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Empirical investigation of generative artificial intelligence acceptability determinants among Moroccan chartered accountants: A structural equation modeling approach

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Résumé. This study examines generative artificial intelligence (GAI) acceptability determinants among Moroccan chartered accountants using the Unified Theory of Acceptance and Use of Technology (UTAUT). Data collection from 262 professionals (31.9% response rate) applied a quantitative methodology based on the UTAUT framework. Partial least squares structural equation modeling assessed relationships between four determinants and GAI acceptability. Results indicate effort expectancy (β=0.538, f^2=0.213) and social influence (β=0.498, f^2=0.109) as primary determinants, while performance expectancy (β=0.319, f^2=0.004) shows limited effect size despite statistical significance. Facilitating conditions demonstrate no substantial contribution (f^2=0.000). The model explains 40.4% of GAI acceptability variance. These findings reveal distinct adoption patterns where ease of use and social factors predominate over performance considerations in the Moroccan accounting profession, contributing empirical evidence from non-Western professional contexts to technology acceptance literature.

Mots-clés: *Generative artificial intelligence; UTAUT; Technology acceptance; Accounting profession; Morocco.*

1. Introduction

Generative artificial intelligence (GAI) represents a category of artificial intelligence (AI) systems designed to create content resembling human production across various domains including text, images, code, and analytics (Bommasani et al., 2021). These systems utilize deep learning architectures such as transformer networks that process input data through multiple computational layers to generate contextually relevant outputs (Brown et al., 2020). The global implementation of generative AI systems has accelerated across sectors to automate routine processes, enhance decision-making capabilities, and develop predictive insights from complex datasets. According to Kaplan and Haenlein (2019), generative AI differs from traditional AI systems through its capability to produce novel content rather than simply analyzing existing data.

In accounting practice, GAI applications manifest through multiple functionalities including automated financial analysis, audit documentation processing, risk assessment, and advisory report generation (Kokina & Blanchette, 2019). The integration of these technologies modifies established workflows through task automation, data processing acceleration, and error reduction in routine operations (Moll & Yigitbasioglu, 2019). Kokina and Davenport (2017) documented efficiency improvements in traditional accounting tasks following GAI implementation, with effectiveness in data extraction from unstructured documents, anomaly detection, and pattern recognition functions. International accounting firms report increased implementation of GAI solutions for audit sampling, fraud detection, and real-time financial monitoring systems (Manita et al., 2020).

Technology adoption research demonstrates contextual variation in acceptance patterns across geographic, cultural, and professional environments (Al-Gahtani et al., 2007). The existing literature on GAI acceptability focuses predominantly on implementation cases in North American and European accounting firms, with limited investigation of acceptability determinants in emerging economies (Dwivedi et al., 2019). Technology acceptance models including UTAUT undergo validation primarily in Western organizational contexts, creating uncertainty regarding their applicability to professional environments with distinct cultural, regulatory, and infrastructural conditions (Venkatesh et al., 2003). The factors influencing GAI acceptance among accounting professionals in North African contexts, including Morocco, remain underexamined in the current literature.

This research examines the acceptability determinants of generative artificial intelligence among Moroccan chartered accountants utilizing the UTAUT framework. The study analyzes relationships between four independent constructs (performance expectancy, effort expectancy, social influence, and facilitating conditions) and one dependent variable (GAI acceptability) measured through behavioral intention. For operational clarity, the research defines GAI as artificial intelligence systems capable of generating creative outputs including text-based reports, data visualizations, and analytical recommendations used in accounting practice (Kaplan & Haenlein, 2019). Acceptability encompasses both the attitudinal disposition toward technology use and the behavioral intention to incorporate these systems into professional workflows, following definitions established in technology adoption literature (Kaplan & Haenlein, 2019; Venkatesh et al., 2003).

Our paper addresses two primary questions: (1) To what extent do performance expectancy, effort expectancy, social influence, and facilitating conditions predict the acceptability of generative artificial intelligence among Moroccan chartered accountants? (2) How do these relationships align with or diverge from the patterns established in previous UTAUT validation studies conducted in different professional and cultural contexts? These questions derive from the observed gap between technological potential and implementation rates in emerging economies, and the limited application of standardized technology acceptance models to North African professional environments.

This research makes three original contributions to technology acceptance literature. First, it provides the first empirical examination of generative AI acceptability among Moroccan chartered accountants, addressing the geographical gap in UTAUT research which has been validated primarily in Western organizational contexts (Venkatesh et al., 2003). Morocco's professional accounting environment—characterized by distinct regulatory frameworks, developing digital infrastructure, and specific cultural orientations—remains unexplored in technology adoption studies (El Omari & Khlif, 2014). Second, it extends UTAUT application to generative artificial intelligence systems capable of producing novel content (text-based reports, data visualizations, analytical recommendations), rather than the traditional information systems examined in previous acceptance research.

These patterns partially confirm previous UTAUT validation studies while revealing contextual distinctions specific to the Moroccan chartered accountancy environment (Venkatesh et al., 2003). The findings provide evidence-based insights for accounting professional bodies developing technology implementation strategies, technology providers adapting solutions to non-Western markets, and educational institutions designing relevant training programs.

The following sections proceed sequentially through an organized structure. Section 2 presents a literature review examining theoretical foundations of generative artificial intelligence, technology acceptance models with emphasis on UTAUT, and previous studies of technology adoption in accounting contexts. Section 3 details the research methodology, including sampling procedures, measurement instrument development, and analytical techniques. Section

4 presents empirical findings from structural equation modeling analysis. Section 5 discusses theoretical and practical implications of these findings. The article concludes with limitations and directions for future research.

