Revue du Contrôle de la Comptabilité et de l'Audit
ISSN: 2550-469X
Volume 10 : numéro 2

Management control in the era of Artificial Intelligence: The case of agri-food SMEs in Morocco

Le contrôle de gestion à l'ère de l'Intelligence Artificielle: le cas des PME agroalimentaires au Maroc

LAMSSARBI Badra
Phd student
Faculty of Legal, Economic and Social Sciences of Agadir
Ibn Zohr University
The Entrepreneurship, Finance and Organisational Management Research Laboratory
Morocco

BOUAZIZ Si Mohamed
Professor of higher education
Faculty of Legal, Economic and Social Sciences of Agadir
Ibn Zohr University
The Entrepreneurship, Finance and Organisational Management Research Laboratory
Morocco

Date de soumission : 02/06/2026

Date d'acceptation : 15/07/2026

Pour citer cet article :

LAMSSARBI B. & BOUAZIZ S (2026) «Management control in the era of Artificial Intelligence: The case of agri-food SMEs in Morocco », Revue du contrôle, de la comptabilité et de l'audit « Volume 10 : numéro 2 » pp : 612-649.

Abstract

The rapid evolution of artificial intelligence (AI) is profoundly disrupting the business world and in particular the finance and management control professions, in fact, the classic tools and roles of MC are being transformed. Our contribution explores the perception of management supervisors in the face of these mutations and analyzes the factors that influence their acceptance or resistance to the adoption of AI in their daily work. This empirical research is based on a quantitative study conducted with 312 management controllers and financial managers from the agri-food industry sector by adopting the UTAUT3 model and the theory of perceived risk, following a post-positivist posture. The results show that the main determinants of the intention to use AI are habit, personal innovation in information technology, social influence, hedonic motivation, and perceived value. As for the intention to adopt, it is mainly influenced by the psychological and privacy dimensions of perceived risk, as well as by personal innovation in information technology.

Keywords : Management Control, Artificial Intelligence, SME.

Résumé

L'évolution rapide de l'intelligence artificielle (IA) bouleverse profondément le monde de l'entreprise et en particulier les métiers de la finance et du contrôle de gestion, en effet, les outils et rôles classiques de MC sont en train de se transformer. Notre contribution explore la perception des contrôleurs de gestion face à ces mutations et analyse les facteurs qui influencent leur acceptation ou leur résistance à l'adoption de l'IA dans leur travail quotidien. Cette recherche empirique s'appuie sur une étude quantitative menée auprès de 312 contrôleurs de gestion et directeurs financiers du secteur de l'industrie agroalimentaire en adoptant le modèle UTAUT3 et la théorie du risque perçu, suivant une posture post-positiviste. Les résultats nous montrent que les principaux déterminants de l'intention d'utiliser l'IA sont l'habitude, l'innovation personnelle en informatique, l'influence sociale, la motivation hédonique et la valeur perçue. Quant à l'intention d'adopter, elle est principalement influencée par les dimensions psychologiques et de confidentialité du risque perçu ainsi que par l'innovation personnelle en technologie de l'information.

Mots clés : Intelligence artificielle ; contrôle de gestion ; PME.

Introduction

In a context marked by the rise of artificial intelligence within management control systems, understanding the adoption factors of these technologies is becoming a central issue (BERROUKECH & HANIN, 2025). The literature on technological acceptance has extensively documented the technological and organizational determinants of this adoption, in particular through the TAM, UTAUT and UTAUT2 models. These frameworks, however, have mostly been developed and tested in "neutral" technology contexts, where the tool is perceived as a simple execution instrument. Artificial intelligence, however, introduces a qualitative breakthrough: it does not merely automate a task, but intervenes in the process of judgment and decision-making, an area hitherto reserved for the human expertise of the management controller. This specificity raises a question that classical technological acceptance models struggle to address, namely that of trust and perceived risk in the face of a tool whose decision-making logic remains partly opaque.

Management control, traditionally focused on the production of financial information, budget monitoring and performance evaluation, is currently undergoing a significant transformation under the effect of intelligent technologies. Instruments based on artificial intelligence now offer the possibility of automating recurring tasks, managing huge volumes of data in real time and optimizing the quality of analyses for decision-making (Lamssarbi & Bouaziz, 2022). This evolution favors the transition from a mainly descriptive management control to a control more oriented towards prediction, analysis and strategy.

In this context, the management controller evolves from a purely technical reporting role to that of a true strategic partner, capable of mobilizing data to support the decision-making process. The integration of artificial intelligence thus modifies professional practices, the necessary skills, and organizational management methods. However, although these technologies offer many opportunities, their adoption remains highly variable from one organization or individual to another.

Indeed, the use of artificial intelligence systems in management control rests on various technological, structural and behavioral elements. Companies face challenges related to the sophistication of the tools, a digital skills gap, a reluctance to change, or the risks associated with the use of AI, particularly in terms of reliability, data security and reduced control over decisions. It is precisely this dimension that a technological acceptance model taken in isolation, such as UTAUT3, fails to capture, designed to explain intention of use through determinants such as performance expectancy, effort expectancy, social influence and facilitating conditions, it remains silent on the dimension of trust and perceived uncertainty. Mobilizing the theory of perceived risk alongside UTAUT3 thus makes it possible to fill this theoretical gap, allowing us to understand not only what motivates the use of AI, but also what, specifically, hinders it.

In this context, it seems essential to identify the factors likely to influence the intention and use of artificial intelligence tools by management control actors. Studying these elements not only makes it possible to better understand technological adoption processes, but also to help organizations succeed in their transition to digital technology. Therefore, the central research question can be formulated as follows: **what are the determinants that influence the use of artificial intelligence technologies in management control within Moroccan agri-food SMEs?**

This problem becomes more acute when observed within the specific context of Moroccan agri-food SMEs. On the one hand, SMEs are distinguished from large organizations by limited resources, generally lower digital maturity (METAILLER & PASCAL, 2022). On the other hand, the moroccan agri-food sector presents constraints (El Ammari, 2015) of its own that make management control both essential and often under-resourced. Finally, the vast majority of studies using UTAUT3 models have been conducted in Western contexts and within large organizations (ELHAMMA & MOUMANE, 2023), however, their validity in an emerging economy such as Morocco, where institutional digital transformation is still being structured (ESSEMAN & NAFZAOUI, 2024), remains largely unexplored. This field therefore constitutes a twofold contextual and sectoral gap, which justifies, beyond mere empirical accessibility, the scientific relevance of this choice.

To address this problem, this research mobilizes the UTAUT3 model to analyze the classical determinants of technological acceptance, enriched by the theory of perceived risk in order to integrate the dimensions of uncertainty and trust specific to the use of artificial intelligence in management control. This articulation aims to propose an integrated analytical framework capable of accounting for both the motivations and the obstacles to the adoption of these technologies in an organizational and sectorial context that remains largely under-studied.

1. Literature review and theoretical framework

Anthony's framework (1965), which distinguishes between strategic planning, management control and operational control, remains heuristically useful but has been considerably enriched by subsequent work. Simons (1995) extends it with the "levers of control," in particular belief systems, boundary systems, diagnostic control and interactive control, which offer a deeper understanding of the dynamics of contemporary systems. This theoretical evolution finds a particular resonance with the emergence of artificial intelligence, understood as the set of techniques enabling computer systems to simulate human cognitive abilities such as learning, reasoning, perception and language generation (L'MGHAIFRI & ZAMMAR, 2025). Predictive algorithms strengthen diagnostic control, while interactive dashboards can support a more agile form of interactive control (Malmi & Brown, 2008).

At the operational level, however, the documented effects of AI remain uneven across processes and across the methodological rigor of the studies mobilized. Regarding budgeting, an activity that absorbed up to 20% of managerial time according to Libby & Lindsay (2010), data-driven rolling forecasts appear to significantly reduce this burden. Rikhardsson & Yigitbasioglu (2018), based on a sample of 45 European companies, measure an average 35% reduction in the budget cycle and a 15 to 25% improvement in forecast accuracy.

The most structuring effect documented in the literature, however, concerns not the processes themselves but the role of the controller. Graham et al. (2012), in a longitudinal study, show that the function is gradually migrating toward that of a decision-making partner. AI accelerates this movement, by taking over data production, it makes possible what the function had long promised without always achieving it (El Mehdi et al., 2025), shifting the controller from a position of measurement to one of influence over the choices themselves (Moinard & Berland, 2020).

The literature specifically devoted to SMEs highlights structural constraints that differ from those of larger organizations. An intercontinental comparative synthesis identifies several recurring categories of barriers: strategic and organizational barriers, notably the absence of a formalized AI strategy, the shortage of qualified staff, high turnover, low awareness, and cultural resistance, as well as financial barriers, in particular the limited resources of SMEs restricting their ability to invest in advanced technologies that often require substantial upfront and recurring costs.

This finding is corroborated at the international level by a G7 ministerial declaration devoted specifically to AI adoption by SMEs, which identifies access to capital as one of the most significant and persistent barriers, since SMEs generally operate with lower margins than large enterprises, which limits their capacity to allocate resources to experimentation, infrastructure, and skills development. The same report points to a shortage of technical talent and cross-functional expertise as a major barrier, as well as gaps in basic digital skills, which nonetheless constitute the necessary foundation for any AI-driven transformation (Muhammad et al., 2025).

