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Technology Innovation and Social and Behavioral Commitment: A Case Study of Digital Transformation in the Moroccan Insurance Industry

Soukaina Abdallah-Ou-Moussa [1], Martin Wynn [2,*], Omar Kharbouch [1], Sara El Aoufi [1] and Zakaria Rouaine [3]

[1] Faculty of Economics and Management, Ibn Tofail University, Kenitra BP242, Morocco; soukaina.abdallahoumoussa@uit.ac.ma (S.A.-O.-M.); omar.kharbouch@uit.ac.ma (O.K.); sara.elaoufi@uit.ac.ma (S.E.A.)
[2] School of Business, Computing and Social Sciences, University of Gloucestershire, Cheltenham GL502RH, UK
[3] Ecole Nationale de Commerce et de Gestion, Université Sultan Moulay Slimane, Beni Mellal BP591, Morocco; z.rouaine@usms.ma
* Correspondence: mwynn@glos.ac.uk

Abstract: Digital transformation (DT) has become an imperative for companies seeking to evolve in a constantly changing industrial ecosystem, driven by the continual development and application of innovative digital technologies. Nevertheless, the success rate of DT initiatives remains surprisingly low, which only serves to highlight the need for a deeper understanding of the factors that determine the success of these initiatives. This study adopts a quantitative methodological approach to address this challenge, focusing on the Moroccan insurance industry. First, a systematic literature review was undertaken to identify the key change dimensions and related factors that influence DT acceptance, at both individual and corporate levels, as well as the potential risks associated with the adoption of DT. A survey of 100 employees of insurance companies in Morocco was then undertaken to statistically establish the key factors that determine the success of DT in these companies. The research results reveal that planned behavioral factors, as well as the innovative features of digital technologies, exert a positive influence on the attitude toward the acceptance of DT. Furthermore, this positivity translates into greater personal acceptance of new technologies within the Moroccan organizations studied. Although this paper focuses on one industry sector in one country, the authors believe the results make a valid contribution to both theory and practice. The findings indicate a clear distinction between individual acceptance of innovation and acceptance at a social level, an approach that has scarcely been addressed in previous research. It also offers valuable insights for leaders and organizational managers seeking to succeed in their DT projects by highlighting key determining factors to effectively guide this complex process.

Keywords: digital transformation; key determinants; acceptance criteria; insurance industry; behavioral factors; technology innovation; regression model

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1. Introduction

Digital transformation (DT) has become a priority for businesses seeking to remain competitive in a global environment increasingly influenced by digital technologies [1]. The rapid transformation of the industrial ecosystem, driven by innovative digital technologies, continues to gather pace [2]. Advances such as the emergence of global platforms, the evolution of business models, and the multiple applications of artificial intelligence across

industry are profoundly redefining business practices. However, this degree of change inevitably involves a range of challenges at both company and individual levels. Indeed, according to Bughin et al. [3], more than 70% of digital transformation initiatives fail, often due to the poor management of human and organizational factors. In this context, "failure" normally refers to initiatives that do not achieve their intended goals, whether strategic, operational, or financial [4]. Failure can manifest itself in a variety of ways, including low adoption rates among employees, incompatibility between new technologies and existing processes, or an inability to deliver measurable improvements in efficiency or customer satisfaction [5]. This failure rate raises the crucial question of how prepared companies are to integrate these technologies in a way that generates real added value. Indeed, DT goes beyond the integration of technological tools; it involves a significant restructuring of internal processes and organizational, economic, and financial behaviors.

Acceptance of digital technologies, both at an individual and a collective level, is a key factor in the success of transformation initiatives. As Vial [6] explains, DT "is not simply a technological transformation, but a profound and continuous organizational reinvention" (p. 121). This change can only be effective if employees and managers adopt a positive attitude toward new technologies, which highlights the importance of understanding the behavioral and social factors that influence this adoption. Previous research has highlighted the importance of a holistic approach, integrating both technological capabilities and human dynamics. Wessel et al. [7] concluded that "the success of a digital transformation depends not only on an organization's ability to integrate advanced technologies, but also on its ability to create an organizational environment favorable to the adoption of these technologies" (p. 236). These authors emphasize that alignment between social and technological dynamics is essential to ensure a smooth and successful transition to a digital enterprise.

Furthermore, the management of human behavior in the face of digital innovation is a critical issue. Warner and Wäger [8], in their research of DT in the context of strategic renewal, found that the dynamic capabilities of an organization play a key role in managing the DT process, especially when it comes to adapting to new technologies and organizational changes. In other words, it is not just about acquiring technologies, but about developing an organizational culture that encourages their adoption and effective use. In this context, this research study focuses on the analysis of the key factors that influence the acceptance of DT. It aims to identify the behavioral factors and innovative characteristics of digital technologies that influence employees' attitudes toward DT.

More specifically, DT has become a strategic imperative for the insurance industry in Morocco, which has become increasingly competitive in the face of rapidly evolving stakeholder expectations. This transition faces particular challenges that slow its adoption and effective implementation [9]. On the one hand, the absence of standardized technology infrastructure, particularly in certain regions, limits access to advanced digital solutions [10]. On the other hand, regulatory frameworks, designed for traditional business models, have not been adapted to accommodate the requirements of emerging technologies, thereby hampering innovation. Additionally, heavy reliance on manual processes and traditional methods remains entrenched in organizational practices, hindering modernization efforts [11].

These challenges are amplified by cultural factors, including resistance to change within teams, often exacerbated by generational gaps. While younger generations easily adapt to new technologies, their older counterparts express increased reluctance, which further complicates the digital transition process [12]. These particularities highlight the need for an in-depth analysis of the human, organizational, and behavioral factors that influence the success of digital transformation initiatives. This study aims to contribute to

addressing this gap by providing a local and targeted perspective on the specific dynamics of the Moroccan insurance sector, thus contributing to a better understanding of the challenges of digital transformation in emerging markets.

Following this brief introduction, there are five further sections to the article. In Section 2, the relevant literature is reviewed, and the research hypotheses are set out. In Section 3, the research methodology is outlined. The results are presented in Section 4, and some key emergent themes are identified and discussed in Section 5. Finally, in Section 6, the overall contribution of the research is discussed, along with the limitations of the study, and possible future areas for research in this field are noted.

2. Literature Review

2.1. Introduction

Digital transformation has become an essential strategic lever for companies aiming to maintain competitiveness in an ever-evolving global environment. Strategic, organizational, and technological dimensions reveal a significant impact on performance, innovation, and agility within organizations. According to Sebastian et al. [13], DT involves a fundamental reinvention of operational processes through the integration of advanced technologies such as artificial intelligence, data analytics, and the Internet of Things. These tools go beyond mere technological adoption; they also entail a profound structural and cultural transformation. Furthermore, the role of organizational culture in the success of digital initiatives is widely emphasized in the literature. Fitzgerald et al. [14] emphasize that a culture centered on experimentation, continuous learning, and adaptability is crucial to overcoming internal resistance to change. Additionally, dynamic capabilities, defined as an organization's ability to respond quickly and effectively to market changes, are considered pivotal for developing and implementing coherent digital strategies [15].

