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Master Thesis

Digital Change Through Individual Readiness: A Human-Centered Approach to Digital Transformation in Higher Education Institutions.

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Declaration of Artificial Intelligence Utilization

During the preparation of this thesis, several artificial intelligence tools were employed to enhance specific aspects of the writing process. The tools and applications are detailed below:

- *DeepL Write*: This instrument was used to improve overall readability and to refine the text style in a manner more aligned with academic standards.
- *Grammarly*: This tool was used to conduct checks of spelling, grammar and punctuation.

The author has conducted a thorough review of the content generated with the support of Artificial Intelligence and takes full responsibility for the content of the work.

Management summary

Situation. Higher Education Institutions (HEIs) have been compelled to adapt to the emerging digital environment, a trend that has been further propelled by the Covid-19 pandemic. Multiple studies have addressed the digitalisation process of HEIs, but the primary focus has been on organisational or technological aspects. The human factor, and in particular the way in which individual readiness can affect technology adoption, was not given as much consideration.

Complication. Frequently, digital transformation efforts fail or underperform because of insufficient individual readiness levels among employees. The relationship between the antecedents of digital readiness, such as perceived organisational support and perceived benefits, and the readiness itself, has not received sufficient attention. Furthermore, the notion of readiness as a proactive factor capable of affecting behaviour has been explored to a limited extent, with greater emphasis placed on the related barriers in the absence of readiness.

Question. What are the antecedents of readiness for digital change in HEI employees, and does readiness increase their engagement in innovative digital behaviours?

Answer. The primary finding of this study indicate that intentional readiness to digital change exhibits a positive influence on innovative digital behaviour. The two main antecedents of readiness are perceived organisational support (POS) and perceived benefits of digitalisation. Self-efficacy, related to employees' belief in their ability to engage in digital change, exerts a direct effect on readiness, rather than moderating the effect of POS. The nature of the job role significantly influences the level of readiness and innovative work behaviour. It has been observed that roles such as administrative and managerial staff are associated with higher readiness levels than those observed in teachers.

Advice to management

a. **Build Self-efficacy through training programmes**: Empower employees, reduce resistance and increase their trust in managerial support by offering digital skills training programmes.
b. **Clearly communicate benefits**: Explain how digital transformation and the introduction of new technologies can improve working conditions and job performance.
c. **Adapt change strategies to each role**: Identify whether employees working in some positions are more ready than others and invest in targeted support to overcome these differences.
d. **Consider readiness as an indicator**: Use readiness levels to predict innovation adoption and find ways to increase them

Abstract

The present study investigates the individual-level factors that contribute to readiness for digital change in Higher Education Institutions (HEIs). The study further explores the manner in which individual readiness affects innovative work behaviours among employees. The research, drawing on the Theory of Planned Behaviour, identifies the relationship between intentional readiness and the performance of innovative behaviours associated with the use of new technologies. Furthermore, it identifies the relationship existing between readiness and organisational support and perceived benefits as antecedents. This study was conducted using data from 445 employees of Spanish HEIs. Structural equation modelling was employed to analyse the data, revealing a positive influence of perceived organisational support and benefits on readiness and the role of readiness as a driver of innovative work behaviours. Furthermore, the study enabled the identification of role-based differences, with administrative and managerial staff demonstrating higher readiness levels than teaching staff. The findings emphasize the importance for HEI managers to focus on change strategies built at the individual level, role-specific interventions, and strong support to ensure successful digital transformation.

Contents

1 Introduction

In the context of a rapidly evolving global environment, in which the advancement of technology is a significant factor, digital transformation represents a crucial element in assessing the competitiveness not only of businesses but also of Higher Education Institutions (HEIs) (Mohamed Hashim et al., 2022). The recent Covid-19 pandemic contributed as an accelerator for the global trend of digital transformation of lifestyle, work processes and business strategies (Amankwah-Amoah et al., 2021). Indeed, studies have shown that companies tend to adopt more entrepreneurial behaviours in hostile environments, characterised by rapidly changing events (Kreiser et al. 2020), consequently increasing their digitalisation level (Amankwah-Amoah et al., 2021). In such circumstances, evidence of "forced digitalisation" is often present. This term refers to a digital transformation that occurs not by choice but rather as a result of external forces (Ganichev & Koshovets, 2021), as for Covid-19 pandemic. This phenomenon presents a series of challenges, including heightened risks, diminished productivity, and constrained access to essential applications (Kelkar, 2020). A multitude of barriers have been identified, particularly at the organisational level, including a paucity of technical expertise, inadequate financial resources, an aversion to change, and employee resistance (Amankwah-Amoah et al., 2021). The presence of such a number of constraints gives rise to questions regarding the actual readiness for digital transformation of the actors involved in the process.

The accelerated digital transformation during the period of the global pandemic has had a disruptive effect on HEIs (Iivari et al., 2020), leading to a process of technological, cultural and organisational change (Kaputa et al., 2022). HEIs are organizations that demand specific managerial practices, given the need to balance their core educational function with the increased emphasis on market mechanisms (Smeenk et al., 2009). Given the pivotal role of these institutions, several studies have analysed their digital transformation, with a particular focus on the repercussions of the pandemic. However, a multitude of studies addressing digital readiness have focused exclusively on the organisational level. Despite acknowledging the pivotal role of organisational members in ensuring the efficacy of readiness to change (Alolabi et al., 2021), these studies have largely regarded this element as a mere factor, neglecting to thoroughly assess its antecedents and the subsequent impact on behavioural outcomes associated with digital transformation. As Toscano-Jara et al. (2023) emphasize, the human factor within the context of digital transformation has been regarded merely as a component of the technological environment's development, rather than investigating its actual role as a barrier or a driver within the digital transformation process. Furthermore, extant literature predominantly focuses on the assessment of digital readiness (Michelotto & Joia, 2024; Nasution et al., 2018) rather than on the actual improvement of its level. In the context of the present literature concerning the digital transformation of HEIs, the prevailing trends are related to educational and e-learning methodologies (Farias-Gaytan et al., 2023; Verma et al., 2024). In this context, the human dimension is frequently perceived in a negative light, regarding its role as an obstacle in the case of resistance to change and inadequate digital capabilities. Multiple studies, such as those of Gkrimpizi et al. (2023) and Singun (2025), have sought to identify and categorise the people-related barriers to digital transformation in HEIs. These studies have identified a range of factors contributing to these barriers, including a lack of digital literacy, inadequate IT support services, a lack of confidence in innovation, distrust and anxiety related to technology, and psychological concerns. Research has primarily focused on teachers and students, neglecting to consider other roles and job positions within this framework (Bhatt et al., 2023; Dima, 2020; Packmohr & Brink, 2021).

The present study aims to contribute to the gap in this body of knowledge by extending the consideration of human factors with two main objectives. The **first objective** is to analyse the antecedents at the individual level that are positively associated with higher readiness for digital change. The **second objective** is to consider the individual attitude toward change in a proactive force, rather than as a barrier, as in the case of resistance, by investigating how high levels of readiness to digital change influence innovative digital behaviours, considered as the individual actions that support digital change within the workplace. To delve more profoundly into the digitalisation process in HEIs, this research encompasses diverse work positions within the university, including not only teaching staff, but also administrative staff and managerial positions.

The endeavour can be encapsulated in the following research questions (RQ), to be addressed through empirical assessment:

RQ1: *Which factors at the individual level should be improved to increase the readiness for digital change level in employees of HEIs?*

RQ2: *To what extent does readiness to digital change influence employees' engagement in digital behaviours within HEIs?*

The aforementioned RQs are addressed through a quantitative analysis of the data collected from three different HEIs in Spain. The sample consists of 445 participants covering teaching, administrative and managerial roles within the university. The proposed research model is founded upon a series of widely accepted theories pertaining to cognition and behaviour, in addition to the most recent framework that has been developed in the aftermath of digital transformation. The overarching theoretical framework selected for this study is the Theory of Planned Behaviour (Ajzen, 1985), with its limitations being integrated with the support of Social Exchange Theory (Blau, 1964), Social Cognitive Theory (Bandura, 1977) and the Technology Acceptance Model (Davis, 1989). The individual-level factors that are to be considered are perceived organisational support and self-efficacy, given their relevant impact on innovation adoption behaviour as reported in the TOE framework (Tornatzky & Fleischer, 1990). Their association with intentional readiness to digital change is examined. To address the second research question, a specific part of the research model examines the direct relationship between employees' intentional readiness to digital change and their engagement in innovative digital behaviours. The hypothesis model proposed in the following section is tested employing partial least squares (PLS) path modelling.

This study contributes to the existing body of literature on digital transformation in HEIs by addressing a research gap concerning individual-level antecedents of readiness to change.

Specifically, it advances theoretical understanding by identifying and analysing personal factors that can facilitate digital readiness (RQ1). Moreover, the integration of innovative digital behaviours as an outcome of digital readiness (RQ2), shifts the focus to exploring how individuals actively contribute to the digital transformation process. A theoretical contribution of this study is the conceptualization of readiness as a proactive factor rather than a resistance mechanism. In fact, drawing on the Theory of Planned Behaviour (Ajzen, 1985), which posits that attitudes, subjective norms, and perceived behavioural control influence behavioural intentions, this research reinforces the role of attitude toward digital transformation and skills in facilitating the process itself within HEIs. Furthermore, this research offers a framework for understanding how readiness can be leveraged for successful digital transformation, thereby contributing to both theory and practice by offering a human-centred approach to evaluate the effectiveness of digital initiatives.

2 Theoretical Background and Hypothesis Development

2.1 “Forced” digitalisation and digital readiness

The primary objective of this research is to address the digital transformation of HEIs. The term “Digital Transformation” is a broad one, referring not to the transformation of specific processes but encompassing changes to products, services and business models in their entirety (Matt et al., 2015). Unruh and Kiron (2017) focused on alteration of behaviour, referring to new digital business models and processes, due to the system-level transition associated with this transformation. Digitalisation, in contrast is a term that is more specifically defined as the application of digital technologies to improve organisational processes (Gradillas & Thomas, 2023). In the context of this research, which is centred on the post-pandemic period, the digitalisation process was not substantiated by the previously stated objectives but rather by the necessity to thrive within the novel market environment. Consequently, the term “Forced Digitalisation” is appropriate, as most countries had to “speed up the digitalisation of the social sphere and public administration” (Ganichev & Koshovets, 2021). This abrupt and widespread transition to digital tools necessitated substantial modifications in individual mindset and behaviours. Specifically, within the organisational context, employees were compelled to quickly develop new digital competencies and adapt to a shifting work environment (Kohnke, 2017). The rapid transition has implications for individual readiness to change, defined as the “extent to which employees hold positive views about the need for organisational change” (Armenakis et al., 1993).

Digital readiness, which must be considered in scenarios where new technologies play a significant role (Gfrerer et al., 2021), is defined as the “inclination and willingness to switch and adapt to digital technology” (Westermann et al., 2014, as cited in Nasution et al., 2018). When this definition is combined with the intentional dimension of readiness proposed by Piderit (2000), which implies an attitudinal response to change "that might range from positive intentions to support the change to negative intention to oppose to it", the concept of employees' intentional readiness to digital change can be introduced. This concept indicates employees' willingness to put their energy and effort into digitalisation, with this determining their behaviour (Becker, 2020, as cited in Höyng & Lau, 2023).

2.2 Relationship between digital readiness and innovative work behaviour

In order to investigate the adoption behaviour associated with a certain level of intentional readiness to change, it is useful to draw from the Theory of Planned Behaviour (Ajzen, 1985). The theory posits that an individual's intention to engage in a particular behaviour, and ultimately the behaviour itself, is influenced by the interplay of three factors: attitude toward the behaviour, subjective norm, and perceived behavioural control. As articulated by Ajzen (1991), the significance of these determinants can vary contingent on the specific behaviour or circumstance. In this context, the attitude toward the behaviour, which represents the degree to which an individual holds a favourable or unfavourable evaluation or appraisal of the behaviour in question (Ajzen, 1991), can be associated with a positive attitude toward change. However, the conventional Theory of Planned Behaviour is based on specific beliefs that are not readily generalizable or applicable across diverse contexts (Mathieson, 1991). Consequently, it falls short in adequately elucidating behavioural decisions within the ambit of digital transformation (Srisathan & Naruetharadhol, 2022). In order to overcome this issue, Srisathan and Naruetharadhol (2022), proposed the novel concept of Digitally Planned and Transformed Behavior (DPTB), with the objective of examining the factors that influence digital human behaviour in the context of Covid-19 pandemic. The core determinants identified in the DPTB framework are based on the constructs of the traditional TPB, re-specified to fit the digital context. A novel factor that has been introduced is the Digital Attitude, which is defined as "individual beliefs, knowledge, mindsets, and prejudices towards either digital or physical behaviour" (Srisathan & Naruetharadhol, 2022). The authors identified evidence suggesting that a favourable digital attitude is associated with a greater propensity to engage in behaviours related to digital transformation. As posited by Armenakis et al. (1993), one of the most frequently cited definitions of change readiness characterises this construct as an individual's beliefs, attitudes, and intentions towards change. Consequently, a correlation can be established between digital readiness to change and digital attitude. Change-supporting behaviours, as defined by Kim et al. (2011) as "actions employees engage in to actively participate in […] planned change," are identified by Rafferty et al. (2013) as outcomes of change readiness. In order to provide a more precise definition of behaviour that supports change in the context of digitalisation, it is possible to consider the individual actions aimed at the generation, processing and implementation of new ideas regarding new technologies, generally defined as Innovative Work Behaviour (Aboobaker & Zakkariya, 2021; Yuan & Woodman, 2010). In accordance with the Theory of Planned Behaviour, an individual who holds a favourable attitude towards a given behaviour is more likely to engage in said behaviour intentionally (Ajzen, 1985). This assertion is also applicable to particular behavioural manifestations associated with change. As Choi (2011) explains, a positive attitude towards change is correlated with high levels of commitment to change. This is defined as "a mind-set that binds an individual to a course of action deemed necessary for the successful implementation of a change initiative" and positively related to innovation implementation behaviour (Michaelis et al., 2010). This finding suggests that employees who demonstrate a high level of commitment to change are more likely to exhibit innovation implementation behaviour. It can therefore be postulated that:

Hypothesis 1 (H1): Intentional readiness to digital change exerts a positive direct effect on digital innovative behaviour.