2. Background

The scientific literature reveals diverse conceptualizations of generative artificial intelligence and technological acceptability. This conceptual variation reflects the complexity of these phenomena and their rapid evolution in professional contexts. The conceptual delimitations presented in this literature review synthesize principal theoretical frameworks applied in research on GAI acceptability.

a. Generative Artificial Intelligence

Generative artificial intelligence represents a subset of AI systems characterized by their ability to create new content rather than merely analyzing existing data (Kaplan & Haenlein, 2019). These systems employ deep learning architectures, particularly transformer networks, that process input data through multiple computational layers to generate contextually appropriate outputs (Brown et al., 2020). Vaswani et al. (2017) established the foundational architecture for modern generative systems through the attention mechanism that enables contextual understanding across input sequences.

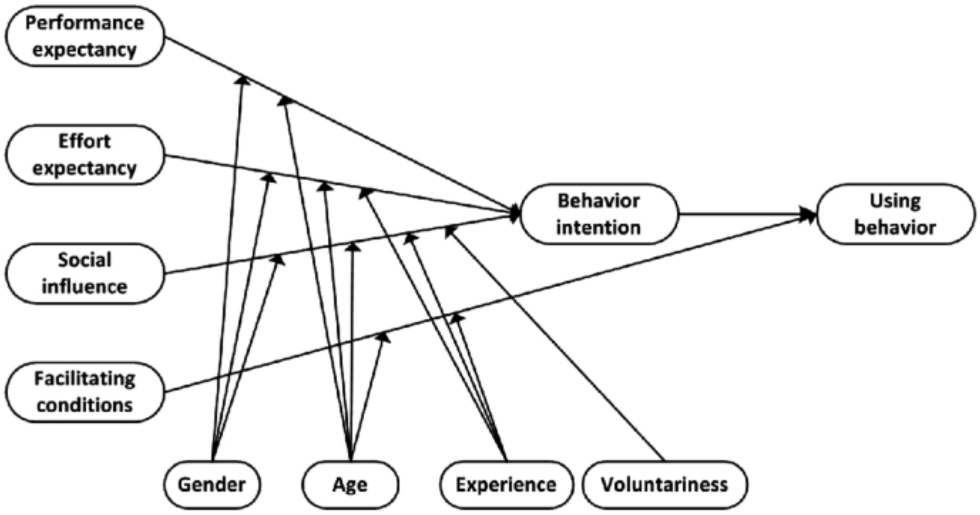
The development of GAI has progressed through several technological iterations, from early generative adversarial networks to contemporary large language models (Bommasani et al., 2021). Contemporary GAI systems demonstrate capabilities including natural language processing, pattern recognition, and analytical reasoning that enable application across professional domains (Silver et al., 2017). These technologies differ from traditional AI through their capacity to produce novel outputs rather than operating within predefined algorithmic parameters (Russell & Norvig, 2020). In accounting applications, GAI technologies manifest across multiple functional domains. Kokina and Davenport (2017) identified implementation cases in audit sampling, data extraction, anomaly detection, and automated reporting. Richins et al. (2017) documented applications in financial statement analysis, regulatory compliance, and client advisory services. According to Munoko et al. (2020), accounting firms increasingly deploy GAI systems for risk assessment, fraud detection, and predictive financial modeling.

b. Technology Acceptance Models

Technology acceptance research examines determinants of user adoption and continued engagement with technological innovations. Early theoretical frameworks including the Technology Acceptance Model (TAM) established perceived usefulness and perceived ease of use as fundamental predictors of behavioral intention (Davis, 1989). Subsequent models incorporated additional constructs to enhance explanatory power across implementation contexts (Venkatesh & Davis, 2000). The Unified Theory of Acceptance and Use of Technology (UTAUT) synthesizes eight previous acceptance models into a comprehensive framework with four principal determinants: performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). This model demonstrates enhanced predictive validity compared to predecessor frameworks, explaining up to 70% of variance in behavioral intention across implementation contexts (Venkatesh et al., 2003).

Multiple studies validate UTAUT applicability across technological domains including mobile applications (Alalwan, 2020), healthcare information systems (Abbott, 1988), and e-learning platforms (Mensah, 2019). UTAUT applications in accounting contexts include studies of enterprise resource planning systems (Chang & King, 2005), audit technologies (Manita et al., 2020), and financial analytics platforms (Cao et al., 2021).

Figure 1. UTAUT Model



- *Performance Expectancy*

Performance expectancy constitutes a fundamental determinant of technological acceptability (Venkatesh et al., 2003). This construct integrates five concepts from previous models: perceived usefulness (TAM/TAM2), extrinsic motivation, job-fit, relative advantage, and outcome expectations. Venkatesh et al. (2003) demonstrated that performance expectancy represents the most powerful predictor of usage intention in different contexts, both organizational and voluntary. In the context of accounting professionals, generative artificial intelligence technologies appear as tools for eliminating repetitive tasks and reducing errors, offering collaborators the possibility to focus on more elaborate questions (Venkatesh et al., 2003). Vărzaru (2022) identified a significant positive correlation between performance expectancy and the intention to employ AI in management accounting, with innovation constituting the predominant factor. Based on the previous investigations, the following hypothesis is proposed:

H1: Performance expectancy positively influences behavioral intention to use generative AI among Moroccan chartered accountants.

- *Effort Expectancy*

Effort expectancy defines as the degree of ease associated with system use. This construct derives from three concepts present in previous models: perceived ease of use (TAM/TAM2), complexity, and ease of use. Effort expectancy significantly influences usage intention, particularly in the initial phases of adoption (Venkatesh et al., 2003). In the accounting domain, effort expectancy has been studied to evaluate AI adoption intention. Vărzaru (2022) employed parameters such as flexibility, speed, personalization, and ease of learning to quantify this construct. Analyses demonstrated an inverse relationship between perceived effort and AI acceptance intention, with speed exerting the strongest influence. Drawing on these insights, the following hypothesis is proposed:

H2: Effort expectancy positively influences behavioral intention to use generative AI among Moroccan chartered accountants.

