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The Impact of Accepting Digital Transformation Technologies on Employees' Intention to Use: Education Level as a Moderator

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Keywords

Digital Transformation.
Unified Theory of Acceptance and Use of Technology.
Intention to use
Education Level
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Abstract

The research aims to examine how employees' intentions to use digital transformation technologies are affected by their acceptance of these technologies, with a particular emphasis on the moderating effect of education level. The researchers developed and examined a conceptual model grounded on the Unified Theory of Acceptance and Use of Technology (UTAUT) framework by empirically examining the education level's role in influencing employees' intention to use digital transformation technologies. Using a quantitative research technique, data was obtained from 401 employees and supervisors in the four and five-star hotels in Hurghada and Sharm El Sheikh Cities. The Partial Least Squares Structural Equation Modeling (PLS-SEM) method was used to analyze the collected data. The results show that performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC) significantly influence employees' intention to use (IU) digital transformation technologies. Moreover, the results revealed that education level moderates the effect of PE and FC on employee intention to use digital transformation technologies, but does not significantly moderate the effect of SI and EE on employee intention to use digital transformation technologies. Additionally, the research contributes to filling a knowledge gap and offers practical implications.

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1. Introduction

Digital transformation is crucial to the revolutionary changes in modern economies' structures (Zehir et al., 2020). Moreover, United Nations Commission on Science and Technology for Development (UNCTAD) and World Bank highlighted that digital transformation is crucial for sustainable development goals and has been pivotal in crisis response and recovery during the COVID-19 pandemic (UNCTAD, 2019; World Bank, 2020). Furthermore, Egypt's Sustainable Development Strategy, Egypt Vision 2030, prioritizes digital transformation, leveraging Information and communication technology (ICT) to enhance efficiency and speed in transactions across all socioeconomic sectors (Abdelaziz & Naama, 2023). Modern technological advancements have significantly transformed numerous industries, enhancing daily operations and prompting an increasing number of companies to leverage these advancements for productivity and expansion (Al-shanableh et al., 2024). Alrawadieh et al. (2021) stated that hotel industry actively involved in supporting digital transformation through organizational structure design, financial support, and qualified employee hiring. Furthermore, organizations are encouraged to create and implement new policies to modify activities, practices, and processes due to the worldwide digital technology revolution (Abdelaziz & Naama, 2023). According to Mahmoud (2018), competent and trained employees are crucial for efficient data analysis and intelligent decision-making in digital transformation.

The hotel industry is leveraging digital technologies like chatbots, delivery robots, and voice controls to improve customer experience and boost employee performance (Kim et al., 2020; Abugabel, 2023). Furthermore, hotels are implementing intelligent features like access control systems, artificial intelligence, and wearable tech to enhance employee performance, manage human resource processes, and improve customer experiences, while integrating internet of things and virtual and augmented reality (Hassan et al., 2022; Abdelaziz & Naama, 2023). Additionally, digital transformation in the hospitality sector presents both opportunities and challenges, including high initial investment costs, resource requirements, and cyber security risks. Challenges include fixed mindsets, hierarchies, and organizational silos (Warner & Wager, 2019; Kraus et al., 2021; Vaz, 2021; Bansal et al., 2023). However, new digital capabilities can enhance performance, expand products, and increase sales (Verhoef et al., 2019; Trenerry et al., 2021). Moreover, Hotels are transforming their operations and guest experiences through digital transformation initiatives, enhancing customer engagement from initial screening to post-stay service assessment (O'Connor, 2020; Alkhatib & Valeri, 2022; Zheng et al., 2022; Jayawardena et al., 2023).

Moreover, behavioral intention (BI) is a crucial factor in technological adoption, serving as a predictive determinant across various theoretical frameworks (Jayawardena et al., 2023). Behavioral expectation (BE) in technology adoption encapsulates the anticipated probability of behavior enactment, offering insights into behavior drivers (Truong et al., 2020; Jeon et al., 2021; Jayawardena et al., 2023). BE integrates volitional and non-volitional determinants to overcome constraints in technology acceptance frameworks (Venkatesh et al., 2006; Maruping et al., 2016). Factors like system flexibility, PE, EE, SI, and FC also play a significant role (Alkhuwaylidee, 2019).

Empirical research focused on the adoption of individual technologies within the hotel sector, such as augmented reality (AR), social media, mobile payments, travel apps, Internet of Things (IOT), and autonomous vehicles (Herrero et al., 2018; Ho & Amin, 2019; Nathan et al., 2020; Saxena & Kumar, 2020; Westmattelmann et al., 2020; Valeri & Baggio, 2021; Shaqrah & Almars, 2022; Ribeiro et al., 2022; Khashan et al., 2023). Moreover, limited studies have applied UTAUT to evaluate technology acceptance in this sector, particularly in Arab countries (Al-Shanableh et al., 2024). Therefore, the previous literature extensively covers the broad impacts of digital transformation across industries; there are notable gaps in understanding its specific effects on employees within the hospitality sector. Existing studies predominantly focus on technological capabilities and customer-facing innovations, often overlooking the critical role of employees' attitudes and behaviors towards these technologies. Furthermore, the moderating effect of education level on technology acceptance and usage remains underexplored, particularly within the context of hospitality (Tan et al., 2014; Martins et al., 2014). Addressing these gaps is crucial for developing a comprehensive understanding of the enablers and barriers to successful digital transformation in this industry.

In order to better understand the application of the modified Unified Theory of Acceptance and Use of Technology in the hospitality sector, the current study focuses on the key factors that influence employees' acceptance of the digital transformation in Egyptian hotels. Furthermore, the goal of this study is to investigate how employees' intentions to use digital transformation technologies are affected by their acceptance of these technologies, with a particular emphasis on the moderating effect of education level. Furthermore, this study looks into how employees' educational backgrounds affect how they accept and use digital technologies. The goal is to shine light on this in order to develop strategies for better technology adoption in the hospitality industry.

2. Literature Review

2.1. Digital Transformation Concept

The concept of digital transformation encompasses various digitalization practices across corporate organizations, fundamentally altering how companies function and deliver value (Westerman et al., 2014). Digital Transformation (DT) is an evolutionary journey leveraging digital capabilities and technologies to generate distinctive value for business models, operational processes, and customer interactions (Morakanyane et al., 2020; Valeri, 2022). It represents a transformative force impacting personal and professional spheres alike, following in the footsteps of historical revolutions such as the steam, steel, electricity, and petrochemical eras (Valeri & Katsoni, 2021). It entails the integration of digital technology into every aspect of business operations, including corporate culture, consumer experiences, and business processes (Al-Jubori, 2021; Feroz et al., 2021). In the hospitality industry, digital transformation is reshaping business models, operational procedures, and customer interactions to provide new value to guests and staff (Hewavitharana et al., 2021; Chatterjee et al., 2022). However, the effectiveness and long-term viability of digital transformation depend on the preconditions that facilitate successful acceptance processes (Jayawardena, 2023).