The potential benefits of DT are also well documented. According to Fang and Liu [16], adopting digital technologies not only enhances internal processes but also enriches the customer experience, opening new avenues for competitive differentiation. However, recent research underscores risks related to cybersecurity, data ethics, and organizational imbalances, which can hinder or disrupt the implementation of digital projects [17,18].

This section comprises three sub-sections. In Section 2.2, some fundamental definitions and perspectives are briefly reviewed. This is followed in Section 2.3 by an examination of some of the theory and practice around the acceptance of DT. Building upon this, Section 2.4 then draws out the key determinants of DT from the extant literature and puts forward the related hypotheses to be tested in the primary research phase.

2.2. Digital Transformation: Definition and Importance

Digital transformation can be defined as a comprehensive process through which companies adopt and integrate digital technologies to improve performance, generate new sources of value, and adapt to changing market dynamics [6,19]. However, DT is not limited to simple technological adoption. According to Kleinert [20], DT entails a fundamental reconfiguration of business models and organizational processes, as well as a major cultural shift. This requires a systemic approach that combines technological innovation, organizational transformation, and stakeholder engagement [21].

Companies must rethink their internal processes and value chains to adapt to a digital economy characterized by uncertainty and rapid cycles of change [22]. Fernandez-Vidal et al. [23] emphasize DT's central role as a catalyst for organizational agility and innovation, enabling companies to better meet market expectations. Warner and Wäger [8] describe it as a transformation of operational paradigms, offering businesses the opportunity to thrive in a dynamic economic context. Moreover, DT redefines the organizational competencies

needed to leverage interconnected digital ecosystems, enhancing collaboration and customer engagement [24]. In the financial sector, technologies such as automation, artificial intelligence, and blockchain have improved operational efficiency while personalizing services to meet customer expectations [25,26].

Furthermore, DT promotes cost optimization through automation and improves value chains [27]. It can also contribute to sustainability by reducing companies' carbon footprints through optimized resource management and digitalized practices [28,29]. According to Sebastian et al. [13], this transformation enhances companies' dynamic capabilities, enabling them to adapt to market disruptions while maximizing financial and operational performance. DT acts as a driver of innovation, with technologies like the Internet of Things, cloud computing, and advanced analytics allowing companies to rethink business models and value chains [7]. However, Faraj and Pachidi [30] stress that the success of these initiatives depends on strategic alignment between organizational objectives, technological requirements, and stakeholder expectations.

2.3. The Acceptance of Digital Transformation

The acceptance of DT by employees and stakeholders is a critical factor for the success of digital initiatives. The perceived usefulness and ease of use of digital technologies remain major determinants of their acceptance, as highlighted by the Technology Acceptance Model (TAM) developed by Davis [31]. These concepts have been expanded in recent research to include elements such as compatibility with existing processes and organizational efficiency [32]. Oh et al. [33] conclude that balancing ease of use with advanced functionalities is crucial to ensuring sustainable adoption, particularly in complex digital environments.

The Unified Theory of Acceptance and Use of Technology (UTAUT), introduced by Venkatesh et al. [34], enriches this perspective by identifying social influence and facilitating conditions as critical factors. Trenerry et al. [35] argue that organizational engagement and employee training are essential to strengthening these dimensions and ensuring the successful adoption of digital technologies. Moreover, Slavković et al. [36] highlight the role of digital capabilities in aligning technology with organizational practices, emphasizing that employees' digital citizenship plays a decisive mediating role in this process. In a similar vein, Wynn and Lam [37], in their study of DT in four major hospitality enterprises, found that workforce adaptability, process agility, and a data culture were key requirements for a successful transition to a digital enterprise (Figure 1).

Building on Rogers' [38] Diffusion of Innovation (DOI) theory, Steiber et al. [39] explain that the acceptance of digital technologies depends on their perceived characteristics, such as their relative advantage, compatibility, and complexity. These findings are supported by ElMassah and Mohieldin [40], who highlight the importance of DT in localizing the Sustainable Development Goals (SDGs). The authors note that the perception of societal or environmental benefits can also drive employee engagement. Organizational factors, such as digital leadership and an innovation-driven culture, directly influence technology acceptance. Benitez et al. [41] argue that leaders with strong digital capabilities foster better innovation performance, encouraging employee adoption of technologies. Schildt [42] addresses this issue from an institutional logic perspective, showing that underlying organizational values must align with DT initiatives to ensure their success.

Figure 1. Requirements (shaded gray) for a successful transition to a digital enterprise in the hospitality sector. Source: Wynn and Lam [37].

2.4. Key Determinants and Hypothesis Development

The acceptance of DT stems from a complex amalgamation of antecedents that depend not only on individuals but also on the organizations in which they operate. This has profoundly influenced management systems underpinning organizational coordination and control, and a range of models and frameworks are being used to assess the key determinants of successful DT in a rapidly evolving technology environment. These include a number of models that pre-date the digital era, such as those noted above (TAM; UTAUT; DOI), which can be applied to identify the determinants that directly impact workers' intention to embrace DT in their professional activities. Such acceptance within organizational ecosystems relies on a triadic framework encompassing behavioral, innovation-related, and attitudinal dimensions (Figure 2).

From the extant literature, including from the three models noted above (See Table A1 in Appendix A), five distinct factors (or determinants) relating to the behavioral dimension can be discerned: resistance to change; attitude toward new technologies; intrinsic motivation; perceived usefulness of technologies; and workplace autonomy. Regarding resistance to change, organizations perceive it as both a hindrance to economic development and an opportunity to understand their workers' abilities and foster learning within a complex ecosystem [43]. This resistance arises from feelings of fear of the unknown and loss of control [44]. Resistance to change is thus considered an inhibitory determinant of DT acceptance. It materializes as anxiety and discomfort, stemming from employees stepping

out of their comfort zones. However, proactive management of this resistance can facilitate transition [45].

