Observatorio (OBS*)

Received: 2026-07-10 | **Accepted:** 2026-10-16 | **Published:** 2026-11-11 | **DOI**: 10.15847/OBS20262955

Factors associated with artificial intelligence adoption among advertising professionals: evidence from the Motivation–Opportunity–Ability (MOA) framework

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Abstract

The integration of artificial intelligence (AI) is reshaping the organizational and productive dynamics of the advertising industry, transforming creative processes, decision-making practices, and professional roles. Despite its growing implementation, empirical evidence on the factors associated with AI adoption among advertising professionals remains limited. This exploratory study analyzes the factors associated with AI tool adoption in the advertising sector through the Motivation–Opportunity–Ability (MOA) model, which enables an integrated examination of motivational, organizational, and competency-related dimensions associated with the use of this technology. A quantitative study was conducted using an online questionnaire administered to 122 advertising professionals, assessing motivational, organizational, and competency-related variables associated with AI use, as well as future adoption intentions. Data were analyzed using Mann–Whitney U tests and Pearson correlation analyses. The findings reveal a favorable attitude toward AI adoption, primarily driven by functional motivations related to productivity and work effectiveness. AI users report higher technological skills and perceive greater organizational support than non-users, while training deficiencies and unequal access to technological resources continue to operate as significant barriers. This study provides empirical evidence on the associations between motivational, organizational, and competency-related factors in AI adoption, highlighting the need to strengthen training and organizational support to foster ethical, sustainable AI integration within advertising.

Keywords: artificial intelligence, AI adoption, advertising, MOA model, organizational support, digital skills

1. Introduction

In recent years, the disruption caused by artificial intelligence (AI) has evolved from a future-oriented expectation into a tangible reality that directly affects organizational structures, dynamics, and cultures. Due to the complexity of its integration, the implementation of AI in the business environment remains heterogeneous, both in terms of the degree of implementation within organizational structures and in the assessment of its economic scope and geographical distribution.

The scientific literature reflects considerable heterogeneity in AI adoption and its economic impact: reported adoption rates range from below 20% in several national contexts (Malik, 2025; Kovič et al., 2024; Fernández-Cerezo et al., 2025) to more advanced implementation still constrained by organizational and cultural barriers, with only 13% of AI projects progressing beyond the pilot stage in some studies (Ångström et al., 2023). Evidence on productivity gains is similarly mixed, with sceptical positions (Ångström et al., 2023; Hainsworth, 2023; Baabdullah, 2024) contrasting with quantitative evidence of competitive advantages in large firms and labour-intensive sectors (Ayinaddis, 2025; Xie & Yan, 2024; Zhai & Liu, 2023). Given this lack of comprehensive data (Agrawal et al., 2019), context-specific research is needed to assess real impact and implementation strategies across sectors.

The complexity of factors shaping AI implementation—spanning domains such as finance (Heaton et al., 2017), healthcare (Buess et al., 2025), marketing (Malthouse & Copulsky, 2023), and education (Xia et al., 2024), and involving technological, motivational, and cultural variables (Kovič et al., 2024; An et al., 2024; Wiese et al., 2024)—calls for context-specific research examining AI adoption from the perspective of each sector's particular characteristics.

Communication and advertising companies, where creativity, data analysis, strategy, and decision-making converge, represent a privileged setting for analysing AI implementation. Advertising corporations are among the sectors that have most intensively embraced AI, reaching 73% implementation among U.S. agencies (Statista, 2023), with forecasts suggesting that by 2030, 30% of administrative employees in agencies could be replaced by automated processes (Hamm & Klesel, 2021).

Perhaps the earliest publication on AI implementation in advertising was Cook and Schleede (1988), which analysed database processing for advertising and media-strategy problems. Since then, numerous authors have contributed definitions of AI in advertising; in 2021, the Journal of Advertising published a special issue on the topic, with authors generally agreeing that AI in advertising is based on using data for intelligent decisions. Rodgers summarized these contributions, defining AI advertising as "brand communication that uses various machine functions that learn to perform tasks with the intention of persuading through the participation of humans, machines, or both" (Rodgers, 2021, p. 2).

AI implementation in agencies has already given rise to new roles—AI-generated content curators, model trainers, creative data analysts—while automating tasks such as copywriting and graphic design, though experts stress the continued necessity of human oversight (Rodgers, 2021).

New AI systems enable the analysis of large data volumes with speed and precision difficult to replicate manually, identifying complex patterns that improve audience segmentation and campaign relevance, increasing purchase intention and consumer satisfaction (Chatterjee et al., 2021; Rivera-Montaño, 2023). Such capabilities facilitate personalized experiences, particularly in programmatic campaigns (Chi et al., 2022); Nike, for instance, uses AI to personalize advertising messages based on sports habits and lifestyle (ICEMD, 2025).

Alongside these analytical capabilities, content generation represents one of the most significant opportunities for agencies, with generative models such as GANs and Transformers enabling automatic or assisted creation of visual and textual advertising content. In 2025, the agency Monks produced a 30-second PUMA commercial generated entirely by AI, completing it 2.8 times faster than conventional production (ReasonWhy, 2025), illustrating the scale of transformation underway in creative and production processes.

Other brands, including Ecoalf, Coca-Cola, and Vodafone, have joined this automation trend (Montero, 2025), requiring firms to balance machine and human intervention as industry roles shift. AI-generated advertising content can significantly increase recipients' psychological and behavioural engagement, particularly when not explicitly labelled as AI-generated (Du et al., 2023), raising ethical concerns.

This emerging machine–human hybridization creates tensions among professionals, who express concerns about full automation and the potential loss of the emotional and ethical dimensions of work (Sánchez-Baldo, 2023); these tensions can be addressed through a hybrid approach combining human and artificial intelligence rather than complete automation (Budhwar et al., 2022; Sánchez-Baldo, 2023). A new line of

scientific inquiry should therefore analyse professional roles within this hybrid environment: understanding how humans relate to AI, and investigating their capabilities and motivations in response to its development, is a necessary condition for ethical, sustainable, and human-centred digital transformation.

In this context, the Motivation–Opportunity–Ability (MOA) model emerges as an appropriate framework for comprehensively analysing key factors that may contribute to a better understanding of this evolving machine–human relationship, as it provides a necessary analytical perspective for advancing knowledge regarding the factors associated with AI adoption in a sector as distinctive as advertising, where research remains at an early stage (Martínez-Martínez et al., 2022). This model explains how these three factors interact to facilitate or inhibit a specific action: motivation refers to an individual's desire or willingness to engage in a behaviour (MacInnis et al., 1991); opportunity encompasses contextual and environmental factors beyond individuals' direct control that facilitate or constrain task performance (Soma et al., 2021); and ability relates to the skills individuals perceive themselves to possess to perform a task effectively (Bigné et al., 2010; Xia & Zheng, 2023).

Within scientific research, the MOA model has been implemented across various studies (Cui et al., 2020; Jaques et al., 2019; Xia & Zheng, 2023, among others). Specifically, in the field of communication, it has been applied by authors such as Gutiérrez-Taño et al. (2013) to analyse the factors determining the use of social media in travel planning and by Soma et al. (2021), who evaluated the effectiveness of awareness campaigns addressing food waste.

From a workforce planning perspective, understanding these motivational, organizational, and competency-related factors is relevant for designing training programmes, allocating technological resources, and anticipating skill gaps as AI reshapes advertising roles. Training deficits and unequal access to technological resources are already recognized barriers to AI adoption in other professional fields (Hassan et al., 2024; Kalim et al., 2025; Zavodna et al., 2024), suggesting the workforce implications documented here may hold broader relevance for HR practitioners and policymakers.