2.3 Relationship between perceived benefits and digital readiness

The digital innovative behaviour contemplated in the aforementioned hypothesis corresponds to the “Digital Behavioural Decision” in the DPTB, which signifies the digitally transformed or transforming behaviour that is executed by the individual as a consequence of the motivational factors affecting the behavioural decision (Srisathan & Naruetharadhol, 2022). In the context of the firm, a number of factors have been identified as influential in the process of innovation adoption and implementation. The TOE framework (Tornatzky & Fleischer, 1990) categorises these factors into three distinct groups: technological, organisational and environmental context. For the purposes of this study, certain factors within these groups are of particular relevance, given their potential correlation with readiness to digital change. The emphasis is placed on perceived benefits associated with the innovation adoption, part of the technological context factors (Chau & Tam, 1997), and the top management support, part of the organisational context factors (Grover, 1993).

As previously mentioned, the TOE framework identifies perceived benefits as one of the main technological factors affecting innovation adoption, consisting in the generation and adoption of new ideas. In general, perceived benefits represent the perception of positive outcomes associated with a particular behaviour and are able to influence the evaluation of the behaviour in question, as well as the decision to engage in it (Zhang et al., 2023). In the digital context, perceived benefits are defined as the extent to which individuals believe that the use of an information technology will improve their performance, productivity and effectiveness at work (Ratnawati & Malik, 2024). To elaborate further, the utility value associated with the benefit, defined as the desired gains from doing a task (Eccles et al., 1983), was found to influence technology adoption behaviour when higher (Taylor & Todd, 1995). The different types of benefits associated with the use of social software, and more broadly, technology within an organisational context, have been methodically categorised by Majumdar et al. (2013). The study identified three major categories of benefits: information benefits, leading to improved sharing of information, knowledge and ideas; communication benefits, related to the development of better communication channels within the workplace; organisation benefits, associated with general better conditions within the business environment. The mechanism through which perceived benefits are able to influence the final digital innovative behaviour can be understood by considering the findings of Ratnawati and Malik (2024). The researchers' work demonstrated the positive effect of perceived benefits on the intention to use a specific technology. The Theory of Planned behaviour can provide a justification for this relationship by reference to the expectancyvalue model of attitudes (Fishbein & Ajzen, 1975), which posits that an individual typically forms positive attitudes and favours behaviours for which largely desirable consequences are expected (Ajzen, 1991). However, the Theory of Planned Behaviour presents certain limitations, which are related to its high level of complexity and specificity, given the necessity of explicitly identifying a behavioural alternative (Mathieson, 1991). In order to overcome the aforementioned limitation associated with the digitalisation process and to provide a more comprehensive explanation of behaviours consisting in technology use at the individual level (Cheng, 2019), it is necessary to introduce the Technology Acceptance Model (TAM), specifically aimed at explaining the acceptance of information systems by individuals (Davis, 1989). As for the Theory of Planned Behaviour, this model is grounded in the Theory of Reasoned Action (Fishbein & Ajzen, 1975) and it postulates that the acceptance of technology is predicted by users' behavioural intention (Marikyan & Papagiannidis, 2024). The fundamental difference pertains to the determinants of behavioural intention, which, according to Davis (1989) are to be ascertained in the perceived ease of use and perceived usefulness of the technology under consideration. Perceived Ease of Use is defined as "the degree to which a person believes that using a particular system is free of effort", while Perceived Usefulness is defined as "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989). The definition of Perceived Usefulness is closely aligned with the previously mentioned definition of Perceived Benefits by Ratnawati and Malik (2024), which have been found to be closely related to the intention to use and accept technology (Siitonen et al., 2024; Visschers & Siegrist, 2014). This intention can be manifested through the willingness to support digital change, which has been found to be higher if the perceived benefits of change outweigh the perceived risks (Vakola, 2014), and for that reason it can be hypothesized that:

Hypothesis 2 (H2): Perceived benefits exert a positive effect on intentional readiness to digital change.

2.4 Relationship between perceived organisational support and digital readiness

As posited by Holt et al. (2007), employees' digital readiness constitutes a critical factor in the success of digital change at the organisational level. In order to explore strategies for enhancing readiness level in an effective manner, it is necessary to first understand its determinants also in relation to the organisational context in which change occurs. However, the Theory of Planned Behaviour does not provide sufficient justification for the effects of environmental determinants (Hagger and Hamilton, 2025; Sniehotta et al., 2014). As explained in Ajzen (2020), the theory acknowledges backgrounds factors believed to influence intentions and behaviour indirectly by providing information on precursors of behavioural beliefs. The theoretical framework posits that these beliefs engender a positive or negative attitude towards the behaviour in question. However, in Ajzen (1985), the external factors for which the theory accounts are solely related to time, opportunity and cooperation of others, rather than the environment itself (Mathieson, 1991).

Desplaces (2005) identified individuals' perceptions of organisational support for change as one of the aforementioned determinants. The concept of Perceived Organisational Support (POS), as outlined in the Organisational Support Theory (Eisenberger et al., 1986), represents the extent to which employees perceive that their supervisor prioritises their career well-being and their personal needs (Li et al., 2022). Employees who perceive strong organisational support will be more likely to develop a sense of trust in the organization, contributing to an increase in their willingness to accept and adapt to organisational change (Ming-Chu & Meng-Hsiu, 2015). As is the case with regard to the relationship between perceived benefits and innovation adoption, the TOE framework identifies management support as one of the main organisational context determinants (AbuAkel & Ibrahim, 2023; Tornatzky & Fleischer, 1990). This relationship is confirmed by Faiz et al. (2024), who define management support as the degree to which management encourages the uptake of technology for business processes, where a positive attitude toward change can enhance the adoption process. The significance of organisational support with regard to technology adoption is associated with the manner in which managerial support through digital training fosters digital empowerment in employees, which consists in the capacity to adapt to rapid changes in business processes and organisational structures (Lingling & Ye, 2023). In order to identify the effect of POS on readiness to change, and consequently on innovative work behaviour, it is useful to employ Social Exchange theory. Social Exchange Theory posits that individuals engage in social exchange actions when they are motivated by the returns they are expected to bring from others (Blau, 1964). This phenomenon is also observed in the context of POS, which often engenders a sense of obligation to contribute positively to the organization through positive workplace behaviour because of the desire to reciprocate a favourable treatment (Kurtessis et al., 2017). Consequently, employees who perceive high organisational support are more likely to trust the organisation's change initiatives and exhibit higher levels of change readiness (Gigliotti et al., 2018; Kirrane et al., 2017). The mechanisms through which perceived organisational support is capable of increasing readiness to change can be explained by considering specific factors identified as its antecedents by Rhoades and Eisenberger (2002) and by Allen et al. (2003). Specifically, effective and open communication has been demonstrated to mitigate employees' uncertainty regarding organisational change (Eisenberger & Stinglhamber, 2011), training during organisational change has been found to reduce resistance to change (Ming-Chu & Meng-Hsiu, 2015), and participation in decision-making has been shown to be positively related to readiness for organisational change (Mathur et al., 2023). The validity of these mechanisms can be further substantiated by examining the findings of Choi and Ruona (2011). The study concluded that individuals who have experienced normative-reeducative strategies, which are aimed at "fostering growth in the persons who make up the system to be changed" through the values of participation, learning and dialogue among others, exhibit higher levels of readiness for organisational change. Consequently, the following hypothesis is proposed:

Hypothesis 3 (H3): POS positively influences employees' Intentional readiness to digital change.

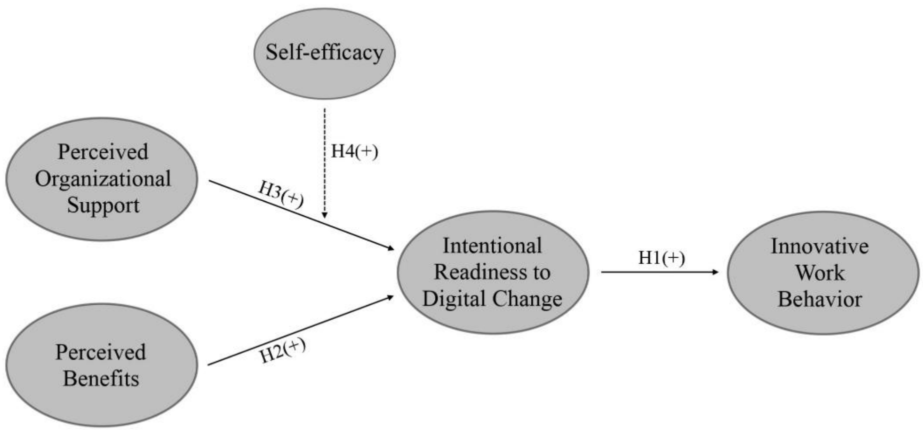
2.5 Self-efficacy as a moderator between POS and digital readiness.

As previously outlined, the Theory of Planned behaviour posits the notion of perceived behavioural control as one of the factors that influence intentions and the subsequent behaviour. Perceived behavioural control is theorized to consist of the “perceived ease or difficulty of performing the behaviour” and it is assumed to reflect anticipated impediments and obstacles (Ajzen, 1991). In general, perceived behavioural control is higher in individuals who believe they possess more resources and opportunities. This increased belief leads to increased intention to perform the behaviour itself (Ajzen, 1991). In Ajzen (2020), the author expounded the absence of a conceptual difference between perceived behavioural control and self-efficacy, defined as an individual’s beliefs regarding their own capacity to attain aspired goals in a specific situation (Bandura, 1977). As articulated in Social Cognitive Theory (Bandura, 2001), self-efficacy functions as a mechanism of the self-regulatory system, exerting a substantial influence on thought, motivation and action. In considering the relationship between human agency, defined as the intentional decision to enact behaviour change, and self-efficacy, it can be observed that individuals tend to choose situations in which they anticipate high personal control (Bandura, 2001). High self-efficacy expectations, shaped by individual experiences and emotional states (Bandura, 1977), have been found to foster favourable intentions toward change and reduced resistance to it, thereby contributing to the development of a readiness attitude (Wortmann & Jauer, 2024). However, self-efficacy is not identified as one of the determinants of individual readiness for change, with evidence supporting specifically the relationship between POS and change readiness (Gigliotti et al., 2018). The extent and level of employees' response to these determinants is influenced by their degree of self-efficacy, which serves to reduce emotional sensitivity and negative feelings associated with change (Alnoor et al., 2020). This suggests that self-efficacy is not a necessary condition for individual readiness itself. In considering the hypothesized direct effect of POS on readiness to change and Desplaces (2005) theoretical foundation, it is proposed that self-efficacy might not exert a direct effect on readiness to change, but rather function as a moderator in the relationship between the two variables. The following hypothesis is postulated:

Hypothesis 4 (H4): Self-efficacy acts as a positive moderator in the relationship between POS and Intentional readiness to digital change.

Figure 1.

Hypothesis model.



3 Research context, design and methodology

3.1 Data collection

The data utilized in this study was provided by Dr. Pauline Weritz and originates from another project. The dataset was collected through the administration of surveys to employees from three Spanish HEIs in 2022.

In the aftermath of the pandemic, Spain has been identified as a country where HEIs have exhibited elevated levels of digital maturity. This is described as the capability of an organization to align its culture, structure and people to be more competitive by taking advantage of new technological opportunities (Kane, 2017). Indeed, as demonstrated by Fernández et al. (2023), during this period Spanish universities increased their digital maturity level, attributable to their considerable commitment, investments dedicated to IT projects and the augmentation of training and technological support, among other factors. Furthermore, research on digital transformation in HEIs is predominantly concentrated in Spain, as evidenced by the preponderance of publications on the subject in that country (Farías-Gaytán et al., 2023). Given the relatively high level of experience and knowledge about the digitalisation process in this country, the three universities selected should present relatively similar starting conditions, which would facilitate the generalization of results for HEIs in different countries by taking into account the differences in terms of digital maturity.

3.2 Sample description

The hypotheses were tested using the data collected by administering a survey to employees working in Spanish HEIs. The sample comprised 445 participants, the majority of which employed in three main locations as shown in Table 1. In consideration of the prevailing interest in examining the divergent attitudes towards digital change of individuals occupying roles that diverge from those of teaching professionals, the participants were requested to indicate their position within the HEI. The predominant proportion was constituted of people working as teaching and research staff (51.7%).

However, a significant group was composed of administrative staff (39.1%). The demographic composition of the respondents was as follows: more than half of the respondents were female (52.1%), and the most represented age groups were 41-50 years old (32.8%) and 51-60 years old (36.4%).

Table 1

Participant Demographics and Institutional Affiliation in the Study.

Participants distribution across universities locations		
University	n	%
Group 1	181	40.7
Group 2	158	35.5
Group 3	93	20.9
Other	13	2.9
Total	445	100
Participants distribution according to their role		
Role	n	%
PDI	230	51.7
PAS	174	39.1
Managerial position	26	5.8
Other	15	3.4
Total	445	100
Participants distribution across age groups		
Age	n	%
18-30	17	3.8
31-40	82	18.4
41-50	146	32.8
51-60	162	36.4
60+	25	5.6
Total	432	97
Participants distribution across gender groups		
Gender	n	%
Female	232	52.1
Male	161	36.2
Non-binary	2	0.5
I prefer not to say it	13	8.3
Total	408	91.7

Note. The sections in the table show the distribution of participants, which total number accounts to 445, according to various criteria, including their work location, role, age and gender. The total number of participants is indicated at the bottom of each section. In instances where the total number of observations is less than 445, this is attributable to the presence of missing values that have not been documented in the table.

3.3 Measures

Perceived organisational support (POS). The construct of perceived organisational support was measured through a set of 3 items ($\alpha = .90$) proposed by Gfrerer et al. (2021) and aimed at measuring the level of perceived digital empowerment due to the support given by organizations managers. The selected items were scored on a 7-point Likert-type scale ranging from 1 (*totally disagree*) to 7 (*totally agree*) and were the following: "The people who manage this university…" "...encourage all employees to embrace digital transformation as an opportunity", "...promote digital transformation with all their efforts", "...provide employees with all the resources they need to achieve the best results from digital transformation".

Intentional readiness (IR). Intentional readiness to digital change was gauged using a set of 3 items ($\alpha = .89$) derived from the questionnaire developed by Bouckenooghe et al. (2009). The selected items were scored on a 7-point Likert-type scale ranging from 1 (*totally disagree*) to 7 (*totally agree*) and were the following: "I want to be involved in the digitalisation process in my job", "I am willing to make a significant contribution to the digitization of my job.", "I am willing to put energy into the process of change involved in digitization.".