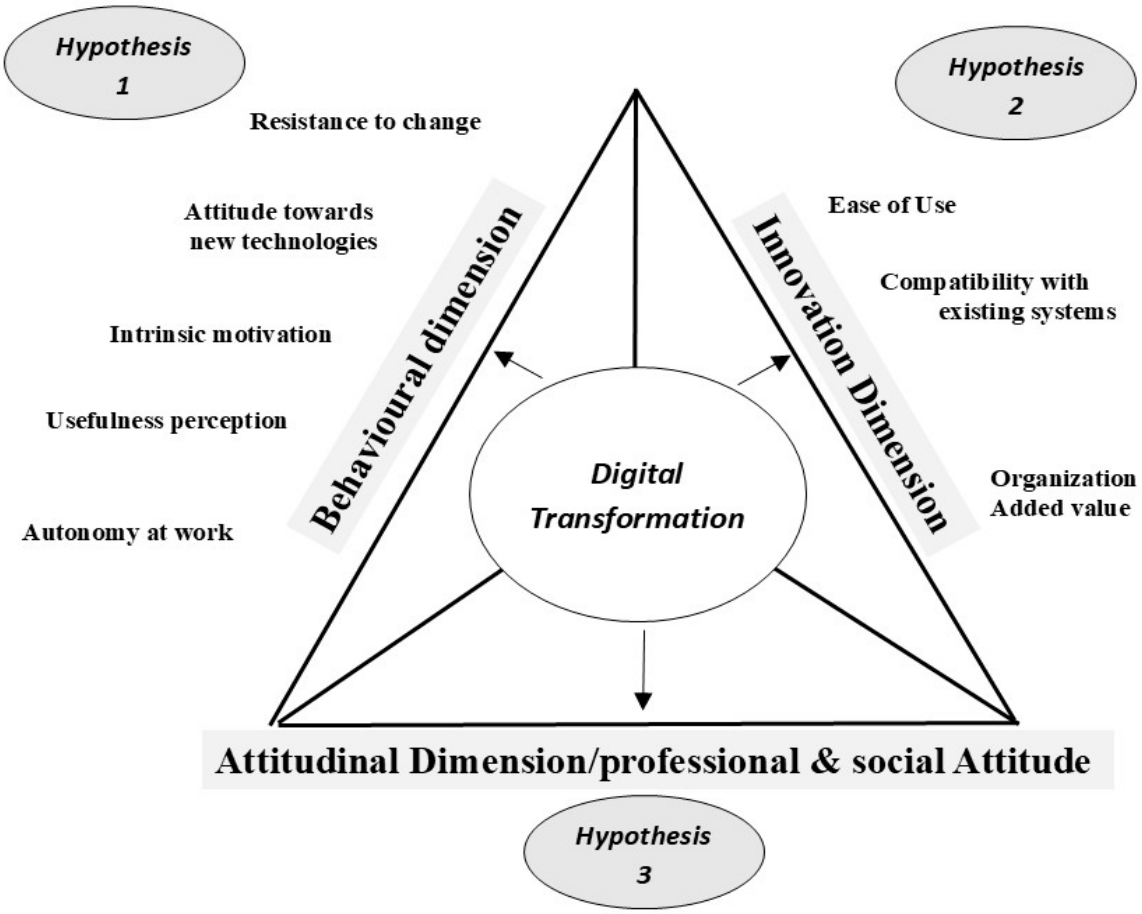

Figure 2. Conceptual framework: the key dimensions of digital transformation and related factors (determinants).

Despite its inhibitory nature, employee resistance to change also highlights positive aspects, as it prompts organizations to prioritize resources for facilitating workers' adaptability to DT [37,46]. In this context, supporting employees throughout the DT process can change resistance into anticipatory engagement [47]. Conversely, positive attitudes toward new technologies can facilitate their use and support the acceptance of DT [48]. Such positive attitudes toward adopting new technologies and integrating them into all professional activities enhance the success and acceptance of the transition, contributing to the sustainable improvement of organizational performance [49].

Intrinsic motivation plays a crucial role in employees' conscientious engagement in the DT process, driven by the personal and professional benefits they derive [50]. High levels of employee motivation contribute to the ease of acceptance and flexibility in adopting complex digital tools, heightening the likelihood of the success of DT [35,51]. The perceived usefulness of new technological advancements is a key predictor of the success and acceptance of DT within organizations [52]. A strong perception of usefulness facilitates smoother acceptance and integration of the transition [53]. The introduction of new technologies that promote workplace autonomy leads to higher job satisfaction and serves as a bridge to the successful acceptance of DT [54]. Furthermore, the autonomy fostered by incorporating new technologies into management processes positively impacts the flexibility of transition acceptance [55,56].

The innovation dimension also has a significant impact on employees' intention to embrace DT. This dimension has three main related factors: the ease of use of new technologies; their compatibility with existing systems; and their organizational added value. Regarding the ease of use of technological advancements, Venkatesh et al. [57] maintain that their user-friendliness reduces initial adoption barriers and increases acceptance levels. Furthermore, employees' perception of the flexibility of these technologies positively influences their acceptance behavior toward DT [58,59]. Additionally, the perception of enhanced ease of use of new technologies can transform negative impressions into enthusiastic acceptance [60]. Employees may exhibit acceptance of complex technologies from a learning and skill development perspective [61].

As regards the compatibility of new technologies with existing organizational systems, Martínez-Peláez et al. [62] argue that harmony between the implemented technological advancements and the existing management system encourages acceptance of DT and reduces employee resistance. Moreover, this alignment with existing practices helps reduce the costs of the transition and limits disruptions in management procedures and practice [63,64]. However, Amini and Javid [65] argue that emphasizing the compatibility between existing systems and newly introduced technologies can constrain innovation. Chaudhuri et al. [66] also point out that, irrespective of the technology compatibility issue, organizations often find themselves at a critical juncture in DT, requiring the adoption of scalable and transformative technologies, regardless of their complexity and the resources needed for their implementation.

Employees' perception of the organizational added value generated by the introduction of new technologies enhances their involvement and commitment to accepting DT. Improvements in productivity and cost reduction support employees' willingness to adopt these new technologies and associated process changes [57]. Conversely, in scenarios where financial improvements are not in evidence, employees' perception of the implementation of these technologies may take a negative turn [67], potentially leading to resistance [68].

The attitudinal dimension also demonstrates a significant correlation with employees' intentions to accept DT [45,69]. This dimension encompasses two main factors: professional attitude and social attitude. The first refers to employees' willingness to develop skills and adapt to changes and new demands. This learning-oriented attitude fosters acceptance of new technologies [70]; moreover, employees engaged in lifelong learning and actively seeking career advancement opportunities will demonstrate greater flexibility during the upheavals involved in DT [71]. Social attitude plays a crucial role in technology acceptance [59]. Specifically, the influence of colleagues and managers in promoting DT creates a positive sensory effect, encouraging employees to align with required initiatives and project goals [72]. However, in some cases, social attitudes may negatively impact employees' intentions when they perceive the technologies as irrelevant to specific organizational practices, thus hindering the acceptance of DT [73].

Building upon this analysis of the extant literature, hypotheses were developed to test the relationships between the three main dimensions in the conceptual framework (Figure 2) in the context of the Moroccan insurance industry: innovative characteristics of digital technologies; behavioral factors; and attitudinal (professional and social) influence on the acceptance of DT. These hypotheses are as follows:

H_1: The behavioral dimension has a significant impact on the acceptance behavior of insurance employees with regard to DT.

$H_{1.1}$: Resistance to change has a significant impact on the acceptance behavior of insurance employees toward DT.

$H_{1.2}$: Attitude toward new technologies has a significant impact on the acceptance behavior of insurance employees toward DT.

$H_{1.3}$: Intrinsic motivation has a significant impact on the acceptance behavior of insurance employees toward DT.

$H_{1.4}$: The perceived usefulness of technologies has a determining effect on the acceptance behavior of insurance employees with regard to DT.

$H_{1.5}$: Autonomy at work significantly influences the acceptance behavior of insurance employees toward DT.

H_2: The innovation dimension has a significant impact on the acceptance behavior of insurance employees with regard to DT

$H_{2.1}$: The ease of use of technologies has a significant impact on the acceptance behavior of insurance employees with regard to DT.

$H_{2.2}$: Compatibility with existing devices suggests a significant impact on employees' acceptance behavior toward DT.

$H_{2.3}$: Organizational added value contributes significantly to employees' acceptance behavior toward DT.

