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AI in Marketing Management: Executive Perspectives from Companies

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Abstract: The integration of artificial intelligence (AI) in marketing and business communication is transforming corporate strategies, offering significant opportunities while presenting notable challenges. This study examines the factors influencing AI adoption by companies, focusing on the perspectives of CEOs. Using a survey of 409 senior executives from Spanish firms, this research develops an advanced framework based on the unified theory of acceptance and use of technology (UTAUT), enriched with additional constructs. The findings reveal that effort expectancy and facilitating conditions are critical drivers of AI adoption. AI aversion**,** reflecting concerns about distrust, complexity, and ethical risks, emerges as a significant barrier, particularly for CEOs of smaller firms, where its impact is notably stronger. Relative advantage and perceived value also influence adoption intentions, albeit to a lesser degree, indicating the perceived benefits and tangible outcomes of AI in improving processes such as segmentation, automation, and predictive analytics. Key differences arise between companies of varying revenue sizes: smaller firms exhibit greater aversion to AI, whereas larger organisations focus on maximizing their strategic benefits to drive innovation. These insights highlight the importance of tailored approaches, such as financial incentives, pilot programs, and targeted training, to reduce aversion and encourage adoption across diverse organizational contexts. This study contributes to the academic discourse by extending the UTAUT framework to address emerging challenges in AI adoption. Practically, it provides actionable strategies for business leaders to address human-centric and technological barriers, fostering a more efficient and data-driven marketing process. By offering a comprehensive understanding of the enablers and barriers to AI adoption, this research equips companies to harness AI's full potential, enhancing their competitive advantage in an increasingly digital landscape.

Keywords: artificial intelligence; marketing; business communication; AI adoption; emerging technologies.

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1. Introduction. The incorporation of artificial intelligence (AI) in the field of communication and marketing is rapidly gaining popularity (Huang & Rust, 2022). AI enables improved customer insights, market segmentation, and advertising strategies, improving user retention and lead conversion and thus enhancing efficiency in business communication (Haleem et al., 2022; Hermann, 2021; Nesterenko & Olefirenko, 2023). Furthermore, according to Huang & Rust (2021), one of the most transformative qualities of contemporary AI lies in its ability to personalize through automated analysis of large volumes of data, allowing companies to tailor both content and communication channels effectively, thereby optimizing the buying process and improving the customer experience. (Hannig & Seebacher, 2023; Huang & Rust, 2022). Along these lines, consumers perceive that a company developing AI strategies can attract more customers, creating a mutually beneficial relationship between the consumer and the company (Wu & Monfort, 2023).

Machine learning and related technologies, such as facial recognition and computer vision, are offering marketers new opportunities to extract valuable data without the need for explicit programming (Jain et al., 2022; Susilo et al., 2023; Yang et al., 2021). These technologies make it possible to create more detailed and personalized customer profiles and deliver highly specialized user experiences that can improve customer retention and increase sales (Wu & Monfort, 2023).

Organizations operating with AI in their marketing areas and digital platforms are also benefiting from this new technology, with the ability to target advertising more effectively and evaluate user information to optimize digital marketing strategies (Hermann, 2021; Hopkins, 2022; Nazir et al., 2023). Chatbots and other forms of conversational AI improve interaction with customers, enabling smoother and more efficient communication (Alt, 2020; Huang & Rust, 2021; Pereira et al., 2023).

However, despite its many advantages, the dilemmas posed by the massive implementation of AI cannot be ignored, emphasizing the need to address these issues with caution (Galaz et al., 2021; Getchell et al., 2022). In this context, important challenges, such as ethical dilemmas and their impact on changing work roles, emerge. Research such as that conducted by Davenport et al. (2020) and Rai (2020) emphasizes ethical dilemmas, especially those related to privacy and bias in data analysis. Other authors (Cardon et al., 2023; Shaik, 2023), while highlighting that many corporate technology leaders promote the transformative and positive nature of these tools, focus on the potential negative impacts of AI. Specifically, they mention the loss of critical thinking and creativity, the authenticity and credibility of outputs generated by AI, and the difficulty in understanding the decisions made by AI. In addition, we cannot ignore that the increase in consumption, driven by the personalization and optimization of marketing strategies through AI, may increase the purchase of products and negatively affect the environment (Dhar, 2020).

On the other hand, concerns about how AI affects jobs in the future are increasing (Nazareno & Schiff, 2021). According to some experts, the increasing adoption of AI is likely to lead to the loss of many jobs and a shift in job roles (Lowrey, 2023). In this context, companies are already beginning to use generative AI technologies (Banh & Strobel, 2023), such as ChatGPT, instead of human employees (Williams, 2023). This highlights the importance of addressing these challenges to ensure that the use of AI is ethical and beneficial to both businesses and consumers (Huang & Rust, 2022).

