NOVA IMS Information Management School

MDDM

Master's Degree Program in

Data-Driven Marketing

Adoption and Impact of Artificial Intelligence in Organizational Decision-Making

Javier Montilla Aguilera

Master Thesis

presented as partial requirement for obtaining a Master's Degree in Data-Driven Marketing with a specialization in Data Science.

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by

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Master Thesis presented as partial requirement for obtaining the Master's degree in Data-Driven Marketing, with a specialization in Data Science for Marketing.

Supervised by

Tiago Oliveira, PhD, NOVA Information Management School

April, 2025

STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism, any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledged the Rules of Conduct and Code of Honor from the NOVA Information Management School.

[Lisbon, 21/04/2025]

Javier Montilla Aguilera

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ABSTRACT

Artificial intelligence (AI) is becoming a critical enabler of data-driven business decision-making, yet the factors driving its successful adoption and organizational impact remain insufficiently explored. This study proposes and validates an integrated model combining the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) with the DeLone & McLean Information Systems Success Model to explain AI adoption in professional contexts. Structural Equation Modeling (PLS-SEM) was applied to data collected from 391 respondents, primarily students and professionals with an active interest and background in AI. The findings confirm that performance expectancy, hedonic motivation, social influence, and habit significantly influence behavioral intention and use behavior about these tools. These, in turn, enhance the perception of net organizational benefits. The model also incorporates age as a moderating factor, revealing generational differences in how users respond to key adoption drivers. The results provide both theoretical contributions to the refinement technology acceptance models and practical implications for the effective implementation of AI in decision-making environments.

KEYWORDS

Artificial intelligence; Decision-making; Generational moderation; Information Success Model; UTAUT2; Technology adoption.

Sustainable Development Goals (SDG):

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LIST OF ABBREVIATIONS AND ACRONYMS

AI – Artificial Intelligence. A field of computer science focused on building systems capable of performing tasks that typically require human intelligence, such as learning, reasoning, and decision-making.

AVE – Average Variance Extracted. A measure used to assess convergent validity, representing the average amount of variance explained by the indicators of a construct.

CR – Composite Reliability. A metric that assesses the internal consistency of a construct, indicating how well the indicators represent the latent variable.

D&M – DeLone and McLean IS Success Model. A framework for assessing the success of information systems based on factors such as system use, user satisfaction, and net benefits.

HTMT – Heterotrait–Monotrait Ratio. A criterion for evaluating discriminant validity between constructs, ensuring that each construct is empirically distinct from others.

PLS-SEM – Partial Least Squares Structural Equation Modeling. A statistical technique used to analyze complex relationships among latent variables.

UTAUT2 – Unified Theory of Acceptance and Use of Technology 2. An extended model for understanding user acceptance of technology, including constructs like performance expectancy, social influence, and habit.

VIF – Variance Inflation Factor. A diagnostic measure used to detect multicollinearity in regression analysis, where values above 5 may indicate problematic correlation.

1) INTRODUCTION

Artificial Intelligence (AI) has emerged as a transformative force across industries, fundamentally reshaping how organizations make decisions, analyze data, and deliver value (Benbya et al., 2020). Its potential to enhance strategic planning, operational efficiency, and innovation makes AI a key enabler of competitive advantage in digital economies (Edwards et al., 2022). As AI systems become more integrated into business processes—from automation to analytics—understanding the dynamics behind their adoption becomes increasingly critical. Despite its growing prominence, successful AI adoption is not solely a matter of technological capability. It also requires behavioral alignment and organizational readiness (Raftopoulos, 2024). Prior research has tended to focus either on technical attributes—such as system and information quality (DeLone & McLean, 2003)—or on user-centric factors—such as performance expectancy and effort expectancy (Venkatesh et al., 2012). However, few studies have explored the intersection between behavioral and organizational dimensions, particularly in AI-enabled decision-making contexts, where user engagement and system outcomes are closely intertwined (Fügener et al., 2021).

To address this gap, this study develops and tests an integrated model combining the UTAUT2 (Unified Theory of Acceptance and Use of Technology 2) and the Updated DeLone & McLean IS Success Model. The framework aims to identify the factors that influence users' behavioral intention, actual use, and perceived net benefits of AI in organizational environments. The model also explores the moderating role of age, acknowledging that adoption behaviors and motivations may differ across generational cohorts (Grassini & Koivisto, 2024).

Empirical data were collected through a survey of 391 including students and professionals with demonstrated interest and knowledge in AI. The study applies Partial Least Squares Structural Equation Modeling (PLS-SEM) to evaluate both the measurement and structural models.

By bridging behavioral intention with organizational impact, this research contributes to both theoretical understanding and practical application. It offers a validated model to guide AI adoption strategies, tailored to different user profiles, and supports organizations and policymakers in designing inclusive and sustainable AI implementation pathways (Benbya et al., 2024).

2) LITERATURE REVIEW

2.1 Theoretical Foundations

2.1.1 UTAUT2 Framework

The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) (Venkatesh et al., 2012) is a widely recognized framework for analyzing technology adoption. It incorporates six core constructs—performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and habit—which collectively explain users' behavioral intention and actual use of technology. UTAUT2 has been extended across various domains due to its predictive power and ability to accommodate moderating variables such as age, gender, and experience.