H_3: The attitudinal dimension exhibits a significant influence on the acceptance of insurance employees with regard to DT.

$H_{3.1}$: Professional attitude has a significant influence on employees' acceptance of DT.

$H_{3.2}$: Social attitude plays a determining role in employees' acceptance of DT.

These hypotheses provided the basis for subsequent data analysis to identify and validate the key determinants for DT in the Moroccan insurance sector. In this context, it is worth noting the distinction between hypothesis testing and parameter measurement, as put forward by Simon [74]. Although this study centers on the hypotheses set out above, it primarily focuses on measuring parameters using a parametric approach (e.g., linear regression models). This methodology makes it possible to quantify relationships between variables [75], such as the impact of resistance to change and perceived ease of use on the acceptance of DT [76]. The inclusion of 95% confidence intervals (discussed below in Section 4.6) ensures statistical rigor and transparency in the interpretation of the results [77]. The approach can thus be seen as exploratory, emphasizing the measurement of the magnitude and direction of the relationships studied.

3. Research Methodology and Design

This study adopts a quantitative approach to analyze the factors influencing the acceptance of DT. This method was chosen for its ability to provide a comprehensive understanding of the phenomena under study, particularly by triangulating the results from quantitative data collected through surveys conducted with employees of Moroccan financial institutions, specifically insurance companies. The determinants of DT acceptance were drawn from a range of studies as discussed above, but they lean heavily on the theoretical models of TAM, UTAUT, and DOI (See Table A1 in Appendix A). A post-positivist epistemological stance was adopted, reflecting a commitment to rigorous analysis of assumptions, while recognizing the complexity and context dependence of human behaviors [78]. This approach accepts that absolute objectivity is difficult to achieve, but seeks to minimize bias through systematic data collection and analysis. By combining rigorous quantitative metrics and a deep understanding of context, this posture provides a balanced analysis of the factors influencing DT and generates actionable insights based on empirical evidence [79]. It places particular emphasis on formulating core hypotheses based on a theoretical framework, with the aim of validating or refuting them within an appropriate empirical context.

There were three main phases in this research study (Figure 3). Phase 1 comprised a literature review that allowed for the identification of the basic conceptual framework for the hypothesis generation, as reported in Section 2 above, and subsequent primary research.

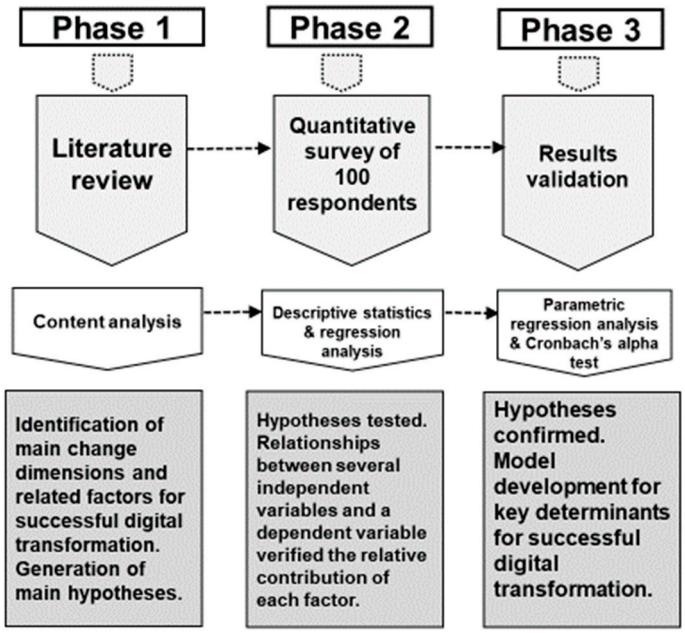

Figure 3. The 3 phases of the research process.

Phase 2 involved a survey of 100 employees from Moroccan insurance companies, which are characterized by significant exposure to digital pressures where technological innovation is essential to maintaining competitiveness [80,81]. The sample of 100 participants was selected using a convenience sampling method. The participants were recruited through professional networks, ensuring diversity in terms of age, gender, education level, and professional roles. No financial incentives were offered to ensure voluntary and unbiased participation. Although convenience sampling has certain limitations, it is suitable for exploratory studies because it allows the identification of trends and exploration of the dynamics of a specific sector. Participants from companies at different stages of DT were included to capture a wide range of experiences and perspectives. The sample size of 100 participants also aligns with methodological recommendations for exploratory studies in organizational behavior and DT research [82]. According to Rousson [83], a sample size of 100 is considered adequate to obtain statistical power in studies using multivariate analyses, such as regression models. This sample size allows for the detection of significant relationships between independent and dependent variables while maintaining manageable data collection requirements, and strikes an appropriate balance between data richness and operational feasibility.

The survey instrument was carefully designed to ensure a comprehensive analysis of the factors influencing DT acceptance. It was based on the TAM, UTAUT, and DOI theoretical models and related literature, and included 34 structured questions divided into four main sections: (1) demographic information, (2) behavioral factors, (3) innovative features of digital technologies, and (4) attitudinal dimensions. Responses were collected using a 7-point Likert scale, ranging from "strongly disagree" (1) to "strongly agree" (7). This scale was chosen to capture the nuanced perceptions and attitudes of the participants, thereby providing a solid basis for statistical analysis. The participants were selected using a non-probability convenience sampling method [84]. This approach was chosen due to its practicality and effectiveness in exploratory studies whose main objective is to identify patterns and relationships [85]. It is commonly applied in exploratory studies and enables preliminary empirical analysis and hypothesis testing on a representative basis [86]. The sample was composed of 100 employees from different hierarchical levels and departments of Moroccan insurance companies. Efforts were made to ensure diversity within the sample,

representing a range of experiences, roles, and perspectives within the sector. This diversity is essential to obtain a holistic view of the DT acceptance in the sector.

The survey was conducted over a 3-week period using both paper and digital formats, which allowed for greater accessibility and participation. The participants were informed of the confidentiality and anonymity of their responses to encourage honest and unbiased contributions. The structured design of the questionnaire, combined with the detailed description of the methodology, ensures that this study can be replicated in similar organizational and cultural contexts. Future researchers can use the same framework to compare results from different sectors or regions.

The analysis relies on using multiple linear regression models to measure the relative impact of each determinant on acceptance intention. All analyses were conducted using IBM SPSS Statistics software, version 27. The multiple linear regression model is a natural extension of the simple regression model for any number of explanatory variables, and more detail is provided in Appendix B.

The quantitative data collected underwent a thorough analysis, including descriptive statistics and regression analyses, to explore and understand the relationships between various behavioral factors and the acceptance of DT. A multiple regression analysis was subsequently conducted to test the research hypotheses by examining the effect of behavioral, innovative, and attitudinal dimensions on the acceptance of DT.

Finally, in Phase 3, a parametric regression analysis was employed to validate the results, ensuring that the assumptions of linearity and normality of residuals were met, thereby guaranteeing the robustness of the conclusions.

4. Results

4.1. Demographic Characteristics of Respondents

Table 1 presents the demographic characteristics of the 100 employees who participated in this study, indicating the profiles of the participants and their distribution according to the main socio-demographic variables.