Accordingly, the objective of this study is to analyse advertising professionals' perceptions and identify key factors associated with AI use within their professional context through the application of the MOA model. The findings seek to examine professionals' intentions to use AI and examine the extent to which motivation, contextual conditions, and individual competencies are associated with these intentions. This information may contribute to fostering innovation, improving AI adoption and professional experience, and enabling organizations to better leverage the opportunities offered by these technologies.

2. Theoretical framework and hypotheses development

To understand the factors that shape the adoption of artificial intelligence (AI) tools in professional settings, the literature has developed different models aimed at explaining processes of technology acceptance and use. Among the most established approaches are the Technology Acceptance Model (TAM) proposed by Davis (1989), the Unified Theory of Acceptance and Use of Technology (UTAUT) developed by Venkatesh et al. (2003), and Rogers' (2003) Diffusion of Innovations Theory. These models have identified variables such as perceived usefulness, ease of use, social influence, and facilitating conditions as relevant factors associated with technology adoption processes.

However, several authors argue that these approaches present limitations for complex organizational environments, particularly creative industries characterized by dynamism and professional transformation. Whereas TAM and UTAUT focus on individual technology acceptance, AI integration into creative work may be associated with motivational, structural, and competency-related factors linked to organizational dynamics and professional adaptation (Dwivedi et al., 2023; Raisch & Krakowski, 2021), calling for more integrative approaches to how individual and contextual dimensions interact in adoption processes mediated by automation.

In particular, the advertising sector is an especially relevant context for these dynamics due to the coexistence of human creativity, algorithmic automation, and the redefinition of professional roles. AI not only automates operational tasks but also intervenes in processes traditionally associated with intuition and human creative capital; the incorporation of automated systems into content generation and strategic conceptualization transforms advertising creation and reconfigures the relationships between technology, creativity, and professional legitimacy.

Recent literature further warns that AI integration into creative industries may generate tensions associated with process standardization, loss of professional autonomy, and dependence on automated systems for activities historically linked to human creativity (Huang & Rust, 2021; Jarrahi, 2018). AI adoption in advertising is thus not merely a technical process but a complex sociotechnical phenomenon in which professional expectations, technological capabilities, and organizational conditions converge—particularly relevant in sectors where competitive differentiation depends on symbolic innovation and strategic adaptability.

Within this context, the Motivation–Opportunity–Ability (MOA) model provides a particularly suitable framework for analysing the professional adoption of AI in the advertising field. Unlike other models primarily focused on individual dimensions of technology acceptance, the MOA model enables the simultaneous integration of motivational, organizational, and competency-related factors, offering a broader and more contextualized approach to understanding technological behaviour in complex work environments.

From the MOA perspective, AI adoption in creative work can be understood in relation to the interaction between individual motivation, organizational opportunity, and perceived ability, rather than on perceived usefulness alone. Motivation includes functional benefits related to productivity and effectiveness, as well as social and hedonic dimensions linked to professional integration. Opportunity refers to organizational and contextual conditions—access to technological resources, time availability, and organizational support—critical in creative settings undergoing digital transformation. Ability involves technological competencies together with self-efficacy and adaptive capacity, central to reducing resistance to AI-based tools.

Accordingly, the present study contributes to expanding the literature on technology adoption by applying the MOA model to the analysis of professional AI integration in creative industries, an area that remains underexplored from empirical perspectives simultaneously focused on motivational, organizational, and competency-related dimensions. Therefore, this research seeks to analyse in an integrated manner how these factors are jointly associated with the adoption of AI tools within the specific context of the advertising sector.

Based on the proposed theoretical framework, this study formulates the following hypotheses:

H1. Professionals who use artificial intelligence tools exhibit significantly higher levels of perceived functional motivation than non-users.

H2. Professionals who use artificial intelligence tools perceive significantly greater organizational opportunities than non-users.

H3. Professionals who use artificial intelligence tools exhibit significantly higher levels of perceived technological competencies than non-users.

3. Methodology

Data were collected through an online questionnaire designed ad hoc and administered to communication and advertising professionals. The questionnaire was grounded in the Motivation–Opportunity–Ability (MOA) model, widely applied to analyse technology adoption and professional behaviour in organizational contexts.

Given the exploratory nature of the study and the difficulty of accessing a highly segmented professional population, a non-probabilistic snowball sampling procedure was adopted. Although this limits statistical generalizability, it is consistent with exploratory research examining emerging phenomena in specialized organizational settings.

The final sample consisted of 122 participants, of whom 61% (n = 75) were women and 39% (n = 47) were men. In addition, 66% reported having used AI tools in their professional activity (n = 81), whereas 34% indicated that they had not (n = 41). Regarding age, participants were distributed as follows: 34.4% were aged 26–35, 24.6% were aged 46–55, 20.5% were under 25, 10.7% were aged 36–45, and 9.8% were over 55. In terms of company size, 38.5% worked in large companies (more than 251 employees), 25.4% in small companies (10–50 employees), 19.7% in microenterprises (fewer than 10 employees), and 16.4% in medium-sized companies (51–250 employees). Regarding professional role, 21.3% of participants worked in creative/design roles, 20.5% in digital roles, 20.5% as account executives, 12.3% in strategic planning, 4.1% were client-side advertisers, 2.5% worked in data and insight roles, 1.6% in research, and the remaining 17.2% reported other professional profiles (e.g., communication, marketing, or management roles). Functional area and level of responsibility, beyond professional role, were not collected in the questionnaire and could not be reported.

The questionnaire included 26 items corresponding to the MOA-related analytical constructs and was organized into five thematic sections. Additional questions addressed AI use and intensity, non-adoption reasons, and other variables related to the study objectives. The first section, common to the entire sample, collected sociodemographic information and variables related to the intensity of AI tool usage. The remaining sections were structured according to whether participants reported using or not using artificial intelligence tools within their professional context (Table 1).

Table 1: Structure of the Questionnaire

Section	Main Content
Professional Profile	Sociodemographic variables and professional profile
AI Use and Intensity	Frequency of use, predisposition, and reasons for non-adoption
Motivation	Functional, social, and hedonic motivations
Opportunity & Ability	Organizational factors, access to resources, and technological competencies
AI Evaluation	Intention to use and professional perception of AI

Source: Developed by the authors.

The intensity of AI tool usage was assessed through questions designed to measure usage frequency among users and future willingness to use among non-users. In the case of professionals who already used AI tools, frequency of use was measured using a five-point Likert scale. For non-users, the main reasons associated with non-adoption were examined, including lack of interest, absence of perceived need, and insufficient training.

Likewise, functional, social, and hedonic motivations were measured using five-point Likert scales adapted from previous studies (Bigné et al., 2010; Cox & Klinger, 1988; Gutiérrez-Taño et al., 2013), reworded to refer to the professional use of AI tools in the advertising context. Each dimension was operationalized through three items aimed at assessing participants' level of agreement or disagreement with different statements related to the professional use of artificial intelligence tools. No formal pilot testing or expert panel review was conducted prior to administration; internal consistency was subsequently assessed through the Cronbach's alpha coefficients reported in Table 3. The complete wording of all items, in the original Spanish and in English translation, is provided in Appendix A.

The opportunity and technological ability dimensions were operationalized through three and four items, respectively. These variables made it possible to analyse both the role of organizational factors—such as access to resources, time availability, and organizational support—and self-perceived technological competencies associated with the professional use of artificial intelligence tools. In addition, intention to use and perceptions of AI tools were measured through five-point Likert-scale items. Intention and continuity of use were assessed through three items, with items adapted to respondents' usage status. The results in Section 4.5 focus on the directly applicable intention item for non-users and the continuity item for current users.