Self-efficacy (SE). Self-efficacy was measured by the Perceived Individual Digital Readiness dimension, which consisted of 3 items ($\alpha = .89$) measured on a 7-point Likert-type scale ranging from 1 (*totally disagree*) to 7 (*totally agree*). The items were "I do not foresee any difficulties in adapting to the new working conditions" "Certain tasks will be required that I can implement in a simple way" "I can meet all the new requirements with ease" and were derived from the results of the study on individual-level perceptions of digital readiness presented by Gfrerer et al. (2021).

Perceived benefits (PB). The assessment of perceived benefits was conducted through the utilization of a set of 10 items ($\alpha = .80$), measured on a 7-point Likert-type scale ranging from 1 (*has decreased* *a lot*) to 7 (*has increased a lot*). The items were constructed by Drzensky et al. (2012) in the context of a study concerning antecedents, consequences and contingencies of readiness to change.

In consideration of the three categories of benefits delineated in the work of Majumdar et al. (2013), the 6 benefits exhibiting the highest loadings on the item were selected for further analysis. The benefits related to digital transformation included the following: “safety in your job”; “quality of your working conditions”; “promotion opportunities”; “your contact with colleagues”; cooperation with other departments”; “the speed of task execution”. The categorization of these benefits within the different types is outlined in Table 2.

Table 2

Categorization of perceived benefits in the three categories outlined by Majumdar et al. (2013).

Categories of benefits	
Information benefits	Speed of task execution
Organization benefits	Safety in your job
	Quality of your working conditions
	Promotion opportunities
Communication benefits	Contact with colleagues
	Cooperation with other departments

Innovative work behaviour (IWB). Innovative work behaviour was measured through a dimension comprising 4 items, which have been adapted from the 9-items scale ($\alpha = .89$) originally proposed by Scott & Bruce (1994). The items were measured on a 7-point Likert scale ranging from 1 (*totally disagree*) to 7 (*totally agree*). The purpose of the items was to investigate whether the participant believed they have been a person capable of: “proposing new ideas”, “working to implement new ideas”, “find improved ways to do things”, “create better processes and routines”.

Control variables. The research incorporated three control variables (i.e., age, gender, job position). The necessity to control for these variables is attributable to their potential influence on employees' readiness to digital change.

Van Volkom et al. (2013) discovered that age was a significant predictor of comfort and adaptation to new technology, with young adults reporting higher levels of these dimensions. The age of the participants was assessed using a five-point ordinal scale with predefined intervals (i.e., 18-30, 31-40, 41-50, 51-60, 60+), each of which was encoded with a numerical value ranging from 1 to 5.

Furthermore, Cai et al. (2017) discovered that, despite the presence of a smaller effect, males exhibited more positive attitudes toward technology use in comparison to females. The variable Gender was incorporated into in the model as a binary control variable. It was created a dummy control variable, coded as 1 for female respondents and 0 for male respondents, with male representing the reference group.

Finally, Sun et al. (2020) provided evidence of the influence of job position on technology acceptance. In certain instances, the role of the individual in either a managerial or an employee capacity has been demonstrated to exert influence on the digital readiness level of the individual (Gfrerer et al., 2021). The variable Position included three different roles: "PDI (teaching and research staff)"; "PAS (administration and services staff)"; "Position of managerial responsibility […]". The categorical variable was transformed into two dummy variables, which were included in the model as binary control variables. The category *PDI* is taken as the reference group. The first dummy variable, *Dummy_PAS,* was coded as 1 for respondents in administrative position and 0 otherwise. The second dummy variable, *Dummy_Managerial,* was coded as 1 for respondents holding managerial positions, 0 otherwise.

3.4 Data Analysis

This study utilized partial least squares structural equation modelling (PLS-SEM) to test the model and the hypotheses. Structural equation modelling (SEM) is a method that enables researchers to concurrently model and estimate relationships between dependent and independent variables (Hair et al., 2021). The PLS technique has been extensively utilized in marketing, strategic management, economics and information system research (Hair et al., 2012; Hensler et al., 2016) and has been identified as a promising technique in recent years (Hair et al., 2021). The employment of PLS-SEM is advantageous for several reasons. Chief among them is its ability to handle metric and ordinal scaled variables and its capacity to manage complex models with numerous relationships between constructs (Hair et al., 2021). As articulated by Hair et al. (2021), the flexibility inherent in PLS-SEM enables the interplay of theory and data, a fundamental aspect in causal-predictive modelling.

The aforementioned characteristics of PLS-SEM represent its strengths in comparison to CB-SEM, a common factor based structural equation modelling method in which the constructs are considered as common factors that explain the covariation between the indicators (Hair et al., 2021). The decision to employ PLS-SEM rather than CB-SEM in this study was substantiated by the rules of thumb provided by Hair et al. (2021) in their guidelines for selecting between these two models. It is evident that PLS-SEM is particularly advantageous when the objective of the research is to explore theoretical extensions of established theories. Conversely, CB-SEM has been proven to be more appropriate for theory confirmation. Moreover, PLS method works better with the presence of formative constructs, in contrast to CB-SEM, where strict specifications must be met to avoid identification and convergence issues. CB-SEM is effective in models involving circular relationships, absent in this situation. However, its capabilities are not optimized in the context of complex models, as the one presented in this study.

The measurement and structural models were estimated using SmartPLS v4.1.0.9 software. The software allowed to estimate through the PLS algorithm both the structural model and measurement model, which respectively show the relationship between the constructs themselves and the relationship between the constructs and the indicators (Hair et al., 2021). Furthermore, the measurement model can be evaluated through various procedures, contingent upon its formative or reflective nature. In the case of a formative measurement model, where the indicators cause the latent variables (Wong, 2013), the procedures to be assessed are convergent validity, indicator collinearity, significance and relevance of indicators (Hair et al., 2021). Conversely, in a reflective measurement model, where indicators exhibit strong correlation and interchangeability (Wong, 2013), the assessment encompasses indicator reliability, internal consistency reliability, convergent validity, and discriminant validity (Hair et al., 2021). The present study utilized SmartPLS software to evaluate the aforementioned metrics, considering the model's integration of both reflective and formative measurement scales.

As PLS-SEM is a statistical methodology, it was necessary to verify that certain underlying assumptions were met prior to conducting the analysis. The assumptions underlying structural equation modelling have been summarised by Kaplan (2001). The first assumption pertains to the sampling mechanism, for which it is conventionally anticipated that data are generated through the utilization of simple random sampling. However, it is very unlikely that data utilized for SEM are generated in this manner, and extensions to the theory have been developed to address alternative sampling strategies. The second assumption is met through the verification of normal data distribution. Nonetheless, as it will be discussed in the following section, the adverse effects of non-normality are limited in case of PLS-SEM technique (Hair et al., 2021). The third assumption is that the number of missing values on one or more of the variables should not be too high. Finally, the fourth assumption requires the absence of specification error, consisting of the omission of relevant variables in the model. The absence of specification error is typically evaluated by considering model fit measures (Kline, 2016). However, it has been demonstrated that these measures are not accurate for PLS-SEM and the approach adopted to assess the absence of specification error involves proving that the model is based on theoretical grounding and evaluating the measurement and structural model (Hair et al., 2021).

The initial phase of the data analysis process entailed the validation of the reliability and validity of the measurement of the constructs, together with the assessment of the model's explanatory and predictive power. Subsequent to this, an assessment of the structural model results was undertaken. SmartPLS enabled the examination of potential collinearity issues and the evaluation of the relevance of the path coefficient, which represents the structural model relationship, through a systematic approach (Hair et al., 2021).

In order to attempt to uncover differences in subgroups part of the total population that might not be evident when analysed as a whole, a multigroup analysis was performed. By considering the relationship in the structural model across the groups and whether they significantly differed between each other, it was possible to account for observed heterogeneity (Sarstedt et al., 2017). The presence of observed heterogeneity is indicated when differences across groups are related to observable characteristics (Hair et al., 2024). Failure to account for this heterogeneity can result in the misrepresentation of results (Hair et al., 2024). The employment of a Bootstrap Multi-Group Analysis, facilitated by SmartPLS, ascertained whether the differences in the path coefficients for the relationships within the three distinct groups were statistically significant. In this particular analysis, Bootstrap MGA was selected as the preferred method over Permutation MGA due to its non-parametric nature, which is particularly advantageous in exploratory studies. A key advantage of Bootstrap MGA is that it provides the p-value for path coefficient differences directly, thus obviating the need for making strict assumptions (Sarstedt et al., 2011).

In the analysis, an additional component had to be considered: a moderation variable. The moderation variable M affects the direction and/or the strength of a relationship between an independent variable X and a dependent variable Y (Baron & Kenny, 1986). The relationship between X, Y and M can be expressed mathematically as follows:

$$Main\ effect: Y = a + bX + cM$$

$$Interaction\ term: Y = a + bX + cM + dX * M,$$

where b represents the main effect when no moderator is included; c accounts for the variation in Y explained by M; d is the size of the change in b when M is increased by one standard deviation unit (Ramayah et al., 2018). To examine the interaction terms, the two-stage approach was selected, which is preferred when formative measures are involved in the model and to determine whether the mediator exerts a significant effect on the relationship (Henseler & Chin, 2010). SmartPLS facilitated the incorporation of an interaction term within the model by leveraging the two-stage approach. This approach enabled the determination of the interaction term's significance and effect size, respectively, through the t-value and Cohen's f^2 (Ramayah et al., 2018).

Despite not having been expressly hypothesised, the following analysis also examined the presence of mediation effects. Mediation effects are defined as a significant intervening mechanism between the antecedent, also defined causal variable X, and the consequent variable, which is the outcome Y (Ramayah et al., 2018), within the considered model. When considering the two variables X and Y as well as the mediator M, the total mediation effect can be decomposed as follows:

$$c = total\ effect\ =\ direct\ effect\ +\ indirect\ effect = c' + a * b,$$

where c' is the direct effect of X on Y when M is held constant, while $a*b$ is the measure of the amount of mediation, given by the product of the effect of X on M (a) and the effect of M on Y (b). In recent years, several scholars have argued that the focus in mediation analysis should be on the indirect effect (Hayes & Rockwood, 2017), and that the most effective method of testing it is bootstrapping, a non-parametric resampling procedure regarded as the most rigorous and powerful method. The type of bootstrapping that is most suitable for detecting mediating effects is Bias-corrected and Accelerated (BCa) Bootstrap, and it can be readily implemented using the selected software (Ramayah et al., 2018).

4 Empirical analysis and results

4.1 Assumptions

The four assumptions discussed in the data analysis section have been verified prior to commencing the actual analysis. The data collection process did not adhere to the principles of simple random sampling. However, as previously stated, the PLS-SEM method was adapted to accommodate data collected through diverse strategies. As Kaplan (2001) demonstrated, if data are collected through a multistage approach, as is the case in this instance, it is possible to still consider the assumption met and to deal with data with multilevel modelling. Furthermore, the minimum R-squared method, as discussed by Hair et al. (2014), supported the conclusion that the sample size was sufficient. The total number of observations (i.e., 445) was higher than estimation for the sample size required for a minimum R^2 of .25 and a maximum of two arrows pointing at a construct, which is 110. The second assumption, requiring normal distribution of data, has not been substantiated, as evidenced by skewness values reported in Table 3. Indeed, the majority of indicators exhibit a left-skewed distribution, as evidenced by the presence of negative values. However, given that PLS-SEM is a non-parametric method, the normality assumption is not essential as it is for CB-SEM, and its absence does not cause excessive distortions (Hair et al., 2021). In addition, as stipulated by the third assumption, missing values were maintained at a reasonable level, given that for all indicators their amount is less than 5% of the total observations. The selected procedure for dealing with missing values is pairwise deletion, and it has been demonstrated that this has limited distorting effects on the analysis results (Hair et al., 2021). As previously mentioned, the absence of any specification error should be checked with procedures different from the traditional model fit measures, typically used for CB-SEM (Kline, 2016). It is reasonable to conclude that the fourth assumption was fulfilled, given the development of the model on theoretical grounds. In order to provide further support, the evaluation of the measurement and of the structural model will be discussed in the following sections.

Table 3

Distributional properties and factors loadings of measurement indicators.

Skewness Values and Latent Variable Loadings		
Indicator	Skewness	Loadings
IndiRead1 ← SE	-1.137	0.933
IndiRead2 ← SE	-1.050	0.840
IndiRead3 ← SE	-1.132	0.941
DigEmp1 ← POS	-0.839	0.914
DigEmp2 ← POS	-0.752	0.923
DigEmp3 ← POS	-0.629	0.882
Intentional1 ← IR	-1.141	0.951
Intentional2 ← IR	-1.088	0.964
Intentional3 ← IR	-1.146	0.932
Inno1 ← IWB	-0.590	0.875
Inno2 ← IWB	-0.967	0.890
Inno3 ← IWB	-1.127	0.907
Inno4 ← IWB	-0.870	0.915
Benefits1-Safety → PB	0.601	0.724
Benefits2-Quality → PB	-0.107	0.792
Benefits3-Promotion → PB	0.019	0.542
Benefits6-Contact → PB	-0.137	0.705
Benefits8-Cooperation → PB	-0.209	0.775
Benefits9-Speed → PB	-0.465	0.694

4.2 Measurement model evaluation

Reliability and validity. The initial step was the evaluation of the indicator reliability, which is indicative of the extent to which a construct is able to explain its indicators' variance (Hair et al., 2021). Loadings above 0.708 are recommended, although values higher than 0.40 are still deemed acceptable, provided that the removal of the indicator beneath the 0.708 threshold does not result in an enhancement of internal consistency reliability or convergent validity (Hair et al., 2021). As demonstrated in Table 3, the vast majority of the indicators included in the model exhibited loadings that exceeded the established threshold. The two indicators with values below 0.708 (i.e. Benefits3-Promotion, Benefits9-Speed) were retained since the elimination of these indicators did not result in a substantial enhancement.

