IADIS International Journal on Computer Science and Information Systems
Vol. 20, No. 2, pp. 49-67
ISSN: 1646-3692

THE EFFECTS OF DIGITAL MATURITY AND BEHAVIORAL INTENTION ON DIGITAL TRANSFORMATION ADOPTION IN LONG-TERM CARE INSTITUTIONS

Chin-Wei Wang and Yu-Shih Lee
Department of Business Administration, Chung Yuan Christian University, Taoyuan City, Taiwan

ABSTRACT

With the growing emphasis on global digitalization strategies, and in the context of both the diverse needs of a super-aged society and the shortage of nursing personnel, this study integrated the Resource-Based View (RBV) and the Unified Theory of Acceptance and Use of Technology (UTAUT) models to examine how internal resources and capabilities of long-term care institutions affect digital maturity. It also analyzed the factors influencing professionals' intention to adopt digital technologies. Within the framework of digital maturity, behavioral intention, and digital transformation application, digital maturity is identified as the most critical component. The results indicated that technology has a significant impact on digital maturity, while cultural and organizational factors do not. Personal innovativeness and performance expectancy significantly affect behavioral intention, whereas effort expectancy and social influence show no significant effect. The empirical analysis validated the key factors influencing digital transformation, providing managerial implications for leaders in formulating digital transformation strategies, and establishing a foundation for how long-term care institutions can leverage digital technologies to enhance service quality and efficiency.

KEYWORDS

Long-Term Care, Digital Transformation, Resource-Based View (RBV), UTAUT, Smart PLS

1. INTRODUCTION

With changes in the demographic structure, a super-aged society faces diverse and complex demands, leading to a rapid increase in the need for elderly care (Fujisawa & Colombo, 2009; Kotschy & Bloom, 2022). In addition, the transformation of social structures and urbanization result in increasingly smaller family units, which gradually weakens the caregiving capacity of individuals and families (Sordi & Magalhães, 2016) and therefore accelerates the demand for long-term care services. Long-term care institutions (hereafter referred to as institutions) provide a new mechanism for integrating medical resources and alleviating the caregiving burden on families. To meet the diverse needs of the elderly or people with disabilities, institutional operations have expanded beyond nursing professionalism into multiple dimensions. Professionals in such institutions are required to possess specialized knowledge and skills, not only in direct and indirect nursing care but also in formulating and delivering daily care plans and life services. In an era of an aging population and rapid development of information technologies, these extensive responsibilities impose greater demands on the skills of nursing personnel (Kotschy & Bloom, 2022). Moreover, nursing staff must meet these demands and make explicit care decisions (Taylor & Donnelly, 2006). Thus, maintaining high-quality care services under limited resources has become a critical challenge for nursing personnel.

However, frontline nursing personnel spend approximately 60% of their working hours on indirect care activities (Davison et al., 2016; Lavander et al., 2016), including charting, medical recordkeeping, and handling various administrative tasks. The validity of such information and its handover process are difficult to manage, leading to omissions or errors during transitions, with accumulated information easily becoming outdated (Hollnagel, 2017). At the same time, nursing work often requires communication through messaging software or telephone, adding to the complexity of information management. These cumbersome tasks exacerbate fatigue and intensify staff turnover (Havaei et al., 2023), contributing to the shortage of nursing personnel (Ansah et al., 2014; White et al., 2021). Consequently, many institutions fail to achieve the intended objectives of their digital transformation initiatives (Tabrizi et al., 2019). Furthermore, numerous healthcare and long-term care institutions lack a clear digitalization strategy, and there is limited managerial awareness of the future impacts of digital operations and services, thereby increasing the risk of failure in digital transformation (Kiron et al., 2016; Carroll et al., 2023).

In the context of nursing staff shortages (De Leeuw et al., 2020; Tortorella et al., 2021), some studies have demonstrated that information and communication technologies (ICT) can support care recipients by helping them better understand daily behavioral changes and by monitoring vital signs more effectively (De Leeuw et al., 2020). Training informal caregivers in digital skills during the early stages of the care process is shown to effectively meet or compensate for the needs of care recipients (Hassan, 2020). However, many institutions lack digitalized processes and adequate infrastructure, and training in digital skills remains insufficient (Wang & Hsu, 2023). The absence of effective digital education for nursing personnel has resulted in a lagging level of digitalization (De Leeuw et al., 2020). These issues are particularly pronounced in resource-limited institutions, leading to failures in achieving digital transformation goals. According to the Resource-Based View (RBV) (Barney, 1991), the design and implementation of effective digital strategies require the comprehensive integration of internal resources and capabilities, which is a central objective of digital transformation. Such integration enables the delivery of cost-efficient and high-quality care services (Batayeh et al., 2018). To remain competitive, managers in small and medium-sized enterprises have adopted digital technologies and successfully leveraged them to improve internal processes and resource utilization (Kwarteng et al., 2024). Despite the relevance of applying long-term care institutions as managerial tools for innovative business models, scholarly discussion on this topic remains relatively limited. (Amankwah-Amoah et al., 2021).

Digital transformation should be regarded as a systemic change, whose core objective is the construction and operation of new business models through digital means (Soto Setzke et al., 2023). Organizations must allocate resources appropriately to invest in digital transformation

(Carroll et al., 2023). However, institutions with limited resources face greater challenges in promoting digital transformation. Throughout this process, organizations need to integrate digital technologies deeply into business processes, organizational structures, and working models (Vial, 2019; Vial, 2021), and companies employing information and communication technologies (ICT) can more easily reorganize workflows. Since efficiency and effectiveness largely depend on resources (Savino & Shafiq, 2018), organizations operating under resource constraints encounter additional challenges, such as insufficient technology and resources, which hinder personnel from keeping pace with technological progress (Del Giudice et al., 2019). A lack of technology acceptance strategies among personnel during digital transformation is often one of the fundamental reasons for failure (Bharadwaj et al., 2013; Di Vaio et al., 2021). Therefore, the acceptance of digital technologies by professionals in institutions constitutes another critical factor influencing the success of transformation. Particularly in uncertain environments, organizations must enhance technological capabilities and market positioning (Del Giudice et al., 2019), and these professionals need to effectively adapt to business demands and respond swiftly to potential disruptions (Forliano et al., 2023). The Unified Theory of Acceptance and Use of Technology (UTAUT) provides a framework for understanding how different factors affect individuals' intentions to adopt new technologies. Identifying attributes that influence the technology acceptance process enables the formulation of effective strategies to build digital transformation (Bharadwaj et al., 2013; Mahardika et al., 2019). In long-term care institutions in particular, factors such as professionals' performance expectancy, effort expectancy, social influence (Venkatesh et al., 2012; Jayawardena et al., 2023), as well as personal innovativeness (Jayawardena et al., 2023), may positively affect digital acceptance intentions. In the process of digital transformation, embedding digital technologies into business processes and building digital platforms can strengthen the organizational capabilities of business teams and accelerate digital transformation. The effective utilization of organizational resources is critical to improving performance and fostering innovation (Savino & Shafiq, 2018).