- *Social Influence*

Social influence represents the degree to which an individual perceives that important others believe they should use the system. This construct integrates subjective norm, social factors, and image. Social influence operates via three mechanisms: compliance, internalization, and identification (Venkatesh et al., 2003). Social influence manifests a significant effect in mandatory usage contexts, particularly in the initial phases of adoption. This influence diminishes with increased user experience. Gender and age moderate the effect of social influence, with a more pronounced impact among women and older workers (Venkatesh et al., 2003). Thus, the following hypothesis is formed:

H3: Social influence positively influences behavioral intention to use generative AI among Moroccan chartered accountants

- *Facilitating Conditions*

Facilitating conditions are defined as the degree to which an individual believes that organizational and technical infrastructure exists to support system use. This construct incorporates perceived behavioral control, facilitating conditions, and compatibility. According to Venkatesh et al. (2003), facilitating conditions directly influence actual usage rather than behavioral intention.

In the chartered accountancy context, facilitating conditions include technical infrastructure, organizational support, compatibility with existing systems, and available training. Age and experience moderate the effect of facilitating conditions on usage, with a more pronounced impact among older and more experienced workers (Venkatesh et al., 2003). Based on this theory, the following hypothesis is formed:

H4: Facilitating conditions positively influence actual usage of generative AI among Moroccan chartered accountants.

In this research, the UTAUT model has been adapted by excluding the moderating variables (age, gender, experience, and voluntariness of use). This model adaptation corresponds to a simplification of Venkatesh et al. (2003) original framework to focus on direct relationships between the main constructs. This methodological decision rests on several considerations:

- Focus on main constructs: this approach permits specific examination of the strength and nature of direct effects of the four principal determinants on GAI acceptability (Tamilmani et al., 2019).
- Sampling constraints: inclusion of moderating variables would require a more substantial sample size to guarantee sufficient statistical power in subgroup analysis (Hair et al., 2019).
- Model parsimony: model simplification facilitates result interpretation and identification of significant relationships.

Methodological precedents exist in literature, with several studies having adopted adapted versions of the UTAUT model without moderating variables (Dwivedi et al., 2019; Sharma et al., 2021).

c. Moroccan Accounting Context

The professional accounting context in Morocco presents distinct characteristics that potentially modify technology acceptance patterns. El Omari and Khlif (2014) documented the professionalization trajectory of Moroccan accounting, identifying regulatory frameworks and professional institutions that shape practice standards. The Moroccan accounting profession operates under specific regulatory conditions established through sequential legislative developments (El Fakir, 2024).

Professional accounting in Morocco experiences ongoing digital transformation challenges. El Fakir (2024) identified infrastructure limitations, educational gaps, and regulatory uncertainties affecting technological implementation. The Moroccan professional environment demonstrates adoption patterns that differ from Western contexts due to these contextual factors (Lafraxo et al., 2018). Limited research specifically addresses technology acceptance among Moroccan accounting professionals. Hassouni (2015) examined gender aspects of accounting technology adoption in Morocco, finding significant differences compared to Western professional contexts. Recent technological initiatives within Moroccan accounting include digital reporting systems and electronic documentation processes (El Arif, 2021).

3. Research Methodology

This research adopts a hypothetico-deductive approach to examine the determinants of GAI acceptability among Moroccan chartered accountants according to the UTAUT model. This approach involves formulating testable hypotheses derived from theory followed by empirical verification of presumed causal relationships (Popper, 1959)..

a. Research Design

The methodological protocol comprises: (1) definition of the conceptual framework based on the UTAUT model (Davis, 1989), (2) hypothesis formulation, (3) quantitative data collection, (4) hypothesis verification through statistical processing, and (5) confrontation of empirical results with initial hypotheses. This study uses a quantitative approach to analyze the determinants of GAI acceptability among Moroccan chartered accountants. The conceptual model examines four independent variables: performance expectancy, effort expectancy, social influence, and facilitating conditions.

b. Data collection

The research methodology targeted chartered accountants registered with the Moroccan Institute of Chartered Accountants through a systematic participant selection approach. Two fundamental criteria guided the selection process: formal registration with the professional body, ensuring adherence to established regulatory frameworks; and baseline familiarity with generative artificial intelligence technologies, ensuring participants' capacity to provide informed perspectives on the investigated phenomenon. This dual-criteria approach aligns with methodological rigor requirements in technology acceptance research, particularly when investigating specialized professional contexts. The initial methodological approach implemented census-based data collection directed at the complete population of 822 registered chartered accountants as documented in August 2024. This comprehensive approach aimed to mitigate sampling bias through exhaustive population coverage, thereby enhancing statistical conclusion validity. Census methodology, while ambitious, was deemed appropriate given the finite and accessible nature of the professional population under investigation. Questionnaire distribution proceeded through sequential implementation of multiple communication channels. Primary distribution occurred via direct email communication utilizing publicly accessible professional information from the official registry. This initial approach was subsequently augmented through three complementary solicitation strategies: LinkedIn professional network communications, direct telephone contact, and in-person data collection at accounting firm locations and regional professional association events. This multi-channel distribution strategy represents a methodologically sound approach to maximize response rates while mitigating non-response bias, a significant concern in professional population sampling.