In this study, UTAUT2 is applied to an AI-driven decision-making context, where behavioral intention is examined as a determinant of use behavior. The model is enriched by exploring the moderating role of age, considering generational differences in motivation, trust, and technology acceptance patterns (Grassini & Koivisto, 2024).

2.1.2 DeLone and McLean Information Systems Success Model

The DeLone and McLean Information Systems (IS) Success Model (DeLone & McLean, 2003) offers a performance-oriented lens to evaluate technology implementation. The model links system quality, information quality, and service quality to user satisfaction, use behavior, and net benefits. It has been extensively applied in assessing the outcomes of digital systems in organizational environments.

In this research, the D&M model is employed to evaluate the impact of AI use behavior on organizational outcomes, particularly perceived net benefits such as improved decision quality, productivity, and strategic agility. By doing so, the model enables an empirical assessment of how actual AI usage translates into measurable organizational performance.

2.2 The Role of AI in Organizational Decision-Making

Artificial Intelligence has transitioned from a back-office tool to a strategic asset in organizational decision-making. AI systems are increasingly used to automate analytical tasks, generate data-driven recommendations, and support real-time decision-making across functional areas such as operations, finance, and HR (Benbya et al., 2020). These systems enhance not only operational efficiency but also strategic foresight, helping firms respond proactively to dynamic market conditions (Fügener et al., 2022; Edwards et al., 2022).

However, AI adoption is not purely technical. Its success depends on the intersection of human behavior, organizational readiness, and trust in algorithmic systems (Raftopoulos, 2024).

Research highlights the challenges of user acceptance, interpretability, and integration into collaborative workflows (Kuhail et al., 2024). Additionally, concerns around transparency, ethical alignment, and role displacement can inhibit engagement with AI in high-stakes decisions (Grassini & Koivisto, 2024).

This study addresses these challenges by adopting a dual-perspective model that integrates both behavioral (UTAUT2) and performance-oriented (D&M) constructs to assess AI's adoption and impact within decision-making environments. This approach enables a nuanced understanding of how users perceive, adopt, and benefit from AI technologies, particularly in organizational settings that are increasingly reliant on hybrid human-machine collaboration.

2.3 Integrating UTAUT2 and DeLone and McLean Models

The integration of UTAUT2 and the DeLone & McLean IS Success Model in this research offers a comprehensive framework for AI adoption and outcome evaluation. While UTAUT2 explains the motivational and attitudinal precursors to AI use, the D&M model captures the resulting organizational impact through perceived net benefits.

Performance expectancy, effort expectancy, and hedonic motivation shape the individual's perception of AI's value and usability. Social influence and facilitating conditions determine the cultural and infrastructural support for adoption. Habit reflects the level of routine engagement, acting as a key driver for sustained usage. Use behavior is positioned as a mediator between intention and net benefits, linking user engagement to tangible business outcomes.

Furthermore, age is considered as a moderating variable, acknowledging the differentiated experiences and expectations of younger versus older users. Prior studies suggest that younger users prioritize intuitive, engaging interfaces, while older users focus on reliability and task efficiency (Grassini & Koivisto, 2024).

This integrative approach allows for a balanced evaluation of both individual behavioral dynamics and organizational-level performance, offering practical implications for AI adoption strategies that are inclusive and results-oriented.

3) RESEARCH MODEL

The conceptual model developed in this study aims to explain the adoption of Artificial Intelligence (AI) in organizational decision-making contexts, as well as the perceived benefits that result from its effective use. The model integrates a set of behavioral constructs—drawn from established technology acceptance and system success frameworks—and proposes a series of direct and moderating relationships that together capture the psychological, contextual, and performance-related dimensions of AI implementation.

Building on the foundations reviewed in the previous section, the model posits that constructs such as performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and habit influence users' behavioral intention to adopt AI systems. This behavioral intention, in turn, is expected to directly predict actual use behavior, which serves as a key driver of perceived net benefits—an outcome operationalized in terms of improved productivity, decision quality, and strategic alignment.

In addition to the core relationships, the model introduces age as a moderating variable. Based on existing evidence of generational differences in technology perceptions and motivations, age is expected to moderate several paths within the model, particularly those linked to behavioral intention and user engagement with AI. The research model is shown in Fig. 1.