This convergence across several studies, conducted at different times and in different contexts, constitutes one of the most robust findings in this literature, yet it concerns the trajectory of the role rather than the individual conditions that enable or hinder its effective appropriation by practitioners. It is precisely on this point that the technological and organizational literature reaches its limit: it explains what AI makes possible, but remains insufficiently equipped to explain why some controllers adopt these tools while others do not. Accordingly, analyzing the adoption of AI tools by management control professionals requires mobilizing theoretical frameworks capable of explaining both individual motivations and obstacles, in particular, the UTAUT3 model and the theory of perceived risk.

1.1. UTAUT 3 model

The choice of a technological acceptance model is not neutral, moreover, several competing executives could have been mobilized. The TAM (Davis, 1989), historically first, remains centered on two determinants, in particular, perceived usefulness and perceived ease of use, which makes it a parsimonious framework but insufficient to account for the contextual and social complexity of adoption in an organizational environment. The TOE model (Tornatzky & Fleischer, 1990), on the other hand, operates at the organizational level (technological, organizational, environmental context) and would have made it possible to explain the adoption at the firm level, but fails to account for the individual motivations and resistance of the management supervisors themselves. The theory of the diffusion of innovation (Rogers, 1995) sheds light on the temporal dynamics of adoption within a population, but remains poorly equipped to explain the psychological determinants of an individual adoption act at a given moment.

Farooq (2017) introduced the UTAUT-3 model to extend UTAUT-2, integrating the variable of Personal Innovation in IT (PI) as an additional determinant. The UTAUT-3 framework thus includes eight determinants: expected performance (PA), expected effort (EA), social influence (IS), hedonic motivation (HM), perceived value (PV), habit (HB), facilitating conditions (FC) and personal innovation in IT (PI). This model has a double advantage for our research object, on the one hand, it operates at the individual level, relevant since the unit of analysis is the management controller and not the organization, on the other hand, it integrates, via the IP variable, a dimension of personal predisposition to technological innovation particularly adapted to a tool as disruptive as AI. UTAUT-3 has been mobilized in various fields, in particular higher education (Gunasinghe et al., 2019) and augmented reality (Pinto et al., 2022), but its application to management control remains, to our knowledge, unexplored, which constitutes the first empirical gap of this research.

1.2. Perceived Risk theory (PR)

While UTAUT-3 makes it possible to model the drivers of usage motivation, it does not explicitly theorize the mechanisms of uncertainty and distrust specific to technologies whose outcomes partially escape the user's control, a configuration typical of AI applied to decision-making. It is this specific gap, rather than a general shortcoming of the model, that justifies the integration of a second theoretical framework. Perceived risk theory addresses this limitation by highlighting the risks likely to affect the behavioral intention to adopt and use a technology. Its association with the UTAUT-3 model is well established empirically in sectors marked by strong sensitivity to trust and data security, notably hospitality (Rajhi, 2025), online banking services (Bhatnagr et al., 2025), cashless payment (Namahoot & Jantasri, 2023), e-banking (Laradi et al., 2025), the restaurant sector (Jeon et al., 2019), mobile payment (Al-Saedi & Al-Emran, 2021), and m-banking (Abu-Taieh et al., 2022). This recurrence in sectors where data is sensitive and where errors carry a direct cost for the user constitutes an argument for transferability to management control, a function in which the reliability of information and the accountability of decisions play a structurally comparable role. To our knowledge, however, none of these studies has been conducted in the context of management control in Moroccan

SMEs, which constitutes the second empirical gap of this research, distinct from but complementary to the first.

The combination of the two frameworks thus reflects a logic of functional complementarity rather than a simple addition: UTAUT-3 models what drives adoption, while perceived risk theory models what holds the user back. This study proposes a conceptual and theoretical model (Figure 1) on the behavioral intention to use, adoption and recommendation, integrated with the theory of perceived risk. This research considers the UTAUT-3 model because it provides more context than previous models to highlight behavioral intention and IT adoption. The lack of digital skills and online fraud have increased the perceived risk. Therefore, the theory of perceived risk is integrated into the theoretical model with the UTAUT-3.

2. Development of hypotheses

The expected performance (AP) is the guarantee that the target technology makes it possible to progress towards a work-related act (Venkatesh et al., 2012). Likewise, the Expected Effort (EA) as a user interface for the technology is hassle-free (Venkatesh et al., 2012).EE is an essential factor for BIU, according to Farah et al. (2018). As for the social influence (IS), it refers to the external pressure created by a society where the technology used, it affects their perception of the use of AI.

In addition, hedonic motivation (HD) is derived from joy or satisfaction in the application of a specific technology, since HD directly influences adoption (Poong et al., 2016). It refers to the pleasure or happiness in the use of technologies, which leads to the adoption of AI. Moreover, habit (HB) is an unconscious or automatic individual behavior reflected by past knowledge (Venkatesh et al., 2012). However, it takes more than just knowledge of this behavior. Habit therefore produces a cognitive adherence to actions and prevents their modification (Murray & Häubl, 2007).
Facilitating conditions (CF) allow the user to believe that the infrastructure and support are always available to help them use the targeted technologies (Venkatesh et al., 2012). However, like HB, CF affect the intentions of users.

As for the capacity for personal innovation (PI), it is linked to the personality traits of a user's propensity to adopt modern technologies (Farooq et al., 2017). In addition, a recent study noted that individual users with an IP are continuing technological advances. In addition, the literature

suggests a close relationship between the behavioral intention to use (ICU) and the behavioral intention to adopt (ICA). The latter indicates behavioral adoption, eagerness and the use of a specific technology (Davis, 1989).
As for the perceived risk factors that prevent the use of new technologies and in particular AI, the perceived financial risk (RFP) implies future financial expenses for the initial purchase price and possible maintenance costs of the product (Olsen, 2010). Perceived privacy risk (PRC) is a user's vulnerability to privacy, perceived as a risk to privacy. A possible violation of the user's privacy occurs when personal data is intentionally kept, disseminated, distributed or sold without the authorization or consent of the consumer or when hackers intercept the information. Then the performance risk (RPP) which represents a weakness that implies the risk of failure of a single component, of not providing the planned and marketed services, and of inability to provide the anticipated benefits and the necessary service. Secondly, the perceived psychological risk refers to the awareness that customers have of the probability that a producer's range of performances could harm their self-perception or their peace of mind (Ping et al., 2003), the potential loss of self-esteem due to anger at not having achieved a purchase goal.

Finally, the relationship between intention to adopt (ICA), intention to use (ICU) and intention to recommend (ICR), it has been proven that people who adopt technology can help others (Lee et al., 2022). Therefore, we theorize a causal link between the consumer's goal of suggesting a service and the recommendations of users of a service to other people. Therefore, the hypotheses of our research are as follows :

H1: The Expected Performance positively impacts the Behavioral Intention to Use AI.
H2: The Expected Effort positively impacts the Behavioral Intention to Use AI.
H3: Social Influence positively impacts the Behavioral Intention to Use AI.
H4: Hedonic Motivation positively impacts the Behavioral Intention to Use AI.
H5: Perceived Value positively impacts the Behavioral Intention to Use AI.
H6a: Habit positively impacts the Behavioral Intention to Use AI.
H6b: Habit positively impacts the Behavioral Intention to Adopt AI.
H7a: Facilitating Conditions positively impact the Behavioral Intention to Use AI.
H7b: Facilitating Conditions positively impact the Behavioral Intention to Adopt AI.
H8a: Personal Innovation in IT positively impacts the Behavioral Intention to Use AI.
H8b: Personal Innovation in IT positively impacts the Behavioral Intention to Adopt AI.

H9: The perceived financial risk impacts the Behavioral Intention to Adopt AI.

H10: The perceived privacy risk impacts the Behavioral Intention to Adopt AI.

H11: The perceived performance risk impacts the Behavioral Intention to Adopt AI.

H12: The perceived psychological risk impacts the Behavioral Intention to Adopt AI.

H13: The perceived temporal risk impacts the Behavioral Intention to Adopt AI.

H14a: Behavioral Intention to Use AI positively impacts the Behavioral Intention to Adopt AI.

H14b: Behavioral Intention to Use AI positively impacts the Behavioral Intention to Recommend AI.

H15: Behavioral Intention to Adopt AI positively impacts the Behavioral Intention to Recommend AI.

3. Methodology

3.1. Design of research instruments

The research instruments are used mainly in the context of Moroccan agro-industrial SMEs. The elements of the survey were measured using a 5-point Likert scale questionnaire. An academic expert and a professional validated the elements of the survey for the validity and reliability of the instrument in order to maintain consistency in the understanding of the methodology, the form of the sentences and the relevance of the text. The final changes were made by obtaining the necessary feedback from the pre-tests. All the data from the pre-test were not taken into account in the analysis of all the data.

3.2. Sampling and data collection

The data were collected by means of a self-administered questionnaire, distributed to management controllers and chief financial officers in the agri-food sector via a Google Forms link, sent through the professional network LinkedIn. However, in the absence of an exhaustive sampling frame listing companies in this sector that actually have a structured management control function, a non-probability convenience sampling technique was adopted. While this choice has the advantage of making the field accessible in a context where no official directory allows for random sampling, it carries methodological limitations. In particular, one limitation concerns the representativeness of the sample: in the absence of a precise census of Moroccan agri-food companies with a management control function, it is not possible to statistically verify that the sample structure reflects that of the parent population. Coverage of Morocco's 12 regions partially mitigates this risk by ensuring geographic diversity, but it does not guarantee proportionality relative to the actual economic weight of each region within the sector.

At the end of the collection process, 312 usable responses were obtained, corresponding to a response rate of 80.83%. The table below presents the profile of the respondents as well as that of the companies in which they work.