The internal consistency reliability of the measurement model, which can be defined as the extent to which indicators associated with a particular construct are correlated with each other (Hair et al., 2021), was evaluated using various criteria. The composite reliability, measured with rho_a and rho_c, for which literature suggests a threshold higher than 0.70 (Jöreskog, 1971), assumed values higher than 0.898 for both measures. Another measure which is regarded as a reliable approximation of internal consistency reliability is $Cronbach's\ alpha$, despite being considered less precise than the previous two. The values assumed by this measure ranged between 0.892 and 1, higher than the threshold of 0.8. The convergent validity of the model, defined as its ability to explain the variance of the indicators by considering how much the constructs converge, was evaluated through the $Average\ Variance\ Extracted\ (AVE)$. The AVE for all the constructs was higher than the threshold of 0.5 (Hair et al., 2021). The comprehensive results are outlined in Table 4.

Discriminant validity. In order to determine the extent to which a construct is empirically distinct from other constructs in the model, the concept of discriminant validity had to be evaluated. The most appropriate measure for the assessment of this metric is the $heterotrait-monotrait\ ratio\ (HTMT)$, which is calculated by the mean value of the indicator correlations (Hair et al., 2021). Consequently, issues may arise when the value is excessively high and the threshold is set to 0.90 (Henseler et al., 2015). For the model under consideration, all the HTMT values between the constructs were lower than this threshold, as presented in Table 4.

Model fit. The model fit indices are utilized to assess the extent to which the hypothesised model structure aligns with the empirical data. The $standardized\ root\ mean\ square\ residual\ (SRMR)$

is a measure of the approximate fit of the model. It is calculated by comparing the observed correlation matrix and the model-implied correlation matrix. The SRMR value for this model was lower than the conventional threshold value of .08 (Garson, 2016) and the model was considered to have an overall good fit. Conversely, when evaluating the exact fit through bootstrapping, it was evident that the value of the SRMR for the estimated model was slightly higher than the values reported for the 95th bootstrapping percentile, which was considered for a significance level of 5%. This result indicated that the discrepancy between the observed and model-implied correlation was statistically significant (McNeish, 2025). However, the notion of model fit, which is typically employed in CB-SEM analysis, is not directly applicable to PLS-SEM, which is more oriented towards the maximisation of the explained variance (Hair et al., 2021). The analysis incorporated a measure of model fit just as a means to evaluate the model's performance. To achieve a more comprehensive interpretation of the model's overall quality, it was necessary to consider additional measures (i.e., R^2, f^2, significance of path coefficients).

Explanatory power of the model. The explanatory power of the model is defined as "the strength of association indicated by a statistical model" (Shmueli & Koppius, 2011) and it is measured through the R^2, which indicated the proportion of the variance of some constructs that is explained. In the context of the model under consideration, the constructs (POS, SE, PB and IR) were found to account for 27.7% of the overall variance in IWB. Furthermore, the variables PB, POS and SE collectively accounted for 26.7% of the variance in IR. The values of the $Adjusted\ R^2$, adjusted for the number of predictors in the model and expected not to overestimate the explanatory power, are shown in Table 4. These values were close to the ones of the R^2.

Multicollinearity test. A necessary step was to assess whether two or more indicators are highly correlated, as this could increase the standard error of the indicator weights. The metric employed to assess indicator collinearity was the $Variance\ Inflation\ Factor\ (VIF)$, with values less than 5 deemed acceptable, as for the indicators included in this model (see Table 4).

Correlation analysis. In order to verify the presence of common method bias, a significant phenomenon that is prevalent in research that is based on self-reported measures and is likely to result in spurious correlations among the items (Kamakura, 2010), the correlation values presented in the correlation analysis (see Table 4) were taken into consideration. The values were lower than 0.90 and proved the absence of common method bias (Lowry & Gaskin, 2014).

Table 4

Measurement model evaluation.

Internal consistency reliability				
	rho_a	rho_c	Cronbach's α	AVE
PB	1.000	0.943	0.919	0.804
IWB	0.922	0.965	0.945	0.901
IR	0.949	0.932	0.892	0.822
POS	0.898	0.932	0.891	0.821
SE	0.923	-	-	-

Discriminant validity	
	HTMT
POS ↔ IR	0.264
IWB ↔ IR	0.561
IWB ↔ POS	0.254
SE ↔ IR	0.451
SE ↔ POS	0.174
SE ↔ IWB	0.438

Model fit			
	SRMR	H_{95}	H_{99}
Saturated model	0.042	0.036	0.041
Estimated model	0.064	0.043	0.049

Predictive Power		
	R^2	Adjusted R^2
IWB	0.277	0.275
IR	0.267	0.260

Multicollinearity	
	VIF
IWB ↔ PB	0.320
IR ↔ PB	0.411
IR ↔ IWB	0.526
POS ↔ PB	0.367
POS ↔ IWB	0.232
POS ↔ IR	0.244
SE ↔ PB	0.355
SE ↔ IWB	0.398
SE ↔ IR	0.422
SE ↔ POS	0.155

Correlation Analysis						
	1	**2**	**3**	**4**	**5**	**6**
(1) IWB	1.00					
(2) IR	0.526***	1.00				
(3) PB	0.320***	0.411***	1.00			
(4) POS	0.232***	0.244***	0.367***	1.00		
(5) SE	0.398***	0.422***	0.355***	0.155**	1.00	
(6) SE x POS	-0.089	0.033	0.108	-0.027	-0.137	1.00

4.3 Structural model evaluation

Complete model. The results of the distinct hypotheses evaluated and associated estimates are presented in Table 5. The results for H1, assuming the positive effect of IR on IWB, revealed that IR positively influenced IWB, with path coefficient β = 0.526 and $p < .05$. This suggested that for every incremental increase in IR, there was a corresponding 52.6% increase in IWB, with the other variables held constant. The effect of the predictor IR on IWB was large, with an $f^2_{IR \to IWB} = 0.383$, signifying that the IR made considerable contribution to the R^2_{IWB} (see Table 5) of IWB and explained a significant portion of its variance (Garson, 2016). In general, H1 was supported.

The following two hypotheses, H2 and H3, were designed to investigate the individual-level antecedents of IR. For both the variables under consideration, a positive effect on IR was hypothesized. In particular, H2 investigated the positive effect of PB on IR. The results showed that an increase in PB related to digitalisation process led to a 25.2% increase in IR (β = 0.252). The p-value ($p < .05$) enabled the hypothesis under consideration to not be rejected. In a similar vein, H3 explored the positive relationship between POS and IR. The effect of POS on IR was positive (β = 0.102) and significant ($p < .05$), yet the increase in IR following an increase in POS was less substantial than the one associated with PB, being equal just to 10.2%. The comparatively minor impact of POS on IR compared to the one of PB on IR can be more readily explicated through an analysis of the value of the f^2 as reported in Table 5. The value of $f^2_{POS \to IR}$, which was equivalent to 0.012 indicated that the effect of POS of IR was very small and non-significant (Garson, 2016), meaning that PB made the actual contribution to R^2_{IR} (see Table 5) with $f^2_{PB \to IR} = 0.065$.

Finally, H4 was aimed to investigate the moderating effect of Self-efficacy (SE) in the relationship between POS and IR. It was hypothesized that this variable augmented the impact of POS on IR. However, this hypothesis was rejected ($p = .429$), thus indicating that self-efficacy was unable to amplify the positive effect of the POS on IR.

It was evident that the relationships supported by H1, H2 and H3 are indicative of the direct effect that exists between the constructs. The present study has sought to examine the effect of the antecedents (i.e., POS and PB) on IWB through IR. The results in Table 5 demonstrate that the specific indirect effects of POS and PB on IWB through IR were positive, with β respectively equal to 0.054 and 0.133 and significant (p < .05), thereby revealing the mediating role of IR in the relationship between the antecedents POS and PB and the outcome IWB.

Table 5

Structural model evaluation.

Hypothesis test				
		Path coefficient β	p-value	Decision
H1	IR → IWB	0.526	0.000	Supported
H2	PB → IR	0.252	0.000	Supported
H3	POS → IR	0.102	0.036	Supported
H4	SE x POS →IR	0.049	0.429	Not supported

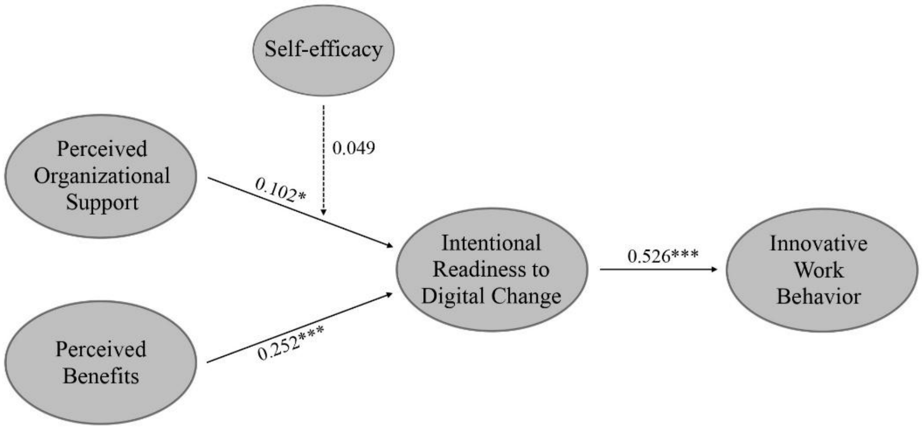
Specific indirect effect		
	Path coefficient β	p-value
POS →IR →IWB	0.054	0.040
PB → IR → IWB	0.133	0.000

Effect size			
	f^2	p-value	Effect size
PB → IR	0.065	0.023	Small
IR → IWB	0.383	0.000	Large
POS → IR	0.012	0.336	No effect
SE → IR	0.121	0.003	Small
SE x POS → IR	0.004	0.759	No effect

Note. To determine effect size, f^2 measure was interpreted following the guidelines in Cohen (1988).

Figure 2

Hypothesis model with path coefficients and significance levels – Complete model.



Exploratory multigroup analysis. In order to gain more insights into group differences and group-specific parameter estimates, it was appropriate to perform a multigroup analysis (Hair et al., 2024). The hypotheses were tested for the three groups identified in the dataset, consisting of the three universities from which the participants were drawn. The respective group sizes are 181, 158 and 93 participants. As shown in Table 6, not all the hypotheses were supported for the three groups as for the complete sample. Specifically, the first hypothesis was significant (p <.05) for the employees in all the universities, with a stronger effect of IR on IWB in group 3 ($\beta_1 = 0.495$; $\beta_2 = 0.539$; $\beta_3 = 0.598$). Furthermore, H2, hypothesising the positive effect of PB on IR, was supported within the three groups, with results showing that an increase in PB caused an increase in IR of a similar amount ($\beta_1 = 0.271$; $\beta_2 = 0.271$; $\beta_3 = 0.276$). In contrast to the analysis conducted on the entire dataset, H3 was not supported for any of the three groups ($p_1 = .064$; $p_2 = .670$; $p_3 = .886$). The phenomenon can be explained on the basis of two main reasons: the presence of the Simpson's paradox (Dong et al., 2024) and the lower statistical power associated with smaller sample size (Hair et al., 2022). In consideration of the Simpson's paradox, the association between POS and IR disappeared following conditioning of the third variable University, based on which the sample was divided into subgroups. Furthermore, the reduced sample size of the groups had a detrimental effect on statistical power, thereby not revealing the significant effect existing in the underlying population. The effects of the Simpson's Paradox could also be observed in H4, where the moderating effect of self-efficacy in the relationship between POS and IR was reversed in Group 2, where the path coefficient assumed a negative value (β_2 = -0.023), despite remaining non-significant in the three groups (p_1 = .797; p_2 = .781; p_3 = .079). The non-significance of H3 exerted an influence on the results of the specific indirect effect in the model. Indeed, the results presented in Table 6 demonstrate that the effect of POS on IWB through IR remained positive, yet it was not significant for any of the groups. However, the effect of PB on IWB through IR was positive and significant, with the stronger effect present in Group 2 (β_1 = 0.134; β_2 = 0.203; β_3 = 0.165).

A comparison of the differences in the path coefficients across the three groups was conducted using a Bootstrap Multi-Group Analysis. Prior to the execution of Bootstrap MGA, it was necessary to check the measurement invariance to ensure the validity of the results (Cheah et al., 2023). The assessment of measurement through measurement invariance of composite models (MICOM) procedure in SmartPLS confirmed configural and compositional invariance, ensuring respectively the presence of the same number of constructs and indicators in each group and the invariance of indicators weights (Garson, 2016). However, scalar invariance, guaranteeing equality of composite means and variances (Garson, 2016), was not guaranteed. The attainment of both configural and compositional invariance served to confirm partial measurement invariance, thereby enabling the comparison of path coefficients with MGA (Cheah et al., 2020). The results presented in Table 6 indicate that the differences in path coefficients were not statistically significant for any of the relationships, as evidenced by 2-tailed p-values that exceed .05. The discrepancies in the results across the three groups can be attributed to random sampling error and it is therefore possible to generalise the results across groups (Hair et al., 2021; Sarstedt et al., 2011).

Figure 3

Hypothesis model with path coefficients and significance levels – Group 1.

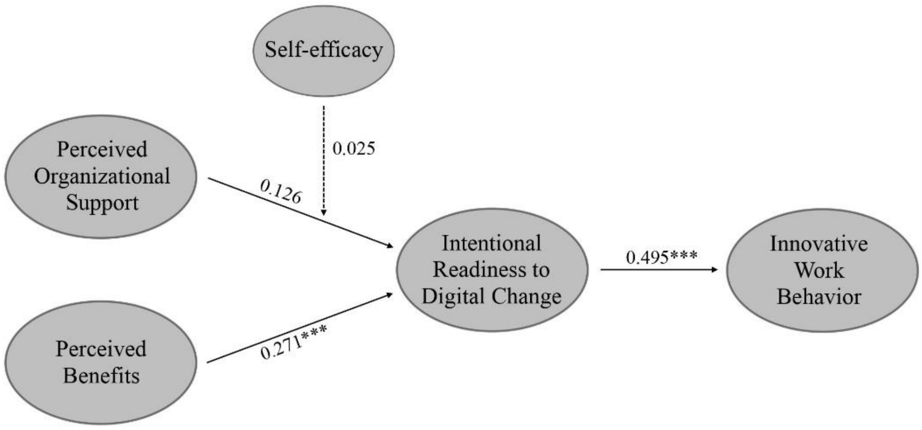


Figure 4

Hypothesis model with path coefficients and significance levels – Group 2.