2.2. Key Elements of Digital Transformation

Digital transformation involves three main stages: digitization, digitalization, and transformation; digitization involves transferring processes and systems to digital formats, while digitalization optimizes digital technologies and IT capabilities, the final step, digital transformation, is triggered by extensive digital capabilities (Verhoef et al., 2021). DT represents a convergence of both technological and non-technological antecedents, illustrating the interconnectedness and dependencies inherent in its implementation (Jayawardena et al., 2023)

Moreover, DT involves the adoption of a suite of technologies, blending non-technical and technological elements to drive multifaceted change (Sergei et al., 2018). High-speed networks such as 5G and fiber optics facilitate rapid data flow, enabling real-time communication, seamless connectivity, and efficient processing, empowering businesses to make informed decisions, optimize processes, and drive innovation (Möller, 2023). Key technologies driving DT in the tourism and hotel sectors involves various methods, including the internet, website services, email, blogs, simultaneous publishing technology, social networks, artificial intelligence, and smart mobile phone software (Wenzel & Wenzel, 2022; Abdelaziz & Naama, 2023).

Digital technologies are transforming employee and organizational performance, with the hotel industry embracing chatbots, delivery robots, and voice controls to enhance customer experience and boost employee performance (Kim et al., 2020; Abugabel, 2023). These technologies facilitate revolutionary changes in organizations, driving significant impacts on organizational evaluation and fostering innovation (Feroz et al., 2021). Furthermore, skilled employees are essential for effective data analysis and decision-making in digital transformation, and their understanding of the change process is crucial for strategic planning (Alam, 2022; Shehadeh et al., 2023).

2.3. Impact of Digital Transformation on Hotels Industry

With the global adoption of DT practices, there's a significant shift in economic paradigms, with ICT and digital initiatives becoming key drivers of innovation and growth across various sectors (Nambisan, 2019; Yoo & Yi, 2022). Hotels are increasingly adopting DT initiatives to engage customers throughout their journey, from initial screening and booking to post-stay service assessment (Lam & Law, 2019). This shift is evident across various industries, including the hotel sector, where technology-driven approaches are transforming operational processes and guest experiences (O'Connor, 2020; Alkhatib & Valeri, 2022; Zheng et al., 2022; Jayawardena et al., 2023). Abdelaziz and Naama (2023) agreed with Hassan et al. (2022) that hotels are utilizing intelligent features to improve employee performance, such as access control systems, analytical tools, artificial intelligence, delivery and concierge robots, identity verification systems, in-room control systems, smart applications, wearable tech, IoT, vertical concierge applications, and virtual and augmented reality overlays.

Moreover, Kraus et al. (2021) stated that DT in the hospitality sector offers both opportunities and challenges, including high initial investment costs, resource requirements, and cyber security risks Additional challenges stem from fixed mindsets, inflexible hierarchies, and entrenched organizational silos within hospitality enterprises (Vaz, 2021). Integrating new digital technologies with existing IT systems, educating employees, and managing cyber risks are key hurdles faced by organizations (Warner & Wager, 2019; Bansal et al., 2023). Moreover, new digital capabilities can enhance performance; expand products, services, and customer bases, leading to increased sales and profits (Warner & Wäger, 2019; Verhoef et al., 2019; Trenerry et al., 2021).

2.4. Unified Theory of Acceptance and Use of Technology

The notion of DT has emerged as a multifaceted phenomenon, intricately woven with the adoption of various technological components (Nadkarni, 2021: Kovacevic-Opacic, 2023). The Unified Theory of Acceptance and Use of Technology have garnered significant attention within research spheres as a pivotal framework for evaluating the acceptability and utilization of diverse technologies across heterogeneous populations (Tosuntas et al., 2015). UTAUT serves as a cornerstone in comprehending the factors influencing the acceptance and usage of information and communication technologies (ICTs) within organizational contexts (Venkatesh et al., 2003). It identifies four primary determinants of technology acceptance: PE, EE, SI, and FC (Venkatesh et al., 2003; Farooq, 2016).

UTAUT was proposed as a theoretical advance above previous theories to analyze adoption and dissemination related studies (Dwivedi et al., 2019). Venkatesh et al. (2003) examined, illustrated, and synthesized eight theories and models: the theory of reasoned action (TRA), the motivational model (MM), the technology acceptance model (TAM), the theory of planned behavior (TPB), the combined theory of planned behavior/technology acceptance model (C-TPB-TAM), the model of PC utilization (MPCU), the innovation diffusion theory (IDT), and the social cognitive theory (SCT). Two of its constructs are comparable to those found in TAMs: Effort expectancy may be mapped to perceived ease of use (PEOU), while performance expectancy can be transferred to perceived usefulness (PU), with social influence and facilitating condition, the final two structures, originating from TPB (Dwivedi et al., 2019).

Empirical investigations consistently underscore the predictive efficacy of UTAUT, with its core components elucidating a substantial proportion of the variability in technology adoption and usage (Rangarajan, 2020; Mohamed & Nafzaoui, 2023; Venkatesh et al., 2023). Researchers have applied UTAUT across a spectrum of industries and technological domains, encompassing e-banking, e-learning, and e-government initiatives (Mohammadi, 2017; Monica, 2019). Furthermore, the empirical utilization of UTAUT and its extensions, both exogenous and endogenous, is prominently featured in studies within the travel and tourism sectors and numerous related domains (Moura et al., 2017; Naranjo-Zolotov et al., 2019; Siyal et al., 2020; Vinodan & Meera, 2020; Yang et al., 2020; Türkmendağ & Tuna, 2021; Ribeiro et al., 2022; Jayawardena et al., 2023).

2.5. Intention to Use Digital Transformation

Employees play a central role in DT, as their acceptance and adoption of transformative technologies determine its success (Vial, 2021; Zhang & Chen, 2023). Information technology in the digital domain can enhance business process relationship management, becoming a crucial component of human resource management operations that promote innovation (Leviäkangas, 2016; Zhang & Chen, 2023). As digital technologies evolve, human resource interacts with information and data, improving service delivery to stakeholders (Mosca, 2020). Moreover, digital transformation fosters a competitive edge for organizations by leveraging digital technologies efficiently (Kumar et al., 2019); enhancing not only internal operations but also human resource management practices, thereby promoting innovation (Leviäkangas, 2016; Mosca, 2020; Zhang & Chen, 2023). Moreover, Abdelaziz and Naama (2023) revealed a strong positive correlation between digital transformation dimensions and employees' job performance in hotels. Therefore, understanding users' intentions, acceptance, and application of digital technologies is essential for organizations seeking to thrive in a dynamic and competitive landscape (Zhang & Chen, 2023).

Behavioral intention (BI) assumes paramount significance in technological adoption paradigms, embodying the subjective probability of participating in a specific behavior (Jayawardena et al., 2023). BI serves as a predictive determinant across various theoretical frameworks, including UTAUT, TAM, TPB, and TRA, with its influence known to diminish over time (Venkatesh et al., 2008). Noteworthy empirical inquiries into technology acceptance delve into the intricate interplay between BI as a dependent variable and its association with factors such as perceived usefulness (Truong et al., 2020; Jeon et al., 2021; Jayawardena et al., 2023). Conversely, behavioral expectation in technology adoption encapsulates the anticipated probability of behavior enactment, delineating the likelihood of a given behavior occurring (Venkatesh et al., 2006). While BI primarily concerns an individual's consciously formulated plan for behavior, BE explores the likelihood of behavior occurrence, thereby offering complementary insights into behavior drivers (Venkatesh et al., 2008). BE endeavors to surmount persistent constraints within technology acceptance frameworks by integrating volitional and non-volitional determinants (Venkatesh et al., 2006; Maruping et al., 2016). Insights gleaned from research, such as Alkhuwaylidee's (2019) findings on intentions to utilize computer-based intelligent tutoring systems, underscore the pivotal role played by factors such as system flexibility, PE, effort expectancy, social influence, and facilitating conditions.