3.3. PLS-SEM data analysis tool

To evaluate and test our hypotheses, we used the partial least squares structural equation modeling method (PLS-SEM). This choice is justified by several arguments: notably, the PLS-SEM approach is more appropriate for predictive research aiming to maximize the explained variance of endogenous constructs (Hair et al., 2019), such as behavioral intention and actual use of AI, unlike CB-SEM, which focuses on confirming an existing theoretical model (Sarstedt et al., 2014). Furthermore, with 16 variables and numerous structural relationships, CB-SEM would require an excessively large sample. PLS-SEM remains effective for complex models even with moderate sample sizes (Chin, 1998). Finally, the PLS approach does not require normally distributed data, which is relevant for data collected through a auto-administered questionnaire.

4. Study results and Analyzes

4.1. Demographic and descriptive results

The profile of the respondents studied (Gender, age, position and seniority) is summarized in Table 1. Taking into account the respondent's gender criterion shows that 83% of respondents are men while women represent only 17%. The sample is thus characterized by 62% of the respondents with more than one year of experience, which can be understood by the age groups [30, 40 years old],[41, 50 years old] and [+50 years old] which accounts for 79% of the observations.

Table N°1 : Profiling of respondents

Categories	Sub categories	Frequency	%
Gender	Female	53	**17**

	Male	259	**83**
Age	Under 30	66	**21**
	Between 30 and 40 years old	90	**29**
	Between 41 and 50 years old	125	**40**
	Over 50 years old	31	**10**
Position within the company	Accountant	50	**16**
	Management Controller	34	**11**
	Financial Manager	140	**45**
	Other operational manager	81	**26**
	Other	7	**2**
Seniority in MC	Less than 1 year	119	**38**
	Between 1 year and 5 years	103	**33**
	More than 5 years	90	**29**

Source : Excel

The respondents were also asked about the companies in which they work. The following table summarizes the profile of the companies in question.

Table N°2 : Profiling of enterprises

Categories	Sub categories	Frequency	%
Company size (*Number of permanent employees*)	Between 10 and 50 employees	75	**23,9**
	Between 51 and 150 employees	146	**46,8**
	Between 150 and 250 employees	91	**29,3**
Branch of activity	Fish industry	136	**43,6**

	Fruit and vegetable industry	82	**26,4**
	Dairy industry Meat industry	44	**14,1**
	Flour and cereals industry	19	**6**
	Beverage industry	2	**0,6**
	Grain processing industry	26	**8,4**
	Other industry	3	**0,9**
Geographical area of the company	Tanger- Tetouan- Al Hoceima	24	**7,7**
	Oriental	6	**2**
	Fèz-Meknès	41	**13**
	Rabat- Salé-Kénitra	34	**11**
	Béni Mella-Khénifra	25	**8**
	Casablanca-Settat	92	**29,5**
	Marrakech-Safi	19	**6**
	Drâa-Tafilalet	0	**0**
	Souss-Massa	69	**22,2**
	Guelmim-Oued Noun	0	**0**
	Laâyoune-Sakia El Hamra	2	**0,6**
	Dakhla-Oued Ed-Dahab	0	**0**

Source: Excel

Medium-sized SMEs (51 to 150 employees) are the most represented in the sample with 46.8%, followed by companies with between 150 and 250 employees (29.3%), while small companies (10 to 50 employees) represent 23.9%.

Regarding the sector of activity, the fisheries industry dominates the sample with 43.6%, followed by the fruit and vegetable industry (26.4%). The dairy and meat industries represent 14.1%, while the other sectors remain poorly represented.

Geographically, the companies are mainly located in the regions of Casablanca-Settat (29.5%), Souss-Massa (22.2%) and Fez-Meknes (13%), reflecting a concentration of agri-food SMEs in the main economic poles of Morocco.

4.2. Modeling by structural equations according to the PLS-SEM approach

4.2.1. Evaluation of the measurement model (Outer model)

The evaluation of the outer model aims to verify the relationship between the latent variables and their observed indicators, by making it possible to verify to what extent the items used faithfully reflect the constructs. To do this, we evaluate the reliability of the items, the reliability of the constructs, the convergent validity as well as the discriminant validity.

4.2.1.1. Reliability of the measurements

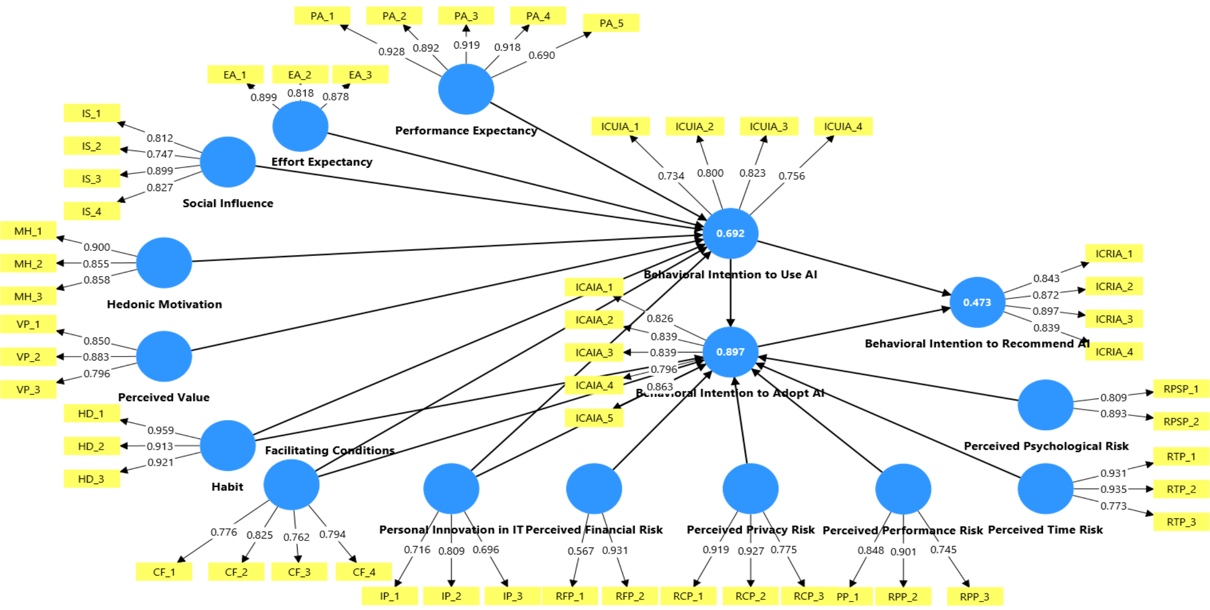
The reliability of the measurements examines to what extent the variance of an indicator is explained by its construction (Hair et al., 2021). It refers to the idea that when the same phenomenon is measured repeatedly using the same measuring instruments.

4.2.1.1.1.*Factorial loads (Loadings)*

According to the recommendations of Hair et al. (2021), the factorial loads of the items must have a value at least equal to 0.708 to be judged satisfactory. Loads below 0.40 must be eliminated. For those between 0.40 and 0.70, deletion should only take place if it improves internal consistency or convergent validity, while also taking into account the validity of the content (Hair et al., 2019).

According to the results obtained, all the outer loads exceed the threshold of 0.708 set by Hair et al. (2021), they present satisfactory correlations, with representation qualities varying between 0.716 and 0.959, except for the item "PA_5" of the "Expected performance" construct, the item "IP_3" of the "Personal innovation in IT" construct and the item "RFP_1" of the "Perceived financial risk" construct. These items, as shown in the following figure, have the following values respectively: 0.690; 0.696 and 0.567. In accordance with the recommendations of Hair et al. (2019), we proceeded with their removal, although their values fell below the standard threshold of 0.70, their elimination optimized the convergent validity and internal consistency indices of their respective latent measurement blocs, thereby consolidating the overall quality of our measurement model.

Fig N° 1: Outer loadings before the elimination of unreliable items



Source : Smart PLS

4.2.1.2. Construct reliability and validity

To evaluate the internal reliability of our measurement model, we first used cronbach's alpha, which is the ratio between the sum of the correlations of the observable variables of a group and the total variance of this group, increased by the number of observable variables in this group when they are standardized (Tenenhaus et al., 2005). The acceptability threshold is conventionally set at 0.7 (Nunnally, 1978).

As far as our research is concerned, the results show that all the constructs exceed the value of 0.7, which indicates a satisfactory internal consistency in excel-lente. Moreover, the composite reliability rho_a, less sensitive to the number of items and considered as more robust than the classic alpha (Dijkstra & Henseler, 2016), confirms these results.

The composite reliability rho_c is an alternative measure superior to the Cronbach's alpha because it takes into account the factorial saturations of each item (Hair et al. 2022). The acceptability threshold is 0.7, and the threshold of good reliability is 0.8. All constructs exceed 0.8, with maximum values for Performance Expectation (rho_c = 0.893) and Habit (rho_c = 0.894). This testifies to an excellent quality of measurement.