Based on these analytical dimensions, the variables included in the questionnaire were grouped into different theoretical constructs aligned with the Motivation–Opportunity–Ability (MOA) model and defined according to their conceptual and functional affinity. Specifically, dimensions associated with functional motivation, social motivation, hedonic motivation, organizational opportunity, and technological ability were established.

The functional motivation dimension included variables associated with the perceived professional usefulness of artificial intelligence, particularly in terms of productivity, efficiency, and task optimization. In turn, social motivation incorporated items related to professional recognition, organizational integration, and the role of the work environment. The hedonic dimension grouped variables associated with interest, curiosity, and enjoyment related to the use of artificial intelligence-based tools.

Likewise, the organizational opportunity dimension integrated variables related to access to technological resources, organizational support, and the availability of favorable conditions for incorporating AI into the professional environment. Finally, the technological ability dimension included variables associated with digital competencies, technological knowledge, and perceived self-efficacy in the use of artificial intelligence tools (Table 2).

Table 2: Operationalization of MOA Model Constructs

Construct	Conceptual Dimension	Variables
Functional Motivation	Professional usefulness and productivity	Productivity, efficiency, task optimization
Social Motivation	Professional integration and recognition	Social influence, adaptation to the work environment
Hedonic Motivation	Technological interest and enjoyment	Curiosity, interest, experimentation
Organizational Opportunity	Facilitating conditions	Technological resources, organizational support
Technological Ability	Competencies and self-efficacy	AI knowledge, digital skills

Source: Developed by the authors.

The questionnaires were administered through the Forms platform between May and October 2024. An earlier stage of this same data collection process (n = 105, fieldwork conducted in April–May 2024) was previously analysed through the lens of Disruptive Innovation Theory, examining intrinsic and extrinsic motivational differences by gender, age, company size, and professional role, using a distinct subset of items not included in the MOA constructs reported here (Laguna-García et al., 2025). Data collection continued through October 2024, reaching the final sample of 122 professionals analysed in the present study.

Participation in the study was voluntary and anonymous. Participants were informed about the objectives of the research and the confidential treatment of the data, ensuring compliance with the ethical principles applicable to research in the social sciences.

3.1. Data Analysis

Data were analysed using SPSS statistical software (Version 26), following a sequential analytical strategy aimed at examining construct reliability, differences between groups, and the relationships among the dimensions under study. In the first stage, descriptive analyses were conducted to characterize the sample and examine the main response patterns associated with the use of artificial intelligence tools in the advertising sector.

Subsequently, Cronbach's alpha coefficients were calculated to assess the internal consistency of the constructs associated with the Motivation–Opportunity–Ability (MOA) model. In addition, assumptions of normality were tested using the Shapiro–Wilk test, revealing deviations from normal distribution in part of the variables analysed.

To examine the relationships among motivational, organizational, and competency-related dimensions, Pearson correlation analyses were performed. To identify potential differences between users and non-users of artificial intelligence tools, Mann–Whitney U tests were applied due to the non-parametric nature of part of the analysed data. For all analyses conducted, statistical significance was established at $p \leq .05$.

To further assess the internal consistency of the scales employed, Cronbach's alpha coefficients were calculated for each construct associated with the Motivation–Opportunity–Ability (MOA) model. The results showed adequate levels of internal reliability across all analysed dimensions, exceeding the threshold values commonly recommended in the literature for exploratory research and studies in the social sciences.

The dimensions related to functional motivation (α = .940), social motivation (α = .900), and technological ability (α = .889) exhibited particularly high levels of internal consistency. Likewise, the dimensions of organizational opportunity (α = .856) and hedonic motivation (α = .800) also demonstrated satisfactory reliability values (Table 3).

Table 3: Internal Reliability of MOA Model Constructs

Construct	No. of Items	Cronbach's Alpha
Functional Motivation	3	.940
Social Motivation	3	.900
Hedonic Motivation	3	.800
Organizational Opportunity	3	.856
Technological Ability	4	.889

Source: Developed by the authors.

Assumptions of normality were tested using the Shapiro–Wilk test. The results revealed deviations from normal distribution across the different dimensions associated with the MOA model, justifying the use of non-parametric tests for comparative analyses between groups (Table 4).

Reliability and normality analyses were computed on the AI-user subsample (n = 81) for the full MOA item battery. Because non-users received a partially reduced questionnaire, equivalent reliability estimates were not calculated for the complete set of MOA constructs. Cross-group comparisons were therefore based only on items administered to both groups (Table 1). For Technological Ability, cross-group comparisons were based on the two items administered to both users and non-users, whereas the two additional ability items were administered only to AI users.

Table 4: Normality Tests for MOA Constructs

Construct	N	Shapiro–Wilk	p
Functional Motivation	81	.845	< .001
Social Motivation	81	.896	< .001
Hedonic Motivation	81	.944	.001
Organizational Opportunity	81	.951	.004
Technological Ability	81	.965	.025

Source: Developed by the authors.

Additionally, Pearson correlation analyses were conducted to examine the relationships among the motivational, organizational, and competency-related dimensions under study. To identify potential differences between users and non-users of artificial intelligence tools, Mann–Whitney U tests were performed due to the non-parametric nature of part of the analysed variables. For all analyses conducted, statistical significance was established at $p \leq .05$.

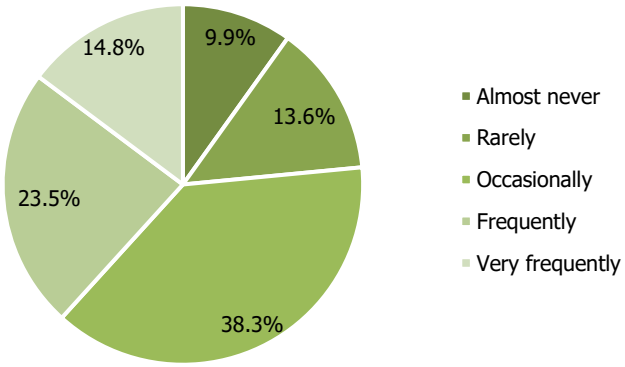
Based on the satisfactory internal consistency observed across the analysed constructs, subsequent statistical analyses were carried out to examine the relationships between the dimensions of the MOA model and the adoption of artificial intelligence tools within the advertising context.

4. Results

4.1. Intensity of Use and Predisposition Towards AI

The results reveal heterogeneous adoption patterns of artificial intelligence tools among professionals in the advertising sector (Figure 1). A total of 38.3% of participants reported using these tools occasionally, whereas 23.5% indicated frequent use and 14.8% reported very frequent use. In contrast, only 9.9% stated that they used them very sporadically, highlighting the increasing presence of AI within the professional dynamics of the sector.

Figure 1: Frequency of AI Tool Use Among Advertising Professionals (n = 81)

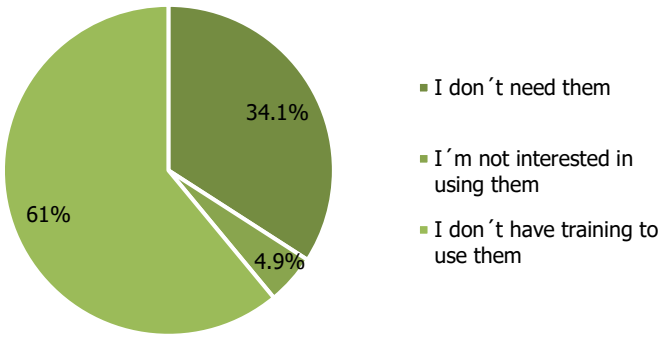


Source: Developed by the authors.