Table 1. Demographic characteristics of respondents.

Variable	Category	Frequency (n)	Percentage (%)
Age	18–25 years old	15	15%
	26–35 years old	45	45%
	36–45 years old	30	30%
	46 years and over	10	10%
Sex	Male	60	60%
	Female	40	40%
Education level	Baccalaureate	30	30%
	Undergraduate degree	50	50%
	Master's or higher	20	20%
Professional seniority	0–5 years	25	25%
	6–10 years old	40	40%
	11–15 years old	20	20%
	16 years or older	15	15%

The majority of the participants (45%) are in the age group of 26 to 35, and 60% of the respondents are men. Regarding the level of education, 50% of the participants have a bachelor's degree, while 20% have a master's degree or higher. In terms of professional

seniority, 40% of the participants have between 6 and 10 years of experience, which suggests a sample mainly composed of relatively experienced employees in the insurance sector.

4.2. Descriptive Statistics of the Main Variables

Table 2 presents the descriptive statistics for the key variables influencing the acceptance of digital transformation, including their mean ($\overline{X}$) and standard deviation (δ).

Table 2. Descriptive statistics of the main independent variables (X).

Dimension	Variables	Coding	$\overline{X}$	δ
Behavioral	Resistance to change	RES-CH	3.20	0.85
	Attitude toward new technologies	ATT-TC	4.80	0.72
	Intrinsic motivation	INT-MT	4.50	0.65
	Perceived usefulness of technologies	PER-TC	4.90	0.78
	Autonomy at work	SE-USE	3.80	0.80
Innovative	Ease of use	EASE-USE	5.10	0.75
	Compatibility with existing devices	COMP-PR	4.70	0.68
	Organizational added value	VAL-ORG	5.20	0.80
Attitudinal	Professional attitude	PRO-ATT	4.72	0.41
	Social attitude	SOC-ATT	4.65	0.38

These results are depicted graphically in Figure 4, showing an overall favorable perception of the variables studied. In the behavioral dimension, the perceived usefulness of technologies (4.90) and the attitude toward new technologies (4.80) stand out as strong points, while resistance to change (3.20) is moderate. In the innovation dimension, ease of use (5.10) and organizational added value (5.20) obtain the highest scores, indicating a strong potential for the adoption of new technologies. Finally, in the attitudinal dimension, professional (4.72) and social (4.65) attitudes demonstrate a positive predisposition of the participants toward DT. These results highlight an overall positive perception of the factors influencing the acceptance of DT, despite some nuances concerning autonomy at work and resistance to change.

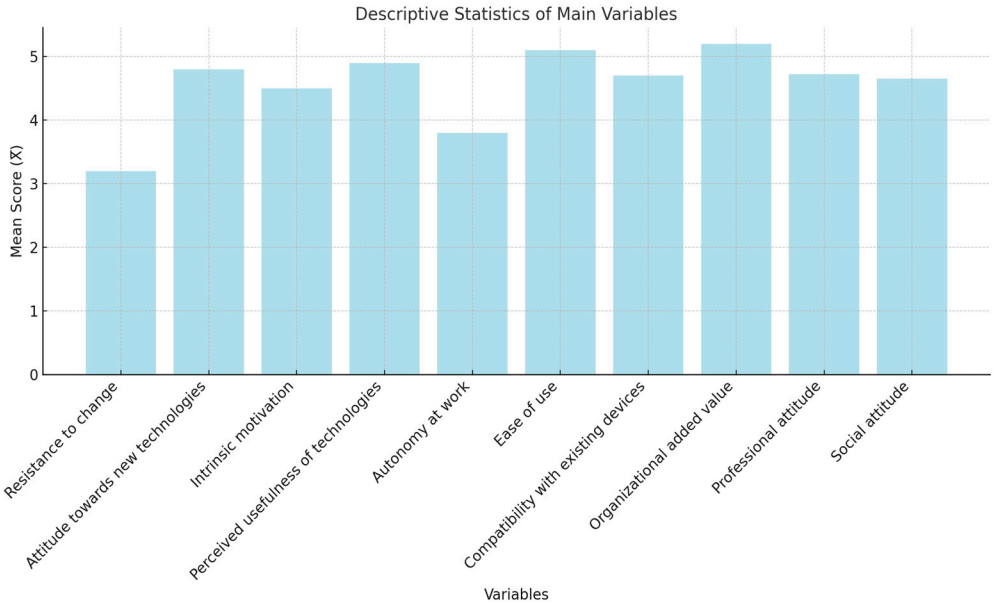

Figure 4. The main independent variables: descriptive statistics.

4.3. Responses of Respondents on "Intention to Accept Digital Transformation"

Table 3 presents the respondents' assessments of their "intention to accept digital transformation", categorized by key dimensions and variables, along with their respective frequency distributions. The combined findings for all three dimensions are presented graphically in Figure 5.

Table 3. Responses of respondents on "intention to accept digital transformation" (Y).

Dimension	Variables	Frequencies				
		*	**	***	****	*****
Behavioral	Resistance to change	-	-	4%	10%	86%
	Attitude toward new technologies	-	-	9%	15%	76%
	Intrinsic motivation	-	-	7%	21%	72%
	Perceived usefulness of technologies	-	-	1%	10%	89%
	Autonomy at work	-	-	2%	21%	77%
Innovative	Ease of use	-	-	3%	23%	74%
	Compatibility with existing devices	-	-	-	21%	79%
	Organizational added value	-	-	2%	10%	88%
Attitudinal	Professional attitude	-	-	6%	10%	84%
	Social attitude	-	-	7%	13%	80%

*: Not at all likely; **: Unlikely; ***: Neutral; ****: Quite likely; *****: Probable.

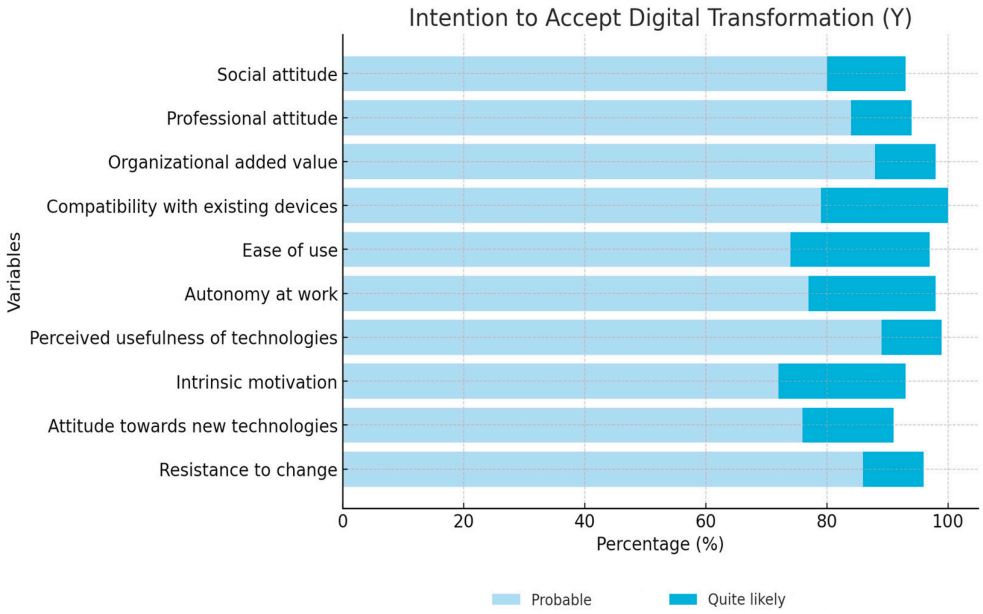

Figure 5. Intention to accept digital transformation (graphical presentation).

