Chatbots and Organizational Outcomes: Attitude, Usage, Management Support, and Organizational Routines

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Abstract

The rapid evolution of Artificial Intelligence (AI) and the imperative for companies to integrate it into their processes to maintain competitiveness is noteworthy. Specifically, chatbots stand out due to their increasing level of penetration. The utilization of this technology differs from previous advancements due to its implications for human interaction. Therefore, it is necessary to contribute to theoretical and empirical development with approaches that transcend particular perspectives to uncover the organizational scope and mechanisms of this technology. A theoretical model is proposed to analyze how attitudes towards chatbots and their usage affect business outcomes, with an emphasis on management support and the redesign of organizational routines. To test this model, a quantitative approach based on a survey design and the partial least squares structural equation modeling (PLS-SEM) technique is employed. Empirical evidence from a sample of 403 Spanish companies confirms a positive effect of attitudes towards chatbots, amplified by management support. Additionally, a positive relationship is observed between the use of chatbots and business outcomes, with a significant indirect effect through the redesign of routines, indicating that organizations must adapt to this disruptive technology for effective integration. It is concluded that the successful adoption of chatbots leads to improved business outcomes, and both academic and practical implications for technology management, digital transformation, and post-adoption strategy design are discussed.

Keywords

Artificial Intelligence, AI, Chatbots, Attitude Towards Usage, Management Support, Organizational Routines, Organizational Outcomes, Technology Management, Digital Transformation, PLS-SEM, Theoretical Models.

1. Introduction

New digital technologies have driven the digital transformation processes of companies and society to unprecedented levels, as well as the emergence of new business models (**Cheng; Wang**, 2022). Among these new technologies, AI has caused a true revolution, radically changing the value creation process in modern companies across various industrial markets (**Atienza-Barba *et al.***, 2024; **Leone *et al.***, 2021), contributing to the culmination of the digital transformation process (**Gong; Ribiere**, 2021).

AI is considered the next frontier of productivity due to its great capacity to transform almost all aspects of intra- and inter-organizational operations across the industry (**Fosso Wamba**, 2022). According to the consulting firm **McCartney** (2023), this technology is having an impact on society comparable to the advent of the Internet, the printing press, or even electricity, with its use having grown 270% in the last 4 years (**Zendesk**, 2023). However, a recent study from **Link and Stowasser** (2024) indicate that AI also generates negative feelings due to dependence on this technology, difficulties to control it, unreliability of technology, fear of job loss, and even work withdrawal behaviors (**Teng *et al.***, 2024). The use of AI raises concerns, particularly regarding social and ethical issues. Such concerns stem mainly from potential job displacement, level of influence on decision making processes, discrimination due to algorithmic opacity, and handling of shared data. Such concerns denote a growing need for policies, frameworks, standards, and legal guidelines to ensure transparency and trust, diminishing thus the resistance to the use of IA (**Ulrich *et al.***, 2023).

Although there is no commonly accepted definition of AI (**Duan *et al.***, 2019), it generally refers to technologies with the ability to mimic human intelligence through the use of decision trees, if-then rules, and learning algorithms. Beyond this definition, AI encompasses a wide range of other technologies, not merely imitating human intelligence but also solving problems in innovative ways. Thus, AI is applied in various contexts, such as automation, predictive analysis, and decision-making (**Ulrich *et al.***, 2023). In this sense, **Davenport** (2021) points out that the adoption of AI-based systems differs from the adoption of other types of digital technologies, as they also operate independently (**Terzopoulos; Satratzemi**, 2019).

Among these types of technologies, chatbots stand out as one of the most widespread in the business field (**Zhang *et al.***, 2023). A chatbot, or conversational robot, is a computer program that uses artificial intelligence (AI) and natural language processing (NLP) to understand customer questions and automate responses to those questions, simulating human conversation (**Mostafa; Kasamani**, 2022). Its application in the organizational field has skyrocketed recently, especially after the launch of version 4 of ChatGPT in March 2023, which, in just 7 months, had one hundred million weekly users (**Porter**, 2023). Predictions regarding the use of this technology are absolutely disruptive. According to *Gartner* (**Elliot; Rigon**, 2023), 38% of companies globally will implement conversational bots to improve customer experience and service (front office). Additionally, it is expected that, within less than five years, its use will extend not only in this context but also in employee-oriented areas (back office), document processing, conversation and voice analysis, meeting transcriptions, or to understand and analyze texts.

From a research perspective, the previous literature is scarce and does not establish a clear relationship between the application of these technologies and business outcomes, focusing instead on their impact on customer satisfaction (**Ruan; Mezei**, 2022; **Yoon; Yu**, 2022) or improving attitudes towards chatbots (**De Cicco *et al.***, 2020), given the reluctance their use generates in different areas (**Cheng *et al.***, 2022). Furthermore, the particular relationship that arises in organizations between this new technology and the personnel who will use it makes it necessary for studies to contemplate the necessary interaction between the technological and human factors to analyze the effective implementation of chatbot usage (**Al-Abrrow *et al.***, 2022; **Leonardi**, 2011). In this sense, although it seems generally accepted that attitudes towards chatbots influence their intended use (**Rese *et al.***, 2020; **Moussawi *et al.***, 2021; **Mostafa; Kasamani**, 2022), existing studies have mainly focused on particular services and sectors (see, for example, **Terblanche; Kidd**, 2022; **Melián-González *et al.***, 2021; **Kasilingam**, 2020; **Rodríguez Cardona *et al.***, 2019).

