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# Balancing performance and ethics: Navigating visual recognition technology adoption in the auditing industry

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ABSTRACT

This study aims to discover the key determinants affecting the adoption of visual recognition technology (VRT), a segment of artificial intelligence (AI) technology, in the auditing industry in Saudi Arabia, highlighting the tension between performance expectancy and ethical concerns. Through a quantitative approach utilizing a bilingual online questionnaire of auditors in Saudi Arabia and path analysis, we find that auditors consider the ethical concerns around VRT to be as important as its performance expectancy, traditionally the most important determinant of new technology adoption. The findings also suggest that facilitating conditions emerge as a dominant factor, raising concerns that VRT adoption is driven by resource availability rather than a thorough discussion of its costs and benefits. This paper contributes to the growing dialogue about AI ethical concerns, quantifying and highlighting the importance of ethical considerations for potential users. The paper also urges policymakers to take a balanced approach to incorporate both performance benefits and ethical considerations of the technology and devise practical ethical guidelines to facilitate the adoption of ethical AI.

## 1. Introduction

The emergence of disruptive technologies has led to a heated debate between performance enhancements and ethical considerations, a phenomenon observed historically with the advent of each significant technology (Bringselius, 2018; Munoko et al., 2020). Standing on the frontlines of the fourth industrial revolution, the introduction of artificial intelligence (AI) promises a transformation in business operations (Ross & Maynard, 2021). At the same time, this technological development introduces a complex array of ethical concerns that can undermine moral principles and the fabric of human society (Rachels & Rachels, 2019). Ethics, a cornerstone in fostering societal harmony, is vital in safeguarding societal values and instilling trust and fairness in human activities (Frank et al., 2023; Hosmer, 1994; Satava et al., 2006). However, the development of AI raises unprecedented ethical dilemmas. For example, unfairness and biases against certain groups embedded in the training datasets, increased surveillance, privacy infringement, and a lack of explainability due to the "black-box" nature of the technology (Griffith, 2023; Jobin et al., 2019; Osoba & Welser, 2017). The "black-box" concerns is exemplified by algorithms such as GPT-4, which generates texts through a staggering 175 billion parameters (IBM, 2022).

In the auditing industry, in particular, the application of AI technologies introduces several ethical concerns, such as bias, fairness, lack of transparency and explainability, concerns about confidentiality and data security, and auditor de-skilling and labor displacement (Fülöp et al., 2023; Lehner et al., 2022; Munoko et al., 2020; Seethamraju & Hecimovic, 2022; Zhang et al., 2023). While the existing body of research has extensively examined ethical concerns around AI, several research questions remain unanswered in the context of auditing. For example, "How important are the ethical concerns of AI in auditing?" and "Are the ethical concerns more (or less) important than the benefits AI can bring in auditing?" This paper aims to address these critical questions. Through this, the paper seeks to make a crucial contribution to the ongoing debate about the performance versus ethics of AI in the field of auditing.

Based on the Unified Theory of Acceptance and Use of Technology (UTAUT) model, a theoretical framework for understanding the behavior of new technology adoption (Venkatesh et al., 2003), we

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surveyed 311 auditors in Saudi Arabia to investigate how they navigate the dilemma between potential performance benefits and ethical concerns of AI technology. We chose the auditing industry because there are major potential benefits from AI due to a significant proportion of its tasks possibly being automated (Issa et al., 2016), while auditors are also required to adhere to professional ethical principles, such as confidentiality, due care, professional competence, and objectivity, that are guided by accounting bodies in order to maintain public confidence and trust. We chose Saudi Arabia due to its distinct cultural emphasis on tradition and communal norms. According to Hofstede's cultural dimensions, Saudi Arabia is characterized as a strong "restraint" and "normative" society[1], where people prefer to maintain tradition and social norms in a collective manner, consistent with ethical principles that emphasize societal values and harmony (Country comparison tool, n.d.). Therefore, the auditing industry in Saudi Arabia provides an exemplary context for exploring the conflict between the performance benefits and ethical concerns of AI.

Our paper focuses explicitly on AI computer visual recognition technology (VRT). Despite the common term "AI", AI technology includes various applications, such as robotic process automation, computer vision, natural language processing, expert systems, neural networks, speech recognition, and planning (Corea, 2018). To reduce the misunderstanding of questions due to the various applications involved in AI, we chose to only investigate VRT, the most prominent application in the auditing industry (Petkov, 2020). VRT is one of the AI technologies that can identify objects, people, places, writing, and actions in images. VRT can autonomously extract data from images and analyze the data to perform specific audit functions, such as asset assessment, identification of people, and data extraction from files, which are essential parts of auditing.

The findings suggest that performance expectations, ethical concerns, and facilitating conditions influence auditors' VRT adoption behavior. The importance of performance expectancy is consistent with the previous literature on new technology adoption (e.g., Handoko et al., 2018; Pedrosa et al., 2019; Ruhnke, 2023). However, this study finds that auditors consider ethical concerns to be as important as performance expectancy when they consider VRT adoption, a noble contribution to the AI ethics and technology adoption literature. The paper also finds that facilitating conditions emerge as the dominant factor in determining VRT's adoption intention and actual usage in the counterbalance between performance expectancy and ethical concerns. The findings raise significant implications and concerns that VRT adoption is mainly driven by the availability of the technology rather than by the outcome of a cost-and-benefit analysis of the technology or addressing its ethical concerns.

This paper contributes significantly to the growing literature on AI ethics in auditing. Notably, it represents the first quantitative study measuring the significance of AI ethical concerns in this context, enriching the ongoing discussion about AI's performance versus ethics. Furthermore, by focusing on the Saudi Arabian context, this research diverges from the Western perspectives prevalent in the previous literature. This non-Western perspective deepens our understanding of the topic and expands the global conversation on AI ethics.

This study also advances the theoretical understanding of new technology adoption behavior by positing ethical concerns as an important determinant in the process, thereby broadening the established theoretical frameworks, such as UTAUT. Traditional technology adoption models were originally developed for technologies that do not self-evolve, and, therefore, their mechanisms are understood by the developers and users. AI, on the contrary, exhibits self-learning and evolving capabilities, with the "black-box" nature of its mechanisms posing great ethical implications to potential users. This paper provides evidence of the importance of ethical considerations in the adoption of AI technology.