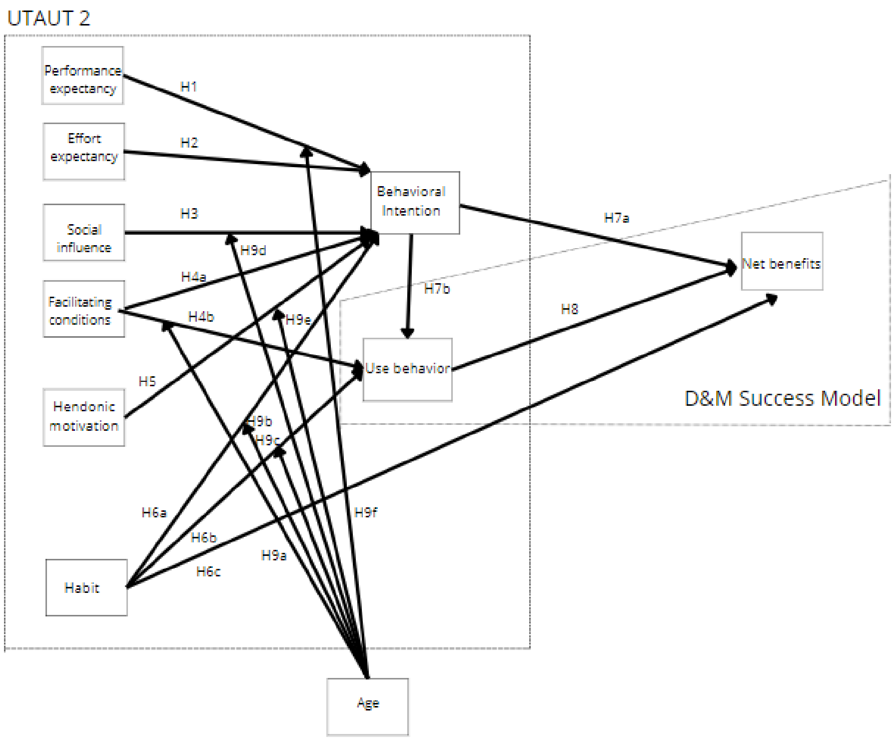

Figure 3-1 Model & Hypotheses

3.1 Hypotheses

In line with the UTAUT2 framework proposed by Venkatesh et al. (2012), this study considers six independent constructs to explain the formation of behavioral intention and use behavior in the context of AI adoption.

Performance expectancy refers to the extent to which individuals believe that using AI will enhance their job performance and decision-making capabilities. Prior studies have emphasized that AI-driven tools can significantly improve operational efficiency and contribute to competitive advantage through optimized decision-making (Benbya et al., 2020; Rana et al., 2022).

H1. Performance expectancy positively influences behavioral intention.

Effort expectancy denotes the perceived ease of use associated with AI systems. Research has shown that intuitive and user-friendly interfaces increase adoption rates, particularly among users with less technical experience (Venkatesh et al., 2012).

H2. Effort expectancy positively influences behavioral intention.

Social influence captures the extent to which individuals perceive those important others (e.g., managers, colleagues, industry leaders) believe they should use AI systems. Previous work highlights that peer recommendations and organizational culture play a significant role in shaping technology acceptance (Cheng et al., 2022).

H3. Social influence positively influences behavioral intention.

Facilitating conditions relate to the organizational and technical support available for AI implementation, including infrastructure, training, and resources. Structured deployment strategies and governance frameworks have been identified as enablers of both intention and usage of AI tools (Benbya et al., 2020; Rana et al., 2022).

H4a. Facilitating conditions positively influence behavioral intention.

H4b. Facilitating conditions positively influence use behavior.

Hedonic motivation refers to the pleasure or enjoyment derived from using a system. In the context of AI, this construct reflects how much users find AI tools engaging and satisfying to interact with. Prior research indicates that when systems are enjoyable to use and offer personalized, rewarding experiences, user adoption tends to increase (Venkatesh et al., 2012; Grassini & Koivisto, 2024).

H5. Hedonic motivation positively influences behavioral intention.

Habit is defined as the extent to which users tend to perform behaviors automatically due to learning. When AI use becomes part of daily routines, it can reinforce behavioral intention and increase the likelihood of continued use. Moreover, habitual use has been shown to influence not only usage frequency but also the realization of organizational benefits from AI systems (Benbya et al., 2020; Alavi et al., 2024).

H6a. Habit positively influences behavioral intention.

H6b. Habit positively influences use behavior.

H6c. Habit positively influences net benefits.

Behavioral intention is a central construct in technology adoption research, representing a user's readiness or plan to engage with a system. It plays a mediating role between psychological drivers (e.g., performance expectancy, habit) and actual system use. In turn, this use is expected to generate benefits for the organization. According to the DeLone and McLean model (2003), both use behavior and intention are antecedents of net benefits, particularly in terms of productivity and decision-making effectiveness.

H7a. Behavioral intention positively influences net benefits.

H7b. Behavioral intention positively influences use behavior

Use behavior refers to the actual usage of AI systems in daily organizational activities. It is considered a key determinant of performance outcomes in IS research. Frequent and consistent use of AI tools has been shown to enhance organizational efficiency, support innovation, and contribute to long-term competitiveness (Benbya et al., 2020). Furthermore, AI-driven business analytics enables more informed and strategic decision-making, which is positively associated with financial and operational performance (Rana et al., 2022).

H8. Use behavior positively influences net benefits.

Prior research has shown that age influences how individuals perceive, adopt, and interact with technology (Venkatesh et al., 2012). Generational differences are particularly relevant in the context of AI, where cognitive familiarity, openness to innovation, and digital fluency vary substantially across age groups (Grassini & Koivisto, 2024). Accordingly, this study examines whether age moderates key relationships in the proposed model, particularly those involving behavioral intention, use behavior, and motivational constructs. It is expected that younger users, who are generally more comfortable with technology, will respond more strongly to constructs such as hedonic motivation and social influence, while older users may place more emphasis on habit formation and structured support.

H9a. Age moderates the relationship between facilitating conditions and behavioral intention.

H9b. Age moderates the relationship between habit and behavioral intention.

H9c. Age moderates the relationship between habit and use behavior.

H9d. Age moderates the relationship between social influence and behavioral intention.

H9e. Age moderates the relationship between hedonic motivation and behavioral intention.

H9f. Age moderates the relationship between performance expectancy and behavioral intention.