Despite the significant advantages and ongoing discussions surrounding AI, there is a noticeable gap in current research specifically focused on the practical implementation of AI within the marketing and corporate communication sectors. Although there is an abundance of research and debate, a significant gap remains in the implementation of AI in the area of marketing and corporate communication (Shaik, 2023; Trofymenko et al., 2023). Recent studies, such as Maldonado-Canca et al. (2024), emphasize the dual nature of AI's impact, highlighting its benefits in optimizing digital strategies while also addressing challenges such as algorithmic bias and the need for transparency. This research seeks to fill this gap by examining both the barriers and enablers that drive the intent to effectively use this new technology in such strategies, aiming to strengthen the competitive market position of companies. By addressing this gap, this study aims to provide a comprehensive understanding of the factors that facilitate or hinder AI adoption, thereby offering actionable insights for practitioners and contributing to the academic discourse on AI implementation in business contexts.

2. Literature Review. The progressive penetration of AI in various domains, including the fields of corporate communication and marketing, necessitates a meticulous exploration of the elements influencing its adoption (Nesterenko & Olefirenko, 2023). To address this exploration, a new model inspired by UTAUT (Venkatesh et al., 2003) is proposed. This model is taken as a reference owing to its robustness and validity for understanding technological acceptance, which has been corroborated in various cultural contexts (Lin et al., 2022). The relevance of this model is particularly noteworthy for analysing emerging technologies, as it highlights its adaptability to various forms of technological innovation (Venkatesh, 2022), a crucial factor in the globalized and multifaceted environment of AI implementation.

However, despite the proven effectiveness of the UTAUT and previous models, such as the TAM, these have been criticized for not considering social and organizational contextual factors in the adoption of advanced technologies such as AI (Khan et al., 2022). The UTAUT model has been validated and applied in numerous studies within business contexts, demonstrating its versatility and relevance for understanding technology adoption in organizations (Chatterjee et al., 2021; Hasija & Esper, 2022; Iyer & Bright, 2024). To address these limitations, our model incorporates four additional factors highlighted in previous research on new technology adoption. These factors are Organizational Compatibility (AlSheibani et al., 2020; Chatterjee et al., 2021), Perceived Value (Kleijnen et al., 2007; Sweeney & Soutar, 2001), Relative Advantage (AlSheibani et al., 2020; Oliveira et al., 2014) and AI Aversion (Chow et al., 2023; Huang & Rust, 2018).

Likewise, the inclusion of these new factors becomes imperative since, despite the multiple AI techniques and their inherent characteristics and differences compared with conventional systems (Nascimento et al., 2018), AI adoption is still not fully understood (Cabrera-Sánchez et al., 2021). This scenario, as demonstrated in this research, has prompted the scientific community to seek extensions of UTAUT that consider other crucial factors (Lin et al., 2022). In summary, the proposed eight-factor model is grounded not only in a solid empirical research base (Kim, 2023; Lin et al., 2022; Venkatesh, 2022) but also in addressing the specific challenges and opportunities related to AI adoption intentions in the communication and marketing areas of companies.

2.1 Behavioural Intention (BI)

Behavioural intention, as defined by Venkatesh et al. (2003), is fundamental to understanding the predisposition of entrepreneurs toward the adoption of AI in their internal or productive processes. According to Kim (2023), it is identified as a primary indicator of the use of new technologies. Furthermore, researchers such as Jameel et al. (2023) and Kim (2023) suggest that although behavioural intention provides valuable information, it does not by itself ensure effective AI adoption because of the influence of contextual and operational factors. Furthermore, Vlacic et al. (2021) highlight the importance of understanding these intentions to prevent and overcome obstacles in the AI adoption process. In line with the above, Upadhyay et al. (2022) argue that focusing their study on such a variable to gain an initial and strategic understanding of AI adoption is key. This is precisely the purpose of the present work.

2.2 Performance Expectancy (PE)

Performance expectancy is defined as the belief that the use of a technological system will improve job performance (Emon et al., 2023; Venkatesh et al., 2003). This factor has been shown to significantly predict the intention to adopt different innovative technologies, such as AI (Gansser & Reich, 2021; Mogaji et al., 2020). Within the context of AI implementation in communication and marketing processes in companies, it is reasonable to anticipate that the expectation of concrete benefits will drive its adoption. AI can provide advanced analytical tools to optimize marketing strategies and improve advertising campaigns (Vlacic et al., 2021). Specifically, the use of AI to refine marketing tactics is associated with improvements in efficiency, content personalization, and customer satisfaction (Mogaji et al., 2022). The dominant perception among marketers of AI as an enhancement of their strategies positively influences their willingness to incorporate it (Mogaji et al., 2022).