The results in the table show a strong intention to accept DT among the respondents. The most used variables include the perceived usefulness of technologies (89%), organizational added value (88%), and compatibility with existing devices (79%), indicating very positive perceptions of these factors. Similarly, the professional (84%) and social (80%) attitudes suggest a favorable climate for the adoption of new technologies. However, some aspects such as the motivation generated (72%) and autonomy at work (77%) show slightly lower scores, suggesting room for improvement to strengthen these behavioral determinants. These data confirm an overall positive predisposition, but with nuances in some dimensions.

4.4. Model Adjustment

Table 4 below indicates how the results fit the model, including key statistical indicators, namely the adjusted R, R^2, the standard error of the estimate R^2, and the significance of changes in the model fit. In Tables 4 and 5, "F" corresponds to the Fisher statistic (F-statistic) used to test the overall significance of the regression model. "ddl1" and "ddl2" signify the degrees of freedom associated with the F test. "Sig." indicates the variation in F—the significance of the variation of the model after the addition of new independent variables.

Table 4. Model fit.

R	R^2	R^2 Adjusted	Standard Error of the Estimate	Modify Statistics				
				R^2 Variance	Change in F	*ddl*1	*ddl*2	Sig. Variation in F
0.92	0.94	0.91	0.081	0.02	0.137	99	891	0.000

Table 5. Assessment of regression model quality (ANOVA).

Source	Sum of Squares	ddl	F	Sig.
Regression (SSR)	653.157	99	56.16	0.000
Residue (SSE)	0.00	0	-	-
Total (SST)	653.157	99	-	-

The value of the correlation coefficient R = 0.92 gives the strength of the relationship between the independent variables (X) and the dependent variable (Y). This value expresses the appropriate adjustment of the observations to the statistical model used. However, the coefficient of determination (=0.94) refers to the proportion of the variation in the response variable Y (acceptance of DT) explained by an assortment of explanatory variables using the multiple linear regression model. This value indicates that the statistical model used is capable of explaining the response variable at a rate of 94% in the sample proposed in this study. However, the Fisher statistics ("F" in Table 4) associated with the linear model are highly significant, suggesting a bilateral asymptotic significance of $p = 0.000 < 0.05$.

4.5. Assessment of Regression Model Quality (ANOVA)

Table 5 provides an assessment of the quality of the regression model (ANOVA), highlighting the distribution of variance via the sum of squares, degrees of freedom, F-statistic, and significance level.

The ANOVA table mentions the contribution of the multiple linear model used in the explanation of the response variable Y (acceptance of DT). Based on the bilateral asymptotic significance of the F value ($p = 0.000 < 0.05$), the null hypothesis (H_0) is rejected, confirming the quality of the adjustment of the model used in the explanation of the dependent variable Y.

4.6. Non-Standardized Coefficients

Table 6 illustrates the non-standardized coefficients of the regression model, along with their statistical significance and 95% confidence intervals. The non-standardized coefficients make it possible to reconstruct the equation of the linear adjustment line, also called the equation of the regression line. The column of non-standardized coefficients β also provides information on the sign of this value (+ or −). This sign is important for interpreting the direction of the relationship between the dependent variable Y and

the independent variables X. The value of these coefficients indicates the direction of variation in the relationship between the response variable "acceptance of DT" and the other explanatory variables introduced in this study. For example, the explanatory variable "resistance to technological change" (RES-CH) exhibits a coefficient $\hat{\beta} = -3.079$, suggesting an inverse interrelation with the dependent variable "acceptance of DT".

Table 6. Table of coefficients (full names of constants are given in Table 2 as variables).

	Unstandardized Coefficients		t	Sig.	95.0% Confidence Interval for β	
	β	Standard Error			Lower	Upper
Constant	4.811	0.780	6.167	0.000	3.262	6.360
RES-CH	−3.079	0.056	−1.425	0.008	−0.031	0.190
ATT-TC	2.089	0.056	1.587	0.006	1.980	2.422
INT-MT	3.067	0.059	1.135	0.009	2.990	3.726
PER-TC	5.022	0.066	0.333	0.000	4.874	5.735
SE-USE	4.028	0.064	0.431	0.000	3.951	4.680
EASE-USE	2.177	0.018	1.115	0.000	1.917	2.837
COMP-PR	1.019	0.042	1.587	0.011	0.790	1.724
VAL-ORG	2.017	0.027	1.135	0.013	1.879	2.398
PRO-ATT	1.291	0.085	0.333	0.007	0.942	1.792
SOC-ATT	1.028	0.020	0.431	0.000	0.916	1.437

On the other hand, the other explanatory variables explain a positive impact on the intention to accept DT. In other words, the other determinants of the behavioral dimension, such as an improvement in attitudes toward new technologies, high motivation, appropriate utility, and accomplished autonomy, generate a positive impact on the intention to accept DT among insurers.

However, the innovation dimension, conglomerating the ease of use of digital tools, the compatibility with existing devices, and the organizational added value, also provides a positive influence on the intention of insurers to accept DT. Similarly, the attitudinal dimension bringing together professional and social attitudes advances positive consequences on the ability of insurer employees to accept DT in the exercise of their daily tasks.

4.7. Parametric Regression Analysis

To further study the influence of the dimensions on the acceptance of DT, a parametric regression analysis was undertaken. This statistical method is particularly suitable for evaluating the contribution of explanatory variables to a continuous dependent variable, respecting the fundamental assumptions of normality, homogeneity of variances, and linearity.

Table 7 indicates that all the variables studied are significant ($p < 0.05$), which confirms their relevance in the model. The variable "perceived usefulness of technologies" (PER-TC) presents the highest β coefficient, highlighting its key role in the acceptance of DT. On the other hand, resistance to change (RES-CH) acts as an inhibiting factor, with a negative effect on the dependent variable. These results reinforce the overall relevance of the model and its ability to explain the determinants of acceptance. These results highlight the importance of technological adaptation and employee behavior in the success of DT.

Table 7. Results of parametric regression analysis (full names of constants are given in Table 2 as variables).