Table N° 3: Construct reliability and validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Behavioral Intention to Adopt AI	0.890	0.891	0.892	0.694
Behavioral Intention to Recommend AI	0.886	0.879	0.890	0.745
Behavioral Intention to Use AI	0.786	0.796	0.860	0.606
Effort Expectancy	0.833	0.832	0.852	0.749
Facilitating Conditions	0.798	0.802	0.869	0.623
Habit	0.823	0.825	0.852	0.868
Hedonic Motivation	0.841	0.846	0.894	0.759
Perceived Performance Risk	0.778	0.801	0.872	0.695
Perceived Privacy Risk	0.815	0.844	0.878	0.768
Perceived Psychological Risk	0.728	0.758	0.841	0.726
Perceived Time Risk	0.841	0.854	0.873	0.779
Perceived Value	0.799	0.807	0.881	0.712
Performance Expectancy	0.850	0.877	0.893	0.867
Personal Innovation in IT	0.718	0.806	0.834	0.664
Social Influence	0.840	0.853	0.893	0.677

Source: SmartPLS

As for convergent validity, which means that the same items belonging to the same latent construct must share more variances with their latent construct than with their measurement errors (Hair et al. 2021). To test this validity, we calculated the AVE indices (Average Variance Extracted) relative to each latent construct. Fornell & Larcker (1981) set the minimum threshold at 0.50, the results show that all the values of the AVE are above the recommended threshold ranging from 0.606 to 0.868.

4.2.1.3. Discriminant validity

According to Henseler et al. (2016), discriminant validity is a step that guarantees that a construct is empirically distinct from the others in the model, in other words, the items measuring the same construct must be weakly correlated to the items forming other constructs, that is to say that discriminant validity is acquired only if the items belonging to a single construct no longer contribute strongly with other constructs or neighboring constructs. This is tested in accordance with the recommendations of Hair et al. (2021) who privilege two criteria to measure the discret-minant validity, in particular, the Cross loadings and the Heterotrait-Monotrait (HTMT) instead of the criterion of "Fornell Larcker" that they consider it insufficient to judge the validity of the variables.

4.2.1.3.1. The *cross loadings*

This technique is used to compare the correlations between the manifest variables of a block and their latent variable to those of the latent variables of the other blocks, in fact, each indicator must show a more intense correlation with its own construct than with any other latent variable of the model (Hair et al., 2021).

As far as we are concerned, the results show that each item loads only on its construct, in fact, as each item loads more on its construct than on the other constructs of the model, the rule of Hair et al. (2021) is then well respected and consequently, the discriminant validity is confirmed by the values of the cross loadings.

4.2.1.3.2. The *HTMT*

Hair et al. (2021) consider the HTMT initiated by Henseler et al. (2016) as a main criterion for verifying discriminant validity. Thus, a high value of the HTMT indicates that two constructs are highly correlated and risk measuring the same concept, which would call into question their discriminant validity.

With regard to our analysis, the results reveal that all the values noted are below the threshold of 0.85 recommended by Hair et al. (2021). This allows us to conclude that the latent variables of the model have a satisfactory discriminatory validity.

4.2.2. Evaluation of the structural model (Inner model)

The evaluation of the Inner model aims to verify the links between the latent variables, in particular between the linear equations which relate the latent variables to each other.

4.2.2.1. Evaluation of the problems of collinearity of the structural model

4.2.2.1.1. *The multicollinearity test (VIF)*

The Variance Inflation Factor (VIF), makes it possible to measure the degree of correlation between the predictor variables. It indicates to what extent the variance of a regression coefficient is increased due to the presence of collinearity with other independent variables. According to the recommendations of Hair et al. (2021), a VIF value of less than 5 is generally considered acceptable, while some authors recommend a stricter threshold of 3.3 in order to guarantee an absence of critical collinearity.

Moreover, in order to rule out any Common Method Bias, a complete collinearity analysis was carried out using SmartPLS. Since the VIF indices are all below the critical threshold of 3.3, we can conclude that this bias does not threaten the validity of our results.

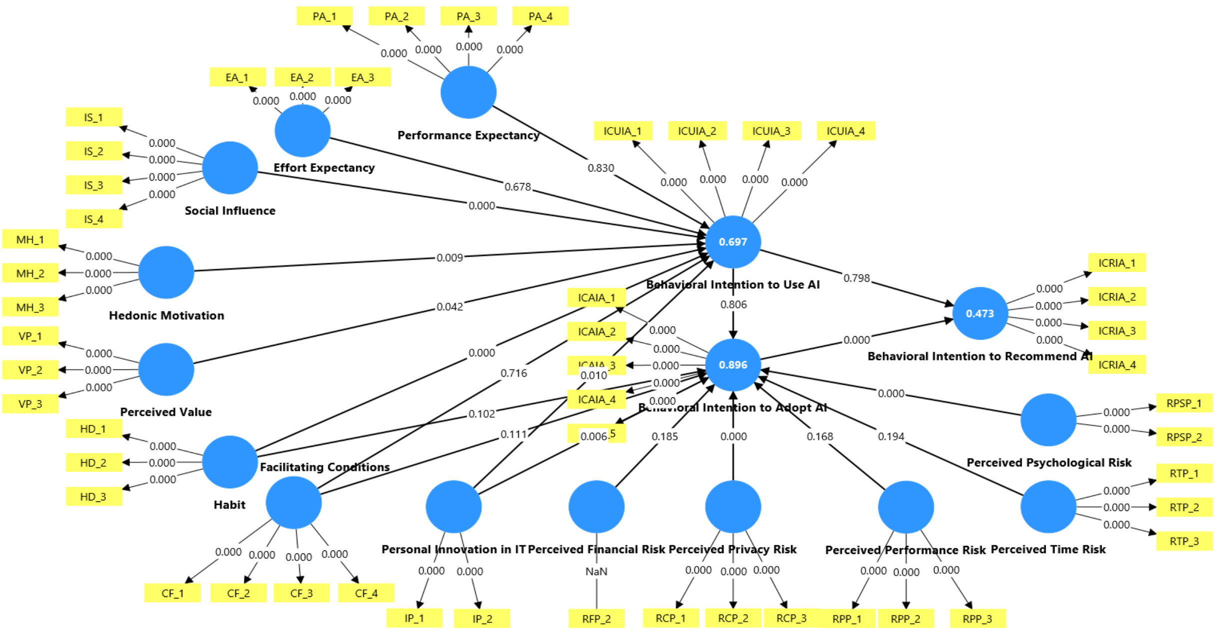
According to the results obtained, all the values are lower than the recommended thresholds, in fact, we can conclude that there are no major problems of multicolinearity within our structural model.

4.2.2.2. Testing of hypotheses

The Path Coefficients constitute a central element of the evaluation of the structural model. They make it possible to analyze the nature, direction and intensity of the hypothetical relationships between the latent variables of the research model.

Hair et al. (2021) emphasize that the evaluation of research hypotheses is mainly based on the statistical significance of these coefficients. This significance is tested using the bootstrapping procedure, which consists in generating a large number of random samples in order to estimate the stability of the coefficients of the model.

Fig N° 2: Path coefficients



Source: Smart PLS

First of all, the results reveal a positive and highly significant relationship between "Behavioral Intention to Adopt AI" and "Behavioral Intention to Recommend AI" (β = 0.678; t = 13.719; p = 0.000). This relationship indicates that the intention to adopt artificial intelligence strongly influences the willingness to recommend this technology. Thus, the more users show a high intention to adopt, the more likely they are to recommend the use of AI to their professional entourage.

On the other hand, the relationships between "Behavioral Intention to Use AI" and "Behavioral Intention to Adopt AI" (β = 0.009; p = 0.806), as well as between "Behavioral Intention to Use AI" and "Behavioral Intention to Recommend AI" (β = 0.016; p = 0.798), appear to be insignificant. These results show that the intention of use is not a direct determinant of the adoption or recommendation of artificial intelligence in our context.

Regarding the variables from the UTAUT model, the results show that "Effort Expectation" does not exert a significant effect on the intention to use AI (β = 0.019; p = 0.678). This suggests that the perceived ease of use of AI tools does not represent a determining factor in the respondents' intention to use. Likewise, the "Facilitating Conditions" do not have a significant effect either on the intention to adopt (β = 0.064; p = 0.111), or on the intention to use AI (β = 0.021; p = 0.716). These results indicate that the available technical and organizational resources do not seem to directly influence the behaviors of the management supervisors interviewed.

Moreover, the variable "Habit" exerts a positive and highly significant effect on the intention to use AI ($\beta = 0.489$; $t = 9.827$; $p = 0.000$). This result shows that the technological habits of users constitute a major determinant of the use of artificial intelligence. However, its effect on the intention to adopt remains insignificant ($\beta = 0.046$; $p = 0.102$).

The results also show that the "Hedonic Motivation" positively and significantly influences the intention to use AI ($\beta = 0.127$; $p = 0.009$). Thus, the pleasure and interest associated with the use of artificial intelligence tools favor their use. The variable "Perceived Value" also has a significant positive effect on the intention to use ($\beta = 0.109$; $p = 0.042$), which means that users are more inclined to use AI when they perceive an added value in its use.

On the other hand, the "Performance Expectation" does not exert a significant influence on the intention to use AI ($\beta = 0.012$; $p = 0.830$), which indicates that the expected performance gains do not constitute a decisive factor in our research context. Likewise, the variable "Personal Innovation in IT" exerts a positive and significant effect both on the intention to adopt ($\beta = 0.136$; $p = 0.006$) and on the intention to use AI ($\beta = 0.169$; $p = 0.010$). This means that individuals with a strong propensity to experiment with new technologies are more inclined to adopt and use artificial intelligence. In addition, "Social Influence" positively and significantly influences the intention to use AI ($\beta = 0.207$; $t = 4.789$; $p = 0.000$). This result highlights the importance of the social and professional environment in the acceptance of artificial intelligence technologies.