In recent studies, the expectation that AI will optimize marketing and communication activities has been significantly related to the intention to adopt it among managers (Jameel et al., 2023) and digital entrepreneurs (Upadhyay et al., 2022). Specifically, they perceive it as a tool to improve marketing decision making and advertising campaign performance (Jameel et al., 2023). Taking this strong evidence as a starting point, the following hypothesis is proposed:

H1: Performance expectancy positively influences the intention to adopt AI in the communication and marketing processes of companies.

2.3 Effort expectancy (EE)

Effort expectancy is defined as the perceived ease of use of a system (Venkatesh et al., 2003). This construct has been shown to significantly predict the adoption of different technologies (Chatterjee et al., 2021; Emon et al., 2023). The expectation that AI will be simple to use has been consistently associated with a greater intention to adopt it in organizational contexts (Jameel et al., 2023; Upadhyay et al., 2022). In particular, digital entrepreneurs tend to prefer tools that involve minimal effort to complete their projects and activities (Upadhyay et al., 2022) while also improving overall marketing performance (Vlacic et al., 2021).

When AI is perceived to be easy to use, its acceptance ultimately increases (Lin et al., 2022). On the basis of previous studies, the following hypothesis is proposed:

H2: Effort expectancy positively affects the intention to adopt AI in the communication and marketing processes of companies.

2.4 Social influence (SI)

Social influence is defined as pressure from important people to use a system (Venkatesh et al., 2003). This contextual factor has been shown to affect the adoption of technological innovations such as AI (Dwivedi et al., 2019; Upadhyay et al., 2022). When implementing AI in business communication and marketing processes, it is feasible to consider the influence of "peers" and superiors on its adoption. Recommendations from key people in the network make individuals more likely to try a new technology (Lin et al., 2022; Upadhyay et al., 2022). In addition, the influence of opinion leaders often generates a perception of trust and social acceptance of the system (Li et al., 2012). Recent studies consistently link social influence with a greater intention to use AI among managers (Jameel et al., 2023; Kuberkar & Kumar Singhal, 2020), although it appears to have limited or no effect among some groups (Andrews et al., 2021). In line with the above, the following hypothesis is proposed:

H3: Social influence positively affects the intention to adopt AI in the communication and marketing processes of companies.

2.5 Facilitating Conditions (FCs)

Facilitating conditions refer to the availability of resources and infrastructure to support the use of a system (Venkatesh et al., 2003). This factor has been shown to determine the acceptance and adoption of technological innovations in organizational contexts (Chatterjee et al., 2021; Emon et al., 2023; Lee et al., 2013). The existence of technical support, training, and resources positively predicts the adoption of AI in companies' internal processes (Chatterjee et al., 2021; Kuberkar & Kumar Singhal, 2020), such as those related to their marketing and communication processes. Having assistance in handling AI and the necessary expertise to do so are considered key facilitating conditions (Jameel et al., 2023).

Previous research supports the influence of facilitating resources such as managerial support and technological compatibility on the positive perceptions of organizational users toward AI use (Dwivedi et al., 2021). Moreover, the availability of these conditions develops favourable attitudes that motivate technological acceptance (Dwivedi et al., 2019; Emon et al., 2023). Considering the relevance of this factor, the following hypothesis is defined:

H4: Facilitating conditions positively affect the intention to adopt AI in the communication and marketing processes of companies.

2.6 Organizational Compatibility (OC)

Organizational compatibility is defined as the degree to which a technological innovation is consistent with an organization's existing values, cultural norms and needs (Rogers et al., 2014). Several authors agree that compatibility is a relevant factor in determining the adoption of new technologies in firms (Alserr & Salepçioglu, 2023; Katebi et al., 2022; Zahra et al., 2021). Within the context of AI implementation, the literature emphasizes the importance of proper integration with existing workflows, values, and organizational norms to facilitate its adoption (Katebi et al., 2022). Otherwise, when an innovation such as AI has little cultural and process compatibility, it can generate resistance to change and rejection (Agrawal, 2023).

Previous research supports the importance of this factor in AI adoption. Chatterjee et al. (2021) reported that organizational compatibility significantly predicts the perceived usefulness of AI, although not its ease of use. Similarly, AlSheibani et al. (2020) argue that organizations with high technological compatibility are better positioned to implement AI, as it is related to having personnel specializing in AI and data analytics. Therefore, a high degree of compatibility between AI and the existing values, culture, processes, and technological structure in the communication and marketing areas of companies will also enhance its effective adoption (AlSheibani et al., 2020). Considering the relevance of this factor, the following hypothesis is proposed:

H5: Organizational compatibility positively affects the intention to adopt AI in the communication and marketing processes of companies.