The first part of this study aims to examine the influence of institutional factors on digital maturity. Digital strategies encompass organizational culture, structure, technology, and management (Nikopoulou et al., 2023). Digital maturity is defined as an organization's ability to efficiently adopt continuous digital transformation through managerial practices. (Nikopoulou et al., 2023). Through digital maturity, the extent of an institution's mission performance can be effectively reflected, and gradually implemented strategies guide its transformation. (Kane, 2015; Kane, 2017). The second part applies the UTAUT framework (Venkatesh et al., 2003) to help us understand how various factors influence individuals' intentions to adopt new technologies. Especially in long-term care institutions, professionals' performance expectancy, effort expectancy, social influence (Venkatesh et al., 2012; Jayawardena et al., 2023), and personal innovativeness (Jayawardena et al., 2023) may positively influence digital adoption intentions. The research findings contribute to institutions' ability to more effectively formulate and implement digital transformation strategies.

2. THEORETICAL BACKGROUND AND MODEL HYPOTHESES

With global demographic changes and in light of the increasing development of interconnectivity, data analytics, and artificial intelligence, organizations today are compelled to pursue digital transformation more than ever before. Digital transformation is no longer a choice but a strategic imperative for survival and success (Omol, 2024). Digitalization refers to the comprehensive conversion of a company's various business activities into digital formats, encompassing the planning of products and services (Omol, 2024). Digital maturity is a complex phenomenon, defined as the state of an organization in the process of digital transformation (Chanias et al., 2019).

During the digital transformation process, corporate culture is regarded as a core foundation (Sunny et al., 2019), as culture has a significant impact on digital transformation (Gill & VanBoskirk, 2016). Culture, serving as a set of shared values and beliefs, may accelerate or hinder the adoption and implementation of technology (Veiga et al., 2001). When organizations plan, govern, and implement digital strategies (Gill & VanBoskirk, 2016), they can not only help teams complete documentation and handovers more efficiently but also reduce burnout among healthcare professionals (Shaharul et al., 2023). Thus, the implementation of digitalization can provide employees with empowering digital technologies, enabling professionals to perceive the value and benefits of their work through digital transformation. This in turn motivates them to support the transformation and fosters the establishment of a learning-oriented culture. At the same time, enhancing professionals' technical capabilities has a positive impact on digital maturity (Nikopoulou et al., 2023) and can further promote the adoption of digital technologies. The establishment of standardized procedures can also ensure smoother handovers. Digitalization optimizes resource allocation, addresses the needs of care recipients, and ensures the safe and effective delivery of services (Siira et al., 2024). In the context of care services, the application of digital information and communication technologies helps shift the focus toward elderly or disabled individuals, aligning professionals and processes with the shared goal of delivering optimal care (Alloghani et al., 2018; Sannino et al., 2018).

According to Nikopoulou et al. (2023), from a managerial perspective, when an organization's culture supports digital transformation, it not only enhances the efficiency and effectiveness of information utilization but also drives the innovation of existing processes. Culture thus exerts a significant positive influence on digital maturity, which indicates a strong adaptive and developmental state of culture in digital transformation. However, institutions still face challenges in the digital transformation process, such as problems of infrastructure integration and technological compatibility, as well as professionals' doubts and passive attitudes toward digital technologies (Siira et al., 2024). Organizations often struggle with resistance to change, a general fear of technology, and adherence to established routines, all of which tend to hinder the implementation of digitalization (Hai & Thi Tuyet, 2021). Nevertheless, the successful application of digital health records is shown to significantly improve the overall operational efficiency of healthcare institutions (Ng'andu & Haabazoka, 2024). At the same time, organizational technological capabilities are confirmed to positively influence the maturity of digital strategies (Nikopoulou et al., 2023). Since many studies have examined different types of digital technologies (Siira et al., 2024), digitalization—defined as the structuring of data and information—supports healthcare professionals in performing their duties and optimizing healthcare. It also serves as a tool for managerial tasks and improves efficiency (Benbya et al., 2020; Chen & Decary, 2020). Digital maturity can motivate and promote professionals' adoption of digital technologies (Gill & VanBoskirk, 2016). The integration of implemented care services and digital maturity can further guide professionals in delivering patient care. Rossmann (2018) points out that digital strategies must be properly implemented, documented, and communicated throughout the organization in order to enhance customer satisfaction (Kim et al., 2020) and service quality (Li et al., 2019). In addition, digital maturity is closely related to readiness and acceptance of digital technology adoption (Lam et al., 2008), which in turn influences organizational technological systems and service performance. Therefore, the digital maturity of an organization has a positive effect on digital technologies, thereby facilitating their utilization (Nikopoulou et al., 2023).

Based on the above, the following hypotheses are proposed.

H1: Culture has a positive effect on digital maturity.

H2: Organization has a positive effect on digital maturity.

H3: Technological capability has a positive effect on digital maturity.

H4: Digital maturity has a positive effect on the use of digital transformation.