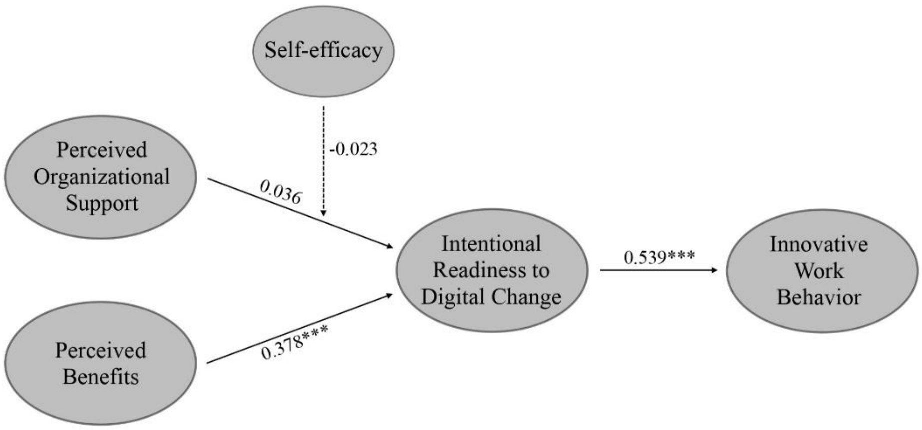
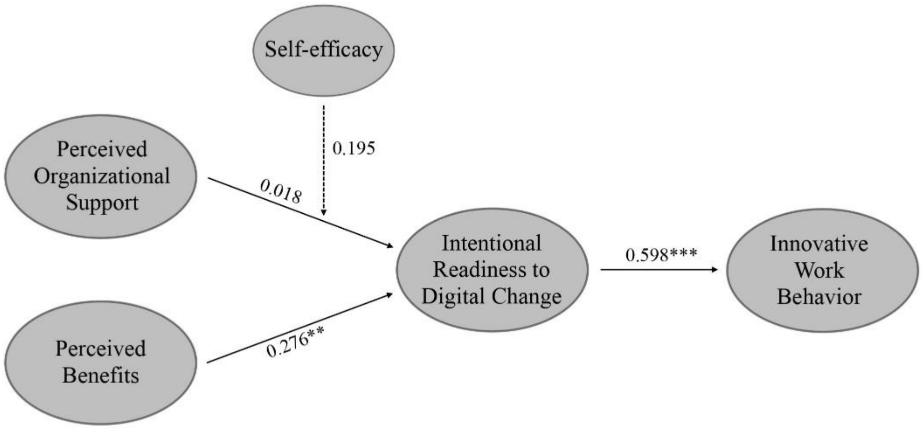


Figure 5

Hypothesis model with path coefficients and significance levels – Group 3.



Results for control variables. The model has been constructed to also include control variables (i.e., Age, Gender and Position), the purpose of which was to test their effect as control variables. These variables were expected to be associated with the outcome variable IWB. Their effect has been analysed in consideration of both their direct and indirect relationships with IWB, the latter being mediated by IR.

The results presented in Table 6 indicate that the variables Age and Gender did not exert a significant effect on IR or IWB, with p-values greater than .05. Conversely, Position had a significant effect on both constructs. To elaborate further, individuals employed in administrative positions demonstrated higher levels of readiness ($\beta_{ADM} = 0.540$; $p < .05$) in comparison to those engaged in teaching roles. The aforementioned findings were consistent with those observed among respondents occupying managerial roles, for whom the readiness level was significantly higher in comparison to teaching staff ($\beta_{MAN} = 0.617$; $p < .05$), when controlling for other variables. In contrast, administrative staff exhibited comparatively diminished innovative work behaviours ($\beta_{ADM} = -0.182$; $p < .05$) in contrast to those observed among teaching staff. No significant difference was identified between innovative behaviours in teachers and managers.

A substantial alteration in the model outcome ensued subsequent to the incorporation of control variables, pertaining to the association between PB and IR. Indeed, following the inclusion of control variables into the model, the previously observed positive relationship between the two constructs became non-significant (p = .081). Consequently, H2 was not supported. This finding suggested that the impact of PB on IR could be partially attributed to the professional role, which can influence the perception of benefits and the intentional readiness to change. The control variable in question was shown to explain part of the variance attributed to IR. This was manifested by an increase in both the R^2 and R^2_{adj} values, which were equal to 0.307 and 0.294, as demonstrated in Table 6.

Table 6

Multigroup analysis (Group 1, 2, 3) and results with control variables (Age, Position, Gender).

Hypothesis test

		Group 1		Group 2		Group 3	
		β	p-value	β	p-value	β	p-value
H1	IR → IWB	0.495	0.000	0.539	0.000	0.598	0.000
H2	PB → IR	0.271	0.000	0.271	0.000	0.276	0.008
H3	POS → IR	0.126	0.064	0.036	0.670	0.018	0.886
H4	SE x POS →IR	0.025	0.797	-0.023	0.781	0.079	0.079

Specific indirect effect

	Group 1		Group 2		Group 3	
	β	p-value	β	p-value	B	p-value
POS →IR →IWB	0.062	0.082	0.020	0.668	0.011	0.887
PB → IR → IWB	0.134	0.002	0.203	0.000	0.165	0.023

Path coefficients differences

	Difference (Group 1 – Group 2)	Difference (Group 1 – Group 3)	Difference (Group 2 – Group 3)	2-tailed p-value (Group 1-2)	2-tailed p-value (Group 1-3)	2-tailed p-value (Group 2-3)
PB → IR	-0.107	-0.005	0.101	0.306	0.945	0.414
IR → IWB	-0.044	-0.103	-0.059	0.617	0.299	0.543
POS → IR	0.090	0.108	0.018	0.411	0.446	0.960
SE → IR	-0.136	0.017	0.153	0.185	0.882	0.185
SE x POS → IR	0.048	-0.169	-0.218	0.702	0.245	0.121

Specific indirect effects differences

	Difference (Group 1 – Group 2)	Difference (Group 1 – Group 3)	Difference (Group 2 – Group 3)	2-tailed p-value (Group 1-2)	2-tailed p-value (Group 1-3)	2-tailed p-value (Group 2-3)
POS → IR → IWB	0.043	0.052	0.009	0.464	0.538	0.965
PB → IR → IWB	-0.069	-0.031	0.038	0.274	0.701	0.650

Path coefficients (control variables effect on IR)		
	β	p-value
Age → IR	0.051	0.086
Dummy_PAS → IR	0.540	0.000
Dummy_Female → IR	0.016	0.837
Dummy_Managerial → IR	0.617	0.000
IR → IWB	0.526	0.000
PB → IR	0.097	0.081
POS → IR	0.174	0.001
SE → IR	0.336	0.000
SE x POS → IR	0.047	0.433

Path coefficients (control variables effect on IWB)		
	β	p-value
Age → IWB	0.057	0.118
Dummy_PAS → IWB	-0.182	0.033
Dummy_Female → IWB	0.128	0.120
Dummy_Managerial → IWB	-0.152	0.419
IR → IWB	0.549	0.000
PB → IR	0.119	0.106
POS → IR	0.171	0.004
SE → IR	0.385	0.000
SE x POS → IR	0.074	0.234

Predictive power of the model (Control variables effect on IR)		
	R^2	Adjusted R^2
IR	0.307	0.294
IWB	0.276	0.274

5 Discussion

5.1 Core findings

The present study aimed to investigate the manner in which readiness for digital change can influence innovative work behaviours, and which individual factors are positively associated with higher levels of readiness. The analysis demonstrated that intentional readiness for digital change, conceptualized as the individual's intention to actively participate in planned change, was positively associated to innovative work behaviours. The present finding corroborates several studies, including Jun and Lee (2023), who demonstrated that a favourable attitude and a high level of commitment to change can engender innovative behaviour. Furthermore, research from (Aboobaker & Zakkariya, 2020; Aboobaker et al., 2022) elucidated the mediating role of readiness to change in the relationship between workplace spirituality and innovative work behaviour, as well as digital learning orientation and innovative work behaviour. The findings supported H1 and were consistent with the Theory of Planned Behaviour (Ajzen, 1991) with regard to the relationship between attitude, intentions and the final behaviour. The findings indicated that both perceived benefits associated with the introduction of new digital tools and POS during the change process positively influenced the intentional readiness of employees within the organization, more specifically the HEIs.

In consideration of the subsequent hypothesis, the PLS-SEM analysis performed in this study provided support for H2, thereby demonstrating that when employees believe that the digitalisation of their workplace is associated with more benefits related to organisational aspects, communication and information, they are more likely to embrace change.

TPB provides support for the positive effect of the benefits that are associated with technology on the intention to adopt the considered tool by considering the formation of a positive attitude towards behaviours for which advantageous consequences are expected (Ajzen, 1991). This assertion corroborates extant research that has demonstrated the positive impact of benefits associated with specific technologies on attitude, subjective norms, perceived behavioural control and, consequently, intention to use (Ivanov et al., 2024). However, TPB presents certain limitations due to the fact that some items require multiple behavioural alternatives to be compared with each other, and for that reason the framework is more difficultly applicable to diverse user contexts (Mathieson, 1991). Conversely, TAM has been demonstrated to exhibit a high degree of generalisability to studies pertaining to individual adoption behaviour (Wang et al., 2023). In the context of digitalisation, the model can be employed to elucidate the relationship between benefits and intention to use by emphasising the correspondence between benefits and perceived usefulness associated with technology use. Multiple studies building on the TAM offer substantiation for the impact of perceived usefulness on behavioural intentions to use technology, without focusing directly on its impact on the actual use (Muftiasa et al., 2022; Nugroho & Fajar, 2017; Wicaksono & Maharani, 2020). The identification of the effect of perceived benefits on intentional readiness for change can be useful in explaining the indirect effect of perceived benefits associated with technology adoption on innovative behaviour. Indeed, the present study lent further support to the relationship already postulated within the TOE framework, with further studies highlighting the impact of perceived benefits on the adoption process (Rivière, 2017) and of perceived advantage associated with the new technology (Wisdom et al., 2014; Zhang & Liu, 2025).

However, when controlling for job position, H2 was no longer supported, suggesting that the different roles within the organization might have a stronger influence on change acceptance than the benefits themselves. This phenomenon is associated with the nature of the role within the organisational structure. Individuals covering roles characterised by greater control, such as managerial roles, have been observed to exhibit a higher degree of readiness for change (Saïd & Nair, 2021). Conversely, role ambiguity is associated with lower levels of readiness (Bernuzzi et al., 2023; Chênevert et al., 2019).

The subsequent hypothesis (H3), which pertains to the positive influence of POS on intentional readiness for change, was supported, albeit with a weaker effect than was expected. TPB assists in explaining the impact of POS on intentional readiness, with consideration given to the association between POS and subjective norm, a pivotal component of intention (Ajzen, 1985). Indeed, as posited by Shin and Kim (2014), employees who perceive that the organization is concerned about their welfare will develop the belief that others in the organization will support their proactive behaviour. However, its effect is mitigated by other factors at the personal level. To elaborate further, the effect of POS on subjective norm for proactive behaviour must also take into account the employees' sense of psychological safety. The presence of this feeling would enhance their perception of workplace changes and increase the likelihood of their development of an intention to engage in proactive behaviour (Serhan et al., 2024; Shin & Kim, 2014).

Höyng and Lau (2023) introduce the significant effect of personal resources, such as proactive personality, on employees' intentional digital readiness. Furthermore, research by Rochmi and Hidayat (2019), provides evidence for the presence of mediators, such as affective commitment, in the relationship between POS and readiness for change. The most significant findings from other studies are the identification of change self-efficacy, which is the belief in the capability of managing change, as a primary determinant of change engagement and, consequently, change readiness, rather than POS (Albrecht et al., 2023).

These outcomes are consistent with the results of the present study, in which H4, considering self-efficacy as a moderator in the relationship between POS and readiness for change, was rejected. In order to justify the non-significance of the moderation effect attributed to self-efficacy, it is necessary to consider its role as a factor exerting a direct effect on intentional readiness for change rather than as a moderator, as suggested by the findings from Quiño and Potane (2023). TPB offers a potential explanation for this relationship, given the similarity between self-efficacy and perceived behavioural control, which is one of the main determinants of intention, as outlined by Ajzen (2020). However, TPB can only partially justify the direct positive effect that self-efficacy might have on intention to take part in a change process, given the limitations of the framework in accounting for emotions (Ho et al., 2024). The necessity to incorporate emotions within the framework is attributable to the established association between self-efficacy and both positive and negative emotions, including joy, pride, anxiety, and boredom (Keller et al., 2024). Indeed, the effect of self-efficacy on intention, and in particular technology use intention, has been found to be moderated by the effect of anticipated emotion, consisting of expectation of individual's feelings when using a new technology (David-Negre & Gutiérrez-Taño, 2024).

The findings demonstrated slight variations when considered across the three universities from which the respondents originate. H1 and H2 were still supported, exhibiting no significant differences between the groups. However, the hypothesis that POS exerts an effect on intentional readiness, and consequently on innovative behaviour, was no longer supported. In the three groups under consideration, the presence of POS as an antecedent of intentional readiness for change was not demonstrated. The results of the multigroup analysis did not reveal significant disparities between the university groups, thereby validating this variation as a statistical occurrence associated with Simpson's Paradox and a variation in sample size. Despite this, it is plausible to partially interpret it as a consequence of disparate contextual factors. Kurtessis et al. (2017) identify multiple antecedents of POS, including the presence of supportive leadership, HR practices and working conditions. These antecedents are not directly related to intentional readiness but are likely to influence the way in which POS is influenced at the individual level and the consequent effectiveness of change strategies. The absence of a consistent POS effect across the groups lent further support to the possibility that POS alone is not a strong driver of intentional readiness, as previously discussed in the context of general findings.