The data collection methodology proceeded without formal endorsement from the Institute, a deliberate methodological decision to minimize potential institutional response bias. This approach aligns with recommended practices in organizational research where institutional affiliation may influence response patterns. The temporal framework for data collection extended across a four-month interval from August through November 2024, providing adequate opportunity for participant engagement while maintaining temporal consistency in the contextual environment. The final sample consisted of 262 responses through convenience sampling methodology, representing a 31.9% response rate. This response rate exceeds the average for organizational research targeting professional populations, which typically ranges between 15-25% according to meta-analytical studies (Baruch & Holtom, 2008). The sample size satisfies minimum requirements for structural equation modeling analysis with the specified number of constructs, following established guidelines requiring at least 10 observations per measured variable (Hair et al., 2019).

Table 1. Measurement instrument - UTAUT model variables and items adapted to the generative artificial intelligence context.

Variable	Code	Item Formulation	Source
Performance Expectancy (PE)	PE1	“Using generative AI allows me to accomplish tasks more quickly”	Inspired from Venkatesh et al. (2003
	PE2	“Using generative AI improves my professional performance”	
	PE3	“Using generative AI increases my productivity”	
	PE4	“Using generative AI improves the quality of my work”	
Effort Expectancy (EE)	EE1	“My interaction with generative AI is clear and understandable”	
	EE2	“It is easy to become skillful at using generative AI”	
	EE3	“Generative AI is easy to use”	
	EE4	“Learning to use generative AI is easy for me”	
Social Influence (SI)	SI1	“People who influence my professional behavior think that I should use generative AI”	
	SI2	“People who are important to me think that I should use generative AI”	
	SI3	“The management of my firm supports the use of generative AI”	
	SI4	“The Institute of Chartered Accountants encourages the use of generative AI”	
Facilitating Conditions (FC)	FC1	“I have the necessary resources to use generative AI”	
	FC2	“I have the knowledge necessary to use generative AI”	

	FC3	"Generative AI is compatible with other systems I use"	
	FC4	"A specific person (or group) is available to assist me with generative AI difficulties"	
GAI Acceptability	ACCEPT1	"I intend to use generative AI in the next 6 months"	
	ACCEPT2	"I predict I will use generative AI in the next 6 months"	
	ACCEPT3	"I plan to use generative AI in the next 6 months"	

4. Results

a. Preliminary analysis and scale refinement

The measurement model underwent evaluation through examination of psychometric properties according to established structural equation modeling protocols. Assessment criteria included factor loadings (threshold > 0.7), Cronbach's alpha (> 0.7), Average Variance Extracted (AVE > 0.5), and composite reliability (CR > 0.7), following thresholds established by Hair et al. (2019).

Table 2. Evolution of psychometric indicators before and after scale refinement

Constructs and Items	**Before Refinement**				**After Refinement**			
	Loadings	Cronbach's Alpha	AVE	CR	Loadings	Cronbach's Alpha	AVE	CR
Effort Expectancy		0.654	0.498	0.719		0.710	0.627	0.834
EE1	0.735				0.730			
EE2	0.858				0.871			
EE3	0.734				0.768			
EE4	0.422				Removed			
Performance Expectancy		0.528	0.465	0.808		0.773	0.815	0.773
PE1	0.903				0.903			
PE2	0.471				Removed			

PE3	-0.101				Removed			
PE4	0.901				0.902			
Facilitating Conditions								
FC1	0.886	0.861	0.782	0.862	0.886	0.861	0.782	0.862
FC2	0.902				0.902			
FC3	0.866				0.866			
Social Influence								
SI1	0.856	0.769	0.677	0.802	0.856	0.769	0.677	0.802
SI2	0.778				0.778			
SI3	0.834				0.834			
GAI Acceptability								
ACCEPT1	0.719	0.614	0.562	0.616	0.716	0.701	0.563	0.795
ACCEPT2	0.804				0.801			
ACCEPT3	0.724				0.731			

Table 2 presents psychometric analysis results before and after scale refinement as generated by SmartPLS (Version 4). For the effort expectancy (EE) scale, removal of item EE4 (loading 0.422) improved psychometric properties. Cronbach's alpha increased from 0.654 to 0.710, while AVE increased from 0.498 (below the recommended 0.5 threshold) to 0.627. Composite reliability (CR) improved from 0.719 to 0.834.

For performance expectancy (PE), two items were removed (PE2 and PE3) due to unsatisfactory loadings (0.471 and -0.101 respectively). This refinement achieved an AVE of 0.815 (compared to 0.465 initially), and a CR of 0.773, identical to Cronbach's alpha. Facilitating conditions (FC) and social influence (SI) scales required no refinement, as their indicators exhibited satisfactory psychometric properties from initial analysis (alpha > 0.7, AVE > 0.5, CR > 0.8).

For GAI acceptability, results show improvement in Cronbach's alpha (from 0.614 to 0.701) and composite reliability (from 0.616 to 0.795) after refinement, while AVE remained stable (0.562 to 0.563). These modifications align with scale validation practices in quantitative research, where items with insufficient loadings are removed to improve reliability and convergent validity (Hair et al., 2017).

Table 3: Correlation matrix based on fornell-larcker criterion

	GAI Acceptability	Facilitating Conditions	Effort Expectancy	Social Influence	Performance Expectancy
GAI Acceptability	**0.750**				
Facilitating Conditions	0.332	**0.885**			
Effort Expectancy	0.550	0.442	**0.706**		
Social Influence	0.498	0.380	0.375	**0.823**	
Performance Expectancy	0.314	0.269	0.257	0.472	**0.682**

The presented matrix displays correlations between latent variables, with the square roots of AVE values on the diagonal. According to the Fornell-Larcker criterion, a construct establishes discriminant validity when the square root of its AVE exceeds its correlations with other constructs. Examination of the data reveals that this condition is satisfied for all variables: GAI acceptability (0.750 > values ranging from 0.332 to 0.550), facilitating conditions (0.885 > values ranging from 0.269 to 0.442), effort expectancy (0.706 > values ranging from 0.257 to 0.550), social influence (0.823 > values ranging from 0.375 to 0.498), and performance expectancy (0.682 > values ranging from 0.257 to 0.472).