> “The particular relationship between this new technology and the personnel who will use it makes it necessary for studies to contemplate the necessary interaction between the technological and human factors”

Similarly, the adoption of a new technology by an organization inevitably depends on two factors. On one hand, formal support from the organization's management can increase the success of its implementation by more than 50% (**McCartney**, 2023); and, on the other, a redesign of organizational routines in which the human organizational factor plays a crucial role (**Leonardi**, 2011). Routines, defined as repetitive and recognizable patterns of action (**Feldman; Pentland**, 2003; **Becker**, 2005), play an important role in coordinating company activities (**Bapuji *et al.***, 2019). In this sense, if properly addressed, the redesign of routines will allow members of the organization to implement the new technology, maximizing its potential (**Bapuji *et al.***, 2019). In the case of organizational use of chatbots, the adaptation of routines is of particular interest because the nature of the relation between the technology -which in this case is autonomous- and the human factor is essentially different from the relations established with previous technologies (**Gursoy *et al.***, 2019).

Therefore, due to the novelty in the area and in line with authors such as **Zhang *et al.*** (2023), there is a knowledge gap regarding the aspects that enable organizations to adapt and benefit from AI-based chatbots, which needs to be filled with new research. Moreover, authors such as **Lin *et al.*** (2019) highlight the lack of empirical studies, noting that the difficulty of data collection hinders academic knowledge (**Pantea *et al.***, 2017; **Verhoef *et al.***, 2021; **Marchiori *et al.***, 2022). Therefore, the objective of this paper is to explore how organizations can react to the advent of chatbots, as a highly disruptive technology with fundamentally different characteristics from previous ones, and understand the role of organizational members in the process. To address this objective, covering the particular aspects discussed, we propose the following research questions:

RQ1: How do individuals' attitudes affect the organizational use of a new technology such as chatbots?
RQ2: What role does management play in aligning the organizational human factor with the adoption of chatbots?
RQ3: How can organizations adequately adapt to a highly disruptive technology such as chatbots?

We contribute to the literature on technology management by providing a study on the organizational adoption of disruptive technology and addressing the debate on the mechanisms that explain its relationship with organizational performance. To this end, a theoretical model is proposed to analyze the importance of social aspects in technology management. Additionally, we contribute to the study of the antecedents of new technology implementation, particularly considering the importance of interactions between social and technical factors, crucial for the successful adoption of new technology. The remainder of the document is structured as follows. The second section reviews the literature on the relevant concepts and analyzes their relationships, the third section describes the methods, the fourth section presents the results, and the final section discusses the results and presents the conclusions.

> The model addresses how organizations can react to the emergence of highly impactful technological innovations

> A theoretical model is proposed to analyze the importance of social aspects in technology management

2. Literature Review

Artificial Intelligence (AI) results from a set of technologies that can replace or support human decision-makers in specific issues (**Berente *et al.***, 2021). Among these technologies, chatbots stand out for their widespread use in the business realm (**Zhang *et al.***, 2023). A chatbot, or conversational robot, is a computer program that employs AI and Natural Language Processing (NLP) to understand customer queries and automate responses, simulating human conversation (**Mostafa; Kasamani**, 2022). Its application in organizational settings has surged recently, with disruptive predictions in terms of penetration rates in activities related to customer service, back-office operations, meeting management, conversational analysis, etc. (**Elliot; Rigon**, 2023).

Despite their growing popularity, the implementation of these AI tools must overcome significant hurdles, such as the need to strengthen customer attitudes toward chatbots (**De Cicco *et al.***, 2020) and, in particular, overcome the reluctance surrounding their use in various domains (**Cheng; Wang**, 2022). In this regard, although it seems generally accepted that attitudes toward chatbots influence their usage intention (**Rese *et al.***, 2020; **Moussawi *et al.***, 2021; **Mostafa; Kasamani**, 2022), studies have predominantly focused on specific services (Terblanche & Kidd, 2022), such as using a smartphone chatbot for shopping (**Kasilingam**, 2020), in the financial and insurance sectors to answer simple queries (**Rodríguez Cardona *et al.***, 2019), or in the tourism sector to organize trips (**Melián-González *et al.***, 2021).

In a general sense, the attitude of employees toward using a new technology is a user's subjective decision about it and can be positive or negative (**Na *et al.***, 2022). It has been shown that the effective level of use of a new technology depends on the user's attitude and its influence on decision-making (**Etter**, 1975; **Wang *et al.***, 2023). There are specific examples illustrating that a user's attitude toward technology implementation is a positive factor for its adoption (**Yuan *et al.***, 2019). Therefore, a positive attitude toward using a technology largely determines its organizational adoption and use. In this regard, the following hypothesis is proposed:

H1: The employee attitude towards chatbots influences its organizational use.

Despite the generalization of the massive use of AI-based technologies by organizations is only recent, various academic and professional studies show the effect of these technologies on organizational outcomes. Thus, the consultancy firm **McCartney** (2023), in a recent survey of 600 organizations, highlighted that most executives indicated that adopting these tools reduced company costs, improved customer service and retention, and helped business growth. Similarly, **Fang *et al.*** (2023) pointed out that adopting new digital technologies by companies can reduce agency costs or improve governance. Even financial markets interpret that the use of chatbots by companies positively impacts business results, as the stock value of these companies tends to increase (**Fotheringham; Wiles**, 2023).

In this sense, organizations that implement AI solutions by developing a structured approach for their adoption and use, and that can develop organizational capabilities around these new technologies, obtain positive effects (**Mikalef; Gupta**,

2021) in significant magnitudes such as financial performance, turnover, or accounting indicators. Based on these arguments, the following hypothesis is proposed:

H2: The use of chatbots positively affects organizational outcomes.