Regarding the dimensions of the perceived risk, the results show that the "Perceived Privacy Risk" negatively and significantly influences the intention to adopt AI ($\beta = -0.426$; $t = 7.245$; $p = 0.000$). As well as the "Perceived Psychological Risk" also exerts a significant negative effect ($\beta = -0.263$; $t = 5.040$; $p = 0.000$). These results suggest that psychological and privacy-related dimensions play an important role in AI adoption behaviors, meaning that higher perceived risks in these areas significantly hinder or reduce users' willingness to adopt AI technologies. However, the effects of the "Perceived Financial Risk" ($\beta = 0.047$; $p = 0.185$), the "Perceived Performance Risk" ($\beta = 0.087$; $p = 0.168$) and the "Perceived Time Risk" ($\beta = 0.056$; $p = 0.194$) appear to be insignificant in our model.

Finally, the results show that the main determinants of the intention to use AI are habit, personal innovation in IT, social influence, hedonic motivation and perceived value. As for the intention to adopt, it is mainly influenced by the psychological and confidentiality dimensions of the perceived risk as well as by personal innovation in information technology.

4.2.2.3. Evaluation of the explanatory power of the structural model

4.2.2.3.1. The coefficient of determination (R^2)

After having ensured that the model estimates do not pose a problem of collinearity, we must evaluate the explanatory power of our model. To do this, we used the coefficient of determination (R^2). This coefficient indicates the part of the variance of a dependent variable (endogenous construct) which is explained by the independent variables (exogenous constructs) of the model. Hair et al. (2021), the R^2 values of 0.75, 0.50, or 0.25 for endogenous latent variables can, as approximate benchmarks, be described as substantial, moderate, or weak, respectively.

Regarding our model, the results show that the variable "Behavioral Intention to Use AI" is explained to 69.7% not its exogenous variables. This result shows a moderate explanatory capacity according to the thresholds recommended by Hair et al. (2021). Thus, the variable "Behavioral Intention to Adopt AI" is explained to 89.6% by its exogenous variables, which indicates a substantial explanatory capacity. However, the value of R^2 of the variable "Behavioral Intention to Recommend AI" is the lowest in our model, with a value of 47.3%, but this value remains satisfactory in terms of explanatory capacity. This explains that this variable partially explains the variance of its two exogenous variables (Behavioral Intention to Use AI and Behavioral Intention to Adopt AI). The following table presents these results.

Table N° 4: The coefficient of determination (R^2)

	R-square	**R-square adjusted**
Behavioral Intention to Adopt AI	0.896	0.892
Behavioral Intention to Recommend AI	0.473	0.468
Behavioral Intention to Use AI	0.697	0.685

Source: SmartPLS

4.2.2.3.2. The effect of size (F^2)

The coefficient F^2 makes it possible to evaluate the importance of the individual contribution of an exogenous variable on an endogenous variable within the structural model (Hair et al. 2022). This indicator measures the impact of the withdrawal of an explanatory construct on the variation of the coefficient of determination R^2. Thus, the F^2 makes it possible to determine whether an independent variable exerts a weak, medium or important effect on the dependent variable studied. It therefore constitutes a complementary indicator to the path coefficient regression coefficient. For the evaluation of this coefficient, Cohen (1988) proposes f^2 values of 0.02, 0.15 and 0.35 which indicate weak, moderate and strong effects, respectively.

Table 6. The effect of size (F^2)

	f-square
Behavioral Intention to Adopt AI -> Behavioral Intention to Recommend AI	0.602
Behavioral Intention to Use AI -> Behavioral Intention to Adopt AI	0.009
Behavioral Intention to Use AI -> Behavioral Intention to Recommend AI	0.011
Effort Expectancy -> Behavioral Intention to Use AI	0.014
Facilitating Conditions -> Behavioral Intention to Adopt AI	0.019
Facilitating Conditions -> Behavioral Intention to Use AI	0.015
Habit -> Behavioral Intention to Use AI	0.396
Habit -> Behavioral Intention to Adopt AI	0.017
Hedonic Motivation -> Behavioral Intention to Use AI	0.236
Perceived Financial Risk -> Behavioral Intention to Adopt AI	0.018
Perceived Performance Risk -> Behavioral Intention to Adopt AI	0.017
Perceived Privacy Risk -> Behavioral Intention to Adopt AI	0.241
Perceived Psychological Risk -> Behavioral Intention to Adopt AI	0.208
Perceived Time Risk -> Behavioral Intention to Adopt AI	0.013
Perceived Value -> Behavioral Intention to Use AI	0.317
Performance Expectancy -> Behavioral Intention to Use AI	0.016
Personal Innovation in IT -> Behavioral Intention to Adopt AI	0.351
Personal Innovation in IT -> Behavioral Intention to Use AI	0.131
Social Influence -> Behavioral Intention to Use AI	0.193

Source: SmartPLS

The analysis of the effect sizes, evaluated according to the Cohen thresholds (1988), reveals that the Behavioral intention to Recommend AI is massively determined by the Behavioral Intention to Adopt AI, which displays the most powerful predictive impact of the model (f^2 = 0.602). The Behavioral Intention to Use AI is based on two major pillars, Habit (f2 = 0.396) and Personal Innovation in IT (f^2 = 0.351), both of which have large-scale effects on adoption and use. In support, several exogenous variables provide medium-sized predictive contributions, in particular the Perceived Value (f^2 = 0.317), the Perceived Privacy Risk (f^2 = 0.241), the Hedonic Motivation (f^2 = 0.236), the Perceived Psychological Risk (f2 = 0.208) and Social Influence (f^2 = 0.193). Conversely, Personal Innovation in IT has only a small effect on the Behavioral Intention to Use AI (f^2 = 0.131), while all the other constructs, including the Expected Effort, the Expected Performance, the Facilitating Conditions as well as the Perceived Financial, Performance and Time risks, display values below the critical threshold of 0.02, thus demonstrating a total absence of substantial predictive impact in this structural model.

4.2.2.4. Evaluation of the predictive power of the structural model

4.2.2.4.1. *PLSpredict*

The PLS-Predict is introduced by Shmueli et al., (2019), it constitutes a recent procedure for evaluating the predictive capacity of PLS-SEM models. It is based on a cross-validation technique making it possible to compare the values predicted by the PLS model with the values observed in the real data, in order to judge whether the model has sufficient predictive relevance. According to the recent methodological literature, in particular Hair et al. (2021), the evaluation of the PLS-Predict is generally carried out on the basis of prediction error indicators such as RMSE[1] and MAE[2].

The results obtained show positive values of the Q^2predict for all the endogenous variables studied, which indicates that the model has a satisfactory predictive capacity.
More precisely, the variable "Behavioral Intention to Use AI" has a value of Q^2predict equal to 0.670, accompanied by an RMSE of 0.579 and an MAE of 0.478. This positive and relatively

[1] (Root Mean Squared Error)
[2] (Mean Absolute Error)

high value of the Q^2predict reflects a good ability of the model to predict the intention to use artificial intelligence. The observed prediction errors also remain moderate, which confirms the predictive quality of the model for this variable.

Regarding the variable "Behavioral Intention to Adopt AI", the results reveal a particularly high Q^2predict value (0.886), associated with an RMSE of 0.340 and an MAE of 0.231. These results indicate a very high predictive relevance of the model. The low error levels recorded show that the model predicts with great accuracy the intention to adopt artificial intelligence. This variable thus seems to be best explained and predicted by the constructs integrated into the theoretical model.

Finally, the variable "Behavioral Intention to Recommend AI" also displays a positive value of the Q^2predict (0.702), reflecting a good predictive capacity. However, the values of the RMSE (0.545) and the MAE (0.517) appear slightly higher compared to the previous variable, which suggests a slightly lower predictive accuracy, although remaining generally satisfactory.

Overall, the results of the PLS-Predict show that the developed model has a high predictive relevance, since all the values of the Q^2predict are well above zero. This means that the model is able to effectively predict behaviors related to the use, adoption and recommendation of artificial intelligence technologies.

Table 7. PLSpredict

	Q^2predict	**RMSE**	**MAE**
Behavioral Intention to Use AI	0.670	0.579	0.478
Behavioral Intention to Adopt AI	0.886	0.340	0.231
Behavioral Intention to Recommend AI	0.702	0.545	0.517

Source: SmartPLS

5. Discussion

This study explored the use of AI as part of management control by management supervisors in 312 agri-food SMEs in Morocco using UTAUT 3 and Perceived Risk theory. Nineteen hypotheses were formulated, nine of which were supported and ten were rejected.

H1: The Expected Performance impacts positively the Behavioral Intention to Use AI.
H2: The Expected Effort positively impacts the Behavioral Intention to Use AI.

The relationships between "Expected Performance" (H1) and "Expected Effort" (H2) on the one hand, and the "Behavioral Intention to Use AI" on the other hand, are not confirmed by our results. This observation is striking with regard to the literature, moreover, the "Expected Performance" historically constitutes the central pillar of UTAUT (Venkatesh et al., 2003) and TAM (Davis, 1989), while the "Expected Effort" perceived at Davis (1989) then at Venkatesh et al. (2003) occupies an equally structuring place in these two founding frameworks.

However, these two non-meanings are anchored in recent work specifically on AI, which suggests that it is not an isolated anomaly but a phenomenon specific to still emerging technologies. Kim et al. (2024), on the adoption of generative AI, obtain the same non-significant result for the expected performance, which they attribute to the still uncertain nature of the real benefits of the technology. Meuter et al. (2005) offer additional insight: for automated service technologies, trust would precede functional evaluation, so that in the absence of established trust, the "Expected Performance" would lose its predictive power. Cram et al. (2017) add that faced with a technology perceived as fundamentally new and potentially threatening, individuals would not engage in a rational cost-benefit calculation, but would first react to emotional and identity dimensions. Regarding the "*Expected Effort*", Rashid (2025) and Lamssarbi et al. (2025) observe a similar convergence, this determinant would lose its relevance for the generations most familiar with digital technology, several recent works no longer finding a significant effect of this construct on the adoption of AI (Rashid, 2025).