2.6. Hypotheses Development

2.6.1. The Influence of Performance Expectancy on Intention to Use DT

PE refers to users' perception of a technology's ability to enhance job performance, as explained by Venkatesh et al. (2003). Research shows that PE significantly influences technology adoption, with studies in e-commerce, augmented reality, and internet shopping (Dajani, 2016; Hewavitharana et al., 2021). This is supported by scientific results from various studies, highlighting the robustness of PE's influence on technology adoption outcomes (Agarwal & Sahu, 2022; Chauhan et al., 2022; Khashan et al., 2023). Similarly, PE emerges as a significant predictor in diverse technological contexts, including online hotel reservations and donor inclination towards charitable projects (Alkhuwaylidee, 2019; Lee, 2023; Gupta, 2023). The scientific results supported the impact of PE on users' IU digital transformation technologies. Based on substantial scientific results, this research proposes the following hypothesis:

H_1: Performance expectancy has a significant positive effect on the employees' intention to use digital transformation technologies in hotels in Egypt.

2.6.2. The Influence of Effort Expectancy on Intention to Use DT

EE constitutes a fundamental aspect of users' perceptions regarding the ease of using a particular technology, encompassing perceived simplicity and complexity (Venkatesh et al., 2003; Turan et al., 2015). Venkatesh et al. (2003) further expound on EE as the degree of ease associated with system use, emphasizing its pivotal role in shaping users' perceptions and behavioral intentions towards technology adoption. As articulated by Alowayr (2022), users' anticipations regarding the mental workload associated with technology usage serve as the underlying basis for EE. Moreover, scientific results across diverse contexts corroborates the significant influence of EE on users' intentions to adopt digital transformation technologies (Dajani, 2016; Hewavitharana et al., 2021). Moreover, EE emerges as a significant determinant of users' behavioral intentions across multiple technological domains, including charitable donations and educational systems (Alkhuwaylidee, 2019; Gupta, 2023). Given the multifaceted nature of EE's influence on technology adoption outcomes, this research posits the following hypothesis: *H_2: Effort expectancy has a significant positive effect on the intention to use digital transformation technologies in hotels in Egypt.*

2.6.3. The Influence of Social Influence on Intention to Use DT

SI, within the realm of technology acceptance, denotes the extent to which individuals perceive that significant others endorse their adoption of a new system (Venkatesh et al., 2003). It encompasses subjective norms, social contexts, and image considerations (Turan et al., 2015). Venkatesh et al. (2003) defining SI as the perceived endorsement from important others regarding the adoption of a new system. Moreover, Alowayr (2022) elucidates SI as the beliefs held by influential individuals regarding an individual's engagement in a specific action. Maruping et al. (2017) assert that SI is expected to be positively related to behavioral intention. Furthermore, numerous studies have corroborated the strong positive influence of SI on behavioral intention to use technology, extending beyond the UTAUT model (Hewavitharana et al., 2021). Scientific evidences across diverse studies supports the association between SI and behavioral intention to use various information technologies (Bhukya & Paul, 2023; Gonzalez & Kanitz, 2023).Given the robust scientific results supporting the influential role of SI on users' intentions to adopt digital transformation technologies, this research formulates the following hypothesis:

H_3: SI has a significant positive effect on the intention to use digital transformation technologies in hotels in Egypt.

2.6.4. The Influence of Facilitating Condition on Intention to Use

FC refer to the perceived organizational and technical infrastructure's adequacy to support system use, including behavioral control, compatibility, and facilitating situations (Venkatesh et al., 2003; Turan et al., 2015). Moreover, Venkatesh et al. (2003) defined FC as the individual's belief regarding the existence of an organizational and technical infrastructure conducive to system utilization. Notably, FC serve as predictors of actual technology usage, as posited in the UTAUT model (Alowayr, 2022). Furthermore, scientific results suggests that favorable conditions directly and positively impact users' intentions to use technology with diminishing effects after initial usage (Venkatesh et al., 2003; Papagiannidis, 2022). Numerous studies across diverse contexts corroborate the influential role of FC in driving technological acceptance (Dajani, 2016; Dwivedi et al., 2019; Park et al., 2022). Given the multifaceted nature of FC and their implications for technology adoption, this research formulates the following hypothesis:

H_4: FC have a significant positive effect on the intention to use digital transformation technologies in hotels in Egypt.

2.6.5. The Moderating Effect of Education Level

UTAUT highlights the intricate relationship between behavioral intention and key determinants such as PE, EE, SI, and FC with demographic factors serving as moderators, as evidenced in empirical studies (Hewavitharana et al., 2021). Furthermore, UTAUT suggests that BI influences system use, with demographic characteristics moderating FC (Muriithi et al., 2016). Maruping et al. (2017) assert that SI is expected to be positively related to behavioral intention and influenced by demographic factors. Jaradat and Al Rababaa (2013) identified education level as a significant moderating factor, highlighting its role in shaping consumers' adoption behaviors. Similarly, Thakur and Srivastava (2013) supported Yap and Hii's (2009) suggestion that university students, due to their higher educational level, are more likely to be early adopters of new technologies. Conversely, Alkhunaizan and Love (2013) found that education level did not significantly influence adoption behavior. Furthermore, Tan et al. (2014) and Tarhini et al. (2017) emphasized the importance of considering various demographic variables as moderators in future research on technology acceptance, specifically emphasizing education as a crucial factor that may influence individuals' acceptance of new technologies (Baudier et al., 2020). Given the robust scientific results, the present research posits the following hypothesis:

H_5: Education level moderates the influence of PE on the IU digital transformation technologies in hotels in Egypt.

H_6: Education level moderates the influence of EE on the IU digital transformation technologies in hotels in Egypt.

H_7: Education level moderates the influence of SI on the IU digital transformation technologies in hotels in Egypt.

H_8: Education level moderates the influence of FC on the IU digital transformation technologies in hotels in Egypt.