Independent Variables (X)	Unstandardized Coefficients (β)	Standard Error	t Value	*p*-Value (Sig.)	Meaning
Constant	4.811	0.780	6.167	0.000	Highly significant
RES-CH	−3.079	0.056	−1.425	0.008	Significant inhibitor
ATT-TC	2.089	0.056	1.587	0.006	Significant contributor
INT-MT	3.067	0.059	1.135	0.009	Significant contributor
PER-TC	5.022	0.066	0.333	0.000	Major contributor
SE-USE	4.028	0.064	0.431	0.000	Significant contributor
EASE-USE	2.177	0.018	1.115	0.000	Significant contributor
COMP-PR	1.019	0.042	1.587	0.011	Significant contributor
VAL-ORG	2.017	0.027	1.135	0.013	Significant contributor
PRO-ATT	1.291	0.085	0.333	0.007	Significant contributor
SOC-ATT	1.028	0.020	0.431	0.000	Significant contributor

5. Discussion

The results of this study demonstrate that the acceptance of DT is based on a combination of behavioral, innovative, and attitudinal factors. The descriptive statistics (Table 2) reveal that innovative characteristics, such as ease of use (M = 5.10) and organizational added value (M = 5.20), achieve the highest averages, highlighting their crucial role in DT acceptance. These findings are supported by the frequencies observed in Table 3, where 88% of the participants consider organizational added value as "highly probable", and 74% view ease of use favorably. This confirms that the innovative characteristics of digital technologies are major predictors of their adoption.

From a behavioral perspective, factors such as attitude toward new technologies (M = 4.80) and motivation (M = 4.50) also play an important role. These factors are rated as "highly probable" by 76% and 72% of the respondents, respectively. However, resistance to change (M = 3.20) remains moderate, although 86% of the participants consider it unlikely to be a significant obstacle to successful DT.

Analysis of the demographic data revealed significant differences in attitudes toward DT across age groups and education levels. Younger employees (aged 18 to 25) showed greater openness to adopting digital technologies, scoring high on ease of use and perceived usefulness, compared to employees aged 46 or more, who displayed increased resistance to change. Additionally, employees with a master's degree or higher expressed more favorable attitudes toward technological compatibility and the strategic benefits of DT compared with those with lower levels of education. These findings suggest that personalized training and engagement strategies need to be developed to meet the specific needs of different demographic groups.

The multiple linear regression analyses (Tables 4 and 5) confirm the excellent fit of the model. The R^2 value of 0.94 indicates that 94% of the variance in the dependent variable (acceptance of DT) is explained by the model. The significance of the F-statistic ($p = 0.000 < 0.05$) supports the robustness of the model.

Finally, the regression coefficients (Table 6) highlight the variables with a significant influence on the acceptance of DT. Among them, the perceived usefulness of technologies ($\beta = 5.022$, $p < 0.001$) and workplace autonomy ($\beta = 4.028$, $p < 0.001$) emerge as the most influential predictors.

Innovative characteristics, such as ease of use ($\beta = 2.177$, $p < 0.001$) and organizational added value ($\beta = 2.017$, $p < 0.001$), further reinforce the idea that positive perceptions of digital technologies are essential for their adoption. From a behavioral perspective, factors like attitude toward new technologies ($\beta = 2.089$, $p < 0.01$) and motivation ($\beta = 3.067$, $p < 0.01$) confirm their importance. Conversely, resistance to change ($\beta = -3.079$, $p < 0.01$) exerts a moderate negative influence on acceptance.

Possible interactions between certain parameters, such as resistance to change and ease of use, were also considered. These behavioral and technological dimensions may be linked, as technology perceived as difficult to use could naturally lead to increased resistance to change. To ensure a clear distinction between these factors, a preliminary analysis of the correlations between the independent variables was conducted. The calculated correlation coefficients showed moderate but not excessive relationships, confirming the relative independence of the variables in the model. In addition, the multiple regression analysis used made it possible to measure the individual impact of each variable while controlling the effects of the others. The results show that the coefficients associated with each factor are statistically significant, which validates their distinct contribution to the model. Although the cross-terms were not explicitly included in the main analysis, the low levels of correlation between key variables, such as resistance to change and ease of use, suggest that their interactions do not constitute a major source of bias. These results reinforce the validity of the conclusions drawn from the statistical analysis.

In terms of practice, the results of this study provide valuable insights for decision-makers and managers facing the challenges of DT in a number of areas. Firstly, the ease of use of technologies emerges as a key determinant of their acceptance. Investment in intuitive and ergonomic technological solutions will reduce resistance to change [87,88]. Companies should prioritize tools tailored to the specific needs of employees, taking into account their level of familiarity with technologies. Additionally, pilot testing and phased deployment can help identify potential deployment barriers and facilitate fine-tuning and customization prior to full roll-out.

Secondly, although training can represent a significant initial cost, it constitutes a strategic lever for strengthening employee confidence in new technologies [89]. Targeted training, focused on developing digital skills and raising awareness of the organizational benefits of DT, can transform resistance into proactive engagement [11]. Companies should also incorporate interactive feedback sessions to identify and address specific employee concerns. Additionally, peer mentoring or training programs could play an important role in accelerating technology adoption. Thirdly, this study also highlights the importance of professional and social attitudes in technology acceptance. Companies could profitably adopt a holistic approach that integrates behavioral dimensions, such as intrinsic motivation, and social dimensions, such as the influence of leaders and peers [90]. Transparent communication on the objectives of DT and awareness campaigns on its organizational benefits can help create an environment favorable to change [91]. In addition, recognition of individual and collective efforts can strengthen employee motivation and engagement.

In summary, this study found that resistance to change can be mitigated through targeted training programs that address employee concerns and improve their digital skills [92]. Additionally, the adoption of intuitive and user-friendly technologies is a critical factor in reducing barriers to adoption [93]. Leaders in the Moroccan insurance sector can leverage this information to develop strategies tailored to the needs of their staff, ensuring a smoother transition to digital operations. These concrete recommendations aim to bridge the gap between theory and practice, making the results directly relevant to industry stakeholders. These results underline that the acceptance of DT depends on an effective alignment between technological innovation and individual behaviors. They also confirm

that positive attitudes toward DT and favorable perceptions of technologies are critical in ensuring their success within organizations.

6. Conclusions

This study provides an in-depth understanding of the key factors that influence the acceptance of DT in the Moroccan insurance industry. It emphasizes the importance of combining behavioral, technological innovation, and attitudinal dimensions in such studies.

The results reveal that behavioral dimensions play a crucial role in the adoption of digital technologies. Factors such as resistance to change, attitude toward new technologies, motivation, perceived usefulness of technologies, and workplace autonomy significantly influence how employees perceive and integrate these innovations. Simultaneously, the innovation dimension, which includes ease of use, compatibility with existing systems, and organizational added value, emerges as a critical driver in encouraging the acceptance of new technologies. Lastly, the attitudinal dimension, encompassing professional and social attitudes, moderates the impact of digital innovations by reinforcing acceptance within social and professional groups.

These findings confirm that an integrated approach is indispensable for successful DT. Deploying innovative technologies alone is insufficient; it is essential to consider human factors, such as raising employee awareness about the benefits of technologies, reducing resistance to change, and fostering an organizational climate conducive to innovation. This study highlights the importance of supporting employees during their transition by valuing their autonomy and implementing tailored strategies to address their behavioral, technological, and social expectations.