2.7 Relative advantage (RA)

Relative advantage is defined as the degree to which an innovation is perceived as superior to existing solutions (Rogers et al., 2014). This factor has proven to be a determinant in the adoption of this new technology in companies (Al Hleewa & Al Mubarak, 2023; Alserr & Salepçioglu, 2023). In the literature, authors such as Kurup & Gupta (2022) and AlSheibani et al. (2020) state that companies that evaluate the benefits of integrating AI into their processes gain a relative advantage. In terms of existing marketing and communication practices, the potential benefits of AI are diverse. These include lead identification, segmentation, personalization, and purchase prediction (Huang & Rust, 2018; Paschen et al., 2020), as well as automation, big data processing, and decision support (Brynjolfsson & McAfee, 2017; Davenport & Harris, 2017).

However, although in some studies this factor is significant, in other cases, the relative advantage does not materialize. This is the case for Pan et al. (2022), where the factor had no effect on the use of AI. Faced with this situation, the following hypothesis seems relevant:

H6: Relative advantage positively affects the intention to adopt AI in the communication and marketing processes of companies.

2.8 Perceived Value (PV)

Perceived value is defined as a cognitive evaluation made by consumers regarding what is received as opposed to what is given (Lin & Lu, 2015). This evaluation has been shown to be a determining factor in the perception of products and services, and its relationship with price is particularly relevant (Ball et al., 2006). The literature indicates that organizations, in this study that act as consumers of AI, perceive that with the inclusion of this new technology, they obtain high value (Akdim & Casalo, 2023; Güngör, 2020), especially in areas such as marketing and sales. A clear example is the development of personalized recommendations, made possible by AI, which enhance the value perceptions of these brands on social platforms (Akdim & Casalo, 2023; Hermann, 2021). Previous studies, such as Kleijnen et al. (2007), have used the cost–benefit paradigm to assess perceived value, supporting the relevance of this component in the evaluation of emerging technologies. The time and effort savings generated by its adoption, together with personalized communications, increase the value that AI offers relative to its price (Hannig & Seebacher, 2023; Komiak & Benbasat, 2006). In line with the above, the following hypothesis is proposed:

H7: Perceived value positively influences the intention to adopt AI in the communication and marketing processes of companies.

2.9 AI Aversion (AIAV)

Aversion to AI stems mainly from the perception that the technology lacks affective and humanized aspects that are valued in certain complex decision-making tasks (Castelo et al., 2019). It is also related to deep-rooted distrust of possible biases in algorithms and the lack of transparency in their actual functioning (Kawaguchi, 2020; Mahmud et al., 2022; Rahman et al., 2023). In the context of AI implementation in strategic processes, such as those within the communication and marketing processes of companies, Mahmud et al. (2022) suggest that this aversion could hinder collaboration between humans and AI technology. This may lead to resistance to adoption, even when AI has proven to be efficient in various tasks (Jain et al., 2022). However, Dietvorst et al. (2015) asserted that this resistance could be mitigated and solved, to a large extent, through education and training within organizations. On the basis of the above, the following hypothesis is proposed:

H8: AI aversion has a negative effect on the intention to adopt AI in companies' communication and marketing processes.

In accordance with the hypotheses proposed, Figure 1 presents the proposed model.

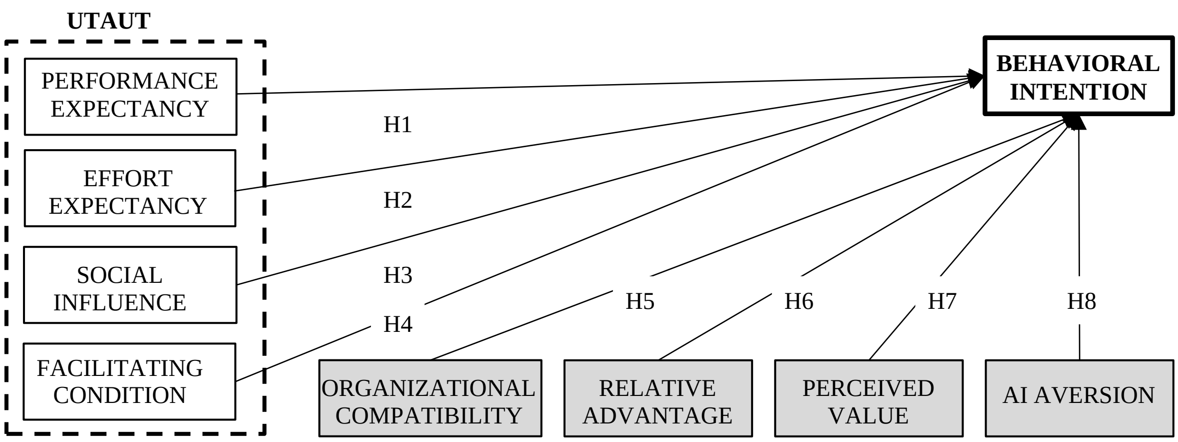

Figure 1. AI acceptance model for business communication and marketing.
Sources: developed by the authors.