Understanding technological readiness enables professionals to recognize the applications of digitalization to facilitate the smooth promotion of digitalization within organizations. In addition, technological readiness aims to assess individuals' intentions to adopt cutting-edge technologies (Blut & Wang, 2020). In order to understand users' behavioral intentions toward digitalization, it is important to note that digitalization refers to the use of technology to modify organizational processes, and the application of information technology and information systems has become inevitable (Ayaz & Yanartaş, 2020). The Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) consists mainly of performance expectancy, social influence, effort expectancy, and facilitating conditions. This theory has been successfully applied in studies of electronic health services (Haikal et al., 2022; Alsyouf et al., 2022). In the context of new technology adoption, behavioral intention can be predicted by effort expectancy, performance expectancy, and social influence. Behavioral intention influences user behavior (Williams et al., 2015), which in turn contributes to the development of a shared understanding and fosters a culture that embraces technology, thereby enabling successful digital transformation (Jayawardena et al., 2023). By acquiring helpful resources through digital tools and facilitating communication across different organizational departments, employees are encouraged to reflect on innovative solutions that improve organizational digital integration. Individual innovativeness, therefore, influences behavioral intention toward digitalization (Jayawardena et al., 2023). Behavioral intention has been considered critical for understanding and predicting attempts to adopt new technologies (Mahardika et al., 2019). Individuals perceive digital tools as easy to learn and simple to use (Carter & Belanger, 2004), and they believe that using a specific system will enhance their job performance. (Venkatesh et al., 2012). Performance expectancy refers to the degree to which an individual believes that using a system will lead to better performance (Ayaz & Yanartaş, 2020). In many studies employing the UTAUT model, performance expectancy has been found to have a significant influence on behavioral intention (Ayaz & Yanartaş, 2020). Effort expectancy is regarded as the degree to which individuals believe that using the system is easy and the perceived ease associated with system use (Venkatesh et al., 2003). At work, individuals' effort expectancy includes measures of system interface design, ease of use, flexibility, and ease of learning (Carter & Belanger, 2004). Using the UTAUT framework, Putra (2023) examined the adoption of Electronic Medical Records (EMRs) and demonstrated that, from the users' perspective, performance expectancy and social influence exert significant influences. Although studies such as Ayaz

& Yanartaş (2020) and Haikal et al. (2022) found that effort expectancy had no positive impact, other research has demonstrated its significant influence on behavioral intention (Chen & Hwang, 2019; Kabra et al., 2017). Based on the above, the following hypotheses are proposed.

H5: Individual innovativeness influences behavioral intention.

H6: Performance expectancy influences behavioral intention.

H7: Effort expectancy influences behavioral intention.

Social influence refers to an individual's perception of others' use of a new system. (Venkatesh et al., 2012). Ayaz and Yanartaş (2020) investigated the implementation of information systems in the public sector to improve electronic document management, and their empirical results indicate that social influence has a positive effect on individuals' intention to use. Similarly, Jayawardena et al. (2023), in the context of digital transformation adoption, demonstrated that social influence is positively associated with the intention to use digital transformation, and that behavioral intention is significantly associated with actual usage. Empirical evidence from Ayaz and Yanartaş (2020) and Haikal et al. (2022) confirmed that social influence has an impact on behavioral intention toward digitalization, which in turn affects the use of digital transformation. Based on the above, the following hypotheses are proposed.

H8: Social influence affects behavioral intention toward digitalization.

H9: Behavioral intention toward digitalization affects the use of digital transformation.

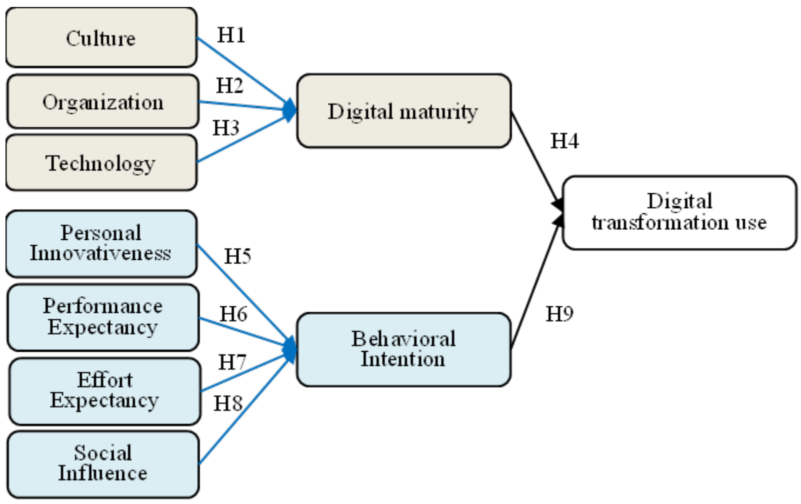

Figure 1. Research model proposed in this study

3. RESEARCH METHODS

The sample for this study consists of professionals from a long-term care institution in Taiwan. The professionals in the institution engage in professional services and management work within long-term care facilities. To ensure the structural integrity of the questionnaire (Brislin, 1980), a free online software was used to construct the survey through the Google® platform. The first part of the questionnaire includes demographic information. The second part assesses the professionals' digital maturity, behavioral intentions, and readiness for digital transformation. A 5-point Likert scale, as per Babakus and Mangold (1992), was used for data analysis to enhance response rates and response quality. In the first phase, descriptive statistical analysis of the demographic data was conducted using SPSS v.20 (IBM Corp., Armonk, NY). In the second phase of data analysis, partial least squares structural equation modeling (SmartPLS GmbH, Hamburg, Germany) was employed to validate the research model and hypotheses. PLS is considered well-suited to create and evaluate explanatory-predictive theories due to its predictive stance coupled with its explanatory strengths (Sarstedt, Ringle and Hair, 2017) PLS has high predictive accuracy across a broad range of conditions (Evermann and Tate, 2016). Therefore, this paper uses the partial least squares method (PLS) to predict the hypotheses of the inferences of this study to predict the causal explanatory power of the model.

4. RESULTS

In the first stage, the structured questionnaire was designed to articulate the research questions, validate the content, and ensure the validity and reliability of the instrument. The structured items addressing the research questions are presented in Table 1. The reliability of the structured questionnaire was assessed using composite reliability (CR) and average variance extracted (AVE). The first section of the questionnaire assessed the sociodemographic characteristics of long-term care professionals through five items covering gender, age, educational level, job position, and years of experience. The second part assessed professionals' readiness in terms of digital strategy maturity, behavioral intention, and digital transformation usage. A five-point Likert scale, as suggested by Babakus and Mangold (1992), was utilized in the data analysis to ensure higher response rates and better response quality. The response scale ranged from 1 = Strongly Disagree, 2 = Disagree, 3 = Undecided, 4 = Agree, to 5 = Strongly Agree.

Table 1. Structured Questionnaire Items for the Empirical Study

Factor	Code	Item	References
Culture	C1	Our institution's business development strategy is based digital technologies.	Gill & VanBoskirk (2016); Nikopoulou et al. (2023)
	C2	Our institution's business management supports the implementation of digitalization.	
	C3	Our institution has qualified staff to manage digital technologies in business operations.	
	C4	Our institution invests in employee education and trainir for the use of digital technologies.	
	C5	Our institution's management clearly communicates the digitalization strategy to employees.	
	C6	Our institution takes all necessary actions to support innovation.	
	C7	Our institution is interested in enhancing customer experience through multiple service channels (e.g., websites, system platforms (dispatching), social media).	