4) METHODS

4.1 MEASUREMENT

To operationalize the constructs defined in the proposed research model, a structured survey instrument was developed based on validated measurement scales from prior studies. The items used were adapted from the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) (Venkatesh et al., 2012) and the Updated DeLone and McLean Information Systems Success Model (DeLone & McLean, 2003). The questionnaire was specifically designed to capture key behavioral, organizational, and performance-related aspects of AI adoption in decision-making contexts.

The survey was divided into two main sections. The first included demographic questions, covering gender, age, education level, monthly gross income (€), and employment status. The second contained construct-based items, corresponding to the latent variables in the research model.

The constructs were grouped as follows:

- UTAUT2 constructs: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, and behavioral intention.
- D&M IS Success Model constructs: use behavior and net benefits.

All items were measured using multi-item reflective indicators on a seven-point Likert scale, ranging from 1 (“strongly disagree”) to 7 (strongly agree”), in line with established practices in technology adoption research.

Before full data collection, a pilot study was conducted with a sample of 30 respondents, primarily students and professionals from Spain and Portugal recruited through LinkedIn and academic networks. The pilot test aimed to ensure clarity of wording, improve construct validity, and assess the internal consistency of the scale items. Feedback received during the pilot phase led to minor adjustments in item phrasing and survey flow.

The final version of the questionnaire was administered using the Qualtrics online platform. Detailed measurement items, their sources, and scale structures are provided in Appendix A.

4.2 DATA

Data collection was conducted through an online survey using Qualtrics, targeting a diverse set of respondents. The survey was distributed via multiple channels, including friends, colleagues, students at NOVA IMS, and LinkedIn groups.

A total of 379 valid responses were collected. The age of respondents ranged from 21 to 65 years old, with a mean age of 33.33 years. The sample was 51% male and 49% female.

The educational background of the respondents varied, with 48% holding a bachelor's degree, 37% a master's degree, and 7% a doctoral degree. Only a small percentage had lower educational qualifications.

Regarding monthly gross income, 45% of respondents earned between €2000 and €3000, while 34% reported earnings above €3000. A smaller proportion earned between €1000 and €2000 (17%) or less than €1000 (3%).

For employment status, the majority were private sector employees (48%) or government employees (20%). Additionally, 19% were self-employed, 6% were interns, 5% were students, 2% were unemployed, and 0.3% were retired.

A detailed breakdown of the demographic information is presented in Appendix B.

This dataset represents a well-distributed sample, making it suitable for analyzing AI adoption trends and behavioral factors in different organizational contexts.

5) DATA ANALYSIS AND RESULTS

5.1 MEASUREMENT MODEL

The measurement model was evaluated to ensure the reliability and validity of the reflective constructs, following the guidelines of Hair et al. (2021). The assessment comprised indicator reliability, internal consistency reliability, convergent validity, and discriminant validity.

Composite Reliability (CR) was used to assess internal consistency. As shown in Table 1, all constructs presented CR values above the recommended threshold of 0.70, with results ranging between 0.812 and 0.890. These values confirm that the measurement scales exhibit acceptable levels of internal consistency reliability.

Indicator reliability was examined by inspecting the outer loadings of each item. In line with established criteria, most items loaded above 0.70. However, three items—PE1, PE2, and EE4—did not meet this threshold and were excluded from the model to enhance its psychometric properties, as is recommended in SEM practices.

Convergent validity was evaluated using the Average Variance Extracted (AVE). All AVE values exceeded 0.50, indicating that the constructs explain a sufficient proportion of variance in their respective indicators (Table 1).

Discriminant validity was assessed through two complementary methods. First, the Fornell-Larcker criterion confirmed that the square root of each construct's AVE was greater than its correlations with other constructs (Table 2). Second, the HTMT (Heterotrait-Monotrait Ratio) was analyzed. All values were below the threshold of 0.90, as recommended by Henseler et al. (2015), except for the pair Facilitating Conditions–Social Influence (HTMT = 0.902), which slightly exceeded the conservative cut-off of 0.85. However, it is still considered acceptable under the broader criterion and does not compromise discriminant validity (Table 3).

These results provide evidence of strong reliability and validity for the reflective measurement model and support its use in the structural analysis.

Table 5-1 Quality criterion (AVE, composite reliability, alpha) and factor loadings.

Construct	Item	AVE	Composite reliabily	Cronbach's alpha	Loading
Performance expectancy	PE3	0.786	0.880	0.730	0.905
	PE4				0.868
Effort expectancy	EE1	0.686	0.868	0.771	0.842
	EE2				0.839
	EE3				0.804
Social influence	SI1	0.591	0.812	0.671	0.798
	SI2				0.717
	SI3				0.789
Facilitating conditions	FC1	0.636	0.839	0.717	0.774
	FC2				0.814
	FC3				0.803
Hendonic motivation	HM1	0.717	0.884	0.804	0.870
	HM2				0.832
	HM3				0.837
Habit	H1	0.625	0.832	0.700	0.868
	H2				0.683
	H3				0.810
Behavioral intention	BI1	0.705	0.877	0.790	0.851
	BI2				0.844
	BI3				0.823
User behavior	USE1	0.650	0.881	0.820	0.857
	USE2				0.806
	USE3				0.786
	USE4				0.772
Net benefits	NB1	0.730	0.890	0.815	0.831
	NB2				0.883
	NB3				0.848

Table 5-2 Fornell-Lacker Criterion: Matrix of correlation constructs and the square root of AVE (in bold).