5.2 Theoretical contributions

The present study places particular emphasis on the individual dimension associated with digital change as an active component of the digitalisation process, and not merely as a factor as it has been previously done in past studies (Toscano-Jara et al., 2023). The heightened focus on individual dimension can be attributed to the investigation of factors associated with elevated levels of readiness for change. This examination particularly encompasses those factors contingent on individual perceptions (POS and Perceived benefits) and beliefs (Self-efficacy), which are deemed to hold equivalent importance to the conventionally considered contextual factors (Eby et al., 2000). The development of a framework encompassing a range of antecedents and the analysis of their simultaneous effect have contributed to the expansion of the extant literature on the topic, previously presenting the major limitation of ignoring a multilevel perspective (Rafferty et al., 2013). To elaborate further, the consideration of intentional readiness for change as a driver of innovative behaviours associated with technology use, contributed to the theoretical advancement of the Theory of Planned Behaviour. The conventional focus of TPB on attitudes, subjective norms and perceived behavioural control as predictors of intention was augmented by the incorporation of the dynamic role of intention, which was identified as a driver of proactive behaviours. Indeed, the present study constitutes a linkage between TPB and TAM and contributes to the field through the substitution of the conventional consideration of technology usage (Davis, 1989) with innovative work behaviours, encompassing from the generation to the implementation of new ideas associated with technologies (Khan & Siddiqui, 2023; Son & Han, 2011).

Furthermore, this research makes a significant contribution to the extant literature on the subject of readiness for digital change in the context of HEIs. It does so by incorporating individuals in the analysis who occupy positions other than teaching roles and by focusing on a type of change that extends beyond the scope of e-learning strategies. The consideration of multiple job positions permits a broader understanding of the impact that the characteristics of a specific job position can have in relation to aspects distinct from career satisfaction (Pinheiro & Palma-Moreira, 2025) or job productivity (Hensher & Wei, 2024). These findings lend support to the under-researched relationship between job position and specific factors associated with employee technology acceptance (Kuciapski, 2019).

5.3 Practical implications

This study contributes to the advancement of both academic and practical knowledge. As data was collected from employees working in HEIs, it is important to remember that these organisations have particular characteristics associated with their economic and social scope (Smeenk et al., 2009). Consequently, it is imperative that the proposed actions are implemented with the utmost caution and consideration when adapting them to different organisational contexts. The results emphasize the importance of intentional readiness for change, which is a precursor to innovative behaviour and to the successful implementation of change initiatives. It is recommended that organizations allocate their resources towards the development of more detailed methods of assessing readiness levels and towards the creation of effective strategies to increase these levels. Indeed, it has been demonstrated that such factors can result in elevated levels of innovative work behaviours, thereby enhancing organisational competitiveness and optimizing performance (AlEssa & Durugbo, 2021; Shanker et al., 2017). Moreover, it would be possible to reduce the likelihood of unsuccessful change implementation, which usually has emotional, social and financial consequences for both employees and the whole organization (Schwarz et al., 2020). In order to develop the correct strategies to increase employees' readiness levels, HEIs should consider multiple factors. It is particularly noteworthy that the adoption of technology is significantly influenced by the perceived advantages associated with it (Erlyani et al., 2023); consequently, the various benefits particular to distinct roles and/or departments should be given careful consideration in communication strategies. Furthermore, despite its weak effect on intentional readiness, POS still remains a relevant component. Institutions should endeavour to reinforce their organisational support system, thereby exerting an indirect effect on change readiness through other relevant factors. For instance, an enhancement in organisational support, evidenced by the implementation of practical measures such as training, leadership commitment and employees' participation, can foster increased individual's confidence in their capacity to implement digital change (i.e., self-efficacy), thereby, consequently, amplifying their readiness (Taufikin et al., 2021).

5.4 Limitations and future research

This research is subject to a number of limitations, which provide a valuable foundation for future research. The primary limitation pertains to the restricted generalisability of the findings derived from data collected from HEIs in Spain. This has as a consequence the fact that the obtained results cannot be generalized to different types of organizations, given the unique financial, structural and strategic conditions in which HEIs operate, and to institutions in different countries, which are likely to present different national digital strategies (Gierten & Lesher, 2022). It is recommended that future research extend the proposed framework to different types of companies operating in diverse industries in multiple countries. This would allow for the different country-levels of digitalisation measured with specific indeces (i.e., Digital Economy and Society Index) to be accounted for, as well as the digital transformation processes that specific industries are going through (Olmstead, 2024).

The second limitation pertains to the self-report methodology employed in the data collection. Indeed, this methodology has been demonstrated to engender responses that are characterised by systematic distortions, which are a consequence of the personal point of view of the participants (Razavi, 2001). To overcome this issue in future research, the methodology utilised should be expanded by requesting third parties to evaluate employees' levels of readiness and innovativeness. A further constraint inherent to the methodology pertains to the cross-sectional design of the study. The concepts examined are measured at a single point in time, which limits the study's capability to effectively distinguish between a cause and the effect over time (Taris et al., 2021). Future researchers may be able to more effectively identify the presence of a causal relationship between the considered antecedents and outcomes with the support of a longitudinal design, in which the units are observed at multiple time points (Voelkle & Hecht, 2020).

The most significant limitation associated with data is related to the nested nature of the observations. Indeed, the presence of nested data, in this case organized in three groups, has as a main consequence a violation of the independence assumption and consequently the presence of biased parameter estimates, such as path coefficients (Galbraith et al., 2010; LeBeau et al., 2018). Conducting MGA proved advantageous in accounting for the differences between the groups. However, to effectively address the dependency of observations, a multi-level analysis is required (Aarts et al., 2024). A multi-level analysis would facilitate the incorporation of each university's characteristics into models and the evaluation of individual and group level indicators, thereby enabling the separation of statistical expressions for employees at the level one and for universities at level two (Faisal et al., 2024).

Finally, the specific findings concerning the disappearance of POS effects on intentional readiness when performing MGA, along with the non-existence of the perceived benefits effects on intentional readiness when controlling for the job position variable, have the potential to serve as a source of inspiration for future research in this field. Specifically, it would be interesting to explore the way in which additional factors, such as participation in decision-making, quality of communication, growth opportunities associated with training (Allen et al., 2003), influence the relationship between POS and change readiness. Furthermore, subsequent studies should examine the divergent advantages perceived in relation to technology adoption across various organisational roles, considering their respective responsibilities, competencies, and qualifications (Pollack et al., 2002).

6 Conclusions

This study identifies individual readiness as a proactive driver of digital transformation in HEIs. In contrast to the prevailing perspective of human factor as a barrier, particularly with regard to the presence of resistance to change and lack of digital skills, the findings underscore the pivotal role of individual readiness as a catalyst for innovative digital behaviour. Leadership should formulate strategies that will enhance readiness levels directed towards its antecedents, which have been identified in perceived benefits and POS. These strategies must also account for the different distribution of readiness levels across roles. The importance of embracing a human-centred perspective cannot be overstated when seeking to ensure the successful implementation of digital transformation strategies.

References

Aarts, E., Verhage, M., Veenvliet, J. V., Dolan, C. V., & van der Sluis, S. (2024). A solution to dependency: using multilevel analysis to accommodate nested data. *Nature Neuroscience, 17,* 491–496. https://doi.org/10.1038/nn.3648

Aboobaker, N., & Zakkariya, K. A. (2020). Influence of digital learning orientation and readiness for change on innovative work behaviour: reflections from the higher education sector. *Development and Learning in Organizations*, *34*(2), 25-28. https://doi.org/10.1108/DLO-08-2019-0191

Aboobaker, N. & Zakkariya, K. A. (2021), Digital learning orientation and innovative behavior in the higher education sector: effects of organizational learning culture and readiness for change. *International Journal of Educational Management*, *35*(5), 1030-1047. https://doi.org/10.1108/IJEM-09-2019-0345

Aboobaker, N., Zakkariya, K. A., & Edward, M. (2022). Workplace spirituality and employees readiness for change as precursors to innovative work behaviour: An empirical examination. *International Journal of Intelligent Enterprise*, *9*(1), 6-23. https://doi.org/10.1504/IJIE.2022.119623

AbuAkel, S. A., & Ibrahim, M. (2023). The effect of relative advantage, top management support and IT infrastructure on e-filing adoption. *Journal of Risk and Financial Management*, *16*(6), Article 295. https://doi.org/10.3390/jrfm16060295

Ajzen, I. (1985). From intentions to actions: A theory of planned behavior. In: Kuhl, J., & Beckmann, J. (Eds.) *Action Control* (SSSP Springer Series in Social Psychology, pp. 11-39). Springer. https://doi.org/10.1007/978-3-642-69746-3_2

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Ajzen, I. (2020). The theory of planned behavior: Frequently asked questions. *Human Behavior and Emerging Technologies, 2*(4), 314–324. https://doi.org/10.1002/hbe2.195

Albrecht, S. L., Furlong, S., Leiter, M. P. (2023). The psychological conditions for employee engagement in organizational change: Test of a change engagement model. *Frontiers in Psychology, 34*. https://doi.org/10.3389/fpsyg.2023.1071924

AlEssa, H., & Durugbo, C. (2021). Systematic review of innovative work behavior concepts and contributions. *Management Review Quarterly, 72*, 1171-1208. https://doi.org/10.1007/s11301-021-00224-x.

Allen, D. G., Shore, L. M., & Griffeth, R. W. (2003). The role of perceived organizational support and supportive human resource practices in the turnover process. *Journal of Management, 29*(1), 99–118. https://doi.org/10.1177/014920630302900107

Alnoor, A. M. R., Al-Abrrow, H., Abdullah, H., & Abbas, S. (2020) The impact of self-efficacy on employees' ability to accept new technology in an Iraqi university. *GBOE, 38*(2), 41–50. https://doi.org/10.1002/joe.21984

Alolabi, Y. A., Ayupp, K., & Dwaikat, M. A. (2021). Issues and implications of readiness to change. *Administrative Sciences, 11*(4), Article 140. https://doi.org/10.3390/admsci11040140

Amankwah-Amoah, J., Khan, Z., Wood, G., & Knight, G. (2021). COVID-19 and digitalization: The great acceleration. *Journal of Business Research, 136,* 602-611. https://doi.org/10.1016/j.jbusres.2021.08.011

Armenakis, A. A., Harris, S. G., & Mossholder, K. W. (1993). Creating readiness for organizational change. *Human Relations, 46*(6), 681-703. https://doi.org/10.1177/001872679304600601

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review, 84*(2), 191–215. https://doi.org/10.1037/0033-295X.84.2.191

Bandura, A. (2001). Social Cognitive Theory: An agentic perspective. *Annual review of psychology, 52*(1), 1-26. https://doi.org/10.1146/annurev.psych.52.1.1

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology, 51*(6), 1173–1182. https://doi.org/10.1037/0022-3514.51.6.1173

Bernuzzi, C., Sommovigo, V., Maffoni, M., Setti, I., & Argentero, P. (2023). A Mixed-method Study on the Bright Side of Organizational Change: Role Clarity and Supervisor Support as Resources for Employees' Resilience. *Journal of Change Management*, *23*(2), 143–176. https://doi.org/10.1080/14697017.2023.2172057

Bhatt, V., Trivedi, T., & Vora, H. (2023). Predicting the antecedents of digital readiness of teachers by examining the mediating role of job satisfaction. *International Journal of Innovation and Learning, 35*(3). https://doi.org/10.1504/IJIL.2024.137682

Blau, P. M. (1964) Justice in social exchange. *Sociological Inquiry, 34*(2), 193-206. http://dx.doi.org/10.1111/j.1475-682X.1964.tb00583.x

Bouckenooghe, D., Devos, G., & Van den Broeck, H. (2009). Organizational change questionnaire–climate of change, processes, and readiness: Development of a new instrument. *The Journal of Psychology, 143*(6), 559–599. https://doi.org/10.1080/00223980903218216

Cai, Z., Fan, X., & Du, J. (2017). Gender and attitudes toward technology use: A meta-analysis. *Computers & Education, 105*, 1-13. https://doi.org/10.1016/j.compedu.2016.11.003

Chau, P. Y. K., & Tam, K. Y. (1997). Factors affecting the adoption of open systems: An exploratory study. *MIS Quarterly, 21*(1), 1–24. https://doi.org/10.2307/249740

Cheah, J., Amaro, S., & Roldán, J. L. (2023). Multigroup analysis of more than two groups in PLS-SEM: A review, illustration, and recommendations. *Journal of Business Research, 156*, Article 113539. https://doi.org/10.1016/j.jbusres.2022.113539

Cheah, J., Thurasamy, R., Memon, M. A., Chuah, F., & Ting, H. (2020). Multigroup analysis using smartpls: Step-by-Step guidelines for business research. *Asian Journal of Business Research*, *10*(3), 1-19 https://doi.org/10.14707/ajbr.200087

Chênevert, D., Kilroy, S., & Bosak, J. (2019). The role of change readiness and colleague support in the role stressors and withdrawal behaviors relationship among health care employees. *Journal of Organizational Change Management*, *32*(2), 208-223. https://doi.org/10.1108/JOCM-06-2018-0148

Cheng, E. W. L. (2019). Choosing between the Theory of Planned Behavior (TPB) and the Technology Acceptance Model (TAM). *Educational Technology Research and Development, 67*(1), 21–37. https://doi.org/10.1007/s11423-018-9598-6

Choi, M. (2011). Employees' attitudes toward organizational change: A literature review. *Human Resource Management, 50*(4), 479-500. https://doi.org/10.1002/hrm.20434

Choi, M., Ruona, W. E. A. (2011). Individual readiness for organizational change and its implications for human resource and organization development. *Human Resource Development Review, 10*(1), 46-73. https://doi.org/10.1177/1534484310384957

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Hillsdale, NJ: Lawrence Erlbau. https://doi.org/10.4324/9780203771587

David-Negre, T., & Gutiérrez-Taño, D. (2024). Self-efficacy and personal innovation in the intention to use of facial recognition systems by tourists: a mediation model moderated by trust and anticipated emotions. *Current Issues in Tourism*, 1–16. https://doi.org/10.1080/13683500.2024.2403130

Davis, F. (1989) Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly, 13*(3), 319-340. https://doi.org/10.2307/249008

Desplaces, D. (2005). A multilevel approach to individual readiness to change. *Journal of Behavioral and Applied Management, 7*(1), 25-39. https://doi.org/10.21818/001c.14568

Dima, A. M., Maassen, M. A., & Mehmanpazir, B. (2020). Perspectives of online education in the context of the covid-19 pandemic crisis. In *Proceedings of the 3rd International Conference on Economics and Social Sciences: Innovative models to revive the global economy* (pp. 381–397). Bucharest University of Economic Studies. https://doi.org/10.2478/9788395815072-041

Dong, Z., Cai, W. & Zhao, S. (2024) Simpson's paradox beyond confounding. *Formal Methods and Exact Sciences, 14*(44), 1-15. https://doi.org/10.1007/s13194-024-00610-8

Drzensky, F., Egold, N., & van Dick, R. (2012). Ready for a change? A longitudinal study of antecedents, consequences and contingencies of readiness for change. *Journal of Change Management, 12*(1), 95–111. https://doi.org/10.1080/14697017.2011.652377

Eby, L. T., Adams, D. M., Russell, J. E. A., & Gaby, S. H. (2000). Perceptions of organizational readiness for change: Factors related to employees' reactions to the implementation of team-based selling. *Human Relations, 53*(3), 419-442. https://doi.org/10.1177/0018726700533006

Eccles J., Adler T. F., Futterman R., Goff S. B., Kaczala C. M., Meece J., & Midgley C. (1983). Expectancies, values and academic behaviors. In J. T. Spence (Ed.), *Achievement and achievement motives: Psychological and sociological approaches* (pp. 75-146). Freeman.