The practical implications of this study are multifaceted, offering contributions to the existing body of knowledge surrounding AI ethics in the auditing sector. By quantitatively measuring the significance of ethical concerns vis-à-vis performance expectancy, this research presents a cornerstone for organizations and policymakers in fostering ethical AI adoption in the audit field. Additionally, the non-Western perspective brought forth by focusing on Saudi Arabia, where its culture emphasizes tradition and social norms rather than individual success, broadens the conversation on AI ethics beyond Western countries. The findings of the paper can be applicable to other emerging countries, particularly in the Middle East and Africa, where similar cultural characteristics are observed. Furthermore, the study sets a precedent by emphasizing the critical role that ethical concerns play in AI adoption, thereby encouraging stakeholders to undertake a balanced approach that does not overlook potential ethical pitfalls in the pursuit of performance enhancements. This prudent approach to ethical AI adoption could potentially spearhead a trend where ethical compatibility becomes a standard prerequisite, thus, fostering a globally responsible progression toward AI adoption.

This paper is structured as follows: Section 2 explains VRT and its potential ethical concerns, followed by the development of hypotheses. Section 3 explains the methodology and data. The measurement validations and results are reported in Section 4, followed by a discussion in Section 5. The paper concludes with Section 6.

## 2. Literature review, theoretical framework, and hypotheses development

### 2.1. VRT in auditing

AI systems, hallmarked by their progressive self-learning capabilities, offer substantial prospects for augmenting efficiency and refining decision making processes in businesses by facilitating a continual evolution of performance and resultant outcomes (Jarrahi, 2018). These advancements have led to remarkable gains in productivity across various sectors (Kolbjørnsrud et al., 2016). In particular, the audit sector may witness a revolutionary phase with AI technologies radically overhauling conventional practices, a trend notably embraced by the Big 4 accounting firms, who have incorporated AI in multifaceted audit processes ranging from document reviews to sophisticated risk analytics (Agoglia et al., 2011; Almufadda & Almezeini, 2022; Kokina & Davenport, 2017). These enhancements enable auditors to delve into voluminous datasets with an unprecedented level of accuracy and speed, potentially discovering insights that might evade detection under traditional methodologies (Tiberius & Hirth, 2019).

Among various applications of AI, VRT plays a prominent role in auditing by enabling the analysis of visual data, such as documents, inventory images, and meeting recordings. For the auditing standards, such as International Standard on Auditing (ISA) 500, *Audit Evidence*, and ISA 501, *Audit Evidence—Specific Considerations for Selected Items*, which mandate the collection of appropriate, sufficient, relevant, and reliable evidence, VRT can substantially improve audit efficiency and effectiveness. For instance, it can automate the repetitive tasks of evidence collection, such as document scanning and inventory counts, which traditionally rely on manual processes. Moreover, in scenarios where physical presence is challenging, such as during the COVID-19 pandemic or in hazardous locations, VRT can offer alternative means for auditors to conduct inventory checks and validate conditions remotely.

### 2.2. Ethical concerns regarding AI

VRT shares common ethical concerns regarding AI, such as

[1] According to Hofstede's cultural dimensions, Saudi Arabia has an indulgence score of 14, classifying it as a high-restraint country, and a long-term orientation score of 27, classifying it as a normative society.

confidentiality, professional skepticism, transparency, explainability, and labor substitution. Waldbauer and Noodt (2015) emphasize the paramount importance of maintaining client confidentiality in auditing, a principle that could be compromised with the advent of AI technologies. They anticipate significant challenges, notably potential breaches in confidentiality and data protection, as audit firms integrate client data within AI frameworks (West, 2019; Wright & Xie, 2019). For example, McKinsey & Company, a consulting firm, has established an in house AI platform, Lilli, to help its consultants search and generate reports based on the firm's past case studies (Middlehurst, 2024). Similar platforms are being developed for auditing firms, such as "EY.ai" (EY, 2022). The compilation and use of client data for AI training can potentially compromise client confidentiality and data protection, as noted by EY: "While AI brings huge benefits, it also raises ethical risks and considerations, from questions of data control and privacy to the perpetuation of human bias in decision making. Left unaddressed, these risks could severely undermine customer trust in new technologies, while also negatively impacting confidence in companies that rely on AI" (EY, 2021, page 2).

Furthermore, concerns arise that AI might diminish auditors' professional skepticism, the fundamental quality for effective auditing (Hurtt, 2010). The theory of technology dominance suggests that prolonged dependency on decision support systems could lead auditors to overly rely on issues flagged by AI, potentially overlooking crucial concerns not identified by the system, thereby impairing their professional judgment (Goddard et al., 2012; Lehner et al., 2022; Seow, 2011; Sutton et al., 2023). This dependency could result in a diminishing capacity to exercise professional skepticism, affecting audits' overall quality and integrity. The lack of transparency in AI decision making processes is another significant ethical concern. As Munoko et al. (2020) and Lehner et al. (2022) argue, audit processes must remain transparent, particularly regarding the use of AI tools and the reasoning behind audit conclusions. This transparency is crucial for maintaining trust in society and for auditors to defend their decisions against potential lawsuits (Gassen & Skaife, 2009). Other ethical concerns involve potential labor substitution and the misuse of client information for purposes beyond the original auditing scope, such as consulting and financial services, calling for a re-evaluation of ethical standards in AI (Autor, 2015; Farisco et al., 2020; Geiger & Gross, 2021; Huang & Rust, 2018; Munoko et al., 2020).