Indeed, the joint absence of effect of these two determinants suggests that the respondents in our sample are not yet in a phase of rational instrumental evaluation of AI, the one that classical models presuppose. This invites us to rethink the strategy for deploying AI in management control, convincing by demonstrating performance gains or ease of use could prove inoperative as long as trust and familiarity with the tool are not established upstream.

H3: Social Influence positively impacts the Behavioral Intention to Use AI.
H4: Hedonic Motivation positively impacts the Behavioral Intention to Use AI.
H5: Perceived Value positively impacts the Behavioral Intention to Use AI.

Unlike the two previous determinants, social influence (H3), hedonic motivation (H4) and perceived value (H5) all three exert a significant positive effect on the intention to use, which is consistent with the existing literature. As for the relationship that studies the impact of social influence on the Behavioral Intention to Use AI, the result obtained confirms a well-established observation in the AI adoption literature. Venkatesh et al. (2003) show in UTAUT that social influence is particularly decisive in the contexts of use, and during the early phases of adoption where the user still lacks a personal reference frame to evaluate the technology. Gallaugher & Ransbotham (2010) specify that in professional environments, legitimization by expert peers weighs more than top-down institutional communication. Moreover, in the context of AI, whose value is still debated in the community of management controllers, social validation plays a role in reducing the uncertainty that Davis et al. (1989) had already identified as a fundamental mechanism in the original TAM under the notion of "*subjective norm*".

Regarding the effect of "Hedonic Motivation" on the "Behavioral Intention to Use AI", the results indicate a modest but significant positive effect, corresponding to the predictions of Venkatesh et al. (2012), who integrate this construct into UTAUT2 precisely to account for non-strictly utilitarian use contexts. Heijden (2004) had established, in his model of acceptance of hedonic systems, that the pleasure felt in use constitutes an independent predictor of intention, distinct from perceived utility. Moreover, in the case of conversational AI interfaces, whose form of interaction is often considered engaging, this hedonic effect is consistent with the results of Nkwe & Cohen (2017), who observe that the quality dimension of the user experience significantly moderates the relationship between usefulness and adoption.

The variable "Perceived Value", for its part, a pursues the same logic of the variable "Hedonic Motivation". It joins the framework of Yu et al. (2017) who define it as the subjective relationship between perceived benefits and sacrifices made. Thus, this result is part of a current of results consistent, first, with the theory of consumption values (Kim et al., 2007), then, with UTAUT2 (Venkatesh et al., 2012) which emphasize a positive relationship between perceived value and intention to use, this indicates that the user perceives the benefits of the technology as superior and more important than the associated costs. So, with the recent work on AI in finance. In addition, Mun & Hwang (2003) show that the quality of the user experience moderates the relationship between perceived usefulness and adoption, which is consistent with the hedonic effect observed for conversational AI interfaces considered engaging.

These three convergent effects draw an adoption profile where the decision to use AI in management control is based less on a rational calculation of performance than on social and experiential dimensions. This suggests that the most effective deployment levers would be less technical training than the visibility of successful uses by recognized peers within the organization.

H6a: Habit positively impacts the Behavioral Intention to Use AI.
H6b: Habit positively impacts the Behavioral Intention to Adopt AI.

The relationships between the "Habit" and the "Behavioral Intention to Use AI" on the one hand, and the "Behavioral Intention to Adopt AI" on the other hand, show opposite results. The first represents the second highest relationship in the model, this fully confirms the central position of the habit in UTAUT2. However, the second relationship, which studies the impact of the "Habit" on the "Behavioral Intention to Adopt AI", shows a result similar to the first. By the way, Venkatesh et al. (2012) define the “Habit” as "*the extent to which people tend to perform behaviors automatically because of learning*", and make it the most robust predictor of continuous use. This result converges with Limayem et al. (2007) who show that habit ends up supplanting behavioral intention as a determinant of real use as soon as technology is sufficiently integrated into routines. In addition, this result has a direct managerial implication, in fact, the challenge for organizations is not to convince by persuasion but to install repeated exposure, what Kim & Malhotra (2005) call the progressive "*behavioral lock-in*" effect. In the same perspective, Verplanken & Aarts (1999) and Lamssarbi et al. (2026) specify that the habit operates in contexts of already established repetition, not in situations of first decision in the face of a new technology, which defines exactly the situation of the respondents vis-à-vis AI in management control. This confirms that "Habit" explains a strong intention to use AI but it does not condition their effective adoption in their work context.

H7a: Facilitating Conditions positively impact the Behavioral Intention to Use AI.
H7b: Facilitating Conditions positively impact the Behavioral Intention to Adopt AI.

The lack of effect of the "facilitating conditions" on the "Behavioral Intention to Use AI" and on the "Behavioral Intention to Adopt AI" indicates that the financial resources, the infrastructure and the organizational and state support do not explicitly determine either the intention to use AI, or their effective adoption in management control. This result diverges from

Venkatesh et al. (2003), show that the facilitating conditions exert a significant effect on the actual use, especially when the access infrastructure is constrained. The absence of effect in this study is plausibly explained by a floor effect. Subawa et al. (2020) had already observed this phenomenon of neutralization of facilitating conditions in well-equipped "knowledge workers" populations, for which the infrastructure constraint has already been lifted. This result converges with Martins et al. (2014), who show that in medium- to large-sized companies, the facilitating conditions no longer explain the variance in adoption once the level of existing equipment is controlled. This observation joins Kim et al. (2024) who find that the "enabling conditions" do not have a significant impact on the intention to adopt technologies of a still emerging nature such as AI.

This result suggests that, in our sample of Moroccan Agri-food SMEs, the obstacle to the adoption of AI is no longer at the level of access to resources or infrastructure, a sign that management controllers intend to use AI applications on the IT infrastructure already in place, but the reason shifts to other registers, cognitive or psychological, identified elsewhere in the model (perceived risk in particular). This shades the conventional wisdom that the equipment deficit would constitute the main obstacle to the digitalization of management control in SMEs.

H8a: Personal Innovation in IT positively impacts the Behavioral Intention to Use AI.
H8b: Personal Innovation in IT positively impacts the Behavioral Intention to Adopt AI.

Regarding the relationship between "Personal Innovation in IT" and "Behavioral Intention to Use AI" and "Behavioral Intention to Adopt AI", the results confirm the dispositional role of innovativeness in use and adoption, as theorized by Agarwal & Prasad (1998), who define "personal innovativeness in IT" as "the willingness of an individual to try out any new information technology". Their work shows that this trait predicts both early adoption and sustained use, regardless of perceptions of usefulness or ease. Rogers et al. (2014) places innovators and early adopters at the heart of the dissemination process, in a context where AI in management control remains an emerging technology with uncertain contours, these profiles constitute the initial vector of organizational legitimation. According to the same perspective, Lu et al. (2005) find that personal innovativeness moderates the effect of perceived risk, which sheds light on a complementary mechanism, otherwise, innovative profiles are less sensitive to the brakes identified above.

H9: The perceived financial risk positively impacts the Behavioral Intention to Adopt AI.
H10: The perceived privacy risk positively impacts the Behavioral Intention to Adopt AI.
H11: The perceived performance risk positively impacts the Behavioral Intention to Adopt AI.
H12: The perceived psychological risk positively impacts the Behavioral Intention to Adopt AI.
H13: The perceived temporal risk positively impacts the Behavioral Intention to Adopt AI.

The relationships between, on the one hand, the "perceived privacy risk" and "perceived psychological risk" and the "Behavioral Intention to Adopt" on the other hand show significant negatif results. These results confirm Bhatia & Breaux (2018), who point out that concerns about data governance constitute the main obstacle to the integration of AI into organizational processes. Featherman & Pavlou (2003) had already established, in their multi-dimensional model of risk, that the privacy risk exerts a particularly strong effect in the services processing sensitive personal or financial data, which corresponds precisely to the scope of management control. More recently, Wirtz et al. (2023) confirm that the fear of algorithmic surveillance and loss of control over data constitutes a structural obstacle to the adoption of AI in companies, regardless of the perception of usefulness.

Moreover, these results are in line with the work of Bhattacherjee & Hikmet (2007), which show that expertise professionals manifest a specific resistance to information systems when they perceive a threat to their professional identity. Moreover, Arenas-Gaitán et al. (2015), in a context of adoption of mobile technologies in companies, find that technological anxiety remains a significant obstacle even among technically competent users. In the case of AI in management control, the perceived threat to analytical expertise can amplify this identity dimension, which is confirmed by Brynjolfsson & McAfee (2014) by emphasizing that AI primarily affects mid-level cognitive jobs, precisely those of management control.

On the other hand, the variables "perceived financial risk", "perceived performance risk" and "perceived temporal risk", exert the positive effects on the "Behavioral Intention to Adopt AI". These results diverge from those of Featherman & Pavlou (2003) who propose a six-dimensional model of perceived risk and find significant effects for each of them on the adoption of e-services. Moreover, the fact that only two of the five risks tested in our study are significant shades this model in the context of professional AI. These findings can be explained by the fact that the financial risk and the time risk are quantifiable and therefore likely to be managed or compensated by the organization, while the confidentiality risk and the psychological risk are perceived as more difficult to control individually. Jacoby & Kaplan (1972), in their founding model of perceived risk, had already noted that the psychological and social dimensions of risk exert more lasting effects than the economic dimensions, precisely because they resist rationalization.