The correlations between variables appear moderate, with the highest observed between effort expectancy and acceptability (0.550), followed by social influence and acceptability (0.498), then between social influence and performance expectancy (0.472). These correlation values indicate the absence of problematic multicollinearity while confirming the existence of significant relationships between constructs, consistent with the hypothesized relationships in the UTAUT model. The discriminant validity assessment provides statistical support for the distinctiveness of each theoretical construct, thereby enhancing confidence in the subsequent structural model evaluation and hypothesis testing.

Table 3. Hypothesis Testing Results

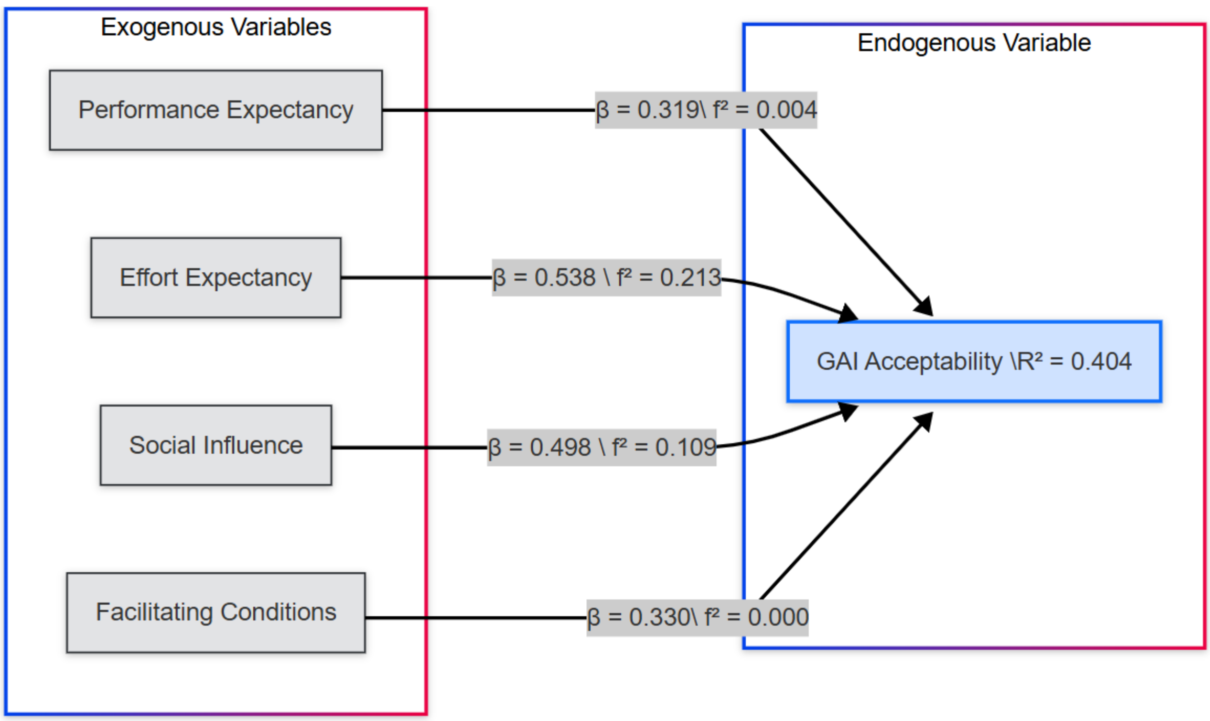
Hypotheses	Coefficient (β)	T-value	P-value
Facilitating Conditions → GAI Acceptability	0.330	7.222	0.000
Effort Expectancy → GAI Acceptability	0.538	12.402	0.000
Social Influence → GAI Acceptability	0.498	10.444	0.000
Performance Expectancy → GAI Acceptability	0.319	5.163	0.000

Statistical results indicate correlations between independent variables and the dependent variable. Standardized coefficients (β) show relationship strength, while T and P values determine statistical significance.

All relationships are statistically significant ($p < 0.001$). Effort expectancy shows the strongest relationship with GAI acceptability ($\beta = 0.538$, $t = 12.402$), followed by social influence ($\beta = 0.498$, $t = 10.444$). Facilitating conditions ($\beta = 0.330$, $t = 7.222$) and performance expectancy ($\beta = 0.319$, $t = 5.163$) demonstrate moderate but significant correlations with acceptability. The R^2 obtained is 0.404, indicating that the four UTAUT determinants (performance expectancy, effort expectancy, social influence, and facilitating conditions) together explain 40.4% of variance in GAI acceptability.

The adjusted value (R^2 adjusted = 0.395) accounts for predictor numbers and provides a less biased estimate of explanatory power. According to criteria established by Chin (1998) for information systems research, this value represents a moderate explanation level ($R^2 > 0.33$), demonstrating the relevance of the UTAUT model in the context of GAI acceptability among Moroccan chartered accountants.