Jobin et al. (2019) examine the growing AI ethical guidelines, which span 84 different documents proposed by a host of international, governmental, and private entities, and observe a convergence toward the principles of transparency, privacy, responsibility, non-maleficence, and fairness. Despite this convergence, these guidelines remain abstract and high level, providing few actionable ethical frameworks. Concurrently, Munoko et al. (2020) extend specific scrutiny to the auditing sector, suggesting that auditors might encounter ethical hurdles in the wake of AI integration, such as due care, professional skepticism, and auditor competence. The "black-box" nature of AI decision making, a focal point of Martin and Waldman's (2023) research, shows a tendency among individuals to consider AI led decisions as legitimate only if they are favorable, highlighting the potential detriment to trust when AI makes the decisions.

Taking a more grounded approach, recent studies have opted for interview methodologies to shed light on the practical ethical challenges that auditors encounter. Zhang et al. (2023) identify the concerns of Chinese management accountants regarding data security and transparency. Fülöp et al. (2023) extend the inquiry to employees of accounting firms, pinpointing transparency, trust, and accountability as potential areas of concern, albeit with a geographical ambiguity in their study. In contrast, Seethamraju and Hecimovic (2022) adopt the technology-organization-environment (TOE) framework to scrutinize factors influencing AI adoption decisions by Australian auditors, highlighting trust in AI and adherence to audit standards as pivotal ethical considerations. This array of studies complements the analysis conducted by Lehner et al. (2022), who summarize the existing literature to identify recurring ethical challenges encountered by auditors, which include issues of objectivity, privacy, and trustworthiness.

### *2.3. The unified theory of acceptance and use of technology model (UTAUT)*

The UTAUT model has emerged as a prominent theoretical framework, incorporating the various factors influencing the adoption behavior of novel technologies. The original construct of UTAUT, as proposed by Venkatesh et al. (2003), stemmed from an in depth evaluation of eight theoretical models prevalent in the information technology sector. Central to UTAUT is the premise that the intention and propensity to embrace new technological advancements are shaped by four pivotal factors: performance expectancy, effort expectancy, social influence, and facilitating conditions. Furthermore, this model asserts that gender, age, experience, and the degree of voluntariness moderate the main effects, as graphically illustrated in Fig. 1. Over the years, the UTAUT framework has been used across diverse domains of technologies, including mobile technologies (Hu et al., 2020; Min et al., 2008; Park et al., 2007), educational technologies (Garone et al., 2019; Moran et al., 2010; Schaik, 2011), and computer assisted audit tools (Curtis & Payne, 2008, 2014; Gonzalez et al., 2012; Handoko et al., 2018; Janvrin et al., 2008; Mahzan & Lymer, 2014; Rawashdeh & Rawashdeh, 2021).

### *2.4. Hypotheses development*

#### *2.4.1. Performance expectancy (PE)*

A fundamental determinant of an auditor's decision making process to adopt VRT is performance expectancy, a subjective assessment of how technology might enhance their professional efficiency (Ruhnke, 2023). Utilizing VRT presents numerous advantages, such as accuracy, efficiency, and timeliness. In the academic literature, several studies highlight the direct and positive correlation between performance expectancy and auditors' willingness to incorporate computer assisted audit tools (CAATs) and analogous technologies (Handoko et al., 2018). A more contemporary study by Pedrosa et al. (2019) finds that perceived utility, a variable closely aligned with performance expectancy, emerges as a central facilitator in the adoption and utilization of CAATs among auditors in a European country. In light of these research insights, we expect that an auditor's perception of performance expectancy has a positive association with their willingness to adopt VRT.

*H1: Performance expectancy has a positive relationship with VRT adoption intention.*

#### *2.4.2. Effort expectancy (EE)*

Effort expectancy represents the necessary endeavor required to adopt VRT in auditing, such as the time span required to develop the prerequisite competencies and the complexity, learning curve, and flexibility of VRT. A large perceived effort could potentially dampen the willingness to adopt VRT. Literature in this area found inconsistent outcomes concerning the influence of effort expectancy on the acceptance of technologies. For example, research by Al-Gahtani et al. (2007) explains that effort expectancy does not have a significant influence on the adoption of desktop computer applications within professional environments in Saudi Arabia. Similarly, Handoko et al. (2018) observe that effort expectancy does not influence auditors' intention to integrate CAAT technology. However, Pedrosa et al. (2019) identifies effort expectancy as a primary determinant for technology acceptance, including CAAT adoption in auditing processes. They posit that perceived ease of use is pivotal, especially for advanced technologies. This sentiment resonates with Alles's (2015) views on adopting big data in auditing. As VRT is considered an advanced technology linked to other AI applications, such as machine learning, we believe that effort expectancy can hinder auditors' willingness to adopt VRT.