Among professionals who did not use artificial intelligence tools, the main barrier identified was the lack of training (61%), followed by the absence of perceived need (34.1%). In contrast, only 4.9% explicitly reported a lack of interest in using these technologies within their professional activity (Fig. 2).

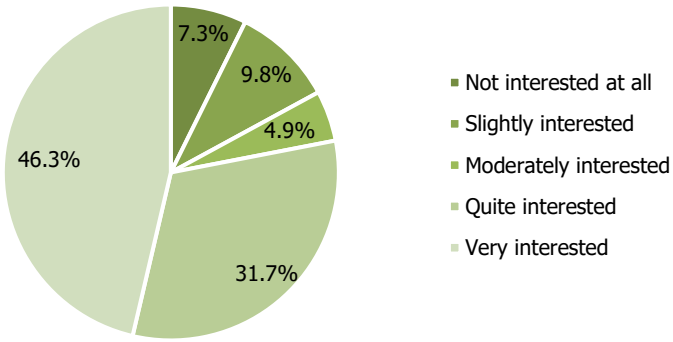
Despite this, the results reveal a high potential predisposition towards the future adoption of AI tools among non-users. A total of 78.0% of participants reported being fairly or highly interested in using these technologies to improve the quality of their work, whereas only 17.1% expressed low levels of interest (Fig. 3).

Figure 2: Reasons for Not Using AI (n = 41)



Source: Developed by the authors.

Figure 3: Interest in Using AI Tools to Improve Work Performance (n = 41)



Source: Developed by the authors.

4.2. Motivations Driving AI Use

The results indicate that functional motivations register the highest scores among the motivational dimensions associated with artificial intelligence tool usage among professionals in the advertising sector (Table 5). In particular, the items related to improved productivity (M = 4.21) and work effectiveness (M = 4.07) recorded the highest scores among AI users. Likewise, within the hedonic dimensions, the perception of enjoyment associated with the use of these tools also showed relatively high values among users (M = 3.65).

By contrast, social motivations registered considerably lower scores across both groups analysed. Among AI users, values associated with the sense of group belonging (M = 1.78), increased personal relationships at work (M = 2.17), and contact with people sharing similar interests (M = 2.25) revealed a lower relevance of social factors in the professional adoption of these technologies.

Likewise, although non-user professionals reported lower mean scores across most motivational dimensions, they also identified functional motivations as the main potential benefits associated with the use of artificial intelligence tools, particularly regarding improved work effectiveness (M = 3.40) and increased productivity (M = 3.28). Within this group, the hedonic dimension associated with the perception of enjoyment linked to AI use also recorded one of the highest scores (M = 3.57).

The Mann–Whitney U test revealed statistically significant differences between AI users and non-users in the dimensions related to improved work effectiveness (p = .008) and increased productivity (p < .001), with higher scores reported among professionals who used these tools. In addition, significant differences were observed in the hedonic dimension associated with the pleasurable nature of AI use (p = .047), which was also higher among users (Table 5).

Pearson correlation analyses showed significant positive associations among the different motivational dimensions examined. The strongest correlations were identified between productivity and work effectiveness in the user group (r = .848, p < .001), as well as between contact with people sharing similar interests and personal relationships in the non-user group (r = .896, p < .001).

Table 5: Functional, Social, and Hedonic Motivations Among AI Users and Non-Users

Motivations	**Non-Users of AI*Mean (SD)***	**AI Users*Mean (SD)***	**Mann–Whitney U Test**
Improve work effectiveness	3.40 (1.392)	4.07 (1.181)	*p* = .008*
Improve work quality	3.23 (1.330)	3.60 (1.252)	*p* = .122
Increase productivity	3.28 (1.377)	4.21 (1.033)	*p* < .001*
Functional Motivation (Mean)	**3.27 (1.320)**	**4.05 (1.128)**	***p* = .001***
Greater contact with people sharing similar interests	2.40 (1.297)	2.25 (1.189)	*p* = .595
Increase personal relationships at work	2.38 (1.390)	2.17 (1.093)	*p* = .667
Increase sense of belonging to a group	2.03 (1.349)	1.78 (1.072)	*p* = .531
Social Motivation (Mean)	**2.30 (1.344)**	**2.09 (1.030)**	*p* = .608
Using AI is enjoyable	3.20 (1.285)	3.32 (1.181)	*p* = .704
Using AI is fun	3.57 (1.152)	3.65 (1.185)	*p* = .722
Using AI is pleasurable	2.85 (1.388)	3.37 (1.269)	*p* = .047*
Hedonic Motivation (Mean)	**3.20 (1.091)**	**3.46 (1.130)**	*p* = .257

Source: Developed by the authors. Values marked with an asterisk () indicate statistical significance at* p ≤ .05.

4.3. Factors Facilitating AI Use

The results show that professionals who use artificial intelligence tools perceive greater organizational opportunities for their use within the workplace than non-users (Table 6). Among AI users, the highest scores were recorded in the dimensions related to access to the technological resources required to use these tools (M = 3.65) and organizational support for AI use (M = 3.44). Likewise, user professionals reported moderate levels of time availability to use or learn these technologies in the workplace (M = 3.11).

By contrast, professionals who did not use artificial intelligence tools reported considerably lower scores across all dimensions analysed, particularly regarding time availability to use or learn AI (M = 2.05), access to technological resources (M = 2.35), and perceived organizational support provided by their companies (M = 2.43). The Mann–Whitney U test revealed statistically significant differences between both groups across all organizational variables analysed (p < .001).

In addition, Pearson correlation analyses showed significant positive associations among the different organizational variables examined in both groups of professionals. In particular, among non-users, a strong relationship was identified between the availability of technological resources and perceived organizational

support (r = .711, p < .001), highlighting the relevance of the organizational context in the potential future adoption of artificial intelligence tools.

Table 6: Organizational Opportunities Associated With AI Use

Opportunities	**Non-Users of AI** ***Mean (SD)***	**AI Users** ***Mean (SD)***	**Mann–Whitney U Test**
I have access to the technology and resources required to use AI tools	2.35 (1.312)	3.65 (1.120)	$p < .001$*
My company supports the use of AI	2.43 (1.375)	3.44 (1.458)	$p < .001$*
I have enough time to use or learn AI	2.05 (1.154)	3.11 (1.235)	$p < .001$*

Source: Developed by the authors. Values marked with an asterisk () indicate statistical significance at* p ≤ .05.

4.4. Skills and Competencies

Professionals who used artificial intelligence tools reported higher levels of perceived competence and technological ability compared with non-users (Table 7). Among users, the highest scores were observed in variables related to technological updating and the ease of keeping up to date with digital innovations (M = 3.88), as well as in the perception of technological abilities applied to the professional use of AI (M = 3.70). Likewise, users considered themselves to possess the necessary knowledge to use artificial intelligence tools (M = 3.42). However, scores associated with advanced mastery of these technologies were more moderate, as reflected in the evaluation of the item "I am good at using AI" (M = 3.21).

In turn, professionals who did not use artificial intelligence tools also reported scores close to the midpoint of the scale regarding their technological predisposition and digital updating, although lower than those observed among users (technological abilities: M = 3.20; keeping up to date with technological developments: M = 3.03).

The Mann–Whitney U test revealed statistically significant differences between both groups in the dimensions related to technological abilities and predisposition towards digital updating (p < .05), indicating that AI users exhibit a higher level of perceived competence and technological capability than non-users.

In addition, Pearson correlation analyses showed significant positive associations among the different competency-related variables examined. In the non-user group, a particularly strong relationship emerged between technological predisposition and digital updating (r = .827, p < .001). Among AI users, high correlations were also observed between perceived mastery of AI tools and the knowledge required to use them (r = .774, p < .001), as well as between AI mastery and general technological abilities (r = .737, p < .001). These findings suggest that, among users, perceived competence is more strongly tied to specific knowledge of artificial intelligence tools than to general technological abilities. Given the cross-sectional design, this pattern is also consistent with the possibility that professionals with greater perceived competence are more likely to adopt these tools in the first place, rather than competence being solely a consequence of usage experience.