Factor	Code	Item	References
Organization	O1	Our institution allocates the necessary resources (human and/or financial) to design, redefine, and implement digi strategies.	Gill & VanBoskirk (2016); Nikopoulou et al. (2023)
	O2	Our institution's employees possess the digital skills required to use information and communication systems	
	O3	Our institution follows specific procedures to manage information systems.	
	O4	Our institution uses digital channels to communicate wit business partners (e.g., suppliers, banks).	
Technology	T1	Our institution sets a specific budget for provisioning an upgrading digital infrastructure and systems.	Gill & VanBoskirk (2016); Nikopoulou et al. (2023)
	T2	Our institution's business can flexibly respond to change related to its digital strategy.	
	T3	Our institution adopts and leverages modern informatior systems and infrastructure.	
	T4	Our institution evaluates the performance of its information systems and infrastructure based on their contribution to achieving business objectives.	
Digital Maturity	MD1	Our institution will implement digitalization.	Rossmann (2018); Forliano et al. (2023); Nikopoulou et al. (2023)
	MD2	Our institution's digitalization will be documented and communicated.	
	MD3	Our institution's digitalization will have a significant impact on existing business models.	
	MD4	Our institution's digitalization is continuously evaluated and adjusted when necessary.	
Personal Innovativeness	PI1	I enjoy trying new technologies and features to support digital transformation.	Tan et al. (2014); Salade et al. (2015); Xu & Gupta (2009); Miltgen et al. (2013); Jayawardena et al. (2023)
	PI2	I am eager to try digital transformation in my workplace	
	PI3	In general, I am the first in my institution to try out new information technologies.	
	PI4	Overall, I like to use new information technologies.	
Performance Expectancy	PE1	I believe digital transformation is useful for the daily operations of long-term care institutions.	Venkatesh et al. (2003); Xu & Gupta (2009); Batara et al. (2017); Ali & Danish (2018); Jayawardena et al. (2023)
	PE2	I believe digital transformation increases the chances of achieving goals, which is important for the institution.	

Factor	Code	Item	References
	PE3	I believe digital transformation enhances work efficiency and enables tasks to be completed more quickly.	
	PE4	I believe digital transformation improves the productivity of long-term care institutions.	
	PE5	I believe digital transformation reduces the time required for daily operations in long-term care institutions.	
Effort Expectancy	EE1	Learning how to use the mobile internet is easy for me.	Venkatesh et al. (2003); Xu & Gupta (2009); Batara et al. (2017); Ali & Danish (2018); Jayawardena et al. (2023)
	EE2	My interaction with mobile internet is clear and understandable.	
	EE3	I find mobile internet easy to use.	
	EE4	It is easy for me to become skillful at using the mobile internet.	
Social Influence	SI1	People who influence my behavior think that I should use information technology.	Venkatesh et al. (2003); Xu & Gupta (2009); Batara et al. (2017); Ali & Danish (2018); Jayawardena et al. (2023)
	SI2	My colleagues and peers think that using information technology is a good idea.	
	SI3	My colleagues and peers use information technology and encourage me to adopt it.	
Behavioral Intention	BI1	I intend to use digital technologies or tools.	Venkatesh et al. (2003); Salade et al. (2015); Weerakkody et al. (2013); Jayawardena et al. (2023)
	BI2	I will always try to use digital technologies or tools.	
	BI3	I plan to continue to or frequently use digital technologies or tools.	
	BI4	If I have the resources, knowledge, and ability, I will use digital technologies or tools.	
Digital Transformation Use	DTU1	I am prepared to apply a digitalized customer experience	Farooq et al. (2017); Venkatesh et al. (2003); Jayawardena et al. (2023)
	DTU2	I am prepared to apply digitalized business processes.	
	DTU3	I am prepared to apply organizational restructuring to facilitate digital transformation.	
	DTU4	I am prepared to apply cultural changes for digital transformation.	

The institutional survey statistics on demographic descriptions show that there was a total of 92 electronic questionnaire responses, all of which were valid. Among the respondents, 11.96% (n=11) were male and 88.04% (n=91) were female. The positions of the respondents were as follows: 14.13% (n=13) were institution heads, 18.48% (n=17) were business supervisors, 4.35% (n=4) were senior executives, 3.26% (n=3) were managers, 2.17% (n=2) were head nurses, 7.61% (n=7) were nurses, 5.43% (n=5) were social workers, 1.09% (n=1) were care supervisors, 32.61% (n=30) were care staff, 5.43% (n=5) were administrative staff, and 5.43% (n=5) were in other positions.

Reliability and validity analyses were primarily conducted to examine whether each measurement item accurately reflected the meaning of each research variable (Carrasco & Jover, 2003). In general, all indicators under a latent variable are expected to exhibit high loadings, and the composite reliability (CR) should exceed 0.6 in order to provide good convergent validity (Shi & Maydeu-Olivares, 2020; Hair et al., 2017; Malhotra et al., 2006), which indicates a high level of internal consistency among all measurement items. For discriminant validity, the analysis can be conducted using the square root of the average variance extracted (AVE). The AVE value should exceed 0.5 (Hair et al., 2021), suggesting that the measurement items more effectively capture the characteristics of each research variable in the model (Shmueli et al., 2019; Dash & Paul, 2021).

To measure the validity of the model structure, this study tested the model structure using Cronbach's alpha, rho A, and composite reliability tests to examine the internal consistency among the items and confirm the reliability of the scale (Table 2). The results of the construct reliability and validity analysis showed that the Cronbach's Alpha coefficients and rho A (α, rho A > 0.7) (Hair et al., 2010) ranged from 0.881 to 0.964, all achieving good and acceptable results. Therefore, the model results indicate that the measurements are reliable and have internal consistency. The composite reliability (CR) ranged from 0.884 to 0.972, and the average variance extracted (AVE) values were all greater than the set standard of 0.5, indicating that the model's reliability is good. Thus, the reliability level of the model structure scale is sufficient.

Table 2. Reliability and Validity Measurement Results

Factor	Cronbach's Alpha	rho_A	CR	AVE
Behavioral Intention	0.962	0.962	0.972	0.898
Culture	0.925	0.931	0.940	0.691
Digital transformation use	0.952	0.955	0.965	0.875
Effort Expectancy	0.960	0.964	0.971	0.893
Digital maturity	0.939	0.945	0.956	0.846
Organization	0.923	0.924	0.946	0.814
Performance Expectancy	0.937	0.946	0.953	0.801
Personal Innovativeness	0.885	0.909	0.920	0.744
Social Influence	0.807	0.881	0.884	0.721
Technology	0.935	0.939	0.953	0.836

Discriminant validity, based on the Fornell-Larcker criterion, is confirmed when the correlations between constructs are lower than the square root of their corresponding Average Variance Extracted (AVE) values. The results in Table 3 indicate strong discriminant validity among the variables.