*H2: Effort expectancy has a negative relationship with VRT adoption*

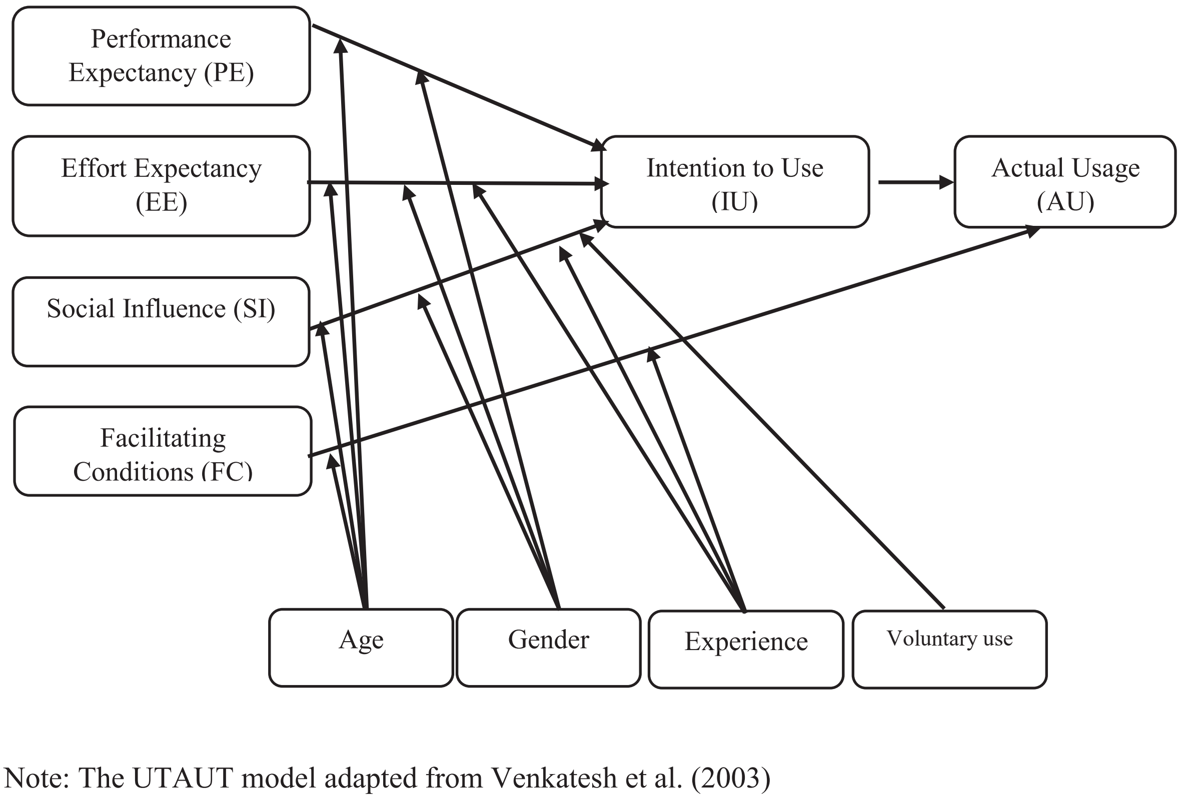


**Fig. 1.** The UTAUT model Note: The UTAUT model adapted from Venkatesh et al. (2003).

*intention.*

### 2.4.3. Social influence (SI)

Social influence comes from colleagues, senior leadership, clientele, and the auditor's general perception of reputation when they contemplate adopting VRT. Prior research presents inconclusive results on the impact of social influence on technology adoption within this field (Handoko et al., 2018; Janvrin et al., 2008; Pedrosa et al., 2019). However, our study argues for a potentially positive relationship, particularly due to the substantial potential benefits of VRT in auditing processes, which can be perceived by senior management, colleagues, clients, and auditors. Drawing from Curtis and Payne's (2008) findings that auditors are more likely to adopt technologies like Excel when their use is favored by their hierarchical superiors, we hypothesize that social influence can significantly increase the willingness of auditors to adopt VRT.

*H3: Social influence has a positive relationship with VRT adoption intention.*

### 2.4.4. Facilitating conditions (FC)

Facilitating conditions refer to the degree to which auditors perceive the presence of necessary regulatory and technological frameworks to support their use of VRT. The literature consistently suggests that facilitating conditions, such as adequate technological infrastructure and supportive regulatory environments, significantly influence the adoption of new technologies in professional contexts (Almutairi, 2008; Dulle & Minishi-Majanja, 2011). Specifically in the auditing industry, studies show that strong organizational and technological supports are crucial in increasing auditors' willingness to adopt CAATs (Handoko et al., 2018; Janvrin et al., 2008; Pedrosa et al., 2019). In a similar vein, technological infrastructure enhances the adoption in auditing of cloud computing and advanced data processing tools, such as Apache Hadoop (Issa et al., 2016). Dai and Vasarhelyi (2017) extend this dialogue by suggesting that blockchain technology enhances automated verification processes in auditing. Given these considerations and in alignment with the perspective of Venkatesh et al. (2003), this paper hypothesizes that facilitating conditions will increase auditors' intention to use VRT.

*H4a: Facilitating conditions have a positive relationship with VRT adoption intention.*

According to Venkatesh et al. (2003), facilitating conditions also directly influence actual usage beyond that explained by behavioral intention. When users perceive that supportive elements are in place, they are more inclined to engage with and utilize the system. For example, access to technical support, comprehensive user training programs, and a well-established infrastructure lowers the barriers to technology use, thereby promoting higher actual usage. Additionally, facilitating conditions builds user confidence and reduces the anxiety of adopting new technology. Knowing that reliable support and resources are available enhances users' self-efficacy, which has been demonstrated to positively influence technology adoption and usage (Compeau & Higgins, 1995). Therefore, in line with the theoretical framework of the UTAUT model and subsequent designs in the literature (Baptista & Oliveira, 2015; Dwivedi et al., 2019; Queiroz & Fosso Wamba, 2019), we posit that facilitating conditions will concurrently influence VRT usage.

*H4b: Facilitating conditions have a positive relationship with VRT usage.*

### 2.4.5. Ethical concerns (EC)

Despite the benefits, auditors may resist VRT adoption due to prevailing ethical concerns. There exists a potential threat of VRT, and AI in general, superseding human auditors, thereby escalating fears of job displacement and de-skilling, as highlighted by the theory of technology dominance (Sutton et al., 2023). Furthermore, the utilization of expansive datasets to train AI algorithms could potentially raise concerns about breaches of privacy, confidentiality, and data security protocols (Munoko et al., 2020). A recent example of DALL·E, a generative image creation tool, ignited a broader societal debate about the ethical concerns of AI and potential infringements of intellectual property rights (Murgia & Johnston, 2023). Within the auditing domain, the influx of client information into AI models during the training periods might potentially breach client confidentiality and violate professional norms, as outlined in the American Institute of Certified Public Accountants (AICPA) Code of Professional Conduct. Consequently, auditors might be reluctant to adopt VRT if they are concerned about the ethical implications of the technology.

*H5: Ethical concerns have a negative relationship with VRT adoption intention.*

#### 2.4.6. Adoption intention (AI) and actual usage (AU)

Finally, according to the theory of planned behavior, the auditor's intention to use VRT will translate into actual technology usage. VRT adoption intention signifies a cognitive commitment entailing planning, resource allocation, and mental preparation to integrate technology into routine activities. This cognitive commitment is crucial in determining the likelihood of transitioning from intention to actual use (Ajzen, 1991). In addition, the intention to use technology typically reflects an individual's motivation, driven by perceived benefits such as increased efficiency, productivity, or enjoyment. This motivation is instrumental in generating the effort needed to overcome barriers to use, including acquiring new skills or incorporating the technology into existing workflows (Venkatesh et al., 2003). Lastly, intentions offer a structured framework for action, guiding individuals on the appropriate times, places, and methods for using the technology. This structured guidance reduces uncertainty and facilitates the intended behavior (Ajzen, 1991; Venkatesh et al., 2003). Therefore, we hypothesize that VRT adoption intention will positively influence its actual usage.