Constructs	BI	EE	FC	H	HM	IDD	NB	PE	SI	USE
Behavioral intention (BI)	**0.839**									
Effort expectancy (EE)	0.620	**0.828**								
Facilitating conditions (FC)	0.553	0.624	**0.797**							
Habit (H)	0.403	0.502	0.509	**0.791**						
Hendonic motivation (HM)	0.607	0.571	0.565	0.404	**0.847**					
Age (IDD)	-0.064	-0.061	-0.004	0.045	-0.011	**1.000**				
Net benefits (NB)	0.540	0.574	0.529	0.627	0.645	-0.089	**0.854**			
Perfomance expectancy (PE)	0.644	0.668	0.515	0.421	0.528	-0.113	0.574	**0.887**		
Social influence (SI)	0.576	0.623	0.623	0.476	0.644	0.014	0.515	0.461	**0.769**	
Use behavior (USE)	0.640	0.606	0.602	0.550	0.640	-0.020	0.713	0.584	0.534	**0.806**

Table 5-3 Heterotrait monotrait ratio (HTMT)

Construct	BI	EE	FC	H	HM	IDD	NB	PE	SI	USE
BI										
EE	0.792									
FC	0.720	0.841								
H	0.528	0.676	0.710							
HM	0.756	0.723	0.737	0.518						
IDD	0.081	0.070	0.057	0.121	0.041					
NB	0.672	0.724	0.690	0.815	0.793	0.099				
PE	0.843	0.892	0.710	0.588	0.688	0.139	0.746			
SI	0.751	0.852	0.902	0.698	0.873	0.032	0.688	0.620		
USE	0.789	0.758	0.777	0.716	0.775	0.054	0.867	0.747	0.688	

5.2 STRUCTURAL MODEL

To assess the relationships between constructs, the structural model was estimated using the PLS-SEM technique with SmartPLS, applying a bootstrapping procedure with 5,000 subsamples. Prior to model estimation, collinearity among indicators was evaluated using the Variance Inflation Factor (VIF). All VIF values were below 3.0, indicating that multicollinearity was not a concern and ensuring the robustness of the results.

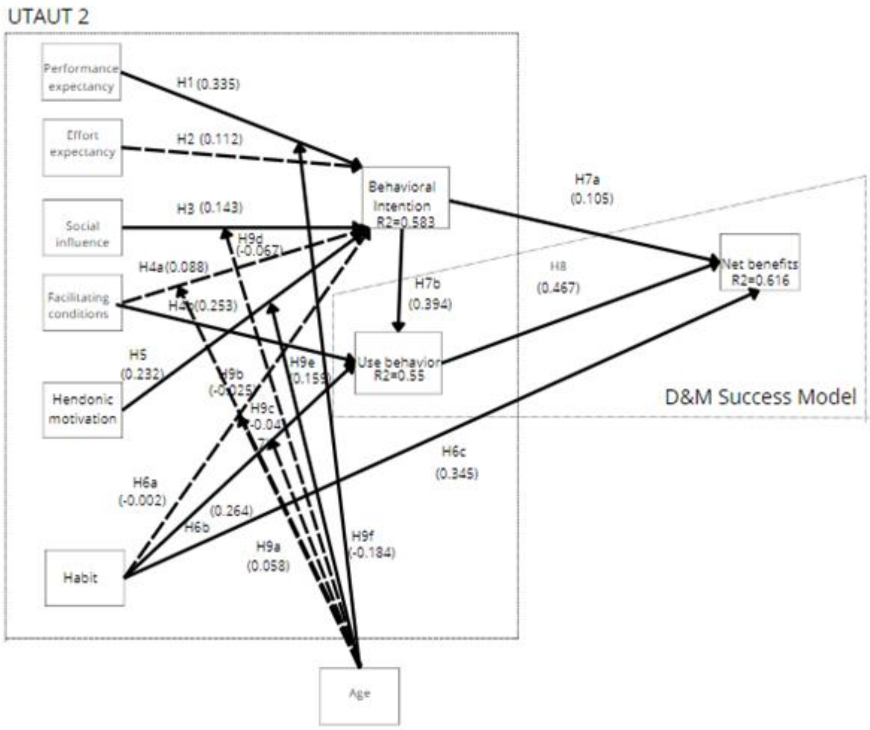

Figure 5-1 Models & Results

The model demonstrated satisfactory explanatory power, accounting for 58.3% of the variance in Behavioral Intention, 55.0% in Use Behavior, and 61.6% in Net Benefits. In line with the proposed hypotheses, the results confirmed that Performance Expectancy, Social Influence, and Hedonic Motivation significantly influence Behavioral Intention, supporting H1, H3, and H5, respectively. Conversely, H2, H4a, and H6a were not supported, as Effort Expectancy, Facilitating Conditions, and Habit did not exhibit statistically significant effects on Behavioral Intention.

With respect to Use Behavior, the results confirmed that Facilitating Conditions, Habit and Behavioral Intention were significant predictors, supporting hypotheses H4b, H6b, and H7b, respectively. These findings highlight the importance of both structural support and personal behavioral tendencies in encouraging actual system use.

Finally, the analysis of the antecedents of Net Benefits revealed that Habit, Behavioral Intention, and Use Behavior had significant positive effects, confirming hypotheses H6c, H7a, and H8. These results reinforce the mediating role of Behavioral Intention and Use Behavior in delivering organizational value from AI and demonstrate that sustained and integrated use of AI systems is essential for realizing tangible benefits such as improved decision quality and efficiency.