3. Methodology and Research Methods. To explore the components that influence the incorporation of AI in the business environment, specifically in marketing and communication processes, a quantitative study was conducted through an online survey. The survey focused on CEOs of Spanish companies across different sectors, and a total of 530 surveys were sent out, of which 409 were validated. The survey was conducted at the national level, ensuring a broad representation of Spanish businesses. The sample details are presented in Table 1.

Table 1. Number of CEOs by company size.

Company Size	Sample	Company Size	Sample
0 employees	55	From 50 to 249 Employees	49
From 1 to 9 Employees	161	From 250 to 499 Employees	32
From 10 to 49 Employees	101	More than 500 Employees	11
		Total sample	**409**

Sources: developed by the authors.

The current situation that Spanish companies are experiencing makes them ideal subjects for this research. According to the Ontsi-Red.es report (2023), in 2021, Spain reached an average level of AI adoption, similar to the EU-27 average, but still lagged behind the leading countries in this technology. With 8% of enterprises adopting AI, Spain is at a stage of significant growth and improvement. Inspired by what Fernandez & Rodriguez (2022) highlighted the potential for development in the use of AI in the Spanish business context in the coming years, this paper seeks to identify the key elements for effective AI implementation, as well as the possible barriers and challenges faced by national companies. The contacts for the CEOs were obtained through a worldwide networking group, allowing us to reach out to them effectively and obtain responses for the survey. Prior to the official publication of the survey, a series of pilot tests were conducted in two phases. In the first phase, senior researchers tested the questionnaire to highlight areas for improvement and clarify ambiguities. To obtain clear and accurate responses, in line with the suggestions of Venkatesh et al. (2003), a set of 20 managers participated in a pretest. The fieldwork was carried out in September and October 2023. Data collection was conducted through a self-administered form, which was distributed to the sample members by email, complemented by telephone confirmations. The sample was deemed valid, as all participants were CEOs of their respective companies. Given that senior managers are the essential actors in decisions concerning technological adoption in their respective organizations (Moore & Benbasat, 1991; Kmecova & Juracka, 2023), the sample chosen was precisely this profile: executives and managers of Spanish companies. The participants were contacted via email, WhatsApp, telephone, or in-person interactions to ensure a high response rate and comprehensive engagement. The survey consisted of 49 questions formulated on a Likert scale that had been validated in previous research (Davis et al., 1989; McAfee & Brynjolfsson, 2012), thus ensuring the reliability and validity of the data collected in the present inquiry.

G*Power software was used to estimate the minimum sample size via an effect size (f^2) of 0.15, an error probability (α) of 0.05, and a power level ($1 - \beta$) of 0.8 with 8 predictors. The actual sample size of 409 far exceeded the required minimum sample size of 109, ensuring the robustness needed to evaluate the proposed conceptual framework.

4. Results. Using the partial least squares structural equation modelling (PLS-SEM) method to evaluate the proposed model, the reliability of the constructs was first confirmed as a crucial preliminary step. Following the recommendations of authors such as Henseler et al. (2015) and Roldán & Sánchez-Franco (2012), a minimum factor loading of 0.7 is required for the constructs measured in Mode A (Table 2).

Table 2. Factor loading, composite reliability, and convergent validity.

Indicators	Factor Loading	CA	Rho_A	Rho_C	AVE
AIAV	0.854-0.927	0.949	0.953	0.960	0.798
BI	0.979-0.986	0.989	0.989	0.992	0.968
EE	0.865-0.954	0.952	0.957	0.963	0.839
FC	0.740-0.929	0.924	0.926	0.946	0.816
OC	0.934-0.965	0.949	0.956	0.967	0.908
PE	0.900-0.951	0.976	0.979	0.980	0.875
PV	0.903-0.954	0.945	0.946	0.960	0.858
RA	0.899-0.947	0.960	0.964	0.969	0.863
SI	0.856-0.906	0.927	0.936	0.944	0.773

Note: CA – Cronbach's Alpha; Rho_A – Composite Reliability; Rho_C – Composite Reliability; AVE – Average Variance Extracted.

Sources: developed by the authors.

After the factor loadings were verified, the reliability of the constructs was analysed via composite reliability (CR) indicators and Cronbach's alpha coefficient. This process followed Nunnally's (1978) recommendation that these indicators should exceed the 0.7 threshold. Additionally, convergent validity was ensured by evaluating the average variance extracted (AVE), where the indicators surpassed the proposed threshold of 0.5 (Straub et al., 2004).