Figure 2. Structural model of generative artificial intelligence acceptability determinants



5. Discussion

The first hypothesis (H1) proposed a positive influence of performance expectancy on GAI acceptability. Results confirm this relationship with a significant coefficient ($\beta = 0.319$, $p < 0.001$). However, the associated effect size is minimal ($f^2 = 0.004$), suggesting limited contribution of this variable when integrated into the complete model. This finding diverges from conclusions by Venkatesh et al. (2003) who identified performance expectancy as the strongest determinant of usage intention. This difference may be explained by the specific nature of generative AI and the professional context of chartered accountancy in Morocco. Chartered accountants, while recognizing potential GAI benefits (bivariate correlation of 0.314), appear to consider other factors more determinant in their acceptance decision. This observation aligns with findings from Vărzaru (2022) who noted that in certain professional contexts, performance expectations do not constitute the predominant acceptance factor. Hypothesis H2 regarding the positive influence of effort expectancy on GAI acceptability receives confirmation from the results. The relationship is statistically significant ($\beta = 0.538$, $p < 0.001$) with effort expectancy presenting the largest effect size ($f^2 = 0.213$), indicating substantial contribution to explaining GAI acceptability variance. This finding differs from previous UTAUT model studies, where effort expectancy was generally considered less influential than performance expectancy (Venkatesh et al., 2003). The predominance of this factor suggests that learning and usage ease of generative AI represents a concern for Moroccan chartered accountants. This observation may be explained by several contextual factors:

- The perceived complexity of generative AI technologies;
- Time constraints experienced by chartered accountants;
- Variable digital competency levels within the profession.

These results align with those of Sharma et al. (2021) who identified ease of use as a factor for AI adoption in accounting and auditing.

Hypothesis H3 predicted positive influence of social influence on GAI acceptability. This hypothesis is validated with a significant coefficient ($\beta = 0.498$, $p < 0.001$) and moderate effect size ($f^2 = 0.109$). The importance of social influence in this context suggests that opinions of peers, hierarchical superiors, and professional institutions exert influence on technological adoption decisions. This finding is consistent with the regulated and collegial nature of the accounting profession, where professional standards and recommended practices play a role. These observations confirm conclusions on social influence in professional contexts (Venkatesh et al., 2003). They also align with studies by Gotthardt et al. (2020) highlighting the role of professional networks in cognitive technology adoption by chartered accountants.

Hypothesis H4 regarding the positive influence of facilitating conditions on GAI acceptability is not supported by the data. While the bivariate correlation is significant ($r = 0.332$, $p < 0.001$), the effect size in the structural model is null ($f^2 = 0.000$). This finding diverges from original UTAUT model predictions (Venkatesh et al., 2003) that established a direct link between facilitating conditions and usage behavior. This divergence may be explained by several factors:

- The early adoption stage of generative AI in the studied context;
- The possibility that facilitating conditions influence acceptability indirectly through other variables;
- The limited development of infrastructure and organizational support for generative AI in Moroccan accounting firms.

These observations suggest that in the current context, individual perceptions (effort expectancy, social influence) exert more influence than environmental and organizational conditions.

The model explains 40.4% of GAI acceptability variance ($R^2 = 0.404$), representing a moderate explanation level according to criteria established by Chin (1998). This performance, while lower than the 70% reported by Venkatesh et al. (2003) for the complete UTAUT model (including moderating variables), remains satisfactory considering the adapted model's simplicity. The model's predictive capacity is confirmed by the positive Q^2predict index (0.260), attesting to its relevance for predicting GAI acceptability beyond a simple mean-based prediction. These results suggest that the UTAUT model, even in its simplified version, offers a theoretical framework for understanding GAI acceptability in the Moroccan chartered accountancy context. They also indicate that other factors not included in the model (approximately 60% of variance) could contribute to explaining acceptability. This study provides several significant contributions to the theoretical corpus regarding technology acceptance, particularly within emerging economy contexts. First, our findings confirm the relevance of the UTAUT model for examining generative artificial intelligence acceptability, thus validating the applicability of this conceptual framework in an emerging technological domain. This validation represents an important extension of existing literature that has primarily focused on more established technologies such as traditional information systems or mobile applications. Second, our analysis highlights a determinant hierarchy that diverges significantly from patterns generally observed in previous research. Contrary to Venkatesh et al.'s (2003) conclusions identifying performance expectancy as the dominant predictor, our results reveal the predominance of effort expectancy (β=0.538, f^2=0.213) in the specific context of Moroccan chartered accountants. This hierarchical inversion suggests the existence of contextual adoption dynamics that necessitate reconsideration of theoretical postulates established in Western environments.

Third, this study demonstrates that UTAUT model adaptation without moderating variables retains substantial explanatory power (R^2=0.404), attesting to the robustness of the model's fundamental conceptual structure. This observation presents important methodological implications for future investigations in contexts where sampling constraints limit the incorporation of complex moderating variables. These practical implications are relevant in the Moroccan context where generative AI remains in an introduction phase within the accounting profession. From a practical perspective, our findings suggest several strategic recommendations for artificial intelligence solution developers and professional accounting organizations. Technology actors should prioritize developing user interfaces characterized by simplicity of use and cognitive accessibility, rather than emphasizing technical performance. This strategic orientation directly addresses the preponderant importance of effort expectancy identified in our empirical model.

Furthermore, results regarding social influence (β=0.498, f^2=0.109) indicate the opportunity to mobilize professional networks as vectors for technological diffusion. Professional orders could thus play a catalytic role in generative artificial intelligence adoption by establishing professional standards and promoting exemplary use cases among their members. Finally, professional training institutions should privilege pedagogical approaches centered on learning ease rather than in-depth technical mastery. This pedagogical orientation aligns with professionals' concerns regarding perceived complexity of generative artificial intelligence technologies and could significantly accelerate their integration into professional accounting practices in Morocco. These practical implications hold particular relevance in the Moroccan context where generative artificial intelligence remains in an introductory phase within the accounting profession, characterized by variable levels of digital maturity and technological infrastructure.