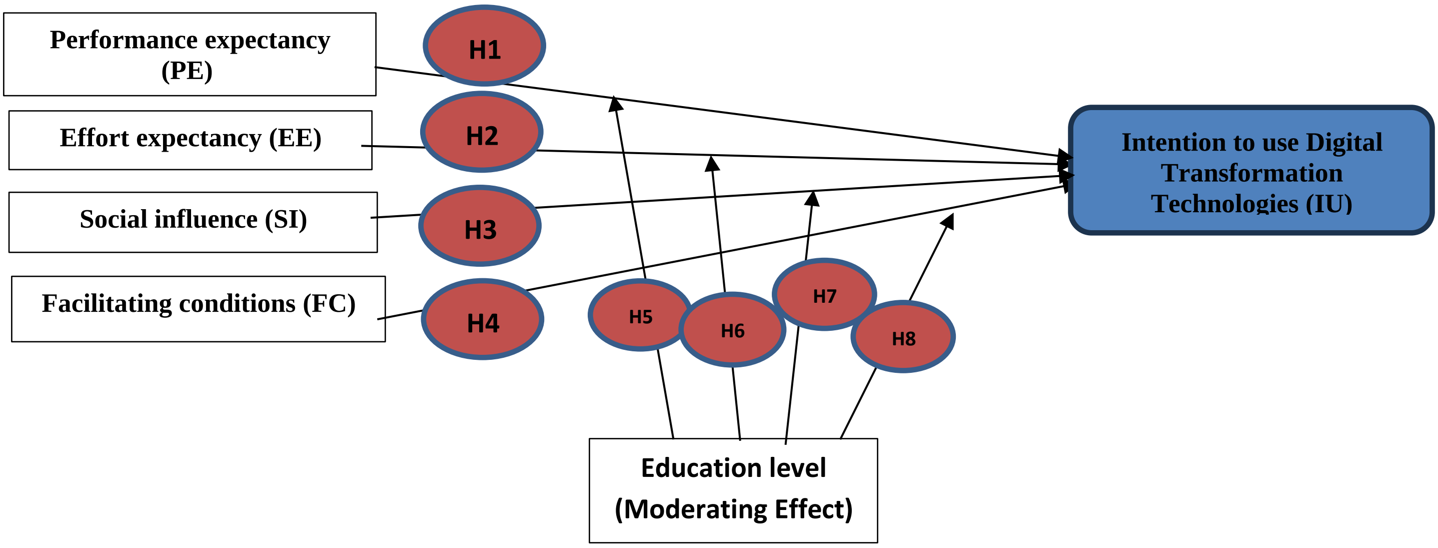

Figure 1: The suggested Framework

3. Methodology

The current research adopts a post-positivism paradigm, associated with the positivist perspective found in business and management literature (Saunders et al., 2016; Creswell, 2018). The research adopts a deductive approach and focuses on establishing the causal relationships between variables. In the context of technology acceptance and adoption research, the relationships being explored may include the influence of factors such as PE, EE, SI, and FC on employees' intention to use digital transformation technologies applying to 4 and 5 star hotels in Hurghada and Sharm El-Sheikh. The research design and methodology are closely linked, as quantitative studies usually use a deductive approach to evaluate theories using numerical data. For this reason, a quantitative research design is used in this research. Furthermore, the survey strategy is congruent with the deductive research approach and associated with the positivist research paradigm (Neuman, 2014; Saunders et al., 2016).

Given that the research involves developing a causal model to explore and test the influence of specific determinants or predictors (PE, EE, SI, and FC) on employees' intention to use digital transformation technologies applying to 4 and 5 star hotels in Hurghada and Sharm El-Sheikh. Moreover, to examine the moderation effect of the education level on (PE, EE, SI, and FC) and employees' intention to use digital transformation, hence, the researchers adopted a questionnaire as it is associated with the positivism philosophy, quantitative research design, explanatory nature, and considerations of time and cost.

3.1. Questionnaire Layout

The research questionnaire aims to include a representative sample, test hypotheses, and achieve research objectives. The questionnaire consisted of three sections comprised of 9 questions that would take responders only (5) minutes to complete, an informed consent form and screening questions, confirming respondents are 16 years or over, their participation in the survey is voluntary, and can terminate participation at any time.

Section (A): The first section comprises seven questions for asking about the demographic characteristics of the respondents namely (gender, age, education level, experience, and hotel department). All the demographic questions are mandatory.

Section (B): The second section comprises five questions every section asks about one of the constructs included in the suggested Framework (accepting digital transformation technologies and intention to use). All of the two questions are measured by the five-point Likert scales ranging from strongly disagree to strongly agree. To examine the suggested Framework, the research employed a total of 20 items from previous studies. All of the two variables included in the model (accepting digital transformation technologies and intention to use) are measured by a five-point Likert scale (1=strongly disagree and 5=strongly agree). To measure accepting digital transformation technologies adopted 15 items with a four-dimension from Venkatesh and Zhang (2010), Farooq et al. (2017), and Gansser and Reich (2021), 4 items scale for PE, 4 items for EE, 4 items for SI, and 3 items for FC. Finally, to measure IU, the researcher adopted 5 items scale with a single dimension from Tan et al. (2010) and Tan et al. (2014).

Table 1: The Questionnaire Layout

Parts	Measured Items	N. of Questions	N. of statements
1	Demographic data	7	1-7
2	The Measurement Items	2	20
Total		**9**	

Source: prepared by the researchers

The researchers slightly modified questionnaire items to suit the research field, ensuring content validity and face validity. Gathering Feedback from hotel managers and experts was used to improve the questionnaire instrument. Moreover, a pilot research of 51 questionnaires was conducted by the researchers and distributed to a sample of hotel employees in the Hurghada and Sharm El Sheikh Cities to validate the data readability, structure, and ability to assess research components (see Table 2).

Table 2: Measurement Items for the Research Variables

Accepting Digital Transformation Technologies		
Performance Expectancy (PE)	**PE1**	Digital transformation technologies would be helpful to me in my work.
	PE2	I can complete jobs faster when I use the digital transformation technology.
	PE3	Digital transformation technologies rises my productivity.

	PE4	Digital transformation technologies improve my chances of getting a raise.
Effort Expectancy (EE)	**EE1**	I would communicate intelligibly and clearly with the digital transformation technology.
	EE2	I could easily pick up the skills necessary to use the hotel's digital transformation technologies.
	EE3	Digital transformation technologies easy to use.
	EE4	I find it simple to pick up the skills necessary to use the digital transformation technology.
Social Influence (SI)	**SI1**	My behavior is influenced by my coworkers at the hotel, who believe that I should utilize digital transformation tools.
	SI2	Important coworkers of mine at the hotel believe that I ought to make use of the digital transformation technologies.
	SI3	Using the digital transformation technology has been made easier by the hotel's executive management.
	SI4	The hotel has generally encouraged the application of digital transformation technologies.
Facilitating Conditions (FC)	**FC1**	I possess the tools required for utilizing the technologies of the digital transformation.
	FC2	I possess the expertise required to apply the digital transformation technologies.
	FC3	There is a technical support team available in the hotel for assistance with digital transformation technologies difficulties.
Intention to use		
Intention to use	**IU1**	I definitely will use digital transformation technologies in my hotel
	IU2	When the chance arises, I will employ digital transformation technologies
	IU3	Digital transformation technologies are something I'm willing to use soon.
	IU4	I'm going to consider utilizing digital transformation technology.
	IU5	I plan to apply digital transformation technologies when the opportunity arises

Source: prepared by the researchers

3.2. The Research Population and Sample

The sampling processes have significantly impacted the generalizability of research results. In this research, the researchers made an effort to identify the most suitable sampling technique, considering factors like cost, time, and available resources. The research specifically focuses on employees and supervisors of four and five-star hotels in the Hurghada and Sharm El Sheikh Cities, which were chosen for their significant use of technology. In current research, random sample was considered vital in this research; this method enhances the accuracy and representativeness of the sample, particularly when the population is diverse or naturally divided into subgroups (Sharma, 2017). Moreover, the current research focused on a sample comprising employees in hotel in the specified cities. As a result, Uakarn et al. (2021) claimed that when the population size is too large, infinite, or unknown, the Cochran's formula (1977) is used to select sample size, as illustrated:

$$n = \frac{Z^2 p(1-p)}{e^2}$$

$$\mathbf{n} = \frac{(1.96)^2 \times 0.5 \times (1-0.5)}{(0.05)^2}$$

$$\mathbf{n} = \frac{3.8414 \times 0.5 \times 0.5}{0.0025} = 384.16$$

Where, Z= confidence level at 95% (1.96), e= error proportion (0.05), and p= probability (50%). e= error proportion (0.05), p= probability (50%) and Z= confidence level at 95% (1.96). The algorithm previously used to determine the research population's data was applied to determine the ideal sample size (n), which came out to be approximately 385 participants.