Discriminant validity was assessed via the Fornell–Larcker criterion, which states that the square root of the average variance extracted (AVE) of each construct should be greater than its highest correlation with any other construct (Fornell & Larcker, 1981). Table 3 presents the results of the Fornell–Larcker test, confirming that this criterion was met.

Table 3. Discriminant validity (Fornell–Larcker test)

	AIAV	BI	EE	FC	OC	PE	PV	RA	SI
AIAV	0.893								
BI	0.739	0.984							
EE	0.701	0.579	0.916						
FC	0.691	0.771	0.720	0.903					
OC	0.730	0.633	0.744	0.652	0.953				
PE	0.731	0.553	0.750	0.557	0.800	0.935			
PV	0.758	0.728	0.689	0.742	0.762	0.675	0.926		
RA	0.798	0.655	0.759	0.619	0.819	0.888	0.759	0.929	
SI	0.717	0.581	0.646	0.605	0.626	0.724	0.670	0.712	0.879

Sources: developed by the authors.

To assess potential common method bias (CMB), a variance inflation factor (VIF) analysis was conducted, following the recommendations of Hair et al. (2011) and Sarstedt et al. (2021). All the VIF values were below the threshold of 5, indicating that there were no significant issues with multicollinearity or biases in the CEOs' responses. The R-squared (R^2) value indicates the extent to which the independent variables explain the variance in the dependent variable. A high R^2 value suggests good model fit. Table 4 presents the R^2 and adjusted R^2 values, which demonstrate that the model explains 70.5% of the variance in Behavioural Intention.

Table 4. R2 of the model.

	R-square	R-square adjusted
BI	0.705	0.700

Sources: developed by the authors.

To evaluate the structural model hypotheses, the path coefficients were analysed. Table 5 shows the coefficients of the proposed hypotheses and their p values. In conclusion, of the eight proposed hypotheses, five were statistically significant.

Table 5. Contrast of the structural model (path coefficients)

Hypotheses	Original sample (O)	P values
H1. Performance Expectancy > Behavioural Intention	-0.125	0.080
H2. Effort Expectancy > Behavioural Intention	0.201***	0.001
H3. Social Influence > Behavioural Intention	-0.006	0.921
H4. Facilitating Conditions > Behavioural Intention	0.500***	0.000
H5. Organizational Compatibility > Behavioural Intention	0.040	0.590
H6. Relative Advantage > Behavioural Intention	0.213**	0.009
H7. Perceived Value > Behavioural Intention	0.154*	0.033
H8. AI Aversion > Behavioural Intention	0.313***	0.000

Note: ***p<0.001, **p<0.01, *p<0.05. (based on a 1-tailed and bootstrap test with 10000 samples)

Sources: developed by the authors.

After the structural model was analysed, a multigroup analysis was conducted to evaluate potential differences between groups. The selected variables were age, revenue, sector, and prior experience. No significant differences were found in age, sector, or prior experience; however, significant and important differences were identified in company revenue, which is associated with firm size.

The analysis revealed that the variable Aversion to AI had a significantly greater effect on companies with lower revenue, with a path coefficient of 0.432, making it the most relevant predictor of adoption intention. In contrast, for companies with higher revenue, this effect was much smaller and not significant (path = 0.118).

In addition to evaluating the structural model and the R^2, a predictive analysis of the latent variables was conducted. As shown in Table 6, the Q^2predict value obtained for behavioural intentions is 0.829, indicating that the model has high predictive power.

Table 6. Summary of the latent variable predictions

	Q^2predict	RMSE
BI	0.829	0.415

Sources: developed by the authors.

5. Discussion and Conclusions. The analysis of the structural model confirmed that standards for reliability and validity were achieved, reinforcing the robustness and interpretability of the results (Hair et al., 2021; Straub et al., 2004). The discriminant validity of the constructs was established, ensuring a clear differentiation of the variables analysed (Henseler et al., 2015). Notably, the model explains 70.5% of the variance in the intention to implement AI, a result that substantially exceeds the recommended threshold of 10% for indicating significant predictive relevance (Falk & Miller, 1992).

In the hypothesis analysis, the study highlights the significant effects of effort expectancy and facilitating conditions on AI adoption intentions. These findings align with prior research (Vlacic et al., 2021; Emon et al., 2023), which emphasizes the importance of reducing technical barriers and ensuring the availability of adequate infrastructure and resources to facilitate implementation. These results underscore the need to eliminate operational complexities and create environments where AI adoption is perceived as an accessible and viable process, particularly for decision-makers such as CEOs.