5.2.1 Moderation Effects of Age

The moderating role of age was tested by introducing interaction terms for selected paths in the research model. The results reveal that age exerts a significant moderating effect in two specific relationships. First, age positively moderates the relationship between Hedonic Motivation and Behavioral Intention, suggesting that older individuals are more likely to engage with AI when they perceive it as enjoyable or entertaining..

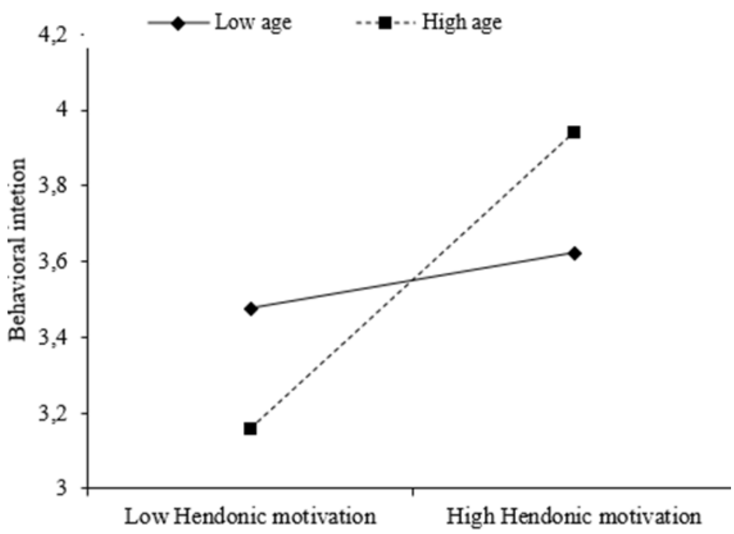

Figure 5-2 Moderating effect of age between hendonic motivation and behavioral intention

Second, a negative moderating effect was observed in the relationship between Performance Expectancy and Behavioral Intention indicating that performance-related motivations are more relevant among younger users than older ones.

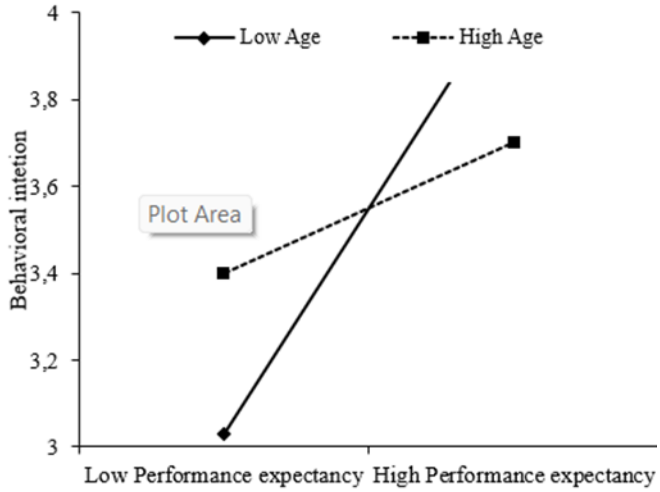

Figure 5-3 Moderating effect of age between Performance expectancy and behavioral intention

Conversely, the remaining moderation hypotheses (H9a to H9d), involving Facilitating Conditions, Habit, and Social Influence, were not statistically supported ($p > 0.05$), suggesting that age does not significantly alter the influence of these factors on AI adoption behaviors. These findings highlight that while age plays a role in shaping certain motivational dynamics, its overall moderating impact on the adoption process appears to be limited. In total, 11 out of the 17 hypotheses were confirmed, reinforcing the relevance of behavioral intention, use behavior, and habit as key drivers of AI-generated value in organizational decision-making.

6) DISCUSSION

This study aimed to examine the factors influencing the adoption and use of Artificial Intelligence (AI) systems in decision-making contexts within organizations, integrating the UTAUT2 model (Venkatesh et al., 2012) and the DeLone and McLean IS Success Model (DeLone & McLean, 2003). The findings provide theoretical and practical insights into how behavioral intention, actual use, and perceived organizational benefits are shaped by individual motivations and organizational factors.

Regarding behavioral intention to use AI, the study confirmed the significant positive effects of performance expectancy, social influence, and hedonic motivation. These results align with previous research indicating that the perceived usefulness of AI technologies (Benbya et al., 2020) and the enjoyment derived from their use (Grassini & Koivisto, 2024) are critical motivators for adoption. Moreover, the influence of peers and organizational endorsement, as conceptualized by Venkatesh et al. (2012), was validated, highlighting the social nature of technology acceptance in professional environments.

Contrary to expectations, effort expectancy and facilitating conditions did not significantly predict behavioral intention. This outcome may reflect the increasing digital competence of the workforce (Alavi et al., 2024), whereby perceived ease of use becomes less relevant when individuals are accustomed to interacting with complex technological systems. This finding echoes previous suggestions that the barriers related to system usability diminish as technology becomes more pervasive and intuitive (Benbya et al., 2020).

Similarly, habit did not show a direct impact on behavioral intention but demonstrated strong positive effects on both use behavior and net benefits. This supports the view that habitual use develops over time and significantly contributes to sustained engagement and benefit realization, as suggested by Fügener et al. (2021) in their exploration of human-AI collaboration dynamics.