Table 7: Technological Abilities Related to the Use of AI Tools

Abilities	Non-Users of AI *Mean (SD)*	AI Users *Mean (SD)*	Mann–Whitney U Test
I have the technological abilities required to use AI in my work	3.20 (1.244)	3.70 (1.101)	$p = .029$*
I find it easy and enjoy keeping up to date with new developments	3.03 (1.291)	3.88 (1.089)	$p < .001$*
I have the necessary knowledge to use AI	—	3.42 (1.139)	—
I am good at using AI	—	3.21 (1.033)	—

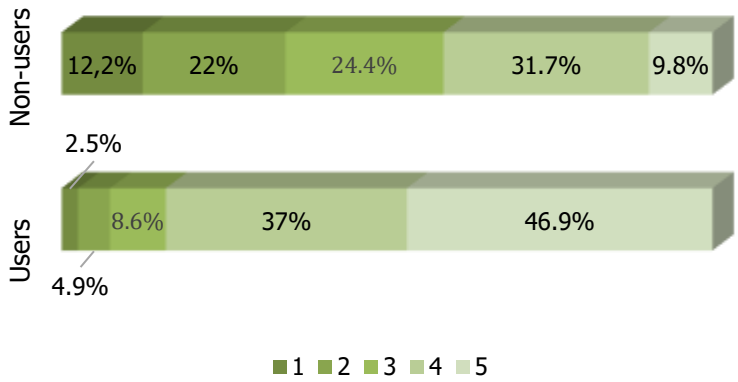
Source: Developed by the authors. Values marked with an asterisk (*) indicate statistical significance at p ≤ .05.

4.5. Intention to Continue Using AI and Perception of AI Tools

The results reveal a high intention to continue using artificial intelligence tools among professionals who already employ these technologies within the advertising sector (M = 4.21). In this regard, only 7.4% of users reported no intention of continuing to use AI tools in their future professional activities.

By contrast, non-users showed a moderate predisposition towards the future adoption of AI in their professional activities (M = 3.05). The Mann–Whitney U test revealed statistically significant differences between both groups (p < .001).

Figure 4: Intention to Use AI Among Non-Users and Intention to Continue Using AI Among Users



Source: Developed by the authors.

The results show that both users and non-users of artificial intelligence tools primarily perceive these technologies as a professional opportunity within the advertising context (Table 8). AI users reported higher scores in the opportunity dimension (M = 4.21) and in the perception of competitive advantage associated with the use of these tools (M = 3.56), whereas non-users also positively valued the potential opportunity offered by AI (M = 3.83). Likewise, both groups identified moderate levels of risk associated with these technologies (users: M = 3.34; non-users: M = 3.49). By contrast, the perception of threat recorded the lowest scores across both groups (users: M = 2.69; non-users: M = 2.71), indicating a relatively limited perception of AI as a direct professional threat.

Although users reported slightly higher evaluations in terms of opportunity and competitive advantage, the Mann–Whitney U test did not reveal statistically significant differences between users and non-users across any of the dimensions analysed.

Pearson correlation analyses showed significant positive correlations among both AI users and non-users between the perceived opportunity associated with AI and the competitive advantages enabled by its use in the workplace ($r = .597$, $p < .001$ for users; $r = .793$, $p < .001$ for non-users), as well as between perceived threat and perceived risk ($r = .641$, $p < .001$ for users; $r = .644$, $p < .001$ for non-users). These associations reflect a consistent relationship between perceptions of opportunity and competitive advantage, as well as between threat and risk, across both groups analysed. By contrast, correlations among the remaining variables were not statistically significant in either group.

Table 8: Perceptions of AI Tools

	Non-Users of AI*Mean (SD)*	**AI Users*Mean (SD)***	**Mann–Whitney U Test**
Opportunity	3.83 (1.243)	4.21 (.910)	$p = .140$
Threat	2.71 (1.582)	2.69 (1.249)	$p = .806$
Risk (plagiarism, job displacement, bias)	3.49 (1.451)	3.34 (1.113)	$p = .402$
Competitive advantage (improving status, opportunities for promotion, differentiation from colleagues)	3.41 (1.341)	3.56 (1.291)	$p = .550$

Source: Developed by the authors. Values marked with an asterisk () indicate statistical significance at* $p \leq .05$.

Overall, the results indicate that the professional adoption of artificial intelligence tools in the advertising sector is primarily associated with functional motivations, the availability of organizational resources, and perceived competence. Likewise, the main barriers identified among non-users appear to be more closely related to training deficits and contextual constraints than to explicitly negative attitudes towards these technologies.

5. Discussion and conclusions

This study aimed to analyse the motivational, organizational, and competency-related factors associated with the professional adoption of artificial intelligence tools in the advertising sector through the Motivation–Opportunity–Ability (MOA) model. The findings indicate that the adoption of these technologies is associated not only with perceptions of functional usefulness but also with the availability of organizational opportunities and professionals' perceived competence. In this regard, the findings are generally consistent with the proposed hypotheses and reinforce the usefulness of the MOA model as an explanatory framework for understanding technology adoption processes in creative and professional environments related to communication and advertising.

The results demonstrate that AI adoption among advertising professionals has already reached a significant level of implementation, comparable to usage levels observed in the United States (Statista, 2023). Nevertheless, the intensity of use remains predominantly moderate, combining frequent use with practices

that are still occasional or exploratory, consistent with research describing AI integration in advertising as still complementary and experimental (Hernández-Gómez & Fernández-Rincón, 2025).

The main barrier among non-users was lack of specialized training, followed by absence of perceived need—consistent with findings in education (Kalim et al., 2025) and healthcare (Hassan et al., 2024), where training deficits limit effective AI adoption and encourage discontinuous use (Zhang & Lee, 2025). Non-users' high interest in future adoption nonetheless points to a favourable context for expansion, provided organizations strengthen training, digital literacy, and ethical guidance.

One of the study's main findings is the predominant role of functional motivations—productivity, work effectiveness, and task optimization—among both users and non-users, with AI users reporting significantly higher levels of functional motivation than non-users, which is consistent with H1.

The central role of pragmatic usefulness observed here is consistent with research identifying operational efficiency as a key factor in AI adoption (Acemoglu, 2025; Filippucci et al., 2024), and converges with Riyath and Eid (2025), who found marketing professionals more willing to adopt AI when perceiving clear efficiency benefits and organizational support.

In contrast, social motivations showed considerably lower relevance, indicating that AI adoption in advertising responds primarily to instrumental criteria rather than group integration or social recognition. Notably, non-users attributed relatively higher value to certain social and hedonic dimensions of AI, especially enjoyment, curiosity, and relational potential—suggesting that among non-users, AI is still perceived partly through an exploratory or aspirational logic rather than as a fully functional component of everyday practice.

Moreover, the differences between users and non-users may be interpreted through Temporal Motivation Theory (Steel & König, 2006): although both groups recognize AI's potential benefits, non-users may exhibit lower self-efficacy expectations and greater uncertainty about its immediate work-related benefits, reinforcing the need for training and organizational strategies that reduce entry barriers and build technological confidence over time.

The findings further suggest that differences in AI adoption are associated not only with motivation but also with organizational opportunities and technological competencies, in line with the MOA model.

In this regard, the findings are consistent with H2 and H3: professionals who use AI perceive significantly greater access to technological resources, greater time availability, and stronger organizational support than non-users, while also reporting higher levels of perceived technological competence and digital updating.