The study also confirms the substantial impact of AI Aversion, reflecting persistent barriers related to trust and perceived risks associated with emerging technologies. In line with Mahmud et al. (2022), aversion to AI is closely linked to factors such as a lack of transparency in algorithmic processes (the ‘black box’ nature), ethical risks (e.g., algorithmic bias), and privacy concerns. Recent findings by Maldonado-Canca et al. (2024) further support this perspective, highlighting that biases in AI models and the opacity of algorithms undermine perceptions of fairness, directly affecting trust and adoption intentions. These insights reinforce the importance of addressing such barriers through trust-building initiatives, such as transparent communication, ethical safeguards, and pilot programs, to mitigate resistance and foster greater acceptance of AI.

The multigroup analysis revealed significant differences between companies with higher and lower revenue, specifically in relation to AI Aversion. For companies with lower revenue, AI aversion was high and significant, suggesting that this variable has the greatest explanatory power over AI adoption intention in this group. This heightened aversion can be explained by a lack of resources and the perception of greater technological barriers, as noted by Chatterjee et al. (2021) and Kuberkar & Kumar Singhal (2020), who highlight that smaller organisations face infrastructure and technical support limitations, which constrain their ability to adopt advanced technologies such as AI.

Conversely, in companies with higher revenue, the impact of AI aversion was low and nonsignificant. This suggests that these organisations, with greater financial and technological resources, are better positioned to strategically implement AI and leverage its competitive advantages (AlSheibani et al., 2020; Kurup & Gupta, 2022). In this context, larger organisations are able to prioritize innovation and focus their efforts on maximizing the strategic benefits offered by AI.

While relative advantage and perceived value demonstrated significant effects, their influence was less pronounced. This suggests that although AI offers tangible benefits, such as improved segmentation, automation, and prediction, these advantages are not always perceived as strong differentiators compared with existing solutions (Güngör, 2020; Kurup & Gupta, 2022). Therefore, it is necessary to communicate AI's unique value propositions more clearly to strengthen its strategic relevance, particularly in marketing and communication contexts.

A critical finding of this study is the lack of significance observed in terms of organisational compatibility and performance expectancy. Organisational compatibility, often considered a key enabler of technology adoption, may not have been significant because of the technological immaturity of many Spanish firms. This misalignment between current organisational capabilities and AI demands could explain the low perception of compatibility, suggesting that the relevance of this construct may evolve as organisations advance in their technological readiness. Similarly, performance expectancy, which is traditionally a key predictor of adoption (Venkatesh, 2022), did not demonstrate a significant effect. This may be explained by the early stage of AI adoption in the surveyed organisations, where CEOs prioritize tangible, immediate outcomes (such as cost efficiency and implementation feasibility) over more abstract performance improvements (Jameel et al., 2023; Upadhyay et al., 2022).

Furthermore, the lack of significance of social influence adds an additional layer of complexity to the findings. Although previous studies have demonstrated its relevance in other contexts (Jameel et al., 2023; Upadhyay et al., 2022), its limited impact here suggests that normative pressures or peer influence carry less weight for CEOs. This can be attributed to the hierarchical and individualistic decision-making processes that characterize executive leadership, where direct organizational benefits take precedence over external expectations.

Taken together, these results underscore the importance of considering contextual factors—such as technological maturity, trust concerns, and leadership priorities—when analysing the dynamics of AI adoption. By focusing on facilitating conditions, managing AI aversion, and effectively communicating relative advantage and perceived value, organisations can create a favourable environment for the successful adoption of AI in marketing and communication processes.

From a theoretical perspective, our study provides a comprehensive and robust framework to analyse—for the first time—the implementation of AI in corporate marketing and communication processes. This approach, grounded in the UTAUT model and enriched with additional constructs, highlights the complexity and multidimensionality of the technological adoption process, encompassing organisational, technological, and human factors. Notably, there is a debate on how, in the opinion of CEOs, AI aversion, relative advantage, and perceived value are key determinants for adopting this technology in corporate marketing, beyond effort expectancy and facilitating conditions, which also proved to be essential.

From a methodological perspective, this study presents a pioneering empirical approach that considers two fundamental aspects. First, the perspectives of CEOs from both large enterprises and SMEs offer a managerial viewpoint that reveals the factors that senior executives consider most relevant for adopting AI in their marketing strategies. Second, the findings provide a holistic view, highlighting managerial conviction regarding the transformative role that AI can play in marketing and communication processes, irrespective of organisational size or sector. These contributions offer a solid theoretical foundation to advance the observation and analysis of AI evolution in marketing across different organisational typologies.

From a practical perspective, to foster favourable facilitating conditions, organisations are advised to invest in robust technological infrastructure, establish continuous AI training programmes for employees, and provide specialized technical support. Implementing pilot platforms can help reduce initial technical barriers and create an environment where AI adoption is perceived as both viable and accessible. To manage AI aversion, it is crucial to prioritize transparent communication regarding the functionality and benefits of the technology, emphasizing its capacity to enhance strategic processes such as segmentation and automation in marketing. Additionally, implementing ethical practices, such as algorithm audits to prevent biases and safeguard data privacy, will help build trust. These strategies, combined with educational programmes that address concerns about the 'black box' nature of AI, will mitigate resistance and facilitate broader adoption across diverse organisational contexts.