Table 3. Discriminant Validity

Factor										
Behavioral Intention	**0.948**									
Culture	0.409	**0.831**								
Digital transformation use	0.611	0.620	**0.935**							
Effort Expectancy	0.644	0.347	0.611	**0.945**						
Maturity of the digital	0.460	0.785	0.646	0.439	**0.920**					
Organization	0.430	0.849	0.542	0.353	0.792	**0.902**				
Performance Expectancy	0.778	0.542	0.592	0.604	0.581	0.452	**0.895**			
Personal Innovativeness	0.786	0.505	0.733	0.729	0.586	0.483	0.791	**0.863**		
Social Influence	0.664	0.694	0.636	0.639	0.669	0.671	0.705	0.723	**0.849**	
Technology	0.385	0.835	0.579	0.405	0.859	0.851	0.503	0.515	0.622	**0.915**

Note: The bolded values indicate the square roots of the AVE values for each construct

In assessing discriminant validity using the HTMT (Heterotrait-Monotrait ratio), the criterion requires that HTMT values be less than 0.90, which indicates adequate discriminant validity of the measurement instrument (Henseler et al., 2016). Table 4 shows that all HTMT values are below the recommended threshold. Accordingly, the results indicate that the model demonstrates good reliability and satisfactory convergent validity.

Table 4. Heterotrait–Monotrait Ratio (HTMT)

Factor									
Behavioral Intention									
Culture	0.434								
Digital transformation use	0.637	0.666							
Effort Expectancy	0.669	0.375	0.642						
Maturity of the digital	0.481	0.831	0.677	0.457					
Organization	0.456	0.891	0.573	0.375	0.847				
Performance Expectancy	0.814	0.586	0.621	0.624	0.622	0.489			
Personal Innovativeness	0.837	0.584	0.814	0.793	0.655	0.553	0.856		
Social Influence	0.725	0.795	0.717	0.717	0.764	0.767	0.812	0.852	
Technology	0.405	0.890	0.611	0.427	0.791	0.891	0.543	0.588	0.720

Table 5. Model Fit: The SRMR values range between 0 and 1, and values approaching 0 suggest better model fit.

Table 5. SRMR Confidence Intervals

	SRMR	Sample Mean (M)	95%
Saturated Model	0.080	0.051	0.061
Estimated model	0.091	0.059	0.072

The explanatory power of the structural model was evaluated based on the R^2 values of the model paths. A higher R^2 indicates stronger explanatory power of the model for the latent variables. According to Cohen (1988), explanatory effect sizes of 0.02–0.13 are considered weak, 0.13–0.26 are moderate, and values above 0.26 are strong.

Structural model analysis focuses on R2 to obtain the predictive relevance of the research theoretical model. R2 refers to the variance explained by all independent structures. Cohen (1988) provided standards for R2, indicating that a value between 0.02 and 0.13 is considered to have weak explanatory power, 0.13 to 0.26 is moderate, and above 0.26 is strong. The results in Table 6 show that the model construct of Digital maturity has an explanatory power of 75.8%, while Behavioral Intention and Digital transformation use have explanatory powers of 69.3% and 54.2%, respectively.

Table 6. Structural model dimensions

	original	sample mean	STDEV	T(|O/STDEV|)	P value
Digital maturity	0.758	0.764	0.065	11.649	0.000
Behavioral Intention	0.693	0.717	0.059	11.747	0.000
Digital transformation use	0.542	0.560	0.113	4.810	0.000

Note: *** $p < 0.001$, ** $p < 0.05$

In addition, the closer the path coefficient of the empirical research model is to 1, the greater and more significant its influence. In the hypothetical model, there are a total of 9 hypotheses, of which 5 are supported and 4 are not supported. The results of the hypotheses are shown in Table 7. All structural model relationships are referenced in Figure 2.

Table 7. Hypotheses Results

Model path	path coefficient	sample mean	STDEV	T (|O/STDEV|)	P value	Results
H1: Culture -> Digital maturity	0.160	0.188	0.091	1.761	0.079	Not supported
H2: Organization -> Digital maturity	0.140	0.123	0.102	1.381	0.168	Not supported
H3: Technology -> Digital maturity	0.606	0.595	0.090	6.718	0.000	support
H4: Digital maturity -> Digital transformation use	0.463	0.467	0.097	4.772	0.000	support
H5: Personal Innovativeness -> Behavioral Intention	0.350	0.352	0.175	1.999	0.046	support
H6: Performance Expectancy -> Behavioral Intention	0.386	0.387	0.161	2.393	0.017	support
H7: Effort Expectancy -> Behavioral Intention	0.114	0.123	0.100	1.140	0.255	Not supported
H8: Social Influence -> Behavioral Intention	0.066	0.059	0.140	0.475	0.635	Not supported
H9: Behavioral Intention -> Digital transformation use	0.398	0.398	0.108	3.683	0.000	support