Eisenberger, R., Huntington, R., Hutchison, S., & Sowa, D. (1986). Perceived organizational support. *Journal of Applied Psychology, 71*(3), 500–507. https://doi.org/10.1037/0021-9010.71.3.500

Eisenberger, R., & Stinglhamber, F. (2011). Perceived organizational support: Fostering enthusiastic and productive employees. *American Psychological Association*. https://doi.org/10.1037/12318-000

Erlyani, N., Suhariadi, F., & Ardi, R. (2023). Does perceived impact of change affect readiness for change in higher education governance?.*Interdisciplinary Social Studies, 2*(12), 526-538. https://doi.org/10.55324/iss.v2i12.526

Faisal, H., Zakria, M., Ali, N., Khalid, N. (2024). Multilevel modeling approach for hierarchical data an empirical investigation. *Open Journal of Statistics, 14*(6), 666-681. https://doi.org/10.4236/ojs.2024.146031

Faiz, F., Viet, L., & Eryadi, K. M. (2024). Determinants of digital technology adoption in innovative SMES. *Journal of Innovation & Knowledge, 9*(4), Article 100610. https://doi.org/10.1016/j.jik.2024.100610

Farías-Gaytán, S., Aguaded, I., & Ramírez-Montoya, M. (2023). Digital transformation and digital literacy in the context of complexity within higher education institutions: a systematic literature review. *Humanities and Social Sciences Communications, 10*; Article 660. https://doi.org/10.1057/s41599-023-01875-9

Fernández, A., Claver, J. M., & Esteban, L. (2023, November). *Digital maturity evolution of Spanish universities*. Conference presentation at EUNIS Congress 2023, Vigo, Spain.

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention, and behavior: An introduction to theory and research*. Addison-Wesley.

Galbraith, S., Daniel, J. A., & Vissel, B. (2010). A study of clustered data and approaches to its analysis. *The Journal of neuroscience: the official journal of the Society for Neuroscience, 30*(32), 10601–10608. https://doi.org/10.1523/JNEUROSCI.0362-10.2010

Ganichev, N. A., & Koshovets, O.B. (2021). Forcing the digital economy: How will the structure of digital markets change as a result of the COVID-19 pandemic. *Studies on Russian Economic Development, 32*(1), 11–22. https://doi.org/10.1134/S1075700721010056

Garson, G. D. (2016). Partial Least Squares: Regression and Structural Equation Models. Statistical Associates Publishers.

Gfrerer, A., Hutter, K., Füller, J., & Ströhle, T. (2021). Ready or not: managers' and employees' different perceptions of digital readiness. *California Management Review, 63*(2), 23-48. https://doi.org/10.1177/0008125620977487

Gierten, D., & Lesher, M. (2022). Assessing national digital strategies and their governance (OECD Digital Economy Papers, No. 324). OECD Publishing. https://doi.org/10.1787/baffceca-en

Gigliotti, R., Vardaman, J., Marshall, D. R., & Gonzalez, K. (2018). The role of perceived organizational support in individual change readiness. *Journal of Change Management, 19*(2), 86–100. https://doi.org/10.1080/14697017.2018.1459784

Gkrimpizi, T., Peristeras, V., & Magnisalis, I. (2023). Classification of barriers to digital transformation in higher education institutions: Systematic literature review. *Education Sciences*, *13*(7), Article 746. https://doi.org/10.3390/educsci13070746

Gradillas, M., & L. D. W. Thomas. (2023). Distinguishing digitization and digitalization: A systematic review and conceptual framework. *Journal of Product Innovation Management, 42*(1), 112–143. https://doi.org/10.1111/jpim.12690

Grover, V. (1993). An empirically derived model for the adoption of customer-based interorganizational systems. *Decision Sciences, 24*, 603-640. https://doi.org/10.1111/j.1540-5915.1993.tb01295.x

Hagger, M. S., & Hamilton, K. (2025). Progress on theory of planned behavior research: advances in research synthesis and agenda for future research. *Journal of Behavioral Medicine, 48*(1), 43–56. https://doi.org/10.1007/s10865-024-00545-8

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sartedt, M. (2014). *A primer on partial least square structural equation modeling*. Sage.

Hair, J.F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R.* Springer Cham. https://doi.org/10.1007/978-3-030-80519-7

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)* (3rd ed.). Sage. https://doi.org/10.1007/978-3-030-80519-7

Hair, J. F., Sarstedt, M., Ringle, C. M., & Gudergan, S. P. (2024). *Advanced Issues in Partial Least Squares Structural Equation Modeling (PLS-SEM)* (2nd ed.). Sage.

Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2012) An Assessment of the Use of Partial Least Squares Structural Equation Modeling in Marketing Research. *Journal of the Academy of Marketing Science, 40*(3), 414-433. https://doi.org/10.1007/s11747-011-0261-6

Hayes, A. F., & Rockwood, N. J. (2017). Regression-based statistical mediation and moderation analysis in clinical research: Observations, recommendations, and implementation. *Behaviour Research and Therapy, 98,* 39–57. https://doi.org/10.1016/j.brat.2016.11.001

Henseler, J., & Chin, W. W. (2010). A comparison of approaches for the analysis of interaction effects between latent variables using partial least squares path modeling. *Structural Equation Modeling, 17*(1), 82–109. https://doi.org/10.1080/10705510903439003

Henseler, J., Hubona, G., & Ray, P. A. (2016). Using PLS path modeling in new technology research: updated guidelines. *Industrial Management & Data Systems, 116*(1), 2-20. https://doi.org/10.1108/IMDS-09-2015-0382

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Hensher, D., & Wei, E. (2024). Job *Performance, Productivity, and the Roles of Employee Motivation and Wellbeing in Employees' Work Arrangement Choices*. Institute of Transport and Logistics Studies. http://dx.doi.org/10.2139/ssrn.5025380

Ho, V. C., Berman A. H., Andrade, J., Kavanagh, D. J., La Branche, S., May, J., Philson, C. S., & Blumstein, D. T. (2024). Assessing immediate emotions in the theory of planned behavior can substantially contribute to increases in pro-environmental behavior. *Frontiers in Climate*, *6*, Article 1344899. https://doi.org/10.3389/fclim.2024.1344899

Holt, D. T., Armenakis, A. A., Feild, H. S., & Harris, S. G. (2007). Readiness for organizational change: The systematic development of a scale. *The Journal of Applied Behavioral Science, 43*(2), 232-255. https://doi.org/10.1177/0021886306295295

Höyng, M., & Lau, A. (2023). Being ready for digital transformation: How to enhance employees' intentional digital readiness. *Computers in Human Behavior Reports, 11*, Article 100318. https://doi.org/10.1016/j.chbr.2023.100314

Iivari, N., Sharma, S., & Ventä-Olkkonen, L. (2020). Digital transformation of everyday life – How COVID-19 pandemic transformed the basic education of the young generation and why information management research should care? *International Journal of Information Management, 55*, Article 102183. https://doi.org/10.1016/j.ijinfomgt.2020.102183

Ivanov, S., Soliman, M., Tuomi, A., Alkathiri, N. A., & Al-Alawi, A.N. (2024). Drivers of generative AI adoption in higher education through the lens of the Theory of Planned Behaviour. *Technology in Society, 77*, Article 102521. https://doi.org/10.1016/j.techsoc.2024.102521.

Jöreskog, K. G. (1971). Simultaneous factor analysis in several populations. *Psychometrika, 36*(4), 409–426. https://doi.org/10.1007/BF02291366

Jun, K.; & Lee, J. (2023). Transformational leadership and followers' innovative behavior: Roles of commitment to change and organizational support for creativity. *Behavioral Science, 13*(4), Article 320. https://doi.org/10.3390/bs13040320

Kamakura, W. A. (2010). Common Methods Bias. In J. Sheth & N. Malhotra (Eds.), *Wiley International Encyclopedia of Marketing*. Wiley. https://doi.org/10.1002/9781444316568.wiem02033

Kane, G., Palmer, D., Nguyen-Phillips, A., Kiron, D., & Buckley, N. (2017). Achieving digital maturity. *MIT Sloan Management Review, 59*(1), 3-29.

Kaplan, D. (2001). Structural Equation Modeling. In *International Encyclopedia of the Social & Behavioral Sciences* (pp.15215-15222). Pergamon. https://doi.org/10.1016/B0-08-043076-7/00776-2

Kaputa, V., Loučanová, E., & Tejerina-Gaite, F. A. (2022). Digital Transformation in Higher Education Institutions as a Driver of Social Oriented Innovations. In C. Păunescu, K. L. Lepik, & N. Spencer (Eds.), *Social innovation in higher education* (pp. 61–85). Springer. https://doi.org/10.1007/978-3-030-84044-0_4

Kelkar, R. (2020, September 7). Forced digital transformation: Rethink, reimagine, redefine. *ETCIO*. https://cio.economictimes.indiatimes.com/news/strategy-and-management/forced-digital-transformation-rethink-reimagine-redefine/77970528

Keller, M. V., Rinas, R., Janke, S., Dickhäuser, O., Dresel, M., & Daumiller, M. (2024). Intertwining self-efficacy, basic psychological need satisfaction, and emotions in higher education teaching: A micro-longitudinal study. *Social Psychology of Education, 27*, 3119–3152. https://doi.org/10.1007/s11218-024-09888-1

Khan, S. U., & Siddiqui, D. A. (2023). *Inspired inefficiency: the effect of technology readiness drivers and inhibitors on innovative work behavior using serial mediation of social technology readiness and usage pattern factors.* SSRN. http://dx.doi.org/10.2139/ssrn.4432133

Kim, T., Hornung, S., & Rousseau, D. (2011). Change-Supportive employee behavior: Antecedents and the moderating role of time. *Journal of Management, 37*(6)*,* 1664-1693. https://doi.org/10.1177/0149206310364243

Kirrane, M., Lennon, M., O'Connor, C., & Fu, N. (2017). Linking perceived management support with employees' readiness for change: The mediating role of psychological capital. *Journal of Change Management, 17*(1), 47–66. https://doi.org/10.1080/14697017.2016.1214615

Kline, R. B. (2016). *Principles and practice of structural equation modeling* (4th ed.). The Guilford Press.

Kohnke, O. (2017). It's not just about technology: the people side of digitization. In *Shaping the Digital Enterprise,* (pp. 1–335). Springer. https://doi.org/10.1007/978-3-319-40967-2_3

Kreiser, P. M., Anderson, B. S., Kuratko, D. F., & Marino, L. D. (2020). Entrepreneurial orientation and environmental hostility: A threat rigidity perspective. *Entrepreneurship Theory and Practice*, *44*(6), 1174-1198. https://doi.org/10.1177/1042258719891389

Kuciapski, M. (2019). How the type of job position influences technology acceptance: A study of employees' intention to use mobile technologies for knowledge transfer. *IEEE Access, 7*, 177397-177413. https://doi.org/10.1109/ACCESS.2019.2957205.

Kurtessis, J. N., Eisenberger, R., Ford, M. T., Buffardi, L. C., Stewart, K. A., & Adis, C. S. (2017). Perceived organizational support: A meta-analytic evaluation of organizational support theory. *Journal of Management, 43*(6), 1854–1884. https://doi.org/10.1177/0149206315575554

LeBeau, B., Song, Y. A., & Liu, W. C. (2018). Model misspecification and assumption violations with the linear mixed model: A meta-analysis. *SAGE Open, 8*(4). https://doi.org/10.1177/2158244018820380

Li, M., Jameel, A., Ma, Z., Sun, H., Hussain, A., & Mubeen, S. (2022). Prism of employee performance through the means of internal support: A study of perceived organizational support. *Psychology Research and Behaviour Management*, *15*, 965-976. https://doi.org/10.2147/PRBM.S346697

Lin, C.-H., Shih, H.-Y., & Sher, P. J. (2007), Integrating technology readiness into technology acceptance: The TRAM model. P*sychology & Marketing, 24(7)*, 641-657. https://doi.org/10.1002/mar.20177

Lingling, L., & Li, Y. (2023). The impact of digital empowerment on open innovation performance of enterprises from the perspective of SOR. *Frontiers in Psychology, 14*, Article 1109149. https://doi.org/10.3389/fpsyg.2023.1109149

Lowry, P. B., & Gaskin, J. (2014). Partial Least Squares (PLS) Structural Equation Modeling (SEM) for building and testing behavioral causal theory: When to choose it and how to use it. *IEEE Transactions on Professional Communication*, *57*(2), 123-146. https://doi.org/10.1109/TPC.2014.2312452

Majumdar, A., Krishna, S., & Bjørn, P. (2013). Managers' perceptions of social software use in the workplace: Identifying the benefits of social software and emerging patterns of its use. In *AMCIS 2013 Proceedings* (pp.1-10). AIS Electronic Library (AISeL).

