LM) prediction benchmark. These results prove the proposed model has a predictive power (Table 5). Hair et al (2022) suggested incorporating the Cross-Validated Predictive Ability Test (CVPAT) to evaluate the predictive capabilities of the PLS-SEM model. In line with this recommendation, Liengaard et al (2021) conducted a CVPAT alongside the PLSpredicts analysis to assess the model's predictive performance. The CVPAT utilized an out-of-sample prediction method to measure the model's prediction error and calculate the average loss value. Two benchmarks were used for comparison: the average loss value based on predictions using indicator averages (IA) as a simple 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 the benchmarks, the average loss value of PLS-SEM should be lower, resulting in a negative difference in the average loss values. The CVPAT aimed to determine if the difference in average loss values between PLS-SEM and the benchmarks was significantly below zero. A significantly negative difference would indicate enhanced predictive abilities of the model. The results of the CVPAT, presented in Table 6, confirm that the average loss value of PLS-SEM was indeed lower than that of the benchmarks. This is supported by the negative difference in the average loss values, providing strong evidence of the model's superior predictive capabilities. According to Ringle and Sarstedt (2016); Hair et al (2018), Importance Performance Analysis (IPMA) is recommended to evaluate the significance and effectiveness of latent variables in explaining acceptance (Table 7). When considering the overall impact, intention was found to have the strongest influence on adoption (0.430), followed by effort expectancy (0.422), performance expectancy (0.233), and self-efficacy (0.146). These values indicate the relative importance of each latent variable in the adoption context. In terms of performance scores, effort expectancy achieved the highest score (67.270), while intention had the lowest score (60.907) on a scale ranging from 0 to 100. This suggests that effort expectancy performed relatively well, while intention had the lowest level of achievement. Despite being the most critical factor for adoption, intention exhibited the lowest performance level. Based on these findings, it is recommended that top management in ODL higher education institutions prioritize and emphasize activities aimed at improving employees' intentions. By focusing on enhancing intention, overall performance can be enhanced as well.

Table 3
Hypotheses Testing Results & f^2

Hypotheses	Beta	T statistics	P values	f^2	2.50 %	97.50 %	Decision
H1: EE -> ACC	0.177	3.125	0.002	0.025	0.066	0.286	*Supported*
H2: PE -> ACC	0.101	1.984	0.047	0.013	0.005	0.205	*Supported*
H3: INT -> ACC	0.430	8.497	0.000	0.256	0.327	0.525	*Supported*
H4: SE -> ACC	0.146	2.358	0.018	0.018	0.028	0.270	*Supported*
H5: EE -> INT	0.349	6.755	0.000	0.125	0.242	0.446	*Supported*
H6: PE -> INT	0.253	4.872	0.000	0.065	0.147	0.352	*Supported*
H7: EE -> SE	0.649	18.263	0.000	0.696	0.574	0.714	*Supported*
H8: PE -> SE	0.159	3.261	0.001	0.042	0.061	0.251	*Supported*
H9: EE -> SE -> ACC	0.095	2.261	0.024		0.018	0.183	*Supported*
H10: PE -> SE -> ACC	0.023	2.070	0.038		0.006	0.054	*Supported*
H11: EE -> INT -> ACC	0.150	5.461	0.000		0.100	0.208	*Supported*
H12: PE -> INT -> ACC	0.108	3.960	0.000		0.058	0.165	*Supported*

Table 4
Inner Model Collinearity VIF

	ACC	INT	SE
EE	2.396	1.372	1.250
INT	1.392		
PE	1.483	1.386	1.371
SE	2.248		

Table 5
PLSpredicts

	Q^2predict	PLS_RMSE	LM_RMSE	PLS-LM
ACC1	0.292	0.641	0.644	-0.003
ACC2	0.187	0.642	0.644	-0.002
ACC3	0.215	0.690	0.700	-0.010
ACC4	0.133	0.733	0.730	0.003
INT1	0.214	0.624	0.626	-0.002
INT2	0.181	0.629	0.637	-0.008
INT3	0.146	0.677	0.685	-0.008
INT4	0.121	0.695	0.704	-0.009
INT5	0.164	0.627	0.638	-0.011
SE1	0.365	0.658	0.544	0.114
SE2	0.406	0.604	0.581	0.023
SE3	0.443	0.581	0.589	-0.008
SE4	0.179	0.725	0.741	-0.016

Table 6
Cross Validated Predictive Ability (CVPAT)

	Average loss difference	t-value	p-value
ACC	-0.119	5.777	0.000
INT	-0.083	4.748	0.000
SE	-0.220	7.377	0.000
Overall	-0.136	8.041	0.000

Table 7
Importance-Performance Map Analysis (IPMA)