6. Conclusion

This research examined the determinants of generative artificial intelligence acceptability among Moroccan chartered accountants using a simplified UTAUT model. Statistical analyses conducted with 262 chartered accountants confirmed three of the four formulated hypotheses. Effort expectancy emerges as the principal determinant ($\beta = 0.538$, $p < 0.001$, $f^2 = 0.213$), followed by social influence ($\beta = 0.498$, $p < 0.001$, $f^2 = 0.109$). Performance expectancy demonstrates a statistically significant relationship but with limited effect size ($\beta = 0.319$, $p < 0.001$, $f^2 = 0.004$), while facilitating conditions exert no significant effect in the complete model despite notable bivariate correlation ($r = 0.332$, $f^2 = 0.000$). The model explains 40.4% of generative AI acceptability variance ($R^2 = 0.404$), corresponding to a moderate explanation level according to criteria established by Chin (1998). This study contributes to technology acceptance literature in three aspects. First, it validates UTAUT model applicability in the specific context of generative AI in accounting practice in Morocco. Second, it documents a determinant hierarchy distinct from typically observed results, with effort expectancy predominance rather than performance expectancy. Third, it demonstrates that UTAUT model adaptation without moderating variables retains substantial explanatory power. From a practical perspective, results suggest that generative AI solution developers should prioritize ergonomics and learning ease in their interfaces. The accounting profession would benefit from training focused on ease of use rather than technical aspects. The significant effect of social influence indicates the potential effectiveness of mobilizing professional networks to promote generative AI adoption.

This research presents several methodological limitations. Non-probabilistic convenience sampling limits result generalization to the entire Moroccan chartered accountant population. Reliance on self-reported measures introduces potential bias in variable assessment. The cross-sectional approach prevents observation of temporal dynamics in the acceptance process. UTAUT model simplification through moderating variable exclusion restricts understanding of effect variations according to individual characteristics. The absence of effective use measurement constitutes an additional limitation, as the model focuses exclusively on acceptability rather than actual usage. Future research could integrate moderating variables (age, gender, experience, voluntariness of use) to analyze their influence on identified relationships. Exploration of additional variables such as AI trust, ethical concerns, and regulatory compliance would increase the model's explanatory power. Adopting longitudinal approaches would provide information on temporal evolution of acceptability at different adoption phases. Comparative studies between countries or regulated professions would enrich understanding of contextual factors influencing generative AI acceptability. Finally, analysis of potentially non-linear effects between determinants and acceptability constitutes a promising research avenue to deepen understanding of technological adoption mechanisms in chartered accountancy.

7. References

- Abbott, A. (1988). *The system of professions: An essay on the division of expert labor*. University of Chicago Press. https://doi.org/10.7208/chicago/9780226189666.001.0001
- Alalwan, A. A. (2020). *Mobile banking adoption: A literature review. Telematics and Informatics*, 47, 101311. https://doi.org/10.1016/j.tele.2019.101311
- Al-Gahtani, S. S., Hubona, G. S., & Wang, J. (2007). *Information technology (IT) in Saudi Arabia: Culture and the acceptance and use of IT*. Information & Management, 44(8), 681-691. https://doi.org/10.1016/j.im.2007.09.002
- Baruch, Y., & Holtom, B. C. (2008). *Survey response rate levels and trends in organizational research*. Human Relations, 61(8), 1139-1160. https://doi.org/10.1177/0018726708094863
- Bommasani, R., Hudson, D. A., Adeli, E., Altman, R., Arora, S., von Arx, S., Bernstein, M. S., Bohg, J., Bosselut, A., Brunskill, E., Brynjolfsson, E., Buch, S., Card, D., Castellon, R., Chatterji, N., Chen, A., Creel, K., Davis, J. Q., Demszky, D., ... Liang, P. (2021). *On the opportunities and risks of foundation models*. arXiv. https://doi.org/10.48550/arXiv.2108.07258.
- Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J. D., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., Agarwal, S., Herbert-Voss, A., Krueger, G., Henighan, T., Child, R., Ramesh, A., Ziegler, D. M., Wu, J., Winter, C., ... Amodei, D. (2020).

Language models are few-shot learners. *Advances in Neural Information Processing Systems*, 33, 1877-1901. https://doi.org/10.48550/arXiv.2005.14165