These findings are consistent with previous studies based on organizational technology adoption models, such as the TOE model (Technology–Organization–Environment), which emphasizes the importance of structural and organizational conditions in technological innovation processes (Tornatzky & Fleischer, 1990).

This pattern suggests that AI adoption is associated with a combination of motivation, access to organizational opportunities, and perceived technological capability, rather than with motivation alone—underscoring the need for organizational strategies combining specialized training, equitable resource access, and innovation-supportive cultures to prevent AI implementation from widening professional inequalities.

Regarding continuity of use, AI users show a strong predisposition to keep incorporating these tools into their work, and perceiving AI as an opportunity and competitive advantage suggests its adoption extends beyond technical considerations into professional positioning and career development. Theoretically, this research reinforces the explanatory capacity of the MOA model for analysing technology adoption in creative and professional environments, extending its application to communication and advertising, a context that remains underexplored from this perspective.

From an applied perspective, the findings highlight the need for advertising organizations to develop technological integration strategies that facilitate access to AI tools while strengthening training, digital literacy, and workers' technological confidence, and to promote ethical, responsible AI implementation that minimizes perceptions of risk, uncertainty, or job displacement. From a workforce planning standpoint, targeted training investment and HR policies could close resource and competency gaps between AI users and non-users, preventing a two-tier advertising workforce.

However, this research presents several limitations that should be considered. First, the non-probabilistic nature of the sample and its size limit the statistical generalizability of the findings. In addition, the cross-sectional design prevents the analysis of temporal changes in technology adoption processes and potential variations derived from the rapid development of generative artificial intelligence tools. The sample description is also limited to gender, age, company size, AI-user status, and professional role; functional area and level of responsibility beyond professional role were not collected, even though usage patterns are likely to vary substantially across these dimensions within the heterogeneous advertising workforce. Additionally, the multiple Mann–Whitney U tests and Pearson correlations conducted across dimensions did not include a correction for multiple comparisons (e.g., Bonferroni), which increases the risk of Type I error and should be considered when interpreting the pattern of significant results. Finally, the use of self-perception measures may introduce biases associated with social desirability or overestimation of competencies.

Accordingly, future research should further explore longitudinal analyses of AI adoption processes in creative professional environments, incorporate comparative samples across sectors and countries, and examine the impact of organizational, ethical, and regulatory variables on the consolidation of sustainable models for integrating artificial intelligence within the advertising industry.

Acknowledgements / Funding
The authors received no financial support for this research.

Conflict of interest
The authors declare no conflict of interest.

Ethical statement
This study was conducted in accordance with the principles of scientific research and did not require additional ethics committee approval.

Declaration of AI usage
Generative AI tools were used exclusively to support the linguistic revision and improve the English writing of this manuscript. All intellectual contributions, including the research design, literature review, hypothesis development, methodology, data collection, statistical analyses, interpretation of the findings, and scientific content, were carried out entirely by the authors, who assume full responsibility for the manuscript.

Data availability

The data supporting the findings of this study are available upon request.

Author contributions

	Noemí Martín-García	Marian Núñez-Cansado	Marta Laguna-García
Conceptualization	X	X	X
Data curation	X	X	X
Formal analysis	X		
Investigation	X	X	X
Methodology	X	X	X
Project administration	X		X
Resources	X	X	X
Software	X		
Supervision	X	X	X
Validation	X	X	X
Visualization	X	X	
Writing - original draft	X	X	X
Writing - review & editing	X	X	

References

Acemoglu, D. (2025) The simple macroeconomics of AI. *Economic Policy, 40*(121), 13-58. https://doi.org/10.1093/epolic/eiae042

Agrawal, A., Gans, J. & Goldfarb, A. (2019) The economics of artificial intelligence: an agenda. *The University of Chicago Press.* https://www.nber.org/books-and-chapters/economics-artificial-intelligence-agenda

An, M., Lin, J. & Luo, X. R. (2024) The impact of human AI skills on organizational innovation: The moderating role of digital organizational culture. *Journal of Business Research, 182*. https://doi.org/10.1016/J.JBUSRES.2024.114786

Ångström, R. C., Björn, M., Dahlader, L., Mähring, M. & Wallin, M. W. (2023) Getting AI Implementation Right: Insights from a Global Survey. *California Management Review*, *66*(1), 5–22. https://doi.org/10.1177/00081256231190430

Ayinaddis, S. G. (2025) Artificial intelligence adoption dynamics and knowledge in SMEs and large firms: A systematic review and bibliometric analysis. *Journal of Innovation & Knowledge, 10*(3). https://doi.org/10.1016/j.jik.2025.100682

Baabdullah, A. M. (2024) The precursors of AI adoption in business: Towards an efficient decision-making and functional performance. *International Journal of Information Management, 75*. https://doi.org/10.1016/J.IJINFOMGT.2023.102745

Bigné, E., Hernández, B., Ruiz, C. & Andreu, L. (2010) How motivation, opportunity and ability can drive online airline ticket purchases. *Journal of Air Transport Management, 16*(6), 346-349. https://doi.org/10.1016/j.jairtraman.2010.05.004

Budhwar, P., Malik, A., De Silva, M. T. T. & Thevisuthan, P. (2022) Artificial intelligence – challenges and opportunities for international HRM: a review and research agenda. The International *Journal of Human Resource Management*, *33*(6), 1065–1097. https://doi.org/10.1080/09585192.2022.2035161

Buess, L., Keicher, M., Navab, N., Maier, A. & Arasteh, S. T. (2025) From large language models to multimodal AI: A scoping review on the potential of generative AI in medicine. *arXiv:2502.09242*. http://arxiv.org/abs/2502.09242

Chatterjee, S., Rana, N.P., Tamilmani, K. & Sharma, A. (2021) The effect of AI-based CRM on organization performance and competitive advantage: An empirical analysis in the B2B context. *Industrial Marketing Management*, *97*, 205–219. https://doi.org/10.1016/J.INDMARMAN.2021.07.013

Chi, O. H., Gursoy, D. & Chi, C. G. (2022) Tourists' Attitudes toward the Use of Artificially Intelligent (AI) Devices in Tourism Service Delivery: Moderating Role of Service Value Seeking. *Journal of Travel Research*, *61*(1). https://doi.org/10.1177/0047287520971054

Cook, R. L. & Schleede, J. M. (1988) Application of expert systems to advertising. *Journal of Advertising Research*, *28*(3), 47–56.

Cox, W. M. & Klinger, E. (1988) A motivational model of alcohol use. *Journal of Abnormal Psychology*, *97*(2), 168–180. https://doi.org/10.1037/0021-843X.97.2.168

Cui, X., Lai, V. S., Lowry, P. B. & Lei, Y. (2020) The effects of bidder factors on online bidding strategies: A motivation-opportunity-ability (MOA) model. *Decision Support Systems*, *138*. https://doi.org/10.1016/j.dss.2020.113397

Davis, F. D. (1989) Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008

Du, D., Zhang, Y. & Ge, J. (2023) Effect of AI Generated Content Advertising on Consumer Engagement. In: Nah F., Siau K. (eds) *HCI in Business, Government and Organizations. HCII 2023. Lecture Notes in Computer Science,* 14039. Springer, Cham. https://doi.org/10.1007/978-3-031-36049-7_9

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M., Al-Busaidi, K. A., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., … Wright, R. (2023) So what if ChatGPT wrote it? Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. International Journal of Information Management, 71, 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642

Fernández-Cerezo, A., Hidalgo, I. & Izquierdo, M. (2025) Adoption of artificial intelligence in Spanish firms: an initial analysis based on the Banco de España Business Activity Survey. *Economic Bulletin*, 2025/Q2, 1-11. https://doi.org/10.53479/39725