3.3. Data Collection

The research utilized the questionnaire data collection method as it is associated with the positivism philosophy, quantitative research design, explanatory nature, and considerations of time and cost**.** As a result, a sample of 401 employees and supervisors in the, four and five-star hotels in the Hurghada and Sharm El Sheikh Cities. The collection of questionnaires took four months, from November 2023 to February 2024. The questionnaire was originally in Arabic and translated into English. In the first method, researchers utilized Microsoft Office Forms for a web-based questionnaire survey, distributed a mobile-friendly online questionnaire invitation link (https://forms.office.com/r/mUS78VgQp1) and messaged the participants through their e-mail addresses. A total of 150 participants responded to the questionnaire invitation link, with 150 completed questionnaires valid for evaluation, reflecting an impressive 100% response rate. In the second method, the researchers distributed 300 paper-based questionnaires. Out of the total distributed, 251 forms were valid for analysis, representing an impressive 83.6% response rate.

Table 3: Number of Questionnaire Forms and the Response Rate

Questionnaire	No. of Forms	Valid Forms	Invalid Forms	Response Rate
Online forms	150	150	-	100%
Hard forms	300	251	49	83.6%
Total	450	401	49	89.1%

Source: prepared by the researchers.

3.4. Data Analysis Techniques

The data analysis stage of the current study employed two software packages. First, the Statistical Package for the Social Sciences (SPSS) version 22 was used to generate the respondents' demographic data. The frequencies, percentages, means, and standard deviations were computed using this application. Second, the data collected was examined using the Partial Least Squares Structural Equation Modeling (PLS-SEM) version 4. As an estimating framework which includes relevant theories and empirical data, smart PLS-SEM is appropriate for analyzing complex research models (Sobaih et al., 2022). Following Leguina's (2015) suggestion, in which a two-step approach was adopted, the proposed theoretical model first tested the outer model (measurement model) for convergent and discriminant validity, and then second the inner model (structural model) was evaluated for hypotheses testing.

4. Data Analysis and Findings

4.1. The Descriptive Statistics of the Sample Demographic Data

In table 4, the descriptive analysis of the demographic data of the research sample namely: gender, age, education level, experience, and hotel department).

Table 4: Descriptive Analysis of the Sample Demographic data

Variable	Frequency	Percentage (%)
Gender		
Male	337	84.0
Female	64	16.0
Total	**401**	**100.0**
Age		
From 21: 30	203	50.6
From 31 :40	159	39.7
From 41 :50	31	7.7
More than 50	8	2.0
Total	**401**	**100.0**
Education level		
Technical education	34	8.5
Bachelor's	94	23.4
Master degree	254	63.3
Ph.D. degree	19	4.7
Total	**401**	**100.0**
Experience		
Less than 5 year	173	43.1
From 5:15 years	192	47.9
More than 15 years	36	9.0
Total	**401**	**100.0**
Hotel Department		
Front office	117	29.2
Housekeeping	120	29.9
Food and beverage	164	40.9
Total	**401**	**100.0**
Hotel Star		
Four star	282	70.3
Five star	119	29.7
Total	**401**	**100.0**

The sample demographic data, presented in Table 4, offers a comprehensive overview. The majority are male (84%), with a significant gender disparity. Most participants are aged 21-30 (50.6%), followed by 31-40 (39.7%). Over 90% are under 40. Education-wise, 63.3% have a master's degree, 23.4% a bachelor's, and 8.5% technical education. Experience-wise, 47.9% have 5-15 years, 43.1% less than 5 years, and 9% over 15 years. Food and Beverage is the most represented department (40.9%), followed by Housekeeping (29.9%) and the Front Office (29.2%). Four-star hotels employ 70.3% of the sample, with 29.7% in five-star hotels. Overall, the data indicates a predominance of young, well-educated, and moderately experienced individuals, especially in Food and Beverage, and high-rated hotels.

4.2. Common Method Bias

Collinearity (or multicollinearity) is an undesirable situation where the correlations among the independent variables are strong; for the multicollinearity test can see the output results through the Collinearity Statistic Variance Inflation Factor (VIF), various recommendations for acceptable levels of VIF have been published in the literature by Micheal and Abiodun (2014). Most commonly, a value of less than 5 has been recommended as the maximum level of VIF (García et al., 2015).

Table 5: Collinearity Statistic Variance Inflation Factor (VIF)

Indicators	VIF
PE -> IU	2.410
EE -> IU	3.426
SI -> IU	3.512
FC -> IU	3.811
Education Level x FC -> IU	3.509
Education Level x SI -> IU	2.945
Education Level x EE -> IU	2.272
Education Level x PE -> IU	2.031
Education Level -> IU	1.331

(VIF = Collinearity statistic variance inflation factor).

The VIF analysis, shown in Table 5, indicates no significant multicollinearity among the variables. Primary constructs influencing intention to use digital transformation technologies have VIF values comfortably below 5: PE (2.410), EE (3.426), SI (3.512), and FC (3.811). Interaction terms with Education Level also exhibit VIF values below 5, affirming no multicollinearity issues. The direct effect of Education Level on IU has the lowest VIF (1.331), reinforcing its stable contribution to the model without inflating standard errors. In conclusion, the absence of multicollinearity ensures reliable regression estimates, supporting confident interpretations of the factors influencing employees' intention to adopt digital transformation technologies.

4.3. Evaluation of the Measurement Model

The research employed various statistical measures included "composite reliability" (CR), "internal consistency reliability" (Cronbach's alpha), "convergent validity," and "discriminant validity." as recommended by Hair et al. (2019) and Cheung et al. (2023) to assess the reliability and validity of the outer model. The researchers evaluated cross-loadings, aiming for an average loading factor above 0.70, as recommended by Hair et al. (2011). Additionally, they assessed the research model's reliability using Cronbach's alpha (α), with a threshold of 0.7 commonly accepted (Wetzels et al., 2009; Hair et al., 2019). Convergent validity was also assessed by examining the average variance extracted (AVE), where values above 0.5 are typically considered acceptable (Hair et al., 2019; Cheung et al., 2023) (See Table 6).

Table 6: The Evaluation of Reliability and Validity of the Measurement Model

Indicators	Outer Loading	α	C R	AVE
PE		**0.907**	**0.908**	**0.782**
PE1	0.886			
PE2	0.908			
PE3	0.894			
PE4	0.847			
Effort Expectancy		**0.899**	**0.902**	**0.767**
EE1	0.896			
EE2	0.910			
EE3	0.917			
EE4	0.900			
Social Influence		**0.889**	**0.891**	**0.751**
SI1	0.861			
SI2	0.892			
SI3	0.879			
SI4	0.834			
Facilitating Conditions		**0.855**	**0.861**	**0.791**
FC1	0.900			

FC2	0.883			
FC3	0.885			
Intention to use		**0.898**	**0.899**	**0.703**
IU1	0.801			
IU2	0.876			
IU3	0.823			
IU4	0.876			
IU5	0.815			

(α = Cronbach's alpha, CR = Composite reliability, AVE = Average variance extracted)

The results presented in the previous table demonstrate strong reliability and validity of the research's outer model. Cronbach's alpha values range from 0.732 to 0.931, surpassing the threshold of 0.7, indicating acceptable internal reliability. Composite reliability values range from 0.855 to 0.907, further confirming internal consistency reliability. Convergent validity, assessed using average variance extracted (AVE), exceeded the threshold of 0.5, suggesting that each latent variable explained more than half of the variance in its indicators. These results indicate the robustness of the measurement model for analyzing factors influencing the intention to use digital transformation technologies.