Note: *** $p < 0.001$, ** $p < 0.05$

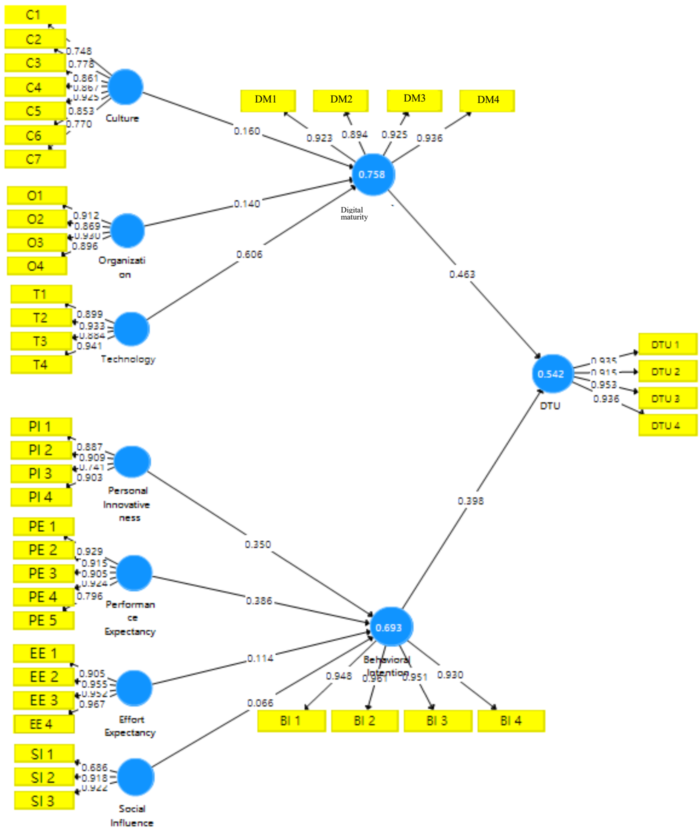

Figure 2. Structural Parameter Estimation and Fit Statistics Chart

5. CONCLUSION

This study, based on the Resource-Based View and an extended Unified Theory of Acceptance and Use of Technology (UTAUT) model, examined the influence of digital maturity and behavioral intention on the use of digital transformation in long-term care institutions. The effective allocation of organizational resources to enhance care capacity becomes a critical factor for gaining competitive advantages in complex environments (Park & Mithas, 2020). Given the increasing importance of nursing staff and their roles in healthcare contexts, the primary aim of digitalization initiatives is to reduce their workload and address the problem of persistent staffing shortages. The findings revealed that within the model, digital maturity, behavioral intention, and digital transformation use exhibited high explanatory power (R^2), suggesting that these three constructs are the most critical determinants for long-term care institutions. Among the nine hypotheses, five were supported and four were not, as detailed below.

Culture plays a critical role in shaping digital maturity; however, the empirical findings of this study did not align with Hypothesis 1. The findings indicated that organizational culture alone was insufficient to advance digital maturity or facilitate professionals in achieving digital transformation. In other words, without cultural support, implementation at the organizational level cannot be fully realized. Institutions should therefore endeavor to reshape and strengthen cultural cohesion to enhance overall preparedness for digital transformation. Only when professionals identify with the cultural values of digitalization (Sunny et al., 2019) can consensus be built and collective goals achieved. This cultural foundation not only enhances acceptance and engagement in digitalization but also promotes higher maturity, ensuring that transformation outcomes are realized and sustained.

Due to the shortage of human resources, professionals find it difficult to adapt to the work mode changes introduced by digital integration, which directly affects the organization's preparedness for transformation. When staffing levels are insufficient, professionals cannot devote enough time to learning and practicing new systems, reducing their commitment and support for digitalization. This result, inconsistent with Hypothesis 2, underscores the importance of sufficient staffing and capability-building resources. Only when institutions ensure that professionals are available in adequate numbers, equipped with the right skills, and supported with training and resources can readiness and maturity be enhanced, thereby increasing the likelihood of successful digital transformation.

The introduction and application of technology have a significant impact on digital maturity. When organizations effectively promote digital practices, they not only enhance operational efficiency but also reduce employee burnout (Shaharul et al., 2023). That is, properly planned and implemented technological tools and information systems not only optimize workflows and resource allocation but also strengthen organizational effectiveness and sustainability. In addition, they can shape the organization's long-term competitive advantage in digital transformation, ensuring that the organizations remain highly adaptive and resilient when facing external environmental challenges and resource constraints.

Digital maturity directly influences the application of digital transformation. It can be regarded as the organization's adaptability and readiness for business digitalization, as well as a reflection of members' recognition and acceptance of the digitalization process. The results supported Hypothesis 4, suggesting that organizations with greater digital maturity possess stronger capabilities to utilize digital transformation in optimizing operations, improving service quality, and ultimately achieving superior performance and outcomes.

Personal innovativeness exerts a significant influence on behavioral intention, reflecting the extent to which organizational professionals acknowledged and accepted digitalization. The findings were consistent with Hypothesis 5. According to Carvalho et al. (2023), individual behavioral practices can trigger and introduce new ideas, processes, products, or procedures to enhance organizational effectiveness. Professionals exhibit greater openness to the adoption of new technologies, thereby exerting a positive influence on the organization's overall digitalization adoption.

Performance expectancy was found to significantly influence behavioral intention, in line with Hypothesis 6. As noted by Venkatesh et al. (2012), the use of digital systems can effectively enhance job performance. Employees' willingness to adopt digital tools rises when they perceive clear improvements in their work performance.

The influence of effort expectancy on behavioral intention was not supported, contradicting Hypothesis 7. Findings revealed that professionals tend to view digital systems as complex and requiring substantial additional effort to learn, which diminishes the role of effort expectancy in enhancing usage intention. These results suggest that organizations should adopt more user-centered system designs and offer comprehensive training resources to lower perceived complexity, thereby facilitating greater acceptance of digitalization.

The effect of social influence on behavioral intention was not supported, which was inconsistent with Hypothesis 8. Social influence refers to the extent to which individuals are affected by others' attitudes toward system use, but the findings indicated that professionals still lacked sufficient understanding of digitalization and were unable to recognize the value and impact of others' use of technology. This phenomenon reflects deficiencies in internal communication and digital advocacy within organizations, which prevents professionals from forming positive perceptions of digital adoption.

Behavioral intention was found to influence the use of digital transformation, and the results were consistent with Hypothesis 9. As noted by Williams et al. (2015), behavioral intention affects user behavior and serves as an important antecedent of user actions. The findings indicate that professionals in the institutions gradually develop a shared understanding and acceptance of digital applications (Jayawardena et al., 2023), demonstrating that behavioral intention can effectively drive the implementation of digital transformation.

This study integrated the Resource-Based View (RBV) and the Unified Theory of Acceptance and Use of Technology (UTAUT) model to examine the impact of internal resources and capabilities on digital maturity in long-term care institutions, and to analyze the factors influencing professionals' intentions to adopt digital technologies. The findings confirmed that within the framework of digital maturity, behavioral intention, and digital transformation use, digital maturity was identified as the most critical component. Technology was found to significantly influence digital maturity and subsequently promote the adoption of digital transformation, whereas cultural and organizational factors were not significant. Although the effects of effort expectancy and social influence were not in line with expectations, these findings provide valuable insights for institutional managers. The advancement of digitalization is relatively slow owing to cultural and other contributing factors. The objective of promoting digitalization remains to alleviate the workload of nursing staff, mitigate the shortage of nursing personnel, and simultaneously enhance service efficiency and quality for more effective resource allocation and management. By means of empirical analysis, this study identified the key factors influencing digital transformation in long-term care institutions, offering evidence-based implications for policymakers and managers to strengthen service quality and efficiency through the adoption of digital technologies. As this study was conducted in Taiwan, to respond to the advent of the digital era, future research is expected to extend to different regions or other industries and can serve as a reference for the digital transformation of other long-term care institutions.