*H6: VRT adoption intention has a positive relationship with VRT usage.*

Based on our hypotheses, we refine the UTAUT model by incorporating ethical concerns as an extra determinant. Accordingly, Fig. 2 illustrates the theoretical framework of the paper.[2]

## 3. Research methodology and data

We examine the determinants of VRT adoption behavior within the audit sector. Due to the absence of data, we used an online survey instrument. The survey was conducted using Qualtrics, offering versions in both English and Arabic to accommodate a diverse respondent pool. The survey is segmented into three distinct sections: an introductory part, a section gathering demographic data, and a final part consisting of 24 close ended queries and one binary query about actual usage. The independent variables (performance expectancy, effort expectancy, social influence, facilitating conditions, and ethical concerns) alongside a dependent variable (intent to use) were evaluated using a five point Likert scale, ranging from 5 (strongly agree) to 1 (strongly disagree). For the actual usage, the other dependent variable, a binary scale of 1 (yes) or 0 (no) was used. The detailed questionnaire is presented in Appendix A.

Our methodology included two preliminary test phases. Initially, the survey was assessed by a panel of five scholarly experts specializing in auditing and information technology. Following their input, we adjusted the question order and answer randomization and reformulated specific questions to curb potential bias. In the subsequent pilot phase, the modified questionnaire was translated into Arabic and presented to three bilingual scholarly experts to confirm the precision of the translation. This pilot questionnaire was then disseminated to 43 auditors, receiving 20 responses. Based on the feedback and results from Cronbach's alpha reliability analysis, final modifications were made to the questionnaire. We used a common factor analysis (principal axis factoring) to formulate independent and dependent variables, followed by a path analysis to assess the impact of independent variables on VRT adoption intention and actual usage.

We used LinkedIn to find potential participants. We wrote "external auditor" in the search bar and used filters, such as people and locations, to identify 593 potential participants who perform audit work in Saudi Arabia. We privately contacted them and received a willingness to participate in the survey from 447 auditors. We sent them a link to the questionnaire explaining the research, its objectives, and the importance of their participation. After a week, we sent a gentle reminder to those who had not completed the questionnaire. This helped us obtain a good response rate. Out of the 447 auditors, 403 responses were received, with a response rate of 90 %. Among the 403 responses, 92 were excluded due to incomplete (79) or monotonic responses (13), resulting in 311 responses in the sample.

Table 1 demonstrates the descriptive statistics. The Saudi Arabian respondents work for Big4 accounting firms (50 %), non-Big4 international accounting firms (25 %), local audit firms (22 %), and other firms (3 %). Male respondents dominated (67 %), and the majority were 21–30 years old (82 %) with 1–5 years of experience (70 %). Most have bachelor's degrees (86 %) and 29 % have a Chartered Public Accountant qualification. The descriptive statistics of each questionnaire variable are also displayed in Appendix B.

## 4. Results and analysis

We examined the psychometric properties of a measurement instrument to assess the construct of interest. The validation process included testing the reliability, validity, and factor structure of the measurement instrument. To assess the quality of the measurement instrument, the Kaiser-Meyer-Olkin (KMO) quality assurance test was conducted, and the results are reported in Table 2. The measurement was of high quality, with a KMO value of 0.831 ($p < 0.001$) (Coetzee & Erasmus, 2017).

Table 3 presents the factor analysis results for latent variables and their corresponding eigenvalues. Six factors explain a total variance of 67 %, with each factor having an eigenvalue greater than 1.

Cronbach's alpha and composite reliability were calculated to test the reliability of the constructs, and these results are presented in Table 4. All composite reliability values are above 0.86, greater than the recommended value of 0.7 (Broberg et al., 2018). All average variances extracted (AVE) are above 0.6, greater than the recommended value of 0.5 (Gonzalez et al., 2012).

Table 5 reports the square root of the AVE of each construct, as well as the Pearson correlation coefficients between the constructs. The square roots of the AVEs, the Fornell-Larcker criterion, are greater than the related correlations, indicating that discriminant validity was established (Gonzalez et al., 2012). Overall, the results of the validation process supported the reliability, validity, and factor structure of the measurement instrument. These findings provide evidence of the usefulness of the measurement instrument in assessing the construct of interest.

The main results of the UTAUT model utilizing a path analysis are presented in Fig. 3.[3] The results indicate that performance expectancy, effort expectancy, facilitating conditions, and ethical concerns are important factors influencing VRT adoption behavior.[4]

The results of performance expectancy support Hypothesis 1. The positive coefficient ($\beta = 0.22$, $z = 3.64$, $p = 0.00$) indicates that

[2] For brevity, we do not present the results of the moderating variables due to their not being significant, which is consistent with the findings of the existing literature in the auditing industry (Curtis & Payne, 2014).

[3] We conduct a path analysis using the STATA software. Specifically, because our two dependent variables are of different types (e.g., "intention to use" variable is a continuous variable, while "actual usage" is a binary variable), we used a path analysis using a gsem command.

[4] As robustness, we tested our results using principal component analysis instead of factor analysis. The results remain qualitatively consistent.