Discriminant validity, a fundamental aspect of construct validity, ensures that each variable in a research model is distinct from others, thereby preventing measurement overlap. The results from the next table indicate that each of the factors had factor loading values greater than 0.70, providing further evidence of the satisfactory reliability of the research measurement items. Factor loadings above this threshold indicate that the indicators adequately represent their respective constructs, contributing to the overall reliability of the measurement model (see Table 7).

Table 7: The Indicators Cross Loadings

Items	EE	FC	IU	PE	SI
EE1	**0.870**	0.628	0.615	0.659	0.618
EE2	**0.900**	0.604	0.607	0.639	0.553
EE3	**0.862**	0.609	0.545	0.593	0.585
EE4	**0.871**	0.624	0.544	0.620	0.576
FC1	0.595	**0.900**	0.589	0.496	0.739
FC2	0.699	**0.883**	0.628	0.629	0.693
FC3	0.576	**0.885**	0.582	0.468	0.728
IU1	0.559	0.658	**0.801**	0.476	0.667
IU2	0.551	0.545	**0.876**	0.563	0.549
IU3	0.545	0.559	**0.823**	0.545	0.497
IU4	0.595	0.569	**0.876**	0.554	0.572
IU5	0.517	0.486	**0.815**	0.474	0.512
PE1	0.609	0.523	0.567	**0.886**	0.511
PE2	0.627	0.502	0.549	**0.908**	0.500
PE3	0.637	0.543	0.564	**0.894**	0.520
PE4	0.669	0.555	0.524	**0.847**	0.552
SI1	0.516	0.680	0.547	0.510	**0.861**
SI2	0.576	0.654	0.604	0.552	**0.892**
SI3	0.611	0.757	0.594	0.517	**0.879**
SI4	0.599	0.716	0.576	0.459	**0.834**

One commonly employed method to assess discriminant validity is the Heterotrait-Monotrait Ratio of Correlations (HTMT) criterion, which compares the correlation of an indicator with its intended construct against correlations with other construct (Henseler et al., 2015). Henseler et al. (2015) recommended a threshold of 0.9 for HTMT as the criterion for establishing discriminant validity. HTMT helps researchers compare indicator correlations with intended constructs versus others, revealing potential overlap, and enhances the research's measurement model robustness (Cheung et al., 2023), In the current research, HTMT is utilized due to its high sensitivity in detecting potential issues with discriminant validity (see table 8).

Table 8: Heterotrait–monotrait Ratio of Correlations

	EE	FC	IU	PE	SI	Edu. X FC	Edu. x SI	Edu. x EE	Edu. x PE
EE									
FC	0.793								
IU	0.734	0.762							
PE	0.795	0.674	0.692						
SI	0.743	0.822	0.748	0.656					
Edu. x FC	0.159	0.259	0.049	0.172	0.198				
Edu. x SI	0.168	0.208	0.099	0.199	0.187	0.789			
Edu .x EE	0.267	0.165	0.107	0.136	0.168	0.604	0.576		
Edu .x PE	0.136	0.181	0.040	0.230	0.199	0.601	0.544	0.551	

The HTMT values, as shown in the previous table, were well below 0.90, indicating strong discriminant validity in the research model. This suggests distinctiveness among constructs, with higher correlations between indicators and intended constructs than with others. Overall, the research model demonstrated reliability, discriminant validity, and convergent validity, ensuring the accuracy and validity of its findings.

4.4. Assessment of the Structural Model (Testing Hypotheses)

The consistent PLS-SEM algorithm in SmartPLS4 provided a robust framework for hypothesis testing and predictive evaluation (Sarstedt et al., 2011). Path coefficients were interpreted as standardized Beta coefficients, with significance determined by a threshold of 0.10 (Wong, 2013; Hair et al., 2019). To assess the significance of each path coefficient, bootstrapping was employed as recommended by Streukens and Leroi-Werelds (2016). Significance was assessed using a two-tailed t-test at a 5% level, with coefficients deemed significant if the T-statistic exceeded 1.96 (Wong, 2013; Hair et al., 2019). This approach ensured reliable and valid findings, supporting meaningful conclusions about hypothesized relationships in the model. The significant path coefficients in the inner model indicate empirical support for the proposed relationships between variables, contributing to the explanation of variation in the endogenous variables (see Figure 2 and Table 9).

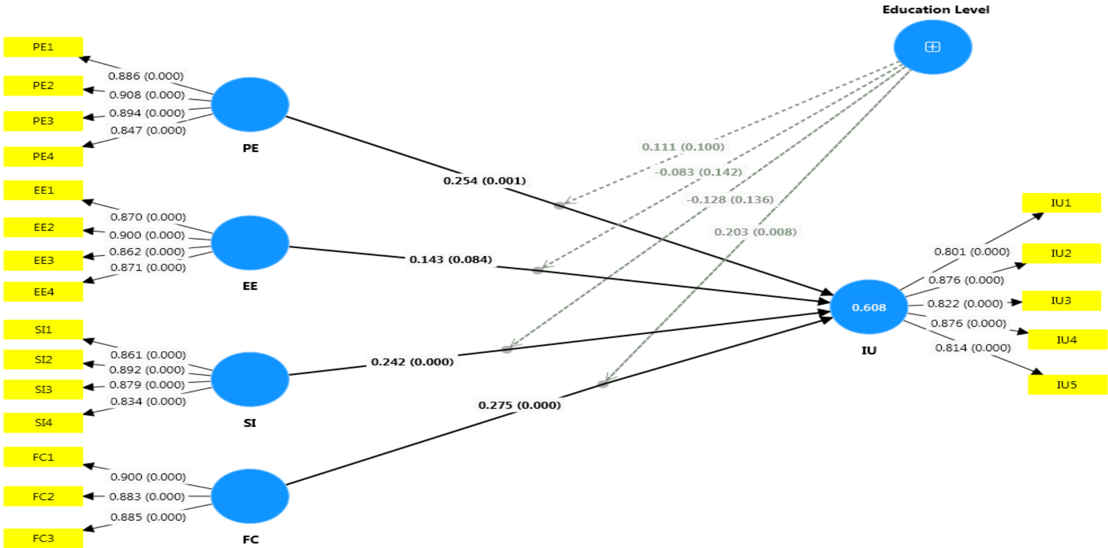

Figure 2: The Structural Inner Model

Table 9: Research Tested Hypotheses

Research Tested Hypotheses		Beta	T value	P value	Results
H_1	PE -> IU	0.250	3.322	0.001	**Accepted**
H_2	EE -> IU	0.176	2.185	0.029	**Accepted**
H_3	SI -> IU	0.198	4.332	0.000	**Accepted**
H_4	FC -> IU	0.304	4.332	0.000	**Accepted**
H_5	Education Level x PE -> IU	0.141	2.262	0.024	**Accepted**
H_6	Education Level x EE -> IU	-0.114	2.089	0.083	**Rejected**
H_7	Education Level x SI -> IU	-0.103	1.329	0.184	**Rejected**
H_8	Education Level x FC -> IU	0.183	2.606	0.009	**Accepted**