ACKNOWLEDGEMENT

The authors gratefully acknowledge the managers of SHIANGBAO Long-Term Care Group, Taiwan, for their invaluable contributions, as well as professionals who generously shared their perspectives through the interviews.

REFERENCES

Alsyouf, A., Ishak, A. K., Lutfi, A., Alhazmi, F. N. and Al-Okaily, M., 2022. The role of personality and top management support in continuance intention to use electronic health record systems among nurses. *International Journal of Environmental Research and Public Health*, *19*(17), 11125.

Amankwah-Amoah, J., Khan, Z., Wood, G. and Knight, G., 2021. COVID-19 and digitalization: The great acceleration. *Journal of business research*, *136*, 602-611.

Ansah, J. P., Eberlein, R. L., Love, S. R., Bautista, M. A., Thompson, J. P., Malhotra, R., & Matchar, D. B., 2014. Implications of long-term care capacity response policies for an aging population: A simulation analysis. *Health Policy*, *116*(1), 105-113.

Ayaz, A. and Yanartaş, M., 2020. An analysis on the unified theory of acceptance and use of technology theory (UTAUT): Acceptance of electronic document management system (EDMS). *Computers in Human Behavior Reports*, Vol. 2, p. 100032.

Babakus, E. and Mangold, W. G., 1992. Adapting the SERVQUAL scale to hospital services: an empirical investigation. *Health services research*, *26*(6), 767.

Barney, J. B., 1991. Firm Resources and Sustainable Competitive Advantage. *Journal of Management*, *17*, 99-120.

Batayeh, B. G., Artzberger, G. H. and Williams, L. D., 2018. Socially responsible innovation in health care: Cycles of actualization. *Technology in Society*, *53*, 14-22.

Bharadwaj, A., El Sawy, O. A., Pavlou, P. A. and Venkatraman, N. V., 2013. Digital business strategy: toward a next generation of insights. *MIS quarterly*, pp. 471-482.

Blut, M. and Wang, C., 2020. Technology readiness: a meta-analysis of conceptualizations of the construct and its impact on technology usage. *Journal of the Academy of Marketing Science*, *48*, 649-669.

Brislin, R. W., 1980. Cross-cultural research methods: Strategies, problems, applications. *Environment and culture*, pp. 47-82.

Carrasco, J. L. and Jover, L., 2003. Assessing individual bioequivalence using the structural equation model. *Statistics in medicine*, 22(6), 901-912.

Carroll, N., Conboy, K. and Wang, X., 2023. From transformation to normalisation: An exploratory study of a large-scale agile transformation. *Journal of Information Technology*, *38*(3), 267-303.

Carter, L. and Belanger, F., 2004. Citizen adoption of electronic government initiatives. In 37th Annual Hawaii International Conference on System Sciences, *Proceedings of the IEEE*, p. 10.

Chanias, S., Myers, M. D. and Hess, T., 2019. Digital transformation strategy making in pre-digital organizations: The case of a financial services provider. *The Journal of Strategic Information Systems*, *28*(1), 17-33.

Cohen, J., 1988. Set correlation and contingency tables. *Applied psychological measurement*, *12*(4), 425-434.

Dash, G. and Paul, J., 2021. CB-SEM vs PLS-SEM methods for research in social sciences and technology forecasting. *Technological Forecasting and Social Change*, *173*, 121092.

Davis, F. D., 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, pp. 319-340.

Davison, J., Schenker, Y., Donovan, H. and Rosenzweig, M., 2016. A Work Sampling Assessment of the Nursing Delivery of Palliative Care in Ambulatory Cancer Centers. *Clinical Journal of Oncology Nursing*, *20*(4), 421-426.

De Leeuw, J. A., Woltjer, H. and Kool, R. B. 2020. Identification of factors influencing the adoption of health information technology by nurses who are digitally lagging: in-depth interview study. *Journal of medical Internet research*, *22*(8), e15630.

Del Giudice, M., Scuotto, V., Garcia-Perez, A. and Petruzzelli, A. M., 2019. Shifting Wealth II in Chinese economy. The effect of the horizontal technology spillover for SMEs for international growth. *Technological Forecasting and Social Change*, *145*, 307-316.

Di Vaio, A., Palladino, R., Pezzi, A. and Kalisz, D. E., 2021. The role of digital innovation in knowledge management systems: A systematic literature review. *Journal of business research*, *123*, 220-231.

Evermann, J., and Tate, M., 2016. Assessing the predictive performance of structural equation model estimators. *Journal of Business Research*, 69(10), 4565-4582.

Fujisawa, R. and Colombo, F., 2009. *The long-term care workforce: overview and strategies to adapt supply to a growing demand*.

Gill, M. and VanBoskirk, S., 2016. *The digital maturity model 4.0. Benchmarks: digital transformation playbook.*

Haikal, F., Tyas, N. K., Felcia, X. D., Oktavia, T. and Sundaram, D., 2022. User acceptance analysis of the e-Health information system using UTAUT2 method. *Journal of Theoretical and Applied Information Technology*, Vol. 100, No. 7, pp. 2193-2206.

Hair Jr, J. F., Black, W. C., Babin, B. J. and Anderson, R. E., 2010. *Multivariate data analysis. vectors*, 7th Edition. Essex: Pearson Prentice Hall.

Hair Jr, J. F., Hult, G. T. M., Ringle, C. M. and Sarstedt, M., 2021. *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage publications.

Hair Jr, J. F., Matthews, L. M., Matthews, R. L. and Sarstedt, M., 2017. PLS-SEM or CB-SEM: updated guidelines on which method to use. *International Journal of Multivariate Data Analysis*, *1*(2), 107-123.

Hassan, A. Y. I., 2020. Challenges and recommendations for the deployment of information and communication technology solutions for informal caregivers: scoping review. *JMIR aging*, *3*(2), e20310.

Havaei, F., Sims-Gould, J., Staempfli, S., Franke, T., Park, M., Ma, A. and Kaulius, M., 2023. Impact of the single site order in LTC: exacerbation of an overburdened system. *BMC Health Services Research*, *23*(1), 666.

Henseler, J., Hubona, G. and Ray, P. A., 2016. Using PLS path modeling in new technology research: updated guidelines. *Industrial management & data systems*, *116*(1), 2-20.

Hollnagel, E., 2017. *Safety-II in practice: developing the resilience potentials*. Routledge. London, Corporate Taylor & Francis Group.

Jayawardena, C., Ahmad, A., Valeri, M. and Jaharadak, A. A., 2023. Technology acceptance antecedents in digital transformation in hospitality industry. *International Journal of Hospitality Management*, Vol. 108, p.103350.