In terms of use behavior, the study found that facilitating conditions, habit, and behavioral intention were significant predictors. This confirms the notion that while infrastructural support may not drive initial adoption, it is crucial for the sustained and effective use of AI systems (Raftopoulos, 2024). The importance of organizational enablers reflects the need for integrated support structures that ensure the continuous operational success of AI initiatives (Uren & Edwards, 2023).

Regarding net benefits, significant relationships were found with behavioral intention, use behavior, and habit. These results validate the DeLone and McLean (2003) proposition that system use is a critical driver of perceived benefits at the organizational level. Moreover, the role of habitual use emphasizes that repeated and routinized engagement with AI tools is essential to realize strategic and operational advantages (Rana et al., 2022).

The moderation analysis revealed that age moderated the relationship between hedonic motivation and behavioral intention, and between performance expectancy and behavioral intention. Specifically, younger users exhibited stronger relationships between enjoyment and intention, while older users were more influenced by performance expectations. These findings are consistent with Fügener et al. (2021) and Grassini & Koivisto (2024), who observed generational differences in cognitive styles and motivations in technology use.

6.1. Theorical Contributions

This study offers several theoretical contributions to the field of AI adoption and IS research. First, it validates the integration of the UTAUT2 framework with the Updated DeLone and McLean IS Success Model (DeLone & McLean, 2003) in the context of AI-assisted decision-making. The model demonstrates that while traditional behavioral constructs—such as performance expectancy, hedonic motivation, and social influence—remain critical to predicting behavioral intention, the inclusion of organizational outcome variables (use behavior and net benefits) allows for a more holistic understanding of AI value creation in professional settings (Benbya et al., 2020).

Second, the study contributes to the refinement of technology adoption models by exploring the role of habit not only as a behavioral antecedent but also as a direct predictor of organizational performance. The evidence shows that repeated AI usage can, over time, develop into habitual interaction patterns that meaningfully contribute to perceived value and strategic benefit—an underexplored dynamic in current IS literature (Fügener et al., 2021; Benbya et al., 2020).

Third, the moderating role of age offers a novel contribution to the discourse on generational differences in digital adoption. While previous studies have established age as a moderator in broader technology acceptance models (Venkatesh et al., 2012), this study reveals that such moderation may be selective and contingent on specific motivational factors, such as enjoyment or perceived utility (Grassini & Koivisto, 2024).

Finally, this research extends prior models by operationalizing net benefits specifically in the context of AI for decision-making. By framing success not only through usage metrics but also through perceived improvements in decision quality and operational efficiency, the study provides a useful framework for future research aiming to capture the full organizational value of AI adoption (Raftopoulos, 2024; Uren & Edwards, 2023).

6.2. Practical Contributions

This research also presents several important implications for practitioners aiming to enhance AI implementation and maximize its value in organizations. First, the findings highlight that both performance-oriented features and user engagement elements are essential to encourage AI adoption. System designers should ensure that AI tools are perceived as useful and enjoyable, offering intuitive interfaces that minimize cognitive load and enhance user experience (Benbya et al., 2020; Grassini & Koivisto, 2024).

Second, the significant role of facilitating conditions and habit in predicting actual use behavior suggests that organizations must go beyond technical deployment. Investment in training programs, continuous user support, and the seamless integration of AI into daily workflows can foster habitual usage, which in turn contributes to tangible organizational benefits (Raftopoulos, 2024; Fügener et al., 2021).

Third, the strong impact of behavioral intention and use behavior on net benefits confirms that strategic value from AI systems is not automatically realized but must be activated through sustained user engagement. Managers should not only track initial adoption rates but also monitor usage frequency, satisfaction, and perceived improvements in decision-making over time to ensure long-term success (Uren & Edwards, 2023).

Finally, understanding how age affects AI-related motivations enables more effective change management strategies. Younger employees may respond more positively to engaging, gamified, and user-centric features, whereas older professionals may require structured training, clear demonstrations of utility, and reassurance about system reliability (Fügener et al., 2021; Grassini & Koivisto, 2024). A differentiated implementation approach can improve acceptance and maximize the return on AI investment across diverse user segments.

6.3 Limitation and future research

As with any empirical study, this research presents several limitations that should be acknowledged. First, although the sample size was adequate for PLS-SEM analysis, it did not exceed 400 respondents, which may limit the generalizability of the findings. A larger and more heterogeneous sample could enhance the robustness of the model and allow for deeper subgroup analyses in future research.

Second, the data collection relied heavily on LinkedIn groups and other professional online networks. While this facilitated access to a wide range of professionals, it may also introduce selection bias, as individuals who are more engaged with digital tools or interested in AI topics might be overrepresented. This could affect the variability and representativeness of responses in relation to the general target population.

Third, although measures were taken to ensure reliability, the use of a self-administered online questionnaire carries inherent limitations. The authenticity and attentiveness of respondents cannot be fully guaranteed, and common method bias may be present due to the use of a single instrument for all variables. Future studies could benefit from using mixed-method approaches, combining surveys with interviews or behavioral usage data.

Furthermore, while this study incorporated age as a moderating variable, it did not explore other potentially relevant factors such as digital literacy, job role, industry sector, or prior experience with AI systems. Including such variables could help develop a more nuanced understanding of the dynamics underlying AI adoption.