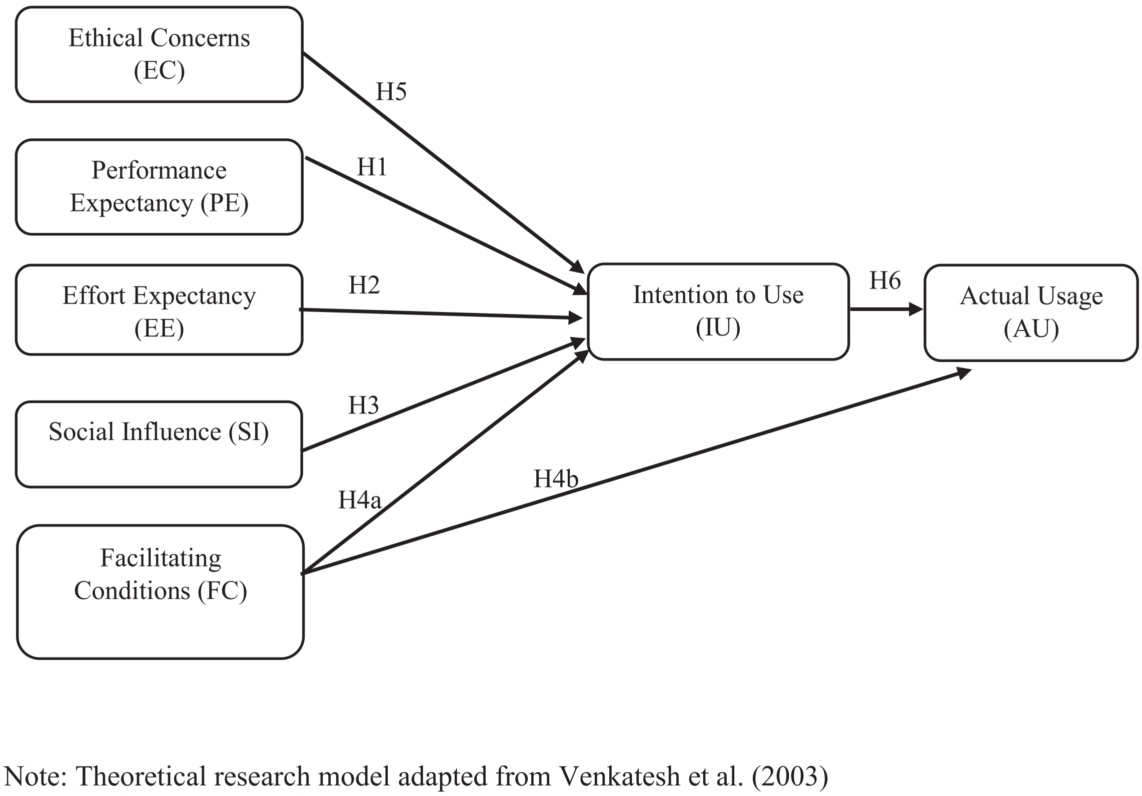


**Fig. 2.** Theoretical research model Note: Theoretical research model adapted from Venkatesh et al. (2003).

**Table 1**
Descriptive statistics for the questionnaire.

| | | Number | Percentage (%) |
|---|---|---|---|
| **Gender** | Male | 209 | 67 % |
| | Female | 102 | 33 % |
| **Age** | 21–30 years old | 254 | 82 % |
| | 31–40 years old | 54 | 17 % |
| | 41–50 years old | 2 | 1 % |
| | Over 50 years old | 1 | 0 % |
| **Experience** | Less than a year | 46 | 15 % |
| | 1–5 years | 217 | 70 % |
| | 6–10 years | 40 | 13 % |
| | 11–15 years | 5 | 2 % |
| | 16–20 years | 2 | 1 % |
| | Over 20 years | 1 | 0 % |
| **Education** | Bachelor's degree | 266 | 86 % |
| | Master's degree | 43 | 14 % |
| | Doctoral degree | 2 | 0 % |
| **Holding CPA** | Yes | 89 | 29 % |
| | No | 222 | 71 % |
| **Position** | Staff | 294 | 95 % |
| | Senior manager | 17 | 5 % |
| **Firm Size (FS)** | Big4 firms | 156 | 50 % |
| | Non-big4 international firms | 77 | 25 % |
| | Local firms | 68 | 22 % |
| | Other firms | 10 | 3 % |

**Table 2**
Results of the Kaiser-Meyer-Olkin and Bartlett Test.

| | | |
|---|---|---|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy | 0.831 | |
| Bartlett's Test of Sphericity | Approx. Chi-Square | 3299.215 |
| | Degrees of freedom | 276 |
| | Significance | 0.000 |

performance expectancy is a significant determinant of auditors' VRT adoption intention. The result aligns with the established literature, which acknowledges performance expectancy as a critical variable in the UTAUT model (Pedrosa et al., 2019; Ruhnke, 2023). The result for effort expectancy offers tentative support for Hypothesis 2, with a significant negative coefficient of $\beta = -0.10$, $z = -1.88$, and $p = 0.06$, suggesting that auditors perceive effort expectancy as a deterrent to VRT adoption. This insight mirrors previous scholarly works, which demonstrate the marginal significance of effort expectancy in technology adoption (Williams et al., 2015).

In contrast, the coefficient of social influence is not significant, indicating that social influence does not markedly affect auditors' VRT adoption intention, rejecting Hypothesis 3. The result diverges from prior studies that identified a positive impact of social influence (Curtis & Payne, 2008; Williams et al., 2015). We suspect that the discrepancy might stem from the fact that auditors have a greater tendency to work independently than the average potential user of other technologies, such as mobile banking. In addition, given the low actual usage of VRT in our sample (15 % actual usage shown in Appendix B),[5] stakeholders such as colleagues, senior management, and customers may not yet exert a strong influence on auditors to adopt VRT in Saudi Arabia.

Furthermore, our results show that facilitating conditions have a significantly positive impact on both the intention to use ($\beta = 0.33$, $z = 6.66$, $p = 0.00$) and actual usage ($\beta = 1.20$, $z = 5.49$, $p = 0.00$) of VRT, supporting both Hypotheses 4a and 4b respectively, and become the dominant determinant of VRT adoption. This contradicts the earlier

[5] Although the 15% actual usage rate of VRT seems low, it is consistent with other AI studies' findings. For example, Estep et al. (2023) find that the average usage rate of AI among United States (US) firms is 30%. Given that VRT is a subset of AI and the AI adoption rates in the Middle East and Africa are among the lowest in the world (Schmelzer, 2020), the 15% VRT usage rate in Saudi Arabian audit firms seems understandable.