- Cao, G., Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2021). *Understanding managers' attitudes and behavioral intentions towards using artificial intelligence for organizational decision-making*. *Technovation*, 106, 102312. https://doi.org/10.1016/j.technovation.2021.102312
- Chang, J. C. J., & King, W. R. (2005). *Measuring the performance of information systems: A functional scorecard*. Journal of Management Information Systems, 22(1), 85-115. https://doi.org/10.1080/07421222.2003.11045833
- Chin, W. W. (1998). *The partial least squares approach to structural equation modeling*. *In G. A.* Marcoulides (Ed.), Modern methods for business research (pp. 295-336). Lawrence Erlbaum Associates.
- Davis, F. D. (1989). *Perceived usefulness, perceived ease of use, and user acceptance of information technology*. MIS Quarterly, 13(3), 319-340. https://doi.org/10.2307/249008
- Dwivedi, Y. K., Rana, N. P., Chen, H., & Williams, M. D. (2011). *A meta-analysis of the unified theory of acceptance and use of technology (UTAUT*). In M. Nüttgens, A. Gadatsch, K. Kautz, I. Schirmer, & N. Blinn (Eds.), Governance and sustainability in information systems. Managing the transfer and diffusion of IT (pp. 155-170). Springer. https://doi.org/10.1007/978-3-642-24148-2_10
- El Arif, H. (2021). *Réformes et perspectives de la profession comptable au Maroc*. MarocPress.
- El Fakir, M. (2024). *La profession de l'expertise-comptable au Maroc : une analyse descriptive et perspectives de recherches*. Journal of Economics, Finance and Management.
- El Omari, S. (2008). *Contribution à l'analyse de l'organisation d'une profession comptable : le cas du Maroc* [Doctoral dissertation, Université Toulouse 1].
- El Omari, S., & Khlif, W. (2014). *Professionnalisation de l'expertise comptable au Maroc : chronique d'une transition inachevée*. Comptabilité-Contrôle-Audit, 20(2), 79-102. https://doi.org/10.3917/cca.202.0079
- Fornell, Claes, and David F. Larcker. "Evaluating Structural Equation Models with Unobservable Variables and Measurement Error." Journal of Marketing Research, vol. 18, no. 1, 1981, pp. 39–50. JSTOR, https://doi.org/10.2307/3151312. Accessed 4 Dec. 2025.
- Gotthardt, M., Koivulaakso, D., Paksoy, O., Saramo, C., Martikainen, M., & Lehner, O. (2020). *Current state and challenges in the implementation of smart robotic process automation in accounting and auditing*. ACRN Journal of Finance and Risk Perspectives, 9(1), 90-102. https://doi.org/10.35944/jofrp.2020.9.1.007
- Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage Learning.
- Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling (PLS-SEM)* (2nd ed.). Sage Publications.
- Hassouni, K. (2015). *Femmes et profession comptable au Maroc* [Doctoral dissertation, Université de Versailles].
- Kaplan, A., & Haenlein, M. (2019). *Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence*. *Business Horizons*, 62(1), 15-25. https://doi.org/10.1016/j.bushor.2018.08.004
- Kokina, J., & Blanchette, S. (2019). *Early evidence of digital labor in accounting: Innovation with Robotic Process Automation*. International Journal of Accounting Information Systems, 35, 100431. https://doi.org/10.1016/j.accinf.2019.100431

- Kokina, J., & Davenport, T. H. (2017). *The emergence of artificial intelligence: How automation is changing auditing*. Journal of Emerging Technologies in Accounting, 14(1), 115-122. https://doi.org/10.2308/jeta-51730
- Lafraxo, Y., Rigar, M., Ahmimid, A., & Loubnani, A. (2018). *Etude d'acceptabilité des technologies de l'information dans le secteur de télé-déclaration comptable et fiscale au Maroc: application du modèle 'UTAUT' modifie*. Revue de Gestion et d'Économie, 6(1-2), 134-172.
- Manita, R., Elommal, N., Baudier, P., & Hikkerova, L. (2020). *The digital transformation of external audit and its impact on corporate governance*. Technological Forecasting and Social Change, 150, 119751. https://doi.org/10.1016/j.techfore.2019.119751
- Mensah, I. K. (2019). *Factors influencing the intention of university students to adopt and use e-government services: An empirical evidence in China*. SAGE Open, 9(2), 1-19. https://doi.org/10.1177/2158244019855823
- Moll, J., & Yigitbasioglu, O. (2019). *The role of internet-related technologies in shaping the work of accountants: New directions for accounting research*. The British Accounting Review, 51(6), 100833. https://doi.org/10.1016/j.bar.2019.04.002
- Munoko, I., Brown-Liburd, H. L., & Vasarhelyi, M. (2020). *The ethical implications of using artificial intelligence in auditing*. Journal of Business Ethics, 167(2), 209-234. https://doi.org/10.1007/s10551-019-04407-1
- Popper, K. (1959). *The logic of scientific discovery*. Hutchinson & Co.
- Richins, G., Stapleton, A., Stratopoulos, T. C., & Wong, C. (2017). *Big data analytics: Opportunity or threat for the accounting profession? Journal of Information Systems*, 31(3), 63-79. https://doi.org/10.2308/isys-51805
- Russell, S., & Norvig, P. (2020). *Artificial intelligence: A modern approach* (4th ed.). Pearson.
- Sharma, M. P., Suthar, M. D., & Maheria, M. S. (2021). Artificial intelligence accounting technology–perception and acceptance. In S. R. Chauhan, D. Chowhan, S. Vij, & A. Jafri (Eds.), *Impact of smart technologies and artificial intelligence (AI) paving path towards interdisciplinary research in the fields of engineering, arts, humanities, commerce, economics, social sciences, law and management-challenges and opportunities* (p. 77). The Write Place.
- Silver, D., Schrittwieser, J., Simonyan, K., Antonoglou, I., Huang, A., Guez, A., Hubert, T., Baker, L., Lai, M., Bolton, A., Chen, Y., Lillicrap, T., Hui, F., Sifre, L., van den Driessche, G., Graepel, T., & Hassabis, D. (2017). *Mastering the game of Go without human knowledge*. Nature, 550(7676), 354-359. https://doi.org/10.1038/nature24270
- Tamilmani, K., Rana, N. P., & Dwivedi, Y. K. (2019). *Use of social media for knowledge sharing among students. Information Systems Frontiers*, 21(2), 289-305. https://doi.org/10.1007/s10796-017-9806-9
- Vărzaru, A. A. (2022). *Assessing artificial intelligence technology acceptance in managerial accounting*. Electronics, 11(14), 2256. https://doi.org/10.3390/electronics11142256
- Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., & Polosukhin, I. (2017). *Attention is all you need. Advances in Neural Information Processing Systems*, 30, 5998-6008.
- Venkatesh, V., & Davis, F. D. (2000). *A theoretical extension of the technology acceptance model: Four longitudinal field studies*. Management Science, 46(2), 186-204. https://doi.org/10.1287/mnsc.46.2.186.11926

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