Despite the effect of a positive attitude towards a new technology for its organizational use (**Yu; Frenkel**, 2013; **Yuan *et al.***, 2019), the successful implementation of chatbots -like any other technological innovation in the business realm- also depends on the organizational structure, leadership, management support, organizational climate, and practices related to knowledge management and communication (**Singh *et al.***, 2021). Thus, management plays a crucial role in facilitating and supporting the relation between the attitude towards chatbots and their effective use in the company (**Singh *et al.***, 2021).

Firstly, just as a negative attitude towards new technology —due to factors such as resistance to change, possible lack of planning and training, or uncertainty regarding the effects of these technologies on tasks and jobs— can hinder its implementation and discourage management support (**Haddad**, 1996), a positive attitude will result in greater support from management. Thus, management is responsible for collecting and analyzing employee feedback on chatbot implementation. This bidirectional process allows continuous adjustment and improvement of technology integration in the company. By considering employees' concerns and suggestions, management can adapt strategies and policies to ensure smoother and more successful chatbot adoption, increasing, according to data from the *Gartner Inc.* report (2023), the likelihood of successful implementation by over 50%.

Thus, management support is recurrently highlighted as a determinant of AI adoption (**Alsheibani *et al.***, 2020; **Demlehner; Laumer**, 2020). AI adoption is a complex process that faces many organizational and technological challenges (**Enholm *et al.***, 2022). Therefore, management must participate in exploring AI technologies and not leave this task solely to technologists (**Alsheibani *et al.***, 2020).

For instance, it has been shown that company culture influences AI adoption, as previously mentioned, and managers play a crucial role in establishing this culture (**Lee *et al.***, 2019). Similarly, management can support AI adoption by allocating resources and providing funding (**Alsheibani *et al.***, 2020). In the same vein, **Zhang *et al.*** (2023) state that leadership and management support are fundamental for the effective application of technological innovation and for creating an organizational climate conducive to innovation. It has also been found that innovation implementation behavior improves when management induces trust and affective commitment to change (**Michaelis *et al.***, 2004).

In summary, management support is essential for establishing a positive connection between employees' attitudes towards chatbots and their effective use in the business environment. By communicating effectively, managing change, fostering innovation, and gathering feedback, leaders can facilitate a successful transition to chatbot integration, ensuring that this technology becomes a valuable tool that enhances organizational efficiency and performance. In this line, the following hypothesis is proposed:

H3: Management support mediates the relationship between the attitude towards chatbots and its organizational use.

On the other hand, despite the literature generally showing that the use of AI in operations allows organizations to achieve significant improvements in organizational, financial, market, and even sustainability outcomes (**Enholm *et al.***, 2022), this effect is not always clear. For instance, **Ransbotham *et al.*** (2018) indicate in their executive study that in seven out of ten companies, AI has not provided a significant impact on business results. **Olan *et al.*** (2022) claim that many organizations do not achieve better business results after implementing these new technologies due to the difficulty of integrating existing and new knowledge into the AI learning process. Additionally, authors like **Nucci *et al.*** (2023) or **Van Ark** (2016) go further, suggesting that distrust and reluctance towards the organization may arise, consistent with the results obtained by **Barba-Sanchez *et al.*** (2022).

In this regard, the effective utilization of a new technology inevitably depends on the human factor. This factor, in contact with the new technology, will undertake a redesign of organizational routines that will enable the implementation of the new technology by exploiting its potentialities (**Leonardi**, 2011; **Wurm *et al.***, 2021). Therefore, the human and technological factors are intertwined in a path-dependent manner, such that a change in technology is linked to the routines that preceded it and those that will follow (**Leonardi**, 2011). Properly redesigning routines results in organizational improvements (**Salvato**, 2009; **Edmondson *et al.***, 2001), representing an effective mechanism to enhance organizational performance (**Cohen; Bacdayan**, 1994; **Bapuji *et al.***, 2019).

Therefore, the implementation and use of AI will lead to improvements in organizational outcomes to the extent that the organization can undertake an adequate redesign of routines, allowing for the exploitation of this new technology's potential. Based on this argument, the fourth hypothesis is proposed:

H4: Routine redesign mediates the relationship between chatbot use and organizational outcomes.

Figure 1 represents the theoretical model and hypotheses.

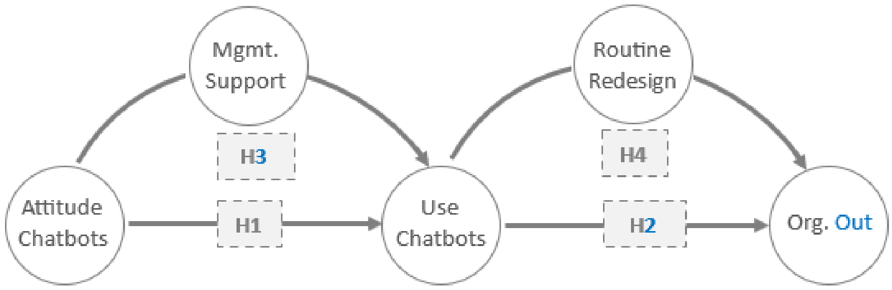

Figure 1: Theoretical Model and Hypotheses - TRA – Normalization.

3. Methods

3.1. Data Collection Techniques, Sampling, and Analysis

To examine the proposed relations, information was collected through online questionnaires targeting a sample of companies from the *Iberian Balance Sheet Analysis System* (*SABI*) database, which contains detailed information on over 2,900,000 Spanish companies and more than 900,000 Portuguese companies. In this research, the study population comprises Spanish companies in general, due to which the *SABI* database is highly useful. Contact persons listed in *SABI*, typically managers or owners, received an email invitation to participate with a link to the survey form. To comply with ethical guidelines for questionnaire surveys, an informed consent document was prepared, providing participants with necessary information about the research and adhering to current personal data protection regulations. The *Social Research Ethics Committee* (*CEIS*) of *UCLM* verified that this study was conducted in accordance with ethical standards developed for social research (CEIS-736484-C4B5).