Filippucci, F., Gal, P. & Schief, M. (2024) Miracle or Myth? Assessing the macroeconomic productivity gains from Artificial Intelligence. *OECD Artificial Intelligence Papers, 29, Organisation for Economic Cooperation and Development Publishing*. https://doi.org/10.1787/b524a072-en

Gutiérrez-Taño, D., Bulchand-Gidumal, J., Díaz-Armas, R. J. & Parra-López, E. (2013) Antecedentes del uso de los medios sociales por el turista: motivación, oportunidad y capacidad (Background on Tourists' Use of Social Media: Motivation, Opportunity, and Capability). *Cuadernos de Turismo*, (31), 153–173. https://revistas.um.es/turismo/article/view/170801

Hainsworth, S. (2023) Does Artificial Intelligence benefit UK businesses? An empirical study of the impact of AI on productivity. *arXiv preprint arXiv:2310.05985*. https://doi.org/10.48550/arXiv.2310.05985

Hamm, P. & Klesel, M. (2021) Success Factors for the Adoption of Artificial Intelligence in Organizations: A Literature Review. In 27th Americas Conference on Information Systems, AMCIS 2021: Digital Innovation and Entrepreneurship. Association for Information Systems. https://n9.cl/xvzw9s

Hassan, M., Kushniruk, A. & Borycki, E. (2024). Barriers to and Facilitators of Artificial Intelligence Adoption in Health Care: Scoping Review. *JMIR Human Factors*, *11*. https://doi.org/10.2196/48633

Heaton, J. B., Polson, N. G. & Witte, J. H. (2017) Deep learning for finance: deep portfolios. *Applied Stochastic Models in Business and Industry*, *33*(1), 3–12. https://doi.org/10.1002/asmb.2209

Hernández-Gómez, O. S. & Fernández-Rincón, A. R. (2025) Presente y futuro de la profesión publicitaria: la incorporación de la Inteligencia Artificial en el trabajo creativo (Present and Future of the Advertising Profession: The Incorporation of Artificial Intelligence in Creative Work). En Jordi Sánchez-Navarro y Pedro Hellín(eds), *Inteligencia Artificial: retos y oportunidades para la formación y el empleo en el*

ámbito de la comunicación (Artificial Intelligence: Challenges and Opportunities for Education and Employment in the Field of Communication), (pp. 255-272). Comunicación Social ediciones.

Huang, M. H. & Rust, R. T. (2021) A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science, 49*(1), 30–50. https://doi.org/10.1007/s11747-020-00749-9

ICEMD (2025, April 15) *Publicidad con IA en 2025*(AI-Powered Advertising in 2025). Instituto de Innovación ESIC.

Jaques, N., Lazaridoy, A., Hughes, E., Gulcehre, C., Ortega, P., Strouse, D.J., Leibo, J.Z. & De Freitas, N. (2019) Social Influence as Intrinsic Motivation for Multi-Agent Deep Reinforcement Learning. In Kamalika Chaudhuri & Ruslan Salakhutdinov (Eds.), *Proceedings of the 36th International Conference on Machine Learning* (Vol. 97, pp. 3040–3049). PMLR. https://proceedings.mlr.press/v97/jaques19a.html

Jarrahi, M. H. (2018) Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons, 61*(4), 577–586. https://doi.org/10.1016/j.bushor.2018.03.007

Kalim, U., Kanwar, A., Sha, J. & Huan, R. (2025) Barriers to AI adoption for women in higher education: a systematic review of the Asian context. *Smart Learning Environments*, *12*(38). https://doi.org/10.1186/s40561-025-00390-5

Kamilaris, A. & Prenafeta-Boldú, F. X. (2018) Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture, 147*, 70–90. https://doi.org/10.1016/j.compag.2018.02.016

Kovič, K., Tominc, P., Prester, J. & Palčič, I. (2024) Artificial Intelligence Software Adoption in Manufacturing Companies. *Applied Sciences*, *14*(16), https://doi.org/10.3390/app14166959

Laguna-García, M., Núñez-Cansado, M.Á., Martín-García, A. y Martín-García, N.C. (2025). La IA desde la perspectiva de los profesionales de la publicidad: perfil de usuario y motivaciones. In Sánchez-Navarro, J. & Hellín, P. (eds.), *Inteligencia artificial: retos y oportunidades para la formación y el empleo en el ámbito de la comunicación.* Observatorio ATIC, 7. Salamanca: Comunicación Social Ediciones y Publicaciones. https://doi.org/10.52495/c13.emcs.36.p114

MacInnis, D. J., Moorman, C. & Jaworski, B. J. (1991) Enhancing and measuring consumers' motivation, opportunity, and ability to process brand information from ads. *Journal of marketing, 55* (4), 32-53. https://doi.org/10.1177/002224299105500403

Malik, O. R. (2025) The emerging AI "revolution tranquille" in America. *arXiv preprint arXiv:2505.14721*. https://doi.org/10.48550/arXiv.2505.14721

Malthouse, E. & Copulsky, J. (2023) Artificial intelligence ecosystems for marketing communications. *International Journal of Advertising, 42*(1), 128–140. https://doi.org/10.1080/02650487.2022.2122249

Martínez-Martínez, I. J., Aguado-Terrón, J. M. & Sánchez-Cobarro, P. H. (2022) Smart Advertising: Innovación y disrupción tecnológica asociadas a la IA en el ecosistema publicitario (Smart Advertising: Innovation and Technological Disruption Driven by AI in the Advertising Ecosystem). *Revista Latina de Comunicación Social, 80*, 69-90. https://www.doi.org/10.4185/RLCS-2022-1693

Montero, N. (2025, March 19) Salta la polémica por el último anuncio de Puma, casi totalmente diseñado con bots de IA (Controversy Erupts Over Puma's Latest Ad, Almost Entirely Designed by AI Bots). MKD. https://www.marketingdirecto.com/creacion/campanas-de-marketing/polemica-anuncio-puma-creado-bots-inteligencia-artificial

Raisch, S. & Krakowski, S. (2021) Artificial intelligence and management: The automation–augmentation paradox. Academy of Management Revie*w, 46*(1), 192–210. https://doi.org/10.5465/amr.2018.0072

ReasonWhy, (2025, March 21) La Inteligencia Artificial ya puede crear anuncios sin intervención humana, y este spot de Puma lo demuestra*. ReasonWhy*. https://www.reasonwhy.es/actualidad/inteligencia-artificial-crear-anuncios-sin-intervencion-humana-spot-puma

Rivera-Montaño, S. A. (2023) Impacto de la inteligencia artificial (IA) en la efectividad de las estrategias de marketing personalizado (Impact of Artificial Intelligence (AI) on the Effectiveness of Personalized Marketing Strategies). *Revista Científica Anfibios, 6*(2), 70–81. https://doi.org/10.37979/afb.2023v6n2.138

Riyath, M. I. & Eid, R. (2025) Marketing professionals' adoption of artificial intelligence and its influence on marketing efficiency. *Benchmarking: An International Journal*. https://doi.org/10.1108/BIJ-01-2025-0005

Rodgers, S. (2021) Themed Issue Introduction: Promises and Perils of Artificial Intelligence and Advertising. *Journal of Advertising*, *50*(1), 1–10. https://doi.org/10.1080/00913367.2020.1868233

Sánchez-Baldo, P. L. (2023) *Inteligencia artificial y publicidad. Perspectivas de creativos publicitarios en España* (Artificial Intelligence and Advertising: Perspectives of Advertising Creatives in Spain) [Trabajo final de Grado]. Universidad Rey Juan Carlos.