**Table 3**
Analysis results for the six extracted factors.

| Total Variance Explained | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Component** | **Initial Eigenvalues** | | | **Extraction Sums of Squared Loadings** | | | **Rotation Sums of Squared Loadings** |
| | **Total** | **% Of Variance** | **Cumulative %** | **Total** | **% Of Variance** | **Cumulative %** | **Total** |
| 1 | 5.414 | 22.558 | 22.558 | 5.005 | 20.854 | 20.854 | 3.824 |
| 2 | 3.880 | 16.166 | 38.724 | 3.444 | 14.351 | 35.205 | 3.136 |
| 3 | 2.286 | 9.526 | 48.249 | 1.841 | 7.669 | 42.874 | 3.437 |
| 4 | 1.941 | 8.087 | 56.337 | 1.522 | 6.340 | 49.215 | 2.699 |
| 5 | 1.505 | 6.271 | 62.607 | 1.069 | 4.455 | 53.670 | 3.000 |
| 6 | 1.025 | 4.272 | 66.880 | 0.741 | 3.086 | 56.756 | 3.039 |
| 7 | 0.778 | 3.240 | 70.119 | | | | |
| 8 | 0.713 | 2.971 | 73.091 | | | | |
| 9 | 0.615 | 2.563 | 75.653 | | | | |
| 10 | 0.598 | 2.494 | 78.147 | | | | |
| 11 | 0.542 | 2.257 | 80.404 | | | | |
| 12 | 0.519 | 2.161 | 82.566 | | | | |
| 13 | 0.506 | 2.106 | 84.672 | | | | |
| 14 | 0.450 | 1.875 | 86.547 | | | | |
| 15 | 0.430 | 1.792 | 88.339 | | | | |
| 16 | 0.422 | 1.758 | 90.097 | | | | |
| 17 | 0.386 | 1.610 | 91.707 | | | | |
| 18 | 0.359 | 1.496 | 93.202 | | | | |
| 19 | 0.340 | 1.416 | 94.619 | | | | |
| 20 | 0.303 | 1.262 | 95.881 | | | | |
| 21 | 0.286 | 1.190 | 97.071 | | | | |
| 22 | 0.262 | 1.092 | 98.163 | | | | |
| 23 | 0.245 | 1.019 | 99.182 | | | | |
| 24 | 0.196 | 0.818 | 100.000 | | | | |

*Notes:* Extraction Method: Common Factor Analysis (Principal Axis Factoring). When components are correlated, sums of squared loadings cannot be added to obtain a total variance.

**Table 4**
Reliability and validity results.

| Latent variable | Indicators | Loading | Average Variances Extracted (AVE) | Composite Reliability | Cronbach's alpha |
|---|---|---|---|---|---|
| Performance Expectancy (PE) | PE1 | 0.787 | 0.641 | 0.873 | 0.809 |
| | PE2 | 0.835 | | | |
| | PE3 | 0.704 | | | |
| | PE4 | 0.567 | | | |
| Effort Expectancy (EE) | EE1 | 0.743 | 0.638 | 0.877 | 0.811 |
| | EE2 | 0.698 | | | |
| | EE3 | 0.699 | | | |
| | EE4 | 0.758 | | | |
| Social Influence (SI) | SI1 | 0.665 | 0.636 | 0.868 | 0.809 |
| | SI2 | 0.663 | | | |
| | SI3 | 0.785 | | | |
| | SI4 | 0.741 | | | |
| Facilitating Conditions (FC) | FC1 | 0.774 | 0.675 | 0.887 | 0.838 |
| | FC2 | 0.874 | | | |
| | FC3 | 0.661 | | | |
| | FC4 | 0.696 | | | |
| Ethical Concerns (EC) | EC1 | 0.741 | 0.605 | 0.900 | 0.868 |
| | EC2 | 0.808 | | | |
| | EC3 | 0.733 | | | |
| | EC4 | 0.688 | | | |
| | EC5 | 0.735 | | | |
| | EC6 | 0.650 | | | |
| Intention to Use (IU) | IU1 | 0.997 | 0.874 | 0.909 | 0.855 |
| | IU2 | 0.714 | | | |

*Notes:* Common Factor Analysis (Principal Axis Factoring) was used as the extraction method, and Promax with Kaiser normalization was used as the rotation method.

**Table 5**
Parameters for discriminating validity, including Pearson correlations of main constructs.

| | AVE | PE | EE | SI | FC | EC | IU |
|---|---|---|---|---|---|---|---|
| | 0.641 | *0.801* | | | | | |
| Effort Expectancy (EE) | 0.638 | −0.168 | *0.799* | | | | |
| Social Influence (SI) | 0.636 | 0.358 | 0.054 | *0.797* | | | |
| Facilitating Conditions (FC) | 0.675 | 0.228 | 0.104 | 0.290 | *0.822* | | |
| Ethical Concerns (EC) | 0.605 | −0.251 | 0.273 | −0.169 | 0.046 | *0.778* | |
| Intention to Use (IU) | 0.874 | 0.399 | −0.158 | 0.267 | 0.396 | −0.274 | *0.935* |

*Notes:* Values in italics represent the square root of average variances extracted (AVE).