To ensure the quality of the responses, recommendations from **Dillman**'s (1991) Total Design Method (TDM) were followed during the final questionnaire design process. Initially, a Teams meeting was held with 5 academic experts and 10 managers from various sectors to assess the questionnaire's appropriateness. Based on their suggestions, the questionnaire was modified and pre-tested with 10 different companies, whose managers had previously participated, to ensure all questions were clearly understood in this new version. Following their feedback, the final version of the questionnaire was drafted.

Furthermore, before the final launch, the minimum required sample size to confirm the validity of this model was calculated (**Hair Jr. *et al.***, 2021). The inverse square root method proposed by **Kock and Hadaya** (2018) was chosen because it is conservative and overestimates the necessary sample size for an effect to be significant at a given power level. This method considers the likelihood that the ratio of a path coefficient and its standard error will exceed the critical value of a statistical test for a specific significance level. In this case, the minimum path coefficient ranges between 0.11 and 0.20, requiring a minimum sample size of 155 observations to achieve a 5% significance level with 80% statistical power (**Hair Jr. *et al.***, 2021). To reach the minimum sample size, invitations to complete the online survey were sent to 1,550 companies. These companies were selected following a simple random sampling technique. A total of 417 questionnaires were collected during the 15 days the survey was open on the MS Forms platform (from June 13 to June 28, 2023), yielding a response rate of 26.90%.

Once the data were obtained, and to ensure their quality before analysis, the dataset was filtered by examining missing data both for observations and each indicator, as well as for any inconsistent response patterns or outliers. Missing data did not exceed 15% of the responses for any observation nor 5% for any indicator, so no observation or indicator was eliminated for this reason. Regarding inconsistent response patterns, such as straight-line or zigzag patterns, or outliers, 14 suspicious observations were identified and removed, in order to diminish result biases. Consequently, 403 valid observations were obtained, exceeding the minimum sample size established by the inverse square root method. As detailed in the post hoc power analysis Table 1, our sample size also significantly exceeds the minimum sample requirements for each path relationship between the constructs in the model, with the highest minimum sample requirement being 371 observations (between Attitude toward Chatbots and Use of Chatbots) for the most stringent 1% significance level and 90% statistical power.

Table 1: Minimum Sample Size for each Path between Two Constructs (post-hoc power analysis).

Relationship between Construct	Path coefficient	Alpha 1% Power 80%	Alpha 5% Power 80%	Alpha 1% Power 90%	Alpha 5% Power 90%
Chatbot Attitude → Support Direction	0.701	21	13	27	18
Chatbot Attitude → Chatbot Use	0.187	287	177	371	245
Management Support → Chatbot Use	0.580	30	19	39	26
Routines → Results	0.478	45	28	58	38
Chatbot Use → Results	0.301	111	69	144	95
Chatbot Use → Routines	0.705	21	13	27	18

Regarding the representativeness of the sample relative to the study population, a mean differences test was conducted using an ANOVA analysis of the data related to company size, primary activity, and location. The results indicate no significant differences for these variables between the population and the sample. Therefore, the sample is predominantly composed of microenterprises (fewer than 10 employees), with over 70% having fewer than 10 employees (see Table 2). This distribution aligns with that of the population. However, microenterprises are slightly underrepresented in the sample, likely due to their lower response rate.

Table 2: Company Size.

Number of Employees	Sample		Population (*SABI*)	
	Nº	%	Nº	%
No employees	87	21.5880	306,397	26.5049
1-9	208	51.6129	622,166	53.8205
10-49	94	23.3251	191,780	16.5899
50-249	12	2.9776	30,082	2.6022
≥250 employees	2	0.4962	5,577	0.4824
Total	403	100,0000	1,156.002	100,0000

Source: *SABI* database (1)
(1) The population in *SABI* corresponds to Spanish companies that provided information on the number of employees.

To test the hypotheses and analyze direct and mediating effects, the partial least squares technique of structural equation modeling (PLS-SEM) was applied. This method was chosen for the following reasons: a) it is one of the best options in the early stages of new theory development (**Hair Jr *et al.***, 2014); b) it allows for the analysis of different causal relationships, both confirmatory and explanatory (**Guenther *et al.***, 2023), as is the case in our study; c) it is a valid method when the sample size is small (**Henseler *et al.***, 2016); and d) it is appropriate for models that analyze complex relationships with numerous indicators and mediating relationships (**Nitzl *et al.***, 2016), which applies to our case. Specifically, we used the Smart PLS 4.1 software (**Ringle *et al.***, 2022), which is based on an iterative algorithm to obtain the weights used to construct linear combinations of the observed indicators as proxies for all the constructs in the model. The procedure involves two steps: the measurement model evaluates the reliability and validity of the theoretical constructs, and the structural model is estimated to examine the hypothesized paths in the research model (**Hair Jr *et al.***, 2014).

3.2. Measures

To measure the variables included in the study, scales previously validated in the literature were utilized. All items, listed in Appendix I, were measured using 5-point Likert scales, where 1 indicates "strongly disagree" and 5 "strongly agree."

Attitude towards Chatbots (AC). This variable was measured using a four-item scale adapted from the Attitude towards Technology Use scale in the UTAUT model proposed by **Venkatesh *et al.*** (2003), which itself was adapted from **Davis**'s (1989) concept of Attitude towards a Specific Behavior. The attitude towards technology use is defined as an individual's overall affective reaction to using a system (**Venkatesh *et al.***, 2003), in this case, chatbots.