	ACC	Performance
EE	0.422	67.270
INT	0.430	60.907
PE	0.233	66.803
SE	0.146	63.602

Discussion & Conclusion

To enhance employee acceptance of digital transformation in online distance learning higher education institutions, it is crucial to formulate comprehensive strategies based on the supported hypotheses and the results provided in the table. Online distance learning higher education institutions should focus on effort expectancy, institutions can invest in user-friendly technologies and platforms that simplify tasks and reduce complexity. Additionally, offering comprehensive training programs and continuous support will empower employees to navigate and utilize digital tools effectively. By streamlining processes and removing unnecessary barriers, institutions can minimize the effort required for employees to embrace digital transformation. Online distance learning higher education institutions should strengthen performance expectancy, it is important to communicate the benefits and positive outcomes associated with digital transformation. Providing concrete examples and success stories of how digital tools and practices have improved teaching and learning experiences can create a compelling case for adoption. Feedback mechanisms, such as regular performance assessments and evaluations, can also play a vital role in highlighting the impact of digital transformation on individual and institutional performance. Online distance learning higher education institutions should foster self-efficacy among employees is crucial for their confidence and willingness to embrace digital transformation. This can be achieved by offering continuous professional development opportunities that focus on enhancing digital skills and competencies. Creating a supportive and collaborative culture, where employees feel encouraged to experiment, share knowledge, and learn from one another, can significantly contribute to building self-efficacy. Recognizing and celebrating individual achievements in digital transformation efforts further reinforces employees' belief in their own capabilities. Lastly, online distance learning higher education institutions should improve employees' intention toward digital transformation requires proactive measures. Involving employees in decision-making processes and seeking their input and ideas can generate a sense of ownership and commitment. Communicating the institution's vision and strategic goals, and how digital transformation aligns with them, can help employees understand the purpose and significance of their efforts. Offering incentives, rewards, or career advancement opportunities tied to digital transformation initiatives can also motivate employees to actively engage in the process.

Theoretical Implications

This study has important theoretical implications for online distance learning higher education and digital transformation. It contributes to our theoretical understanding of how digital transformation is accepted and adopted in educational institutions. By examining the relationships between latent variables such as effort expectancy, performance expectancy, self-efficacy, and intention, the study provides empirical evidence of their significance in influencing employee acceptance of digital transformation. This expands upon existing theoretical frameworks like the Technology Acceptance Model (TAM) by highlighting the specific factors that play a crucial role in the context of online distance learning. The study emphasizes the need to address multiple dimensions of acceptance in digital transformation efforts, focusing on effort expectancy, performance expectancy, self-efficacy, and intention. By doing so, it underscores the complex nature of employee acceptance and emphasizes the need for a comprehensive approach. This enhances our understanding of acceptance theories by emphasizing the multidimensionality and interplay of various factors in the online distance learning context. The research also highlights the importance of individual factors, such as self-efficacy and intention, in driving acceptance and adoption of digital transformation. By demonstrating their influence on employee acceptance, it underscores the role of individual beliefs, attitudes, and motivations in the process. This has implications for designing and implementing strategies to enhance employee acceptance by addressing both individual and organizational factors. Additionally, the study provides practical insights into the role of institutional strategies in fostering employee acceptance. By suggesting specific strategies related to effort expectancy, performance expectancy, self-efficacy, and intention, the research offers practical guidance for online distance learning higher education institutions. These strategies can inform decision-making and resource allocation, enabling institutions to design targeted interventions that promote acceptance and successful implementation of digital transformation initiatives.

Practical Implications

The study's findings have practical implications for online distance learning institutions aiming to foster employee acceptance of digital transformation. Strategies can be developed based on the supported hypotheses and results to enhance the acceptance and successful implementation of digital initiatives. Institutions should prioritize improving effort expectancy by investing in user-friendly technologies, simplifying tasks, and providing comprehensive training. Streamlining processes and removing barriers will reduce the effort required for employees to embrace digital transformation. Strengthening performance expectancy involves effectively communicating the benefits and showcasing success stories of digital tools. Implementing feedback mechanisms, such as performance assessments, highlights the impact on individual and institutional performance. Fostering self-efficacy requires offering professional development opportunities, creating a supportive culture, and recognizing individual achievements. Addressing employees' intentions involves involving them in decision-making, communicating the institution's vision, and providing incentives tied to digital initiatives. These strategies will enhance acceptance and engagement in digital transformation, ensuring its successful integration.

Suggestions for Future Study

Future research can explore several avenues to advance understanding. Additional latent variables like perceived usefulness, social influence, and organizational support can be investigated to create a more comprehensive model that encompasses the acceptance process. Longitudinal studies are valuable in assessing the long-term effects of digital transformation on employee acceptance and organizational outcomes, providing insights into sustainability and effectiveness. Cultural and contextual factors can be examined as moderators of the relationships between latent variables and employee acceptance, revealing unique challenges and opportunities in diverse settings. Qualitative methods, such as interviews or focus groups, can supplement quantitative findings by exploring employees' subjective experiences, perceptions, and attitudes toward digital transformation, uncovering underlying mechanisms and complexities. Replication studies across various educational contexts and diverse samples can enhance the generalizability and robustness of the relationships between latent variables and employee acceptance. By pursuing these research avenues, a deeper understanding of employee acceptance in online distance learning can be achieved, informing the development of effective strategies and interventions for the successful implementation of digital transformation initiatives.

Conclusion

This study provides valuable insights into employee acceptance of digital transformation in online distance learning higher education institutions. The findings underscore the significance of latent variables, including effort expectancy, performance expectancy, self-efficacy, and intention, in shaping acceptance. By expanding existing theoretical frameworks, the study highlights the multifaceted nature of these factors within the context of online distance learning. Further exploration in these domains has the potential to deepen our understanding of employee acceptance and facilitate the development of targeted strategies for successful digital transformation. Online distance learning institutions can leverage these insights to enhance their practices, cultivate a supportive environment, and fully embrace the transformative potential of digital technologies in education. This study contributes to the existing knowledge base on digital transformation and lays a solid foundation for future research endeavours in this field.

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