Future research could also adopt a longitudinal approach to examine how intention, behavior, and perceived benefits evolve over time as AI becomes more integrated into decision-making processes. Additionally, cross-cultural comparative studies would be valuable to determine whether the relationships observed in this model hold across different cultural or organizational contexts.

7) CONCLUSION

This study provides a comprehensive model to understand the adoption and organizational impact of Artificial Intelligence (AI) in decision-making environments. By integrating behavioral constructs from UTAUT2 with outcome-oriented components from the DeLone & McLean IS Success Model, the research offers a dual perspective that connects user motivation with actual usage and perceived net benefits.

The findings confirm that motivational factors such as performance expectancy, hedonic motivation, and social influence are significant predictors of behavioral intention. Moreover, facilitating conditions and habit play an essential role in shaping actual use behavior, which, in turn, strongly influences the realization of organizational benefits. Notably, the results reinforce the importance of behavioral intention as a mediator between psychological antecedents and system use, validating assumptions drawn from both theoretical frameworks.

Although effort expectancy and certain aspects of habit were not statistically significant in explaining intention, their role in sustained use behavior and value generation cannot be overlooked. Furthermore, the moderating role of age—particularly in the relationships involving hedonic motivation and performance expectancy—highlights the need for segmented adoption strategies tailored to different generational profiles.

From a theoretical standpoint, the study extends the application of established technology acceptance and IS success models into the AI domain, demonstrating their relevance and adaptability. Practically, it offers clear guidance for system designers and organizational leaders seeking to maximize the value of AI through sustained engagement and user-centered implementation.

In sum, this research contributes to the growing understanding of how AI can be effectively integrated into decision-making processes and provides a foundation for future studies to further explore the behavioral and contextual variables that shape technology-driven transformation within organizations.

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APPENDIX A: QUESTIONNARE

TABLE A

Constructs	Items	Authors
Performance expectancy	PE3- I think that using AI systems would increase my productivity. PE4- I think that using AI systems would improve my performance.	(Venkatesh et al., 2012)
Effort expectancy	EE1- My interaction with AI systems would be clear and understandable. EE2- It would be easy for me to become skillful at using AI systems. EE3- I would find AI systems easy to use.	(Venkatesh et al., 2012)
Social influence	SI1- People who influence my behavior think that I should AI systems. SI2- People who are important to me think that I should use AI systems. SI3- I find AI systems trendy.	(Venkatesh et al., 2012)
Facilitating conditions	FC1- I have the resources necessary to use AI systems. FC2- I have the knowledge necessary to use AI systems. FC3- AI systems is compatible with other systems I use	(Venkatesh et al., 2012)
Hendonic motivation	HM1-Using AI systems are fun. HM2-Using AI systems are enjoyable. HM3-Using AI systems are very entertaining	(Venkatesh et al., 2012)
Habit	H1 - Using AI systems has become a natural part of my daily routine. H2 - I use AI systems automatically, without thinking much about it. H3 - I feel strange if I don't use AI systems in my work.	(Venkatesh et al., 2012)
Behavioral intention	BI1 - I intend to use AI systems in the next months. BI2 - I will try to use AI systems in my daily work. BI3- I want to know more about AI systems	(Belanger&Carter,2008;Venkateshetal., 2012)
Use behavior	USE1 – I use generative AI tools. USE2 – I use generative AI tools to enhance productivity. USE3 – I use generative AI tools to automate repetitive tasks. USE4 – I use generative AI tools to brainstorm and generate innovative ideas.	(Zhou et al., 2010)
Net benefits	NB1 - Using AI systems has significantly improved my job performance. NB2 - AI systems have contributed to improved efficiency and effectiveness in my organization. NB3 - The benefits of AI systems outweigh their costs in my organization on my own study	DeLone, W. H., & McLean, E. R. (2003)

APPENDIX B: DEMOGRAPHIC INFORMATION

Table B

Demographic information	#	%
Gender		
Male	193	51%
Female	188	49%
Education		
Below high school	5	1%
High school	29	8%
Bachelor's Degree	182	48%
Master's degree	139	37%
Doctoral degree	25	7%
Monthly gross income (€)		
<1000€	12	3%
1000€-2000€	63	17%
2000€-3000€	172	45%
>3000€	129	34%
I prefer not to answer	5	1%
Current employment status		
Student	18	5%
Intern	23	6%
Private sector employee	183	48%
Goverment employee	76	20%
Self-employed	72	19%
Unemployed	8	2%
Retired	1	0%

APPENDIX C: ETHICS COMMITTEE REPORT

FIGURE A

This is to certify that
Project No.: **DDMKT2025-4-216510**
Project Title: **Adoption and Impact of Artificial Intelligence in Organizational Decision-Making**
Principal Researcher: **Javier Montilla**

according to the regulations of the Ethics Committee of NOVA IMS and MagIC Research Center this project was considered to meet the requirements of the NOVA IMS Internal Review Board, being considered **APPROVED** on 4/21/2025.

It is the Principal Researcher's responsibility to ensure that all researchers and stakeholders associated with this project are aware of the conditions of approval and which documents have been approved.

The Principal Researcher is required to notify the Ethics Committee, via amendment or progress report, of
- Any significant change to the project and the reason for that change;
- Any unforeseen events or unexpected developments that merit notification;
- The inability of the Principal Researcher to continue in that role or any other change in research personnel involved in the project.

Lisbon, 4/21/2025

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