This study clearly has limitations. It is based on an analysis of the relevant literature and a 100-respondent survey. The survey respondents were selected through non-probabilistic convenience sampling. Generalizations from such a study must therefore be treated with caution. In addition, this study focuses on a specific context—the Moroccan insurance sector—which restricts the extrapolation of the results to other regions or industries. The cultural, organizational, and economic specificities of Morocco generally influence the dynamics of technological acceptance. Nevertheless, the authors believe this research contributes to the development of theory and practice relating to DT. From a theoretical perspective, this research situates DT within the specific context of emerging economies, specifically Morocco. By exploring the interactions between the behavioral, innovation, and attitudinal dimensions, it proposes a comprehensive framework that goes beyond traditional paradigms often limited to Western contexts. This contribution enriches the understanding of the complex dynamics of technological adoption while emphasizing the importance of social acceptance and organizational compatibility in the success of digital projects.

From a practical standpoint, business leaders must adopt change management strategies that integrate training initiatives, organizational support mechanisms, and awareness campaigns. These efforts will strengthen employee engagement and maximize the success of DT. By focusing on the identified dimensions and related change factors, companies can develop tailored solutions to encourage the adoption of technologies while addressing behavioral and organizational barriers.

In conclusion, while this study has provided valuable insights into the factors influencing DT in Morocco's insurance sector, it also provides a platform for future research. Future studies could explore these dynamics in other sectors or cultural contexts to broaden the understanding of critical change factors. DT is ultimately a multidimensional process that requires harmonious integration between technological innovations and human dimensions to ensure successful adoption. Future studies could explore several possible

avenues of research. Comparative studies across different sectors, such as banking or retail, could help determine whether the determinants of DT acceptance are sector-specific or universal. Longitudinal studies could examine the long-term impact of DT initiatives on organizational performance and employee satisfaction. Qualitative approaches, involving, for example, focus group interviews, could complement this quantitative study by exploring employees' lived experiences and perceptions in more depth. In addition, an examination of the interactions between behavioral dimensions and organizational change policies could be of value, particularly by investigating the effect of participative leadership strategies on the adoption of digital technologies. Future research can thus build on the findings reported here to further explore the complex dynamics of technological acceptance in diverse environments and through varied methodological approaches.

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Appendix A. Synthesis of Key Variables Derived from the TAM, UTAUT, and DOI Models

Table A1. Synthesis of key variables and concepts in the UTAUT, TAM, and DIO models.

Variable	UTAUT	TAM	DIO	Authors
Resistance to change	Linked to facilitating conditions and effort expectancy, which address perceived barriers to adoption	Potential negative influence on attitude toward use and intention	Mentioned in the categorization of adopters, particularly for late adopters	[31,34,38,94,95]
Attitude toward new technologies	Approached via intent to use, influenced by factors such as performance expectancy	Central variable: attitude toward use determines intention to use	Linked to the notions of compatibility and relative advantage	[31,34,38,59,96,97]
Intrinsic motivation	Associated with effort expectancy and the role of moderators	Included in attitude toward use, influenced by ease of use	Not directly mentioned in the model	[31,32,34,98]

Table A1. *Cont.*

Variable	UTAUT	TAM	DIO	Authors
Perceived usefulness of technologies	Corresponds to performance expectancy, one of the main determinants of acceptance	One of the two main variables under the name of perceived usefulness	Equivalent to relative advantage, a key adoption factor	[31,34,38,59,98]
Autonomy at work	Addressed in the facilitating conditions that facilitate the autonomous use of technologies	Not mentioned, but may influence attitude	Not directly mentioned	[34,99]
Ease of use	Corresponds to effort expectancy, a key determinant of adoption	Central variable under the name of perceived ease of use, directly influencing attitude	Similar to the concept of complexity, one of the five main factors	[31,34,38]
Compatibility with existing devices	Indirectly covered by facilitating conditions, which include integration with existing systems	Can directly influence perceived usefulness	Mentioned as one of the main variables under the name of compatibility	[34,38]
Organizational added value	Addressed in performance expectancy, which includes organizational benefits	Can be included in perceived usefulness, if the benefits are organizational	Related to relative advantage, which considers organizational benefits	[31,34,38]
Professional attitude	Influenced via moderators such as professional experience	Influence on attitude toward use and intention	Not directly mentioned	[31,34]
Social attitude	Corresponds directly to social influence, a major determinant	Can explicitly influence attitude toward use	Related to observability, which depends on social context	[28,38]

Appendix B. The Multiple Linear Regression Model Used in the Research Project

The linear model is the most frequently used statistical model for analyzing multidimensional data. The term "multiple" refers to the fact that there are several explanatory variables x_i to explain y (response variable). The information is supposed to be derived from the observation of a statistical sample of size n ($n > p + 1$) of $\mathbb{R}^{(p+1)}$. In this situation, the linear model is written assuming that the expectation of Y is the element of the subspace of $\mathbb{R}^{(n)}$ created by $\{1, x_1, x_2, \cdots, x_p\}$, where 1 is the vector of $\mathbb{R}^{(n)}$ composed of "1". In other words, the random variables $(p + 1)$ are checked:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip} + \varepsilon_i \quad i = 1, \cdots, n$$

where y_i denotes the random variable to be explained, x_{ij} represents known, non-random numbers making explicit the explanatory variables, β_j refers to the unknown but non-random parameters to be estimated, and ε_i confers the random error terms of the model.

Using the least squares estimator, the unknown model parameters β are estimated by minimizing the least squares criterion (L.S.) or maximizing the likelihood (L.L.). In this survey, the least squares (L.S.) criterion was used to estimate the parameter $(\hat{\beta}) \in \mathbb{R}\ (p+1)$ that minimizes the sum of squared errors:

$$\varepsilon_i^2 = \left(y_i - \beta_0 - \beta_1 x_{i1} - \beta_2 x_{i2} - \cdots - \beta_p x_{ip} \right)^2$$

To estimate the unknown parameters $(\hat{\beta})$, the following optimization problem was solved:

$$\hat{\beta} = \arg \min_{\beta \in \mathbb{R}^{(p+1)}} \sum_{i=1}^{n} \left[(y_i - \left(\beta_0 + \sum_{j=1}^{p} \beta_j x_{ij} \right) \right]^2 = \arg \min_{\beta \in \mathbb{R}^{(p)}} \| Y - X\beta \|^2$$

By positing that

$$\begin{aligned} F(\beta) &= \sum_{i=1}^{n} \left[(y_i - \left(\beta_0 + \sum_{j=1}^{p} \beta_j x_{ij} \right) \right]^2 \\ &= \| Y - X\beta \|^2 \\ &= (Y - X\beta)^T (Y - X\beta) \\ &= Y^T Y - 2 Y^T X\beta + \beta^T X^T X\beta \end{aligned}$$

To deduce the regression coefficients β, the optimization problem was solved, conferring the minimum of $F(\beta)$, noting $\min_{\beta \in \mathbb{R}^{(p+1)}} F(\beta)$. By matrix derivation of the last equation, the "normal equations" in β were obtained as

$$\frac{\partial F(\beta)}{\partial \beta} = 0$$

$$X^T Y - X^T X\, \beta = 0$$

Assuming that the matrix (XX^T) is invertible, i.e., that the matrix X is of rank $(p+1)$, explaining the absence of collinearity between its columns, the parameter estimate β_j is given by

$$\hat{\beta} = \left(XX^T \right)^{-1} X^T Y$$

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