H14a: Behavioral Intention to Use AI positively impacts the Behavioral Intention to Adopt AI.

H14b: Behavioral Intention to Use AI positively impacts the Behavioral Intention to Recommend AI.

H15: Behavioral Intention to Adopt AI positively impacts the Behavioral Intention to Recommend AI.

The relationship between "Behavioral Intention to Adopt AI" and "Behavioral Intention to Recommend AI" displays the highest coefficient in our model, it confirms the classic attitudinal sequence of the theory of planned behavior (Ajzen, 1991) which emphasizes that the intention to engage in a behavior predicts the intention to promote its adoption to others. Thus, Rogers (2003) describes this mechanism as the transition from the status of adopter to that of "champion" in the process of diffusion of innovations. In addition, Zeithaml et al. (1996), in their model of the behavioral consequences of the quality of service, show that the propensity to recommend constitutes the strongest form of post-adoption commitment. The strength of this coefficient suggests that, in professional management control environments, individual adoption quickly produces a prescription effect between peers, which reinforces the importance of prioritizing influential profiles in deployment strategies.

While the relationships between "Behavioral Intention to Use AI" on the one hand and "Behavioral Intention to Adopt AI" and "Behavioral Intention to Recommend AI" on the other hand, do not display significant values. Moreover, the literature on the diffusion of innovations makes it possible to understand why the intention of use does not predict the intention of formal adoption. For Rogers (2003), adoption is a strategic decision to fully engage with an innovation, separate from the trial or occasional use. An individual can regularly use an AI tool made available by his organization without having formulated an intention of adoption in the strong sense of the term, that is to say without having decided to make a lasting commitment to it and to claim it as part of his professional practice.

The IS literature explicitly distinguishes the use phase (post-adoption) from the adoption decision, and emphasizes that attitudinal models comparing use and intention to adopt show that the same variables exert different effects depending on whether we are in the pre-adoption or post-adoption phase. In the case of AI in management control, the use can be forced, partial or experimental, without the individual having crossed the decision-making threshold of real adoption.

Moreover, the non-significance of the link between "Behavioral Intention to Use AI" and "Behavioral Intention to Recommend AI" can theoretically be explained by the distinction between use and post-use satisfaction in the continuity literature. Bhattacherjee (2001) shows that it is the satisfaction and not the intention of use that determines the post-adoption prosocial behaviors, of which the recommendation is part. Zeithaml et al. (1996) position the recommendation as the most committed behavior of the post-adoption chain, which presupposes not only the use but the positive evaluation of this use and the active will to promote its dissemination.

Recent work on AI tools confirms that peer-to-peer recommendation is a separate process from individual use. In other words, the intention to recommend AI to one's peers presupposes that the individual has already passed the stage of use to access a positive qualitative evaluation of this use, which the intention of use alone does not guarantee.

Our results converge with recent work on the acceptance of AI which confirms that attitudes towards the use of AI vary greatly from one individual to another, and that behavioral intention does not capture the entire decision-making process that leads to formal adoption or active recommendation. In the specific context of professional AI, where the tool remains perceived as potentially threatening to professional identity, use may coexist with a reluctance to publicly identify as an adopter or to actively recommend the tool to colleagues.

Finally, the decoupling between use and adoption and recommendation is consistent with what the organizational literature calls symbolic adoption as a concept developed by Wang & Hsieh (2010) in the context of complex information systems in compulsory settings. Recent research confirms this phenomenon in AI contexts by emphasizing that the act of use occurs even if the user symbolically rejects the tool, which creates a structural misalignment between usage behavior and actual adoption.

6. Conclusion

Our research examines management controllers' perceptions of the transformations induced by AI and analyzes the factors influencing their acceptance or resistance toward adopting these technologies in their daily practice. The empirical study is based on a quantitative survey conducted among 312 management controllers and chief financial officers within the Moroccan agribusiness sector, framed under a post-positivist stance. The contributions of this work are presented across three complementary dimensions.

On a theoretical level, this research extends the UTAUT-3 model (Farooq, 2017) beyond its initial scope of application. While this model has been primarily deployed in fields other than management control, this study articulates it for the first time, based on our literature review, with perceived risk theory within the specific context of AI applied to management control. This articulation constitutes a conceptual extension of the model; indeed, it enriches its eight motivational determinants with a dimension of uncertainty and trust that UTAUT-3, taken in isolation, does not theorize. Furthermore, it highlights mechanisms of dissociation among usage intention, adoption intention, and recommendation intention that remain scarcely documented in the existing UTAUT literature.

On a methodological level, this research constitutes, to our knowledge, the first application of the UTAUT-3 model combined with perceived risk theory within the field of management control. This field, traditionally analyzed through the lens of organizational frameworks (Anthony, 1965; Simons, 1995), had not yet been subjected to an individual behavioral modeling of technological adoption on this scale. By deploying a PLS-SEM approach tailored to the complexity of the tested model, this study also proposes a replicable methodological protocol for future research focusing on the adoption of emerging technologies by specialized professional populations.

Finally, on a managerial level, the findings of this research offer concrete action levers for organizations engaged in the digitalization of their management control function. Regarding training, the non-significance of the expected performance and effort determinants suggests that training programs centered on demonstrating efficiency gains or ease of use are insufficient as long as trust in the tool is not established; training initiatives would benefit from integrating dimensions of repeated exposure and peer-to-peer support rather than technical arguments alone. Regarding AI skills development, the confirmed role of personal innovation in IT encourages organizations to identify and rely on internal early adopters capable of serving as catalysts for collective appropriation of the tool. Lastly, concerning job transformation, the weight of psychological and privacy risks in resistance to adoption emphasizes that the stakes extend beyond technical issues; however, it entails a redefinition of the management controller's role, the guidance of which must include an explicit clarification of how AI repositions analytical expertise and professional judgment at the core of management control.

BIBLIOGRAPHY

Abu-Taieh, E. M., Alhadid, I., Abu-Tayeh, S., Masa'deh, R. E., Alkhawaldeh, R. S., Khwaldeh, S., & Alrowwad, A. A. (2022). Continued intention to use of M-Banking in Jordan by integrating UTAUT, TPB, TAM and service quality with ML. *Journal of Open Innovation: Technology, Market, and Complexity*, *8*(3), 120.

Agarwal, R., & Prasad, J. (1998). The antecedents and consequents of user perceptions in information technology adoption. *Decision support systems*, *22*(1), 15-29.

Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes*, *50*(2), 179-211.

Al-Saedi, K., & Al-Emran, M. (2021). A systematic review of mobile payment studies from the lens of the UTAUT model. *Recent advances in technology acceptance models and theories*, 79-106.

Anthony, R. N. (1965). Planning and. *Control Systems: A Framework for Analysis*.

BERROUKECH, M., & HANIN, F. (2025). Intelligence Artificielle et Contrôle de Gestion: mutations, tensions et perspectives d'une gouvernance algorithmique. *Revue du contrôle, de la comptabilité et de l'audit*, *9*(3).

Bhatnagr, P., Rajesh, A., & Misra, R. (2025). Digital banking adoption in India-UTAUT-3 and perceived risk model. *International Journal of Financial Innovation in Banking*, *3*(3), 215-240.

Bhattacherjee, A. (2001). Understanding information systems continuance: An expectation-confirmation model1. *MIS quarterly*, *25*(3), 351-370.

Bhattacherjee, A., & Hikmet, N. (2007, January). Physicians' resistance toward healthcare information technologies: a dual-factor model. In *2007 40th Annual Hawaii International Conference on System Sciences (HICSS'07)* (pp. 141-141). IEEE.

Brynjolfsson, E. (2014). The second machine age: Work, progress, and prosperity in a time of brilliant technologies. *New York and London: WW Norton & Company*.

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. In Modern methods for business research (pp. 295-336). Psychology Press.

Cram, W. A., Proudfoot, J. G., & D'arcy, J. (2017). Organizational information security policies: a review and research framework. European Journal of Information Systems, 26(6), 605-641.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, *13*(3), 319-340.

Dijkstra, T. K., & Henseler, J. (2015). Consistent partial least squares path modeling1. MIS quarterly, 39(2), 297-316.

El Ammari, Y. (2015). *Classement des entreprises agroalimentaires marocaines selon les 13 catégories de l'ISO 22003 v 2007 & analyse des contraintes relatives à la sécurité des aliments* (Doctoral dissertation, Université Ibn Tofail).

El Mehdi, B., Hind, C., Slimane, S., & Abdelali, L. (2025). Vers une modélisation conceptuelle de la performance globale des entreprises de services à travers le contrôle de gestion, les systèmes d'information et l'intelligence artificielle. *Revue Internationale de la Recherche Scientifique (Revue-IRS)*, *3*(3), 2599-2620.

ELHAMMA, A., & MOUMANE, R. (2023). Impact de la taille sur la digitalisation du contrôle de gestion des entreprises marocaines: Résultats d'une enquête. *Alternatives Managériales Economiques*, *5*(3), 182-199.

ESSEMAN, H., & NAFZAOUI, M. A. (2024). La transformation digitale des entreprises à l'ère de l'adversité: Etude de l'impact de la maturité digitale sur la résilience organisationnelle. *Revue du contrôle, de la comptabilité et de l'audit*, *8*(2).