Soma, T., Li, B. & Maclaren, V. (2021) An evaluation of a consumer food waste awareness campaign using the motivation opportunity ability framework. *Resources, Conservation and Recycling, 168*, 105313. https://doi.org/10.1016/j.resconrec.2020.105313

Statista, (2023) Generative AI and advertising agencies worldwide – statistics & facts. *Statista*. https://www.statista.com/topics/11766/generative-ai-and-ad-agencies-worldwide/

Steel, P. & König, C-J. (2006) Integrating Theories of Motivation. Academy of Management Review, *31*(4), 889-913. https://doi.org/10.2307/20159257

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

Venkatesh, V., Morris, M. G., Davis, G. B. & Davis, F. D. (2003) User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478. https://doi.org/10.2307/30036540

Wiese, S. A., Lehmann, J. & Beckmann, M. (2024) Organizational culture and the usage of Industry 4.0 technologies: evidence from Swiss businesses. *arXiv:2412.12752*. https://doi.org/10.48550/arXiv.2412.12752

Xia, B. & Zheng, L. (2023) Research on the Communication Effect of Knowledge-Based Videos on Youth Subculture Groups Based on MOA Model. *Journal of South China Normal University (Natural Science Edition*), *55*(4), 87-99. https://doi.org/10.6054/j.jscnun.2023053

Xia, Q., Weng, X., Ouyang, F., Lin, T. J. & Chiu, T. K. F. (2024) A scoping review on how generative artificial intelligence transforms assessment in higher education. *International Journal of Educational Technology in Higher Education*, *21*(1). https://doi.org/10.1186/s41239-024-00468-z

Xie, X. & Yan, J. (2024) How does artificial intelligence affect productivity and agglomeration? Evidence from China's listed enterprise data. *International Review of Economics & Finance, 94*. https://doi.org/10.1016/j.iref.2024.103408

Zavodna, L. S., Überwimmer, M. & Frankus, E. (2024) Barriers to the implementation of artificial intelligence in small and medium sized enterprises: Pilot study. *Journal of Economics and Management*, *46*, 331–352. https://doi.org/10.22367/jem.2024.46.13

Zhai, S. & Liu, Z. (2023) Artificial intelligence technology innovation and firm productivity: Evidence from China. *Finance Research Letters,58*. https://doi.org/10.1016/j.frl.2023.104437

Zhang, A. & Lee, M. K. (2025, April) Knowledge Workers' Perspectives on AI Training for Responsible AI Use. *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems* (pp. 1-18). https://dl.acm.org/doi/epdf/10.1145/3706598.3714100

Zhou, Y., He, T. & Lin, F. (2022) The Digital Divide Is Aging: An Intergenerational Investigation of Social Media Engagement in China. *International Journal of Environmental Research and Public Health*, *19*(9). https://doi.org/10.3390/ijerph191912965

Appendix A. Full Wording of Questionnaire Items

Item wording, organised by MOA dimensions and related analytical sections. Non-user items used conditional, forward-looking phrasing (e.g., "would help" instead of "helps"); slashes indicate the user/non-user variant. † These four items were administered as part of the same data collection but were analysed separately, under a different theoretical framework, in an earlier companion study based on a partial subsample (n = 105; Author(s), 2025). They are therefore not part of the MOA constructs reported in Tables 5–8.

Dimension	Group	Item (Spanish)	Item (English)
Functional Motivation	Users	Usar la IA me ayuda a mejorar la efectividad de mi trabajo	Using AI helps me improve the effectiveness of my work
Functional Motivation	Non-users*	Creo que la IA ayudaría a mejorar la efectividad de mi trabajo	I believe AI would help improve the effectiveness of my work
Functional Motivation	Users	La IA aumenta la calidad de mi trabajo	AI increases the quality of my work
Functional Motivation	Non-users*	Creo que la IA aumentaría la calidad de mi trabajo	I believe AI would increase the quality of my work
Functional Motivation	Users	Usar IA aumenta mi productividad (ahorra tiempo, costes...) y mejora los resultados de mi trabajo	Using AI increases my productivity (saves time and costs) and improves my work results
Functional Motivation	Non-users*	Creo que la IA aumentaría la productividad y mejoraría los resultados de mi trabajo	I believe AI would increase productivity and improve my work results
Social Motivation	Both*	Las herramientas de IA me permiten/permitirían estar en contacto con gente que comparte los mismos intereses en relación con la publicidad	AI tools allow/would allow me to be in contact with people who share the same interests in advertising
Social Motivation	Both*	Hacen/aumentarían la relación personal que tengo con personas que también las usan en su trabajo	They increase/would increase the personal relationships I have with people who also use them at work
Social Motivation	Both*	Son/serían herramientas que me aportan un fuerte sentimiento de pertenencia a un grupo/mi grupo de trabajo	They are/would be tools that give me a strong sense of belonging to a group/my work team
Hedonic Motivation	Both*	Usar la IA en mis trabajos de publicidad es/sería agradable	Using AI in my advertising work is/would be enjoyable
Hedonic Motivation	Both*	Usar la IA es/sería divertido para mí	Using AI is/would be fun for me
Hedonic Motivation	Both*	Es/sería placentero usar herramientas de IA en mis trabajos	It is/would be pleasurable to use AI tools in my work
Organizational Opportunity	Both	Tengo acceso a la tecnología y medios necesarios para usar las herramientas de IA	I have access to the technology and resources required to use AI tools
Organizational Opportunity	Both	Mi empresa favorece el uso de la IA en nuestro trabajo	My company supports the use of AI in our work
Organizational Opportunity	Both	Tengo el tiempo para usar la IA o aprender a usarla	I have enough time to use AI or learn to use it
Technological Ability	Both*	Soy una persona con habilidades tecnológicas para usar/que podría usar la IA en mi trabajo	I am a person with the technological abilities to use/who could use AI in my work
Technological Ability	Both	Me resulta fácil y me gusta estar al día de las novedades	I find it easy and enjoy keeping up to date with new developments
Technological Ability	Users only	Tengo los conocimientos necesarios para usar la IA	I have the necessary knowledge to use AI

Technological Ability	Users only	Soy bueno usando la IA	I am good at using AI
Intention / Continuity	Both	Tengo la intención de usar IA en mis proyectos de publicidad en el futuro	I intend to use AI in my advertising projects in the future
Intention / Continuity	Users only	Continuaré usando herramientas de IA en mi trabajo	I will continue using AI tools in my work
Intention / Continuity	Both	Usar la IA es algo que yo haría	Using AI is something I would do
AI Evaluation	Both	Una oportunidad	An opportunity
AI Evaluation	Both	Una amenaza	A threat
AI Evaluation	Both	Un riesgo (plagio, destrucción de empleo, sesgos, etc.)	A risk (plagiarism, job displacement, bias, etc.)
AI Evaluation	Both	Una ventaja competitiva (mejoraría mi estatus profesional, posibilidad de ascender, diferenciarme de compañeros, etc.)	A competitive advantage (it would improve my professional status, provide opportunities for promotion, differentiate me from colleagues, etc.)
Usage & Satisfaction	Users only	Frecuencia de uso de IA en el trabajo; grado de satisfacción con la IA en el trabajo	Frequency of AI use at work; level of satisfaction with AI at work
Non-adoption reasons	Non-users only	No las necesito / No tengo formación para usarlas / No me interesa usarlas	I do not need them / I lack training to use them / I am not interested in using them
Companion study only†	Both	Reconocimiento/prestigio; ingresos/retribución; logro/satisfacción; desafío de dominar la IA	Recognition/prestige; income/compensation; achievement/satisfaction; challenge of mastering AI