Marikyan, D. & Papagiannidis, S. (2024). Technology Acceptance Model: A review. In S. Papagiannidis (Ed.). *TheoryHub Book.*

Mathieson, K. (1991). Predicting user intentions: Comparing the Technology Acceptance Model with the Theory of Planned Behavior. *Information Systems Research, 2*(3), 173–191. https://doi.org/10.1287/isre.2.3.173

Mathur, M., Kapoor, T., & Swami, S. (2023). Readiness for organizational change: the effects of individual and organizational factors. *Journal of Advances in Management Research, 20*(4), 730-757. https://doi.org/10.1108/JAMR-02-2023-0032

Matt, C., Hess, T., & Benlian, A. (2015). Digital Transformation Strategies. *Business & Information Systems Engineering, 57*(5), 339–343. https://doi.org/10.1007/s12599-015-0401-5

McNeish, D. (2025). Less heuristic approximate local fit evaluation in Structural Equation Models. *Structural Equation Modeling: A Multidisciplinary Journal*, *32*(1), 1–16. https://doi.org/10.1080/10705511.2025.2473342

Michaelis, B., Stegmaier, R., & Sonntag, K. (2010). Shedding light on followers' innovation implementation behavior: The role of transformational leadership, commitment to change, and climate for initiative. *Journal of Managerial Psychology, 25*(4), 408–429. https://doi.org/10.1108/02683941011035304

Michelotto, F., & Joia, L. A. (2024). Organizational digital transformation readiness: An exploratory investigation. *Journal of Theoretical and Applied Electronic Commerce Research, 19*(4), 3283-3304. https://doi.org/10.3390/jtaer19040159

Ming-Chu, Y., & Meng-Hsiu, L. (2015). Unlocking the black box: Exploring the link between perceived organizational support and resistance to change. *Asia Pacific Management Review, 20*(3), 177-183. https://doi.org/10.1016/j.apmrv.2014.10.003

Mohamed Hashim, M., Tlemsani, I., & Matthews, R. (2022). Higher education strategy in digital transformation. *Education and Information Technologies, 27*(3), 3171–3195. https://doi.org/10.1007/s10639-021-10739-1

Muftiasa, A., Sugesko, S., Sultan, M. A., & Ahmad, R. (2022). The integration of perceived usefulness, ease of use and perceived risk in increasing customer usage intention to access e-channel during Covid-19: Evidence from Indonesia. In *Advances in Economics, Business and Management Research,* (Vol. 220, pp. 262-266). Atlantis Press. https://doi.org/10.2991/aebmr.k.220701.051

Nasution, R., Rusnandi, L., Qodariah, E., Arnita, D., & Windasari, N. A. (2018). The evaluation of digital readiness concept: Existing models and future directions. *The Asian Journal of Technology Management (AJTM), 11*(2), 94-117. https://doi.org/10.12695/ajtm.2018.11.2.3

Nugroho, M. A., & Fajar, M.A. (2017). Effects of technology readiness towards acceptance of mandatory web-based attendance system. *Procedia Computer Science, 124*, 319–328. https://doi.org/10.1016/j.procs.2017.12.161

Olmstead, L. (2024, February 21). Digital transformation & tech adoption by sector. *Whatfix*. https://whatfix.com/blog/digital-transformation-by-sector/

Packmohr, S.; & Brink, H. (2021). Impact of the pandemic on the barriers to the digital transformation in Higher Education - Comparing pre- and intra-Covid-19 perceptions of management students. Perspectives in Business Informatics Research. In R.A. Buchmann, A. Polini, B.

Johansson, & D. Karagiannis (Eds.), *Perspectives in Business Informatics Research* (Lecture Notes in Business Information Processing, Vol 430, pp.1-17). Springer. https://doi.org/10.1007/978-3-030-87205-2_1

Piderit, S. K. (2000). Rethinking resistance and recognizing ambivalence: A multidimensional view of attitudes toward an organizational change. *Academy of Management Review, 25*(4), 783-794. https://doi.org/10.2307/259206

Pinheiro, A., & Palma-Moreira, A. (2025). Job satisfaction, perceived performance and work regime: What is the relationship between these variables? *Administrative Sciences*, *15*(5), Article 175. https://doi.org/10.3390/admsci15050175

Pollack, L. J., Simons, C., Romero, H., & Hausser, D. L. (2002). A common language for classifying and describing occupations: The development, structure, and application of the standard occupational classification. *Human Resource Management, 41*(3), 297-307. https://doi.org/10.1002/hrm.10042

Quiño, J. B., & Potane, J. D. (2023). Post-pandemic digital self-efficacy and online learning readiness of pre-service teachers. *International Journal of Advanced Research, 11*(5), 47-64. https://dx.doi.org/10.21474/IJAR01/16848

Rafferty, A. E., Jimmieson, N. L., & Armenakis, A. A. (2013). Change readiness a multilevel review. *Journal of Management, 39*(1), 110-135. https://doi.org/10.1177/0149206312457417

Ramayah, T., Cheah, J., Chuah, F., Ting, H., & Memon, M. A. (2018). Partial *least squares structural equation modeling (PLS-SEM) using SmartPLS 3.0: An updated guide and practical guide to statistical analysis* (2nd ed.). Pearson.

Ratnawati, A. T., & Malik, A. (2024). The effect of perceived ease of use, benefits, and risks on intention in using the quick response code Indonesian standard. *Global Business & Finance Review (GBFR)*, *29*(7), 110-125. https://doi.org/10.17549/gbfr.2024.29.7.110

Razavi, T. (2001). *Self-report measures: An overview of concerns and limitations of questionnaire use in occupational stress research* (Papers 01-175). University of Southampton, Department of Accounting and Management Science.

Rhoades, L., & Eisenberger, R. (2002). Perceived Organizational Support: A Review of the Literature. *The Journal of applied psychology*, *87*(4), 698–714. https://doi.org/10.1037/0021-9010.87.4.698

Rivière, A. (2017). Towards a model of the perceived value of innovation: The key role of perceived benefits ahead of the adoption process. *Recherche et Applications En Marketing (English Edition)*, *30*(1), 5-27. https://doi.org/10.1177/2051570714560317

Rochmi, A., & Hidayat, A. E. (2019). The mediating role of affective commitment in perceived organizational support and readiness for change. In *Proceedings of the 2nd International Conference on Intervention and Applied Psychology (ICIAP 2018)* (pp. 785–795). Atlantis Press. https://doi.org/10.2991/iciap-18.2019.65

Saïd, K. & Nair, A. S. (2021). An International Comparison of Enablers of Individual Readiness for Change: The Case of Executives Working in France, GCC and India. *Management international / International Management / Gestiòn Internacional*, *25*(3), 220–232. https://doi.org/10.7202/1079221ar

Sarstedt, M., Henseler, J. & Ringle, C. M. (2011). Multigroup analysis in Partial Least Squares (PLS) path modeling: alternative methods and empirical results. In *Measurement and Research Methods in International Marketing* (Advances in International Marketing, Vol. 22, pp.195-218). Emerald Group Publishing Limited, Leeds. https://doi.org/10.1108/S1474-7979(2011)0000022012

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2017). Treating unobserved heterogeneity in PLS-SEM: a multi-method approach. In H. Latan, R. Noonan (Eds.), *Partial Least Squares Path Modeling* (pp.197-217). Springer. https://doi.org/10.1007/978-3-319-64069-3_9

Schwarz, G. M., Bouckenooghe, D., & Vakola, M. (2020). Organizational change failure: Framing the process of failing. *Human Relations, 74*(2), 159-179. https://doi.org/10.1177/0018726720942297

Scott, S. G., & Bruce, R. A. (1994). Determinants of Innovative Behavior: A Path Model of Individual Innovation in the Workplace. *The Academy of Management Journal, 37*(3), 580–607. https://doi.org/10.2307/256701

Serhan, C., Abdo, R., Iskandar, D. & Gharib, M. (2025). Navigating the change: exploring emotions, psychological safety and organizational support in the transition to home working – insights from the MENA region. *Journal of Organizational Change Management,38*(2), 340-360. https://doi.org/10.1108/JOCM-04-2024-0181

Shanker, R., Bhanugopan, R., Heijden, B., & Farrell, M. (2017). Organizational climate for innovation and organizational performance: The mediating effect of innovative work behavior. *Journal of Vocational Behavior*, *100*, 67-77. https://doi.org/10.1016/J.JVB.2017.02.004

Shin, Y., & Kim, M.-J. (2015). Antecedents and mediating mechanisms of proactive behavior: Application of the theory of planned behavior. *Asia Pacific Journal of Management, 32*(1), 289–310. https://doi.org/10.1007/s10490-014-9393-9

Shmueli, G., & Koppius, O. R. (2011). Predictive analytics in information systems research. *MIS Quarterly, 35*(3), 553–572. https://doi.org/10.5555/2208923.2208926

Siitonen, P., Honkapuro, S., Annala, S., & Wolff, A. (2024). Effects of trust and perceived benefits on consumer adoption of smart grid technologies: a mediation analysis. *International Journal of Sustainable Energy, 43*(1), 235-250. https://doi.org/10.1080/14786451.2024.2350756

Singun, A. (2025). Unveiling the barriers to digital transformation in higher education institutions: a systematic literature review. *Discover Education, 4*, Article 37. https://doi.org/10.1007/s44217-025-00430-9

Smeenk, S., Teelken, C., Eisinga, R., & Doorewaard, H. (2009). Managerialism, organizational commitment, and quality of job performances among european university employees. *Research in Higher Education, 50*(6), 589–60. https://doi.org/10.1007/s11162-009-9132-0

Sniehotta, F. F., Presseau, J., & Araújo-Soares, V. (2014). Time to retire the theory of planned behaviour. *Health Psychology Review, 8*(1), 1–7. https://doi.org/10.1080/17437199.2013.869710

Son, M., & Han, K. (2011). Beyond the technology adoption: Technology readiness effects on post-adoption behavior. *Journal of Business Research, Elsevier, 64*(11), 1178-1182. https://doi.org/10.1016/j.jbusres.2011.06.019

Srisathan, W. A., & Naruetharadhol, P. (2022). A COVID-19 disruption: The great acceleration of digitally planned and transformed behaviors in Thailand. *Technology in Society*, *68*, Article 101912. https://doi.org/10.1016/j.techsoc.2022.101912

Sun, S., Lee, P. C., Law, R., & Hyun, S. S. (2020). An investigation of the moderating effects of current job position level and hotel work experience between technology readiness and technology acceptance. *International Journal of Hospitality Management, 90*, Article 102633. https://doi.org/10.1016/j.ijhm.2020.102633

Taris, T. W., Kessler, S. R., & Kelloway, E. K. (2021). Strategies addressing the limitations of cross-sectional designs in occupational health psychology: What they are good for (and what not). *Work & Stress, 35*(1), 1–5. https://doi.org/10.1080/02678373.2021.1888561

Taufikin, F., Wahab, Z., Munawar, M., & Farida, M. (2021). Readiness to change during the covid-19 pandemic: Study of self-efficacy and perceived organizational support on lectures performance. *Academy of Strategic Management Journal, 20*(4), Article 11226.

Taylor S., & Todd P. A. (1995). Understanding information technology usage: A test of competing models. *Information Systems Research, 6*(2), 144–176. https://doi.org/10.1287/isre.6.2.144

Tornatzky, L. G., & Fleischer, M. (1990). *The processes of technological innovation.* Lexington Books.

Toscano-Jara, J., Loza-Aguirre, E., Segura-Morales, M. & Franco-Crespo, A. (2023). Digital Transformation: A systematic literature review from the theoretical lenses of the toe framework. *Innovar. 34*(93), 9-28. https://doi.org/10.15446/innovar.v34n93.98245

Unruh, G., Kiron, D. (2017, November 6). *Digital transformation on purpose.* MIT Sloan Management Review. http://sloanreview.mit.edu/article/digital-transformation-on-purpose/

Vakola, M. (2014). What's in there for me? Individual readiness to change and the perceived impact of organizational change. *Leadership & Organization Development Journal, 35*(3), 195–209. https://doi.org/10.1108/LODJ-05-2012-0064

Van Volkom, M., Stapley, J., Malter, J. (2013). Use and perception of technology: Sex and generational differences in a community sample. *Educational Gerontology, 39*(2), 105-119. https://doi.org/10.1080/03601277.2012.756322

Verma, S., Sahni, S., & Kaurav, R. (2024). Understanding digital transformation challenges for online learning and teaching in higher education institutions: a review and research framework. *Benchmarking: An International Journal, 32*(5), 1487-1521. https://doi.org/10.1108/bij-04-2022-0245.

Visschers, V. H. M., & Siegrist, M. (2014). Find the differences and the similarities: Relating perceived benefits, perceived costs and protected values to acceptance of five energy technologies. *Journal of Environmental Psychology, 40*, 117–130. https://doi.org/10.1016/j.jenvp.2014.05.007

Voelkle, M. C., & Hecht, M. (2020). Longitudinal research designs. In V. Zeigler-Hill, T. K. Shackelford (Eds.), *Encyclopedia of Personality and Individual Differences* (pp. 1-8). Springer. https://doi.org/10.1007/978-3-319-24612-3_1323

Wang, J., Li, C., Wu, J., & Zhou, G. (2023). Research on the Adoption Behavior Mechanism of BIM from the Perspective of Owners: An Integrated Model of TPB and TAM. *Buildings, 13*(7), Article 1745. https://doi.org/10.3390/buildings13071745

Westerman, G., Bonnet, D. & McAfee, A. (2014). *Leading digital, turning technology into business transformation*. Harvard Business Press.

Wicaksono, A., & Maharani, A. (2020). The effect of perceived usefulness and perceived ease of use on the technology acceptance model to use online travel agency. *Journal of Business Management Review, 1*(5), 313-328. https://doi.org/10.47153/jbmr15.502020

Wisdom, J. P., Chor, K. H., Hoagwood, K. E., & Horwitz, S. M. (2014). Innovation adoption: A review of theories and constructs. *Administration and policy in mental health, 41*(4), 480–502. https://doi.org/10.1007/s10488-013-0486-4

Wong, K. K. (2013). Partial Least Squares Structural Equation Modeling (PLS-SEM) techniques using SmartPLS. *Marketing Bulletin, 24,* 1-32.

Wortmann, A., & Jauer, S. (2024). B*uilding change-ready organizations: The critical role of self-efficacy and adaptability*. Zenodo. https://doi.org/10.5281/zenodo.14563886

Yuan, F., & Woodman, R. W. (2010). Innovative behavior in the workplace: The role of performance and image outcome expectations. *Academy of Management Journal, 53*(2), 323–342. https://doi.org/10.5465/AMJ.2010.49388995

Zhang, S., Yang, O., Wei, C., Shi, X., & Zhang, Y. (2023). Study on the influence mechanism of perceived benefits on unsafe behavioral decision-making based on ERPs and EROs. *Frontiers in Neuroscience, 17*, Article 1231592. https://doi.org/10.3389/fnins.2023.1231592