Kane, G. C., 2015. *Strategy, not technology, drives digital transformation*. MIT Sloan Management Review and Deloitte University Press.

Kane, G. C., 2017. Digital maturity, not digital transformation. *MIT Sloan management review*, 1(1), 1-15.

Kim, J. J., Lee, M. J. and Han, H., 2020. Smart hotels and sustainable consumer behavior: Testing the effect of perceived performance, attitude, and technology readiness on word-of-mouth. *International Journal of Environmental Research and Public Health*, *17*(20), 7455.

Kiron, D., Kane, G. C., Palmer, D., Phillips, A. N. and Buckley, N., 2016. Aligning the organization for its digital future. *MIT Sloan management review*, *58*(1).

Kotschy, R. and Bloom, D. E., 2022. A comparative perspective on long-term care systems. *International Social Security Review*, 75(3-4), 47-69.

Kwarteng, M. A., Ntsiful, A., Diego, L. F. P. and Novák, P., 2024. Extending UTAUT with competitive pressure for SMEs digitalization adoption in two European nations: a multi-group analysis. *Aslib Journal of Information Management*, *76*(5), 842-868.

Lavander, P., Meriläinen, M. and Turkki, L., 2016. Working time use and division of labour among nurses and health-care workers in hospitals–a systematic review. *Journal of Nursing Management*, *24*(8), 1027-1040.

Li, J. J., Bonn, M. A. and Ye, B. H., 2019. Hotel employee's artificial intelligence and robotics awareness and its impact on turnover intention: The moderating roles of perceived organizational support and competitive psychological climate. *Tourism Management*, *73*, 172-181.

Mahardika, H., Thomas, D., Ewing, M. T. and Japutra, A., 2019. Predicting consumers' trial/adoption of new technology: revisiting the behavioral expectations–behavioral intentions debate. *The International review of retail, distribution and consumer research*, *29*(1), 99-117.

Malhotra, N. K., Kim, S. S. and Patil, A., 2006. Common method variance in IS research: A comparison of alternative approaches and a reanalysis of past research. *Management science*, *52*(12), 1865-1883.

Nikopoulou, M., Kourouthanassis, P., Chasapi, G., Pateli, A. and Mylonas, N., 2023. Determinants of digital transformation in the hospitality industry: Technological, organizational, and environmental drivers. *Sustainability*, *15*(3), 2736.

Park, Y. and Mithas, S., 2020. Organized complexity of digital business strategy: A configurational perspective. *MIS quarterly*, *44*(1), 85-128.

Putra, N. G. D., 2023. Analysis of e-medical record utilization with UTAUT method to perceive behavioral use. *Jurnal Bisnis dan Manajemen*, 3(1), 120-135.

Rossmann, A., 2018. *Digital maturity: Conceptualization and measurement model*.

Sarstedt, M., Ringle, C. M. and Hair, J. F., 2017. Treating unobserved heterogeneity in PLS-SEM: A multi-method approach. In *Partial least squares path modeling: Basic concepts, methodological issues and applications*. Cham: Springer International Publishing, pp. 197-217.

Savino, M. M. and Shafiq, M., 2018. An extensive study to assess the sustainability drivers of production performances using a resource-based view and contingency analysis. *Journal of Cleaner Production*, *204*, 744-752.

Shaharul, N. A., Ahmad Zamzuri, M. A. I., Ariffin, A. A., Azman, A. Z. F. and Mohd Ali, N. K., 2023. Digitalisation Medical Records: Improving Efficiency and Reducing Burnout in Healthcare. *International Journal of Environmental Research and Public Health*, *20*(4), 3441.

Shi, D. and Maydeu-Olivares, A., 2020. The effect of estimation methods on SEM fit indices. *Educational and psychological measurement*, *80*(3), 421-445.

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J. H., Ting, H., Vaithilingam, S. and Ringle, C. M., 2019. Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. *European journal of marketing*, *53* (11) 2322-2347.

Siira, E., Tyskbo, D. and Nygren, J., 2024. Healthcare leaders' experiences of implementing artificial intelligence for medical history-taking and triage in Swedish primary care: an interview study. *BMC Primary Care*, 25(1), 268.

Sordi Carrara, B. and Magalhães Franco Espírito Santo, P., 2016. Old age institutionalized in postmodern times: the identity in parallel universe?. *Journal of Nursing UFPE/Revista de Enfermagem UFPE*, *10*(5).

Soto Setzke, D., Riasanow, T., Böhm, M. and Krcmar, H., 2023. Pathways to digital service innovation: The role of digital transformation strategies in established organizations. *Information Systems Frontiers*, *25*(3), 1017-1037.

Sunny, S., Patrick, L. and Rob, L., 2019. Impact of cultural values on technology acceptance and technology readiness. *International Journal of Hospitality Management*, *77*, pp. 89-96.

Tabrizi, B., Lam, E., Girard, K. and Irvin, V., 2019. Digital transformation is not about technology. *Harvard business review*, *13*, pp. 1-6.

Taylor, B. J. and Donnelly, M., 2006. Professional perspectives on decision making about the long-term care of older people. *British Journal of Social Work*, *36*(5), 807-826.

Tortorella, G. L., Saurin, T. A., Fogliatto, F. S., Rosa, V. M., Tonetto, L. M. and Magrabi, F., 2021. Impacts of Healthcare 4.0 digital technologies on the resilience of hospitals. *Technological Forecasting and Social Change*, *166*, 120666.

Venkatesh, V., Morris, M. G., Davis, G. B. and Davis, F. D., 2003. User acceptance of information technology: Toward a unified view. *MIS quarterly*, pp. 425-478.

Vial, G., 2019. Reflections on quality requirements for digital trace data in IS research. *Decision Support Systems*, *126*, 113133.

Vial, G., 2021. Understanding digital transformation: A review and a research agenda. *Managing digital transformation*, pp. 13-66.

Wang, W. H. and Hsu, W. S., 2023. Integrating artificial intelligence and wearable IoT system in long-term care environments. *Sensors*, *23*(13), 5913.

White, E. M., Wetle, T. F., Reddy, A. and Baier, R. R., 2021. Front-line nursing home staff experiences during the COVID-19 pandemic. *Journal of the American Medical Directors Association*, 22(1), 199-203.

Williams, M. D., Rana, N. P. and Dwivedi, Y. K., 2015. The unified theory of acceptance and use of technology (UTAUT): a literature review. *Journal of enterprise information management*, *28*(3), 443-488.