Table 9 shows the results of hypothesis testing for the research model, presenting standardized beta coefficients and p-values for each hypothesis. These results illuminate the relationships between various constructs and the intention to use digital transformation technologies, along with the moderating effect of education level. Notably, hypotheses 1, 2, 3, and 4 are all supported, indicating significant positive impacts of PE, effort expectancy, social influence, and FC on intention to use digital transformation. This is supported by scientific results from various studies that there the significant impact of PE on the successful adoption of technology (Agarwal & Sahu, 2022; Khashan et al., 2023). Moreover, Scientific results shows that EE significantly influences users' intentions to adopt digital transformation technologies across various technological domains (Dajani, 2016; Hewavitharana et al., 2021; Lee, 2023; Gupta, 2023). Furthermore, scientific results across diverse studies supports the association between SI and behavioral intention to use various information technologies (Maruping et al., 2017; Hewavitharana et al., 2021; Bhukya & Paul, 2023; Gonzalez & Kanitz, 2023). Additionally, FC predict technology usage, positively impacting users' intentions, and driving technological acceptance, as evidenced by the UTAUT model and numerous studies across various contexts (Venkatesh et al., 2003; Dajani, 2016; Dwivedi et al., 2019; Alowayr, 2022; Papagiannidis, 2022; Park et al., 2022)

However, hypothesis 6 is rejected, suggesting that higher education levels slightly weaken the positive impact of EE on intention to use. Hypothesis 7 is also rejected, indicating that education level does not significantly moderate the relationship between SI and intention to use. This findings is consists with Alkhunaizan and Love (2013) who found that education level did not significantly influence adoption behavior. On the other hand, hypothesis, 5 and 8 is supported, indicating that higher education levels enhance the impact of PE and FC on intention to use. This is consists with Muriithi et al. (2016) who stated that demographic characteristics moderating facilitating conditions. Similarly, Thakur and Srivastava (2013) supported Yap and Hii's (2009) suggestion that university students, due to their higher educational level, are more likely to be early adopters of new technologies. Additionally, the researchers examine the Effect size (F2) to find out the goodness of this research model (Ialongo, 2016). In certain situations, researchers report F2 effect size to explain partial or full mediation (Purwanto, 2021).

Table 10: The Effect size (F^2)

Research Tested Hypotheses		F^2	Effect size
H_1	PE -> IU	0.398	High
H_2	EE -> IU	0.202	Medium
H_3	SI -> IU	0.150	Medium
H_4	FC -> IU	0.169	Medium
H_5	Education Level x PE -> IU	0.034	Small
H_6	Education Level x EE -> IU	0.022	Small
H_7	Education Level x SI -> IU	0.025	Small
H_8	Education Level x FC -> IU	0.075	Small

Table 10 illustrates the Effect size (F2) for each tested hypothesis in the research model. Among them, PE stands out with the most significant impact on employees' intention to use digital transformation technologies, boasting a high effect size of 0.398. EE, SI, and FC also influence intention to use, though to a lesser degree, with effect sizes of 0.202, 0.150, and 0.169 respectively, categorized as medium. The moderating effects of education level on these relationships are generally small, with effect sizes ranging from 0.022 to 0.075. These findings emphasize the pivotal role of performance-related benefits and ease of use in driving technology adoption, while also acknowledging the influence of education in shaping these perceptions.

In summary, the findings confirm that PE, effort expectancy, social influence, and FC positively influence employees' intention to use digital transformation technologies. Additionally, education level significantly moderates the relationships between these factors and intention to use, except for Social Influence. Therefore, these insights shed light on the factors driving the acceptance and use of digital transformation technologies among employees

4.5. Assessment of Overall Model Fit

Assessing the structural model in PLS-SEM involves examining key indicators such as the Determination Coefficient (R2) and Predictive Relevance (Q^2), as highlighted by Hair et al. (2019) and Purwanto (2021). R2 quantifies the proportion of variance explained by the model in endogenous constructs, with values above 0.10 considered satisfactory (Lowry & Gaskin, 2014; Usakli & Kucukergin, 2018; Hair et al., 2019; Purwanto, 2021). Q^2 evaluates the model's predictive performance, with values exceeding 0 indicating relevance in predicting dependent variables (Wetzels et al., 2009; Hair et al., 2019).By analyzing R2 and Q^2 values, researchers can assess the overall goodness of fit and predictive capability of the structural model, ensuring meaningful insights into the research phenomenon.

Table 11: Coefficient of determination R-square and Q-square

Endogenous latent factors	R^2	Q^2
PE	0.705	0.704
EE	0.795	0.794
SI	0.768	0.789
FC	0.775	0.773
IU	0.608	0.570

Table 11 illustrates the coefficient of determination (R^2) and Q-square values for the endogenous latent factors in the research model, indicating both explanatory power and predictive accuracy. R^2 values for PE, effort expectancy, social influence, and FCrange from 0.705 to 0.795, explaining 70.5% to 79.5% of the variance. Corresponding Q^2 values, ranging from 0.704 to 0.794, demonstrate accurate prediction in new samples. For intention to use, while R^2 is 0.608, explaining 60.8% of the variance, the Q^2 value of 0.570 suggests moderate predictive relevance. Overall, these findings underscore the model's robustness in understanding and predicting employees' intention to use digital transformation technologies.

5. Conclusion and Practical implications

Based on the comprehensive analysis conducted in this research, several key conclusions can be drawn regarding the impact of accepting digital transformation technologies on employees' intention to use, as well as the moderating role of education level in this context. The research findings reveal that factors such as PE, EE, SI, and FC significantly influence employees' intention to use digital transformation technologies. Specifically, higher levels of PE, which encompass the perceived benefits and utility of these technologies, contribute substantially to fostering employees' intention to embrace them. Similarly, perceptions of effort expectancy, reflecting the ease of use and accessibility of digital tools, play a pivotal role in shaping employees' willingness to engage with such technologies. Moreover, the influence of social influence highlights the importance of peer interactions and social norms in driving technology adoption among employees. Additionally, the presence of facilitating conditions, including organizational support and resources, significantly enhances employees' inclination to utilize digital transformation technologies effectively. These findings underscore the multifaceted nature of factors influencing employees' intention to adopt digital transformation technologies, highlighting the need for organizations to address various dimensions to facilitate successful technology implementation and utilization.

Furthermore, the research elucidates the moderating effect of education level on the relationship between these factors and employees' intention to use digital transformation technologies. While education level amplifies the positive impact of PE on intention to use, it slightly diminishes the influence of EE. Moreover, education level enhances the effect of FC on intention to use, albeit to a lesser extent. Conversely, education level does not significantly moderate the relationship between SI and intention to use. These findings suggest that employees' educational backgrounds play a nuanced role in shaping their perceptions and attitudes toward digital transformation technologies. Organizations can leverage these insights to tailor technology adoption strategies based on employees' educational profiles, thereby optimizing the effectiveness of technology implementation initiatives.