Farooq, M. S., Salam, M., Jaafar, N., Fayolle, A., Ayupp, K., Radovic-Markovic, M., & Sajid, A. (2017). Acceptance and use of lecture capture system (LCS) in executive business studies: Extending UTAUT2. Interactive Technology and Smart Education, 14(4), 329-348.

Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: a perceived risk facets perspective. International journal of human-computer studies, 59(4), 451-474.

Gallaugher, J., & Ransbotham, S. (2010). Social media and customer dialog management at Starbucks. *MIS Quarterly Executive*, *9*(4).

Gunasinghe, A., Hamid, J. A., Khatibi, A., & Azam, S. F. (2020). The adequacy of UTAUT-3 in interpreting academician's adoption to e-Learning in higher education environments. *Interactive Technology and Smart Education*, *17*(1), 86-106.

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). Partial least squares structural equation modeling (PLS-SEM) using R: A workbook. Springer international publishing.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European business review, 31(1), 2-24.

Henseler, J., Hubona, G., & Ray, P. A. (2016). Using PLS path modeling in new technology research: updated guidelines. Industrial management & data systems, 116(1), 2-20.

Heston , R. (2023). AI and Digital Transformation for SMEs: Regional Challenges and Global Opportunities Across Continents. Harvard Business Review, 2-61. AI_and_Digital_Transformation_for_SMEs_Regional_Challenges_and_Global_Opportunities_Across_Continents. https://www.researchgate.net/publication/390980145.

Jacoby, J., & Kaplan, L. B. (1972). The components of perceived risk. ACR special volumes.

Jeon, H. M., Ali, F., & Lee, S. W. (2019). Determinants of consumers' intentions to use smartphones apps for flight ticket bookings. The Service Industries Journal, 39(5-6), 385-402.

Kim, H. W., Chan, H. C., & Gupta, S. (2007). Value-based adoption of mobile internet: an empirical investigation. *Decision support systems*, *43*(1), 111-126.

Kim, S. S., Malhotra, N. K., & Narasimhan, S. (2005). Research note—two competing perspectives on automatic use: A theoretical and empirical comparison. *Information systems research*, *16*(4), 418-432.

Kim, Y., Blazquez, V., & Oh, T. (2024). Determinants of generative AI system adoption and usage behavior in Korean companies: Applying the UTAUT model. Behavioral Sciences, 14(11), 1035.

L'MGHAIFRI, H., & ZAMMAR, R. (2025). Revue de littérature sur l'intégration de l'Intelligence Artificielle (IA) dans les pratiques du Contrôle de Gestion: Opportunités et Défis. *Revue de l'Intelligence Artificielle et du développement territorial durable*, *2*(01).

Lamssarbi, B., & Bouaziz, S. M. (2022). Mutation du rôle de contrôleur de gestion à l'ère de la digitalisation: Revue de littérature. *International Journal of Financial Accountability, Economics, Management, and Auditing*, *4*(4), 434-445.

LAMSSARBI, B., BOUAZIZ, S. M., & MAMOUDOU, A. (2025). The impact of digitalization on management control and performance: A Systematic Literature Review. *Revue Française d'Economie et de Gestion*, *6*(1).

Lamssarbi, B., Mamoudou, A., & Bouaziz, S. M. (2026). The Decision Makers' Perceptions Toward the Adoption of Artificial. In *Impact of Artificial Intelligence (AI) and the Global Financial Crisis on Development in Africa: Current Business Issues in African Countries (CBIAC) Conference, Hoboken, New Jersey, May 27–28, 2024* (p. 1). Springer Nature.

Laradi, S., Elfekair, A., Rehman, H. M., Hanna, D., & Alrawad, M. (2025). Continuance intention of m-Banking adoption: the dynamics of UTAUT3, trust and attitudes. *FIIB Business Review*, 23197145251358049.

Lee, H. Y., Chung, C. Y., & Wei, G. (2022, February). Research on technological pedagogical and content knowledge: A bibliometric analysis from 2011 to 2020. In *Frontiers in education* (Vol. 7, p. 765233). Frontiers Media SA.

Libby, T., & Lindsay, R. M. (2010). Beyond budgeting or budgeting reconsidered? A survey of North-American budgeting practice. *Management accounting research*, *21*(1), 56-75.

Limayem, M., Hirt, S. G., & Cheung, C. M. (2007). How Habit Limits the Predictive Power of Intention: The Case of Information Systems Continuance1. MIS quarterly, 31(4), 705-737.

Lu, J., Yao, J. E., & Yu, C. S. (2005). Personal innovativeness, social influences and adoption of wireless Internet services via mobile technology. *The journal of strategic Information Systems*, *14*(3), 245-268.

Malmi, T., & Brown, D. A. (2008). Management control systems as a package—Opportunities, challenges and research directions. *Management accounting research*, *19*(4), 287-300.

Martins, C., Oliveira, T., & Popovič, A. (2014). Understanding the Internet banking adoption: A unified theory of acceptance and use of technology and perceived risk application. International journal of information management, 34(1), 1-13.

METAILLER, T., & PASCAL, A. (2022). Maturité digitale des PME: des modèles à réinventer?. *Management & Datascience*.

Meuter, M. L., Bitner, M. J., Ostrom, A. L., & Brown, S. W. (2005). Choosing among alternative service delivery modes: An investigation of customer trial of self-service technologies. Journal of marketing, 69(2), 61-83.

Moinard, C., & Berland, N. (2020). Intelligence artificielle et contrôle de gestion: un rapport aux chiffres revisité et des enjeux organisationnels. *Annales des Mines-Enjeux numériques*, *12*(4), 44-50.

Muhammad, S. S., Dey, B. L., Kamal, M. M., Samuel, L., & Alzeiby, E. A. (2025). Digital transformation or digital divide? Smes' use of AI during global crisis. *Technological Forecasting and Social Change*, *217*, 124184.

Mun, Y. Y., & Hwang, Y. (2003). Predicting the use of web-based information systems: self-efficacy, enjoyment, learning goal orientation, and the technology acceptance model. *International journal of human-computer studies*, *59*(4), 431-449.

Murray, K. B., & Häubl, G. (2007). Explaining cognitive lock-in: The role of skill-based habits of use in consumer choice. *Journal of Consumer Research*, *34*(1), 77-88.

Namahoot, K. S., & Jantasri, V. (2023). Integration of UTAUT model in Thailand cashless payment system adoption: the mediating role of perceived risk and trust. *Journal of Science and Technology Policy Management*, *14*(4), 634-658.

Nkwe, N., & Cohen, J. (2017). The effects of intrinsic, extrinsic, hedonic, and utilitarian motivations on IS usage: An updated meta-analytic investigation.

Olsen, R. A. (2010). Financial risk perceptions: A behavioral perspective. *Advances in entrepreneurial finance: With applications from behavioral finance and economics*, 45-67.

Pinto, A. S., Abreu, A., Costa, E., & Paiva, J. (2022). Augmented reality for a new reality: using UTAUT-3 to assess the adoption of mobile augmented reality in tourism (MART). *Journal of Information Systems Engineering and Management*, *7*(2), 14550.

POONG, Y. S., & Poong, Y. S. (2016). Study of Perceptions on Behavioral Expectation to Preserve World Heritage Site through Mobile Learning Application in Luang Prabang, Lao PDR. *(No Title)*.

Rajhi, I. (2025). Motivations et résistances à l'usage des chatbots dans l'hôtellerie: une analyse basée sur le modèle UTAUT 3.

Rashid, S. (2025). Habit Predicting Higher Education EFL Students' Intention and Use of AI: A Nexus of UTAUT-2 Model and Metacognition Theory. Education Sciences, 15(6), 756. https://doi.org/10.3390/educsci15060756.

Rikhardsson, P., & Yigitbasioglu, O. (2018). Business intelligence & analytics in management accounting research: Status and future focus. *International journal of accounting information systems*, *29*, 37-58.

Rogers, E. M., Singhal, A., & Quinlan, M. M. (2014). Diffusion of innovations. In *An integrated approach to communication theory and research* (pp. 432-448). Routledge.

Sarstedt, M., Ringle, C. M., Smith, D., Reams, R., & Hair Jr, J. F. (2014). Partial least squares structural equation modeling (PLS-SEM): A useful tool for family business researchers. Journal of family business strategy, 5(1), 105-115.

Simons, R. (1995). Control in an age of empowerment. *Harvard business review*, *73*(2), 80-88.

Tornatzky, L. and Fleischer, M. (1990) The process of technology innovation, Lexington, MA, Lexington Books.

Van der Heijden, H. (2004). User acceptance of hedonic information systems1. *MIS quarterly*, *28*(4), 695-704.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view1. *MIS quarterly*, *27*(3), 425-478.

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the Unified Theory of Acceptance and Use of Technology1. *MIS quarterly*, *36*(1), 157-178.

Verplanken, B., & Aarts, H. (1999). Habit, attitude, and planned behaviour: is habit an empty construct or an interesting case of goal-directed automaticity?. European review of social psychology, 10(1), 101-134.

Wang, W., & Hsieh, P. A. (2006). Beyond routine: Symbolic adoption, extended use, and emergent use of complex information systems in the mandatory organizational context. *ICIS 2006 Proceedings*, 48.

Yu, J., Lee, H., Ha, I., & Zo, H. (2017). User acceptance of media tablets: An empirical examination of perceived value. *Telematics and Informatics*, *34*(4), 206-223.

Zeithaml, V. A., Berry, L. L., & Parasuraman, A. (1996). The behavioral consequences of service quality. *Journal of marketing*, *60*(2), 31-46.