Managerial Support for Chatbot Use (MS). This variable was measured using a four-item scale adapted from the Managerial Support scale by **Lin** (2010), which in turn was adapted from **Premkumar and Ramamurthy** (1995).

Chatbot Use (CU). This variable was measured using a three-item scale adapted from **Singh *et al.*** (2021), which itself was adapted from the original digital transformation scale by **Aral and Weill** (2007).

Redesign of Organizational Routines Resulting from Chatbot Use (RR). This variable was operationalized as a multidimensional construct comprising four dimensions, following **Pluye *et al.*** (2004), who adapted it from **Goodman *et al.*** (1993): memory (4 items), adaptation (3 items), values (4 items), and norms (4 items). This variable was included in the model as a second-order construct.

Organizational Outcomes (OrgO). To measure this variable, we adapted a scale from **Lee *et al.*** (2011), dividing it into two dimensions, each comprising four items: financial performance and non-financial performance. This variable was included in the model as a second-order construct.

Finally, gender and industry were included as control variables. The reason is that gender is an interesting variable to consider in technology-related research (**Fėlix; David**, 2019), while industry is essential to control for environmental factors unique to each sector (**Dess; Beard**, 1984).

3.3. Endogeneity Analysis

Before analyzing the validity of the theoretical model, it is essential to assess the presence of endogeneity in the model to identify potential omitted variables (**Becker *et al.***, 2022; **Hult *et al.***, 2018). According to **Park and Gupta** (2012), the issue of endogeneity can be addressed using the Gaussian Copulas approach, which we will employ following the procedure for PLS-SEM outlined by **Hult *et al.*** (2018).

First, we verified that the independent variables are not normally distributed by conducting the Cramer-von Mises test on the standardized composite scores of the dependent variables. Table 3 shows that the p-value is less than 0.05 for all variables, indicating that these variables do not follow a normal distribution.

Table 3: Cramer-von Mises Test.

Construct	Cramer-von Mises Test	Cramer-von Mises *p* value
Attitude towards Chatbots	0.335	0.000
Management Support	0.319	0.000
Routine Redesign	2.995	0.000
Outcomes	2.147	0.000
Sector	4.563	0.000
Gender	1.142	0.000
Chatbot Use	0.620	0.000

The next step is to perform the Gaussian Copula analysis by adding a copula for each relationship of the final dependent variable and calculating the significance of these copulas using the standard Bootstrap method. According to Table 4, the results indicate that none of the copulas introduced in our model are significant, suggesting that endogeneity is not a concern for the estimation of the established relationships.

Table 4: Minimum Sample Size for each Path between Two Constructs.

Gaussian Copula	Estimates	Mean	Standard Deviaion	t-Value	*p*-Value
CG (Routines) → Results	0.153	0.148	0.165	0.925	0.355
CG (Chatbot Use) → Outcomes	-0.158	-0.137	0.245	0.647	0.517
Management Support→ Chatbot Use	-0.003	-0.005	0.063	0.053	0.958

4. Results

In order to test the hypotheses proposed in the theoretical model using SmartPLS, the analysis was divided into three phases, following **Henseler *et al.*** (2016): firstly, evaluating the overall model fit; secondly, analyzing the measurement model through convergent and discriminant validity, as well as construct reliability; and finally, assessing the structural model to examine the proposed relationships in our model.

4.1. Evaluation of Model Fit

Regarding the evaluation of model fit, as shown in Table 5, our model achieved an SRMR of 0.058 for the saturated model, below the established threshold of 0.08 (**Hu; Bentler**, 1998), and an NFI between 0.8 and 0.9 (**Mulaik *et al.***, 1989), with a value of 0.872. Thus, we can consider the model to have good fit because the theoretical and empirical correlation matrices are sufficiently similar.

Table 5: Fit Indices.

Indicator	Saturated Model	Estimated Model
SRMR	0.058	0.058
d_ULS	0.520	0.520
d_G	0.348	0.348
Chi-cuadrado	861.653	861.653
NFI	0.872	0.872

4.2. Measurement Model Analysis

Given that the model consists of two second-order constructs, routines and outcomes, the evaluation begins with the assessment of first-order constructs. To evaluate the measurement model of these constructs, first, the individual reliability of items was assessed through analysis of correlation loadings, which should exceed 0.708 (**Hair Jr. *et al.***, 2021). This criterion is met by all items across all constructs (see Figure 2). Subsequently, the reliability and validity of the model's construct indicators were analyzed. Table 6 presents the indicators assessing internal consistency and convergent validity of these constructs, indicating a good measurement model (Cronbach's Alpha, Rho_A, CR > 0.7 and AVE > 0.5).

Table 6: Reliability and Convergent Validity Estimators of Model Constructs.

Construct	Cronbach's Alpha	Rho_A Dijkstrqa-Henseler	Composite relialbility (CR)	Average Variant Extracted (AVE)
Attitude towards Chatbot (AC)	0.921	0.929	0.944	0.808
Management Support (MS)	0.891	0.896	0.925	0.755
Chatbot Use (CU)	0.904	0.909	0.940	0.836
Memory Routines (MR)	0.912	0.912	0.938	0.790
Adaptation Routines (AR)	0.759	0.861	0.861	0.683
Values Routines (VR)	0.888	0.892	0.922	0.748
Norms Routines (NR)	0.935	0.938	0.953	0.836
Financial Results (FR)	0.916	0.916	0.941	0.799
Non-Financial Results (NFR)	0.941	0.942	0.958	0.851

Finally, for reflective constructs, discriminant validity was evaluated. Table 7 presents **Fornell** and **Larcker's** (1981) criterion, where the square root of the AVE of each construct exceeds the correlation between both constructs in the model. Additionally, the HTMT ratio is less than 0.9 (**Henseler *et al.***, 2016). Based on both criteria, we can affirm that the constructs represent distinct concepts, demonstrating their discriminant validity.