From a practical standpoint, these findings offer valuable implications for organizations seeking to foster a culture of technology adoption and innovation among employees. Firstly, organizations should prioritize initiatives aimed at enhancing employees' perceptions of the performance benefits and utility of digital transformation technologies. This may involve providing comprehensive training programs, highlighting the potential impact of these technologies on job performance and productivity. Secondly, efforts should be made to streamline the user experience and minimize perceived barriers to technology use, thereby promoting a seamless adoption process. Organizations can achieve this by investing in user-friendly interfaces, providing adequate technical support, and soliciting feedback from employees to address usability issues effectively. Additionally, fostering a supportive organizational climate that encourages collaboration and knowledge sharing can amplify the influence of social factors on technology adoption. Finally, recognizing the diverse educational backgrounds of employees and tailoring technology adoption strategies accordingly can enhance the effectiveness and inclusivity of technology implementation efforts. By integrating these insights into their organizational practices, companies can empower employees to embrace digital transformation technologies effectively, thereby driving innovation, efficiency, and competitive advantage in the digital era.

6. Theoretical contribution

The research findings presented in this research make several significant theoretical contributions to the existing literature on technology acceptance and adoption, particularly within the context of digital transformation initiatives in organizational settings. Firstly, the research extends the Unified Theory of Acceptance and Use of Technology (UTAUT) framework by empirically examining the moderating role of education level on the relationships between key determinants (i.e., Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions) and employees' intention to use digital transformation technologies. By incorporating education level as a moderator variable, the research advances our understanding of how individual differences in educational backgrounds influence the process of technology adoption, shedding light on the nuanced interactions between socio-demographic factors and technology acceptance.

Moreover, the research contributes to the literature by providing scientific results of the differential effects of various determinants on employees' intention to use digital transformation technologies. Specifically, the findings highlight the varying degrees of influence exerted by factors such as PE, EE, SI, and FC on technology adoption outcomes. By elucidating the relative importance of these determinants and their interactions, the research offers valuable insights into the underlying mechanisms driving employees' decision-making processes regarding technology adoption, thus enriching our theoretical understanding of technology acceptance models.

Furthermore, the research advances theoretical knowledge by highlighting the importance of considering multifaceted determinants and their interactions in predicting employees' intention to use digital transformation technologies. By adopting a comprehensive approach that integrates multiple determinants and their interrelationships, the research provides a more nuanced understanding of the complex dynamics underlying technology adoption behaviors. This holistic perspective underscores the need for researchers and practitioners to adopt a multidimensional framework that accounts for the diverse factors influencing technology acceptance, thereby enhancing the predictive accuracy and explanatory power of technology acceptance models.

Additionally, the research contributes to theory development by identifying education level as a key moderator that shapes the strength and direction of the relationships between determinants and technology adoption outcomes. By empirically examining the moderating effects of education level, the research underscores the importance of considering individual differences in socio-demographic characteristics when designing and implementing technology adoption strategies. This insight has implications for theory refinement and model development within the broader field of technology acceptance research, paving the way for future studies to explore additional moderator variables and their implications for technology adoption processes. In summary, the theoretical contributions of this research lie in its advancement of the UTAUT framework through the incorporation of education level as a moderator variable, its empirical validation of the differential effects of determinants on technology adoption outcomes, and its elucidation of the complex interrelationships between determinants and technology adoption behaviors. These contributions have implications for theory development, model refinement, and practical application within the realm of technology acceptance research, ultimately enhancing our understanding of the factors influencing technology adoption in organizational contexts.

7. Limitations and Future Research Suggestions

Despite this research contributes valuable insights to the understanding of technology acceptance and adoption in organizational contexts, it is essential to acknowledge several limitations that may impact the generalizability and robustness of the findings. Firstly, the research was conducted within a specific industry or organizational context, potentially limiting the generalizability of the results to other industries or sectors. Future research could explore technology acceptance across diverse industries to determine the extent to which the findings apply universally or are context-specific. The research was conducted within a single geographical region, which may limit the cultural and contextual diversity of the sample. Future research could adopt a cross-cultural approach to explore how cultural differences influence technology acceptance behaviors and examine the generalizability of the findings across diverse cultural contexts. Additionally, the research utilized a cross-sectional research design, which provides a snapshot of technology adoption behaviors at a single point in time. Longitudinal studies that track technology adoption behaviors over time could provide deeper insights into the dynamics and trajectories of technology acceptance within organizations.

Additionally, the research focused primarily on individual-level determinants of technology acceptance, neglecting potential contextual or organizational factors that may influence technology adoption outcomes. Future research could explore the role of organizational culture, leadership support, and technological infrastructure in shaping employees' attitudes and behaviors towards technology adoption. Furthermore, the research examined education level as a moderator of the relationships between determinants and technology adoption outcomes. While education level is an important individual difference variable, other socio-demographic factors such as age, gender, and job tenure may also influence technology acceptance behaviors. Future research could explore the moderating effects of these additional variables to provide a more comprehensive understanding of the factors shaping technology adoption within organizations. Moreover, the research focused primarily on intention to use digital transformation technologies, which may not always translate into actual technology usage behaviors. Future research could investigate the factors influencing actual technology usage and explore potential discrepancies between intention and behavior.

Finally, the research was conducted within a single geographical region, which may limit the cultural and contextual diversity of the sample. Future research could adopt a cross-cultural approach to explore how cultural differences influence technology acceptance behaviors and examine the generalizability of the findings across diverse cultural contexts. By addressing these limitations and expanding the scope of inquiry, future research can further advance our understanding of technology acceptance and ultimately informing the development of more effective strategies for promoting technology adoption and utilization within organizations.

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أثر قبول تقنيات التحول الرقمي على نية العاملين للاستخدام: المستوى التعليمي كمعدل

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الكلمات الدالة

التحول الرقمي
نظرية القبول واستخدام التكنولوجيا الموحدة.
نية الاستخدام.
المستوى التعليمي
صناعة الفنادق

الملخص

يهدف البحث إلى النظر في كيفية تأثر نوايا الموظفين لاستخدام تقنيات التحول الرقمي بقبولهم لهذه التقنيات، مع التركيز بشكل خاص على التأثير المعدل للمستوى التعليمي. قام الباحثون بتطوير وفحص نموذج مفاهيمي يرتكز على إطار النظرية الموحدة لقبول واستخدام التكنولوجيا (UTAUT) من خلال الفحص التجريبي لدور المستوى التعليمي في التأثير على نية الموظفين لاستخدام تقنيات التحول الرقمي. تم الحصول على البيانات من 401 موظفًا ومشرفا في الفنادق الأربع والخمس نجوم في مدينتي الغردقة وشرم الشيخ باستخدام تقنية البحث الكمي. تم استخدام طريقة نمذجة المعادلات الهيكلية بالمربعات الصغرى الجزئية (PLS–SEM) لتحليل البيانات التي تم جمعها. أظهرت النتائج أن الأداء المتوقع، والجهد المتوقع، والتأثير الاجتماعي، والظروف الميسرة يؤثر بشكل كبير على نية الموظفين في استخدام تقنيات التحول الرقمي. علاوة على ذلك، كشفت النتائج أن مستوى التعليم يخفف من تأثير توقع الأداء و الظروف الميسرة على نية الموظف لاستخدام تقنيات التحول الرقمي، لكنه لا يخفف بشكل كبير من التأثير الاجتماعي وتوقع الجهد على نية استخدام تقنيات التحول الرقمي. بالإضافة إلى ذلك، يساهم البحث في سد الفجوة المعرفية وتقديم نتائج تطبيقية قيمة.