The results highlight the need to intensify efforts to address AI aversion in companies with lower revenue. To overcome this barrier, it is recommended that policymakers and industry leaders prioritize specific measures, such as financial incentives, technical assistance, and accessible pilot programmes. These initiatives will help smaller organisations build confidence in the technology by gradually and tangibly demonstrating its value and feasibility. In contrast, for larger companies, strategies should focus on maximizing the strategic benefits of AI and fostering continuous innovation to maintain their competitive advantage in the market. This approach will create the necessary conditions for a more effective and sustainable adoption of AI across various organisational contexts. The organisational compatibility and performance expectancy were not significant in the present study, this does not imply that they should be disregarded. As specialization and AI training among personnel increase and as its implementation expands in marketing processes, these factors may gain relevance in the future. Therefore, it is recommended that both academics and organisations monitor their evolution over time. Although this study provides significant contributions to understanding AI adoption in marketing and communication processes from the perspective of CEOs, there are certain opportunities for future research that could further enrich these findings. While the study focuses on Spanish companies, which adds depth and context to the results, future research could explore comparative studies across different countries or regions. This would help validate the findings in broader contexts and provide additional insights into how cultural, economic, and technological differences influence AI adoption. Although the quantitative approach adopted in this study provides robust and generalizable findings, combining it with qualitative methods, such as in-depth interviews or case studies, could offer a more detailed understanding of the challenges and perspectives of CEOs. This complementary approach would enhance the interpretive richness of the study. While this study identifies adoption factors applicable across companies, developing specific recommendations tailored to different industries and organisational sizes would improve the practical applicability of the findings, allowing organisations to adapt AI strategies to their unique operational environments. Although this study has found significant differences on the basis of company revenue levels, it would be advisable to further expand this methodology. Conducting comparative analyses in diverse cultural and organisational contexts, as well as including additional moderating variables, could uncover more subtle variations and offer specific strategies to optimize the implementation of artificial intelligence in different settings. These suggestions represent natural extensions of the current study, offering avenues to validate and expand upon its findings while maintaining the robustness and practical relevance of the results presented.

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Штучний інтелект у маркетинговому менеджменті: перспективи для керівників компаній

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Інтеграція штучного інтелекту (ШІ) у маркетинг і бізнес-комунікації радикально змінює корпоративні стратегії, створюючи значні можливості, але й супроводжуючись численними викликами. У цьому дослідженні аналізуються чинники, які впливають на впровадження ШІ у компаніях, зокрема експертні думки генеральних директорів. За результатами опитування 409 керівників іспанських підприємств, було розроблено розширену модель, засновану на єдиній теорії прийняття і використання технологій (UTAUT), доповнену додатковими концептуальними складниками. Результати дослідження свідчать, що очікувана зручність використання технологій і сприятливі умови є ключовими факторами впровадження ШІ. У той же час, настороженість щодо ШІ, яка включає занепокоєння стосовно недовіри, складності та етичних ризиків, виступає значним бар’єром, особливо для генеральних директорів малих компаній, де цей вплив є найбільш відчутним. Такі чинники, як відносна перевага та сприйнята цінність, також впливають на наміри впровадження ШІ, хоча меншою мірою, що вказує на важливість очікуваних переваг і конкретних результатів, наприклад, у покращенні сегментації, автоматизації процесів та прогнозної аналітики. Виявлено значні відмінності між компаніями різного масштабу. Малі фірми демонструють більшу настороженість щодо ШІ, тоді як великі організації зосереджуються на максимізації стратегічних переваг для стимулювання інновацій. Ці висновки підкреслюють важливість адаптованих підходів, таких як фінансові стимули, пілотні програми та цільове навчання, які сприяють подоланню бар'єрів і заохочують впровадження ШІ в різних організаційних контекстах. Це дослідження робить вагомий внесок в академічний дискурс, розширюючи модель UTAUT для врахування нових викликів у впровадженні ШІ. З практичної точки зору, воно пропонує керівникам компаній дієві стратегії подолання людських і технологічних перешкод, сприяючи більш ефективному, даними керованому маркетинговому процесу. Забезпечуючи комплексне розуміння чинників, які сприяють впровадженню ШІ, та бар’єрів, це дослідження допомагає компаніям максимально використовувати потенціал ШІ, підвищуючи їх конкурентоспроможність в умовах зростаючої цифровізації.

Ключові слова: штучний інтелект; маркетинг; бізнес-комунікації; впровадження ШІ; новітні технології.