Table 7: Discriminant Validity of Model Constructs (Reflective constructs, Model A) based on Fornell-Larcker and HTMT.

Construct	AC	AD	UC	RM	RA	RV	RN	RF	RNF	Gen	Sect
AC	**0.899**	*0.765*	*0.634*	*0.562*	*0.666*	*0.564*	*0.441*	*0.482*	*0.550*	*0.069*	*0.079*
MS	0.701	**0.869**	*0.780*	*0.762*	*0.771*	*0.762*	*0.637*	*0.679*	*0.651*	*0.141*	*0.026*
CU	0.583	0.702	**0.916**	*0.750*	*0.742*	*0.744*	*0.644*	*0.677*	*0.672*	*0.024*	*0.069*
MR	0.518	0.683	0.684	**0.889**	*0.891*	*0.801*	*0.878*	*0.715*	*0.671*	*0.027*	*0.026*
AR	0.566	0.660	0.635	0.784	**0.826**	*0.838*	*0.775*	*0.682*	*0.661*	*0.058*	*0.025*
VR	0.519	0.683	0.675	0.812	0.807	**0.865**	*0.846*	*0.742*	*0.687*	*0.042*	*0.071*
NR	0.411	0.578	0.595	0.812	0.697	0.858	**0.914**	*0.660*	*0.581*	*0.025*	*0.049*
FR	0.448	0.585	0.618	0.655	0.597	0.672	0.613	**0.894**	*0.896*	*0.037*	*0.032*
NFR	0.517	0.597	0.622	0.623	0.586	0.546	0.632	0.889	**0.923**	0.041	*0.018*
Gender	-0.069	-0.133	-0.015	-0.027	-0.043	-0.041	0.009	-0.027	-0.040	**1.000**	0.076
Sector	-0.076	-0.003	0.065	0.018	0.024	0.056	0.046	0.024	0.017	0.076	**1.000**

The diagonal elements (in bold) are the square root of the shared variance between constructs and their measures (AVE). The value below the diagonal is the correlation between both constructs (Fornell-Larcker). The value above the diagonal is the HTMT ratio.

4.3. Structural Model

After confirming that the measurement models of the constructs exhibit satisfactory levels of quality in terms of reliability and validity, we proceed to analyze the proposed structural model. Following **Benitez *et al.*** (2020), we first rule out the presence of collinearity in the structural model, as all VIF values are below 3 (**Hair *et al.***, 2019), with the highest being 2.006 between AD and UC. Subsequently, we analyze the significance of path coefficients (see Table 11), using the bootstrap procedure (10,000 subsamples) based on percentiles of the confidence interval (**Aguirre-Urreta; Rönkkö**, 2018). The results indicate that AC (H1: β=0.187; p<0.001) significantly and positively influences UC in the business context, and UC (H3: β=0.302; p<0.001) in turn significantly influences business outcomes. Furthermore, although not hypothesized, a relevant indirect effect of AC on business outcomes through UC is observed (β=0.379; p<0.001).

Regarding the control variables, gender and sector both positively and significantly influence UC (β=-0.070; p<0.05 and β=-0.075; p<0.05, respectively), indicating that chatbot usage is more prevalent among men and in service-oriented companies, focusing on conversational language models to enhance customer relations or generating original and relevant content tailored for different purposes, audiences, channels, and languages. In the IT sector, chatbots are commonly used for scripting and code analysis. However, gender does not have a positive and significant influence on AC (β=-0.069; p>0.1). Moreover, sector does not positively and significantly influence business outcomes (β=-0.017; p>0.1), suggesting that the relationship between chatbot usage and business outcomes is not moderated by sector.

Finally, the model explains 51.9% of the variance in the endogenous construct (Business Outcomes), indicating moderate predictive power (**Hair *et al.***, 2011). Additionally, examining Table 8 for the individual contributions of each variable through effect sizes (f^2), notable effects include AC on management support (f^2 = 0.965) and UC on organizational routine redesign (f^2 = 0.988), both well above **Cohen**'s (1988) threshold of 0.35 for considering them large. Moreover, AD on UC exhibits an effect close to this threshold (f^2 = 0.349), thus also considered substantial, while the effect of Routines on Business Outcomes (f^2 = 0.237) is moderate, falling between 0.15 and 0.35, and the effects of AC on UC (f^2 = 0.037) and UC on outcomes (f^2 = 0.095) are small, indicating values below 0.15. The reason why the hypothesized relationships are small might lie in the presence of other mediating variables that enhance this relationship, as discussed below.

Table 8: Effects of Endogenous Constructs.

Construct	Direct effect[1]	*t*-Value[2]	*p* Value[2]	Confidence Interval (CI)	f^2
Organizational Outcomes (R^2 = 0.519)					
H2: UC	0.301	5.518	0.000	[0.194; 0.408]	0.095
Routines	0.478	7.918	0.000	[0.355; 0.589]	0.237
Sector	-0.017	0.513	0.608	[-0.081; 0.047]	0.001
Organizational Routine Redesign (R^2 = 0.497					
UC	0.705	28.372	0.000	[0.654; 0.751]	0.988
Uso de Chatbots (R^2 = 0.520					
H1:AC	0.187	3.618	0.000	[0.085; 0.288]	0.037
AD	0.580	12.111	0.000	[0.484; 0.672]	0.349
Gender	0.070	2.002	0.045	[0.003; 0.138]	0.010
Sector	0.075	2.062	0.039	[0.004; 0.148]	0.012
Management Support (R^2 = 0.491)					
AC	0.701	28.004	0.000	[0.650; 0.748]	0.965
Attitude Towards Chatbots (R^2 = 0.005)					
Gender	-0.069	1.381	0.167	[-0.166; 0.029]	0.005

[1] Path Paths based on hypothesized effects evaluated using two-tailed t-test at 5% significance level [2.5%, 97.5%].
[2] Bootstrapping based on n = 10,000 bootstrap samples.

Furthermore, to test the mediation hypotheses, indirect effects were analyzed (**Nitzl *et al.***, 2016). As shown in Table 9, the total effect of AC on UC is greater than the direct effect, yet equally significant (β=0.594; p<0.001 and β=0.187; p<0.001, respectively), suggesting a significant mediation effect of AD, with a substantial indirect effect (β=0.407; p<0.001), accounting for nearly 70% (VAF=68.52%). This result indicates that management support is a key variable in converting attitudes toward chatbots into effective use, supporting hypothesis 3. Additionally, regarding the mediation effect between UC and organizational outcomes, a significant total effect higher than the direct effect is observed as well (β=0.638; p<0.001 and β=0.301; p<0.001, respectively), indicating a relevant and significant indirect effect (β=0.337; p<0.001). This conclusion is further supported using the VAF index, determining the size of the indirect effect in relation to the total effect. Specifically, more than 50% of the total effect of UC on business outcomes is through the mediation of routines, confirming hypothesis 4.

Table 9: Summary of Mediation Effects.

Hypothesis	Total effects (*p* Value)[2]	Direct effects[1] (*p* Value)[2]	Indirect Effects		
			Path[1] (*p* Value)[2]	Percentile confidence interval[2]	VAF (%)
H3: AC→AD→UC	0.594 (0.000)	0.187 (0.000)	0.407 (0.000)	[0.523, 0.659]	68.52
H4: UC→Routines→Organizational Outcomes	0.638 (0.000)	0.301 (0.000)	0.337 (0.000)	[0.566; 0.703]	52.28

[1] Hypotheses tested using two-tailed t-test at 5% significance level [2.5%, 97.5%].
[2] Bootstrapping based on n = 10.000 bootstrap samples.

In summary, all proposed hypotheses are supported. Figure 2 displays the path coefficients of the structural model as a whole.

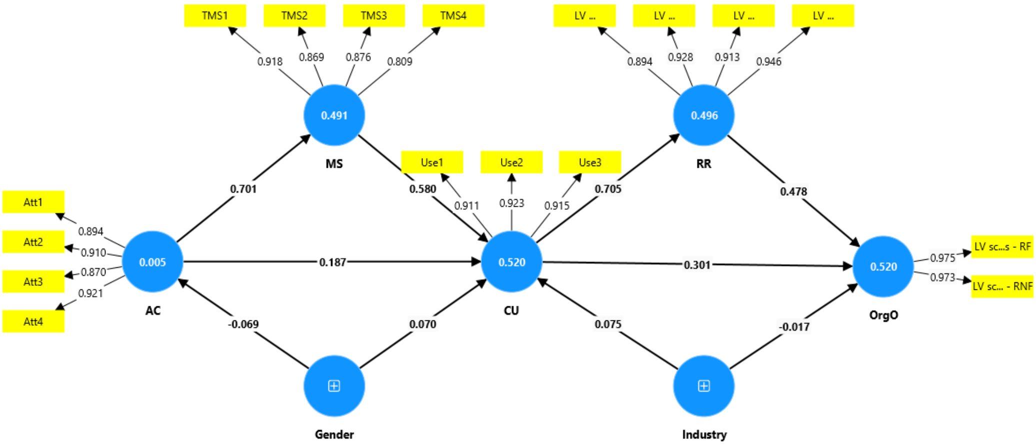

Figure 2: Structural Model Results.

5. Discussion and Conclusion

This research makes a pioneering contribution to the current literature on the key variables in the process of integrating chatbots into the business domain, addressing recent demands for a deeper understanding of the mechanisms of integrating new AI technologies (**Fosso Wamba**, 2022). To timely respond to this need, adequately addressing how to effectively integrate chatbots into organizations and their contribution to business outcomes, a theoretical model associated with the redesign of organizational routines and their intrinsic characteristics is proposed. The model encapsulates the challenges any innovation must face to successfully complete its implementation, effective integration, and maintenance process, i.e., normalization, considering the necessary interaction between the human factor and the new technology.

Thus, the model addresses the proposed objective regarding how organizations can react to the emergence of highly impactful technological innovations, such as chatbots, surpassing the dominant approach focused on the intention to use these new technologies. In this sense, the main contribution of this work is to enhance the understanding of the relationship between the attitude towards chatbots, their effective use, and organizational outcomes. The findings confirm that organizational outcomes, both financial and non-financial, improve due to the use of chatbots. Concerning the research questions, it is confirmed that a positive attitude towards chatbots, supported by management, encourages their effective use. Regarding how organizations can adapt to highly

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disruptive technology like chatbots, the study indicates that the generation of routines and the redesign of existing ones play a key role in realizing the potential of chatbots. Consequently, in line with **Pluye *et al.*** (2004), attention should be focused on how to memorize the processes of adoption and use of chatbots in organizations, adapting them to each context and situation to respect shared values and rules in each case. Thus, these results help organizations enrich their understanding of the mechanisms by which the potential of chatbots, described in the literature, translates into organizational outcomes. The main theoretical and practical implications are presented below.

5.1. Theoretical and Practical Implications

Two main theoretical implications are derived. This research enriches the understanding of business outcomes related to the use of chatbots in the business domain in general, as opposed to the dominant approach that is limited to the intention to adopt chatbots, ignoring the consequences of their use (see, for example, **Yoon; Yu**, 2022; **Mostafa; Kasamani**, 2022; **De Cicco *et al.***, 2020; **Rese *et al.***, 2020). Consequently, it broadens perceptions about the relationship between usage, organizational routines, and organizational outcomes. Nevertheless, the work also provides new evidence on the formation of the intention to use chatbots, supporting the argument that a positive attitude towards the use of chatbots results in greater usage, but identifying that with managerial support, this effect is enhanced, optimizing the use of chatbots. Therefore, this study is one of the first to illuminate the role of AI-based chatbots in business outcomes, both financial and non-financial.

Regarding practical implications for professionals and management, this new technology can adequately support the digital transformation process and improve business outcomes, making it advisable to consider it and analyze the attitude of both organizational members and management towards this technology, as both factors facilitate its efficient use. Furthermore, the human factor plays a crucial role in enabling the organization to translate the use of this new technology into results, through the adaptation of organizational routines, which encompass the knowledge of the human factor about technology and organizational processes. Hence, the success of implementing new technology largely depends on the human factor and its integration with technology. Management can develop mechanisms to support the appropriate redesign of routines according to the organizational and personal objectives and interests of the members of the organization.

> This new technology (chatbots) can adequately support the digital transformation process and improve business outcomes

> The success of implementing new technology largely depends on the human factor and its integration with technology

5.2. Limitations and Future Research

Several limitations can be identified in this study, which need to be highlighted as they could affect the generalizability of the results obtained. First, the sample used to test our model, while representative of the analyzed population, Spanish companies, may lead to limited generalization of the findings to other countries with different business ecosystem. Additionally, possible sectoral differences were not considered, an issue that seems not to affect the results given that this control variable does not have a significant effect on them, but it does on the use of chatbots. Therefore, future studies should employ a multi-country sample, also discriminating by various sectors and firm size to increase generalizability and offer more significant contributions. Second, chatbot usage was captured as an essential behavioral outcome in our study, but the involved individuals may adopt other post-adoption behaviors, such as recommendation or rejection (**Jenneboer *et al.***, 2022). Therefore, the intention to continue using chatbots can be addressed in future studies to gain a deeper understanding of sustained user behaviors towards chatbots in the business domain, in this sense, the use of mixed methods can be useful. Third, this is a cross-sectional study that, although allowing us to delve into the proposed relationships, does not permit the analysis of the sustainability of these relationships over time. Moreover, the measurement of variables was done subjectively, through a self-administered questionnaire by the participants themselves, which, despite using validated scales, could introduce a bias in the research. In this sense, future research could use objective data for the measurement of financial outcomes, obtained, for example, from secondary data sources such as the *SABI* database. Another limitation of the study is the lack of consideration of contextual factors in the successful adoption of this technology (**Nguyen *et al.***, 2022). Thus, a future line of research would imply analysis the impact of environmental factors on the mediating role of managerial support on the relation between the attitude towards the use of chatbots and the success or failure of their adoption. Finally, our findings show that gender has significant effects on the use of chatbots, so a future research line could analyze whether this variable presents moderation effects between attitude and use, and even on the antecedents of the attitude itself.

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Annex 1: Survey Items.

Attitude toward chatbots (AC)	
Adapted from ***Venkatesh et al.*** *(2003)*	
Att1	Using the system is a bad/good idea.
Att2	The system makes work more interesting.
Att3	Working with the system is fun.
Att4	I like working with the system
Top management support (MS)	
Adapted from ***Lin*** *(2010)*	
TMS1	Top management is highly interested in using ERP.
TMS2	Top management believes the cost of ERP is a long-term investment.
TMS3	Top management is aware of the benefits ERP for future success of firm.
TMS4	Top management has allocated adequate financial and other resources for the development and operation of ERP.
Chatbot use (CU)	
Adapted from ***Singh et al.*** *(2021)*	
DT1	The new business processes built on technologies such as big data, analytics, cloud, mobile and social media platform
DT2	The digital technologies such as social media, big data, analytics, cloud and mobile technologies are integrated to drive change
DT3	The business operations are shifting toward making use of digital technologies such as big data, analytics, cloud, mobile and social media platform.
Routine redisign (RR)	
Adapted from ***Pluye et al.*** *(2004)*	
Memory	
RRM1	Does the formal budget include the financial resources necessary to employ key personnel with permanent funding?
RRM2	Are there human resources in place in the form of permanent positions, either managerial or otherwise?
RRM3	Are there material resources such as permanent office space or tools required for the activities?
RRM4	How much time is committed to the activities, and is it on a permanent basis?
Adaptation	
RRA1	Are the activities adapted to the local context?
RRA2	Are the activities adapted to their estimated effects, for example, are they adapted to annual activity reports or to assessment results?
RRA3	Are the activities carried over from one year to the next because they were enjoyed and in spite of uncertainty concerning their continued relevance?
Values	
RRV1	Do the activities correspond to written objectives?
RRV2	Are symbols such as logos attached to the activities?
RRV3	Are there established rituals, such as periodic meetings, related to the activities?
RRV4	Has a specific language, like jargon, been developed in relation to the activities?
Rules	
RRN1	Is a supervisor formally assigned to the activities?
RRN2	Are the activities included in a formal planning process?
RRN3	Are specific activities covered by task descriptions?
RRN4	Are there activities that are subject to written rules, such as procedural manual?
Organizational Outcomes (OrgO)	
Adapted from ***Lee et al.*** *(2011)*	
Financial performance	
RF1	Sales growth
RF2	Production costs saving
RF3	Process improvement
RF4	Market share extension
Non-financial performence	
RNF1	Customer satisfaction improvement
RNF2	Corporate image improvement
RNF3	Brand value improvement
RNF4	Employee capacity improvement