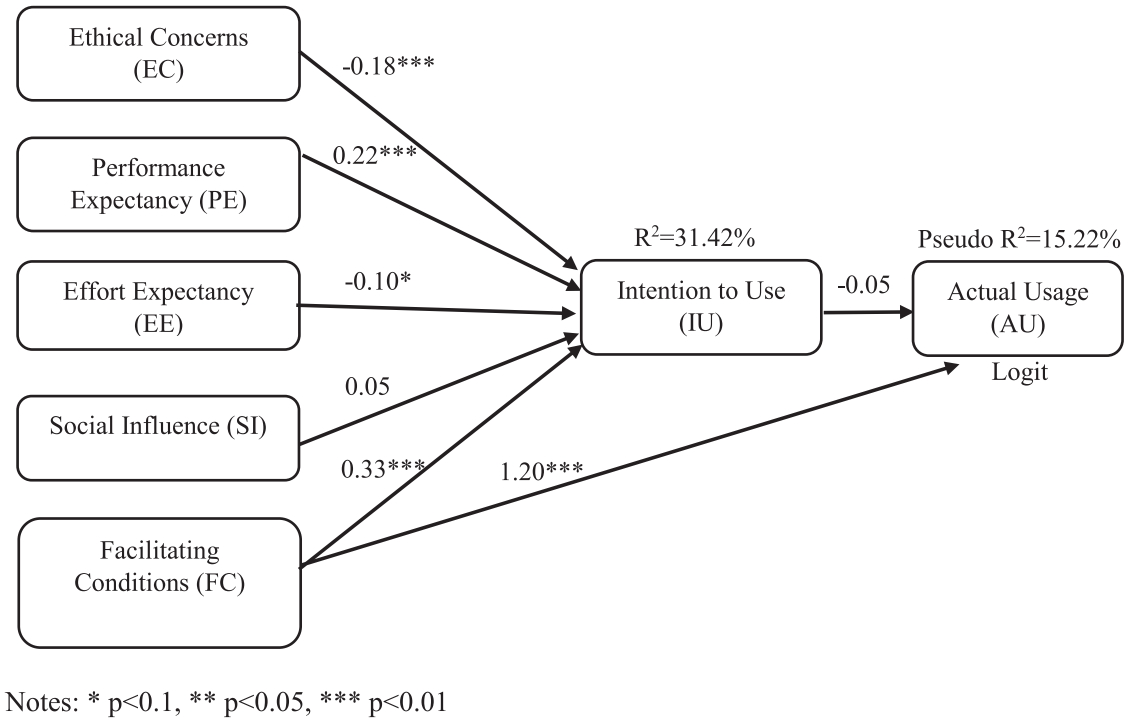


**Fig. 3.** Path analysis results Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

*meta*-analysis findings of UTAUT model research, which indicate a sporadic impact of facilitating conditions on adopting new technologies (Khechine et al., 2016). With an average VRT usage rate of 15 % (Appendix B), the results indicate that Saudi auditors currently feel that a lack of facilitating conditions in terms of resources, knowledge, and system compatibility slows their VRT adoption.

The results also demonstrate that ethical concerns significantly influence the adoption behavior of VRT, with a negative coefficient of $\beta = -0.18$, $z = -3.65$, $p = 0.00$, supporting Hypothesis 5. The negative coefficient indicates that ethical concerns deter auditors from VRT adoption, with a magnitude analogous to performance expectancy, albeit in contrasting directions. Consequently, these cost and benefit factors nullify each other's impacts, resulting in a dilemma for auditors.

Our results indicate that the intention to use VRT does not significantly impact its actual usage, leading to the rejection of Hypothesis 6. We speculate that this finding may be attributed to the substantial investment required to implement VRT, or AI technologies in general, which contrasts with consumer-level technologies like mobile banking and computer-assisted audit tools. For instance, The Economist (2023) reported that the training cost of the ChatGPT-4 model is nearly $100 million. Although the cost of VRT is expected to be significantly lower than that of ChatGPT-4, the overall investment required for implementing AI tools is generally considerable, suggesting that such implementations are more likely to occur at the organizational level. This explanation aligns with our findings on facilitating conditions, which emerged as the most significant determinant of VRT's actual usage.

## 5. Discussion

The economic implications of the findings are manifold. The paper contributes to the ongoing dialogue about AI ethics and adoption, highlighting the importance that auditors place on ethical concerns and equating them with the potential performance benefits that AI can bring, particularly in the context of VRT. This understanding provides a cornerstone for ethical AI development and adoption, especially in countries traditionally bound by stringent ethical standards. The findings suggest that ethical compliance is not just a regulatory requirement but a fundamental component of the technology's value proposition. Consequently, regulators, businesses, and technology developers may need to reassess how they can integrate ethical components into AI when promoting technology adoption in professional environments.

Furthermore, the study's findings highlight that facilitating conditions, such as resource availability, knowledge, and compatibility with other systems, significantly influence the intention to adopt and the actual usage of VRT in the auditing sector. The absence of adequate facilitating conditions can hinder VRT usage, as evidenced by the situation in Saudi Arabia, where only 15 % of auditors use VRT. Conversely, robust facilitating conditions can enhance both the intention to adopt and use VRT. Therefore, businesses and organizations should promote a balanced consideration of facilitating conditions, performance expectations, and ethical concerns when implementing VRT.

## 6. Conclusion

This study demonstrates the significance of ethical considerations in adopting AI technologies, specifically VRT, within the auditing sector. Our findings indicate that auditors consider ethical concerns important in their decision making processes, on par with the anticipated performance benefits such technologies promise. This equilibrium between ethical concerns and performance benefits sheds light on the understanding of AI adoption behavior, especially within sectors that are heavily regulated and ethically bound, such as auditing.

The findings from this study have implications for practice and literature. They contribute to the ongoing dialogue on ethical AI, suggesting that a harmonious integration of efficiency and ethics is desirable and essential. Furthermore, based on the findings of the dominant role played by facilitating conditions in the adoption process, this study raises a concern and suggests that AI adoption should not solely be based on availability or potential efficiency gains but should also consider the broader ethical implications of the technology. This insight provides a valuable perspective for practitioners and policymakers, urging a more balanced and conscientious approach to AI adoption. Furthermore, our study extends the theoretical framework of UTAUT by incorporating ethical considerations into the model. Therefore, the paper offers a more holistic view of the factors influencing technology adoption, adding a novel dimension to existing theories and providing a foundation for future research to build upon.

However, it is important to acknowledge the limitations of our study, such as its focus on a specific technology and geographical location, which may affect the generalizability of our findings. Therefore, future research should aim to broaden the scope of investigation to include a variety of AI technologies and cultural contexts to enhance our understanding of the global dynamics of AI adoption. Additionally, the development of comprehensive ethical guidelines and frameworks for AI adoption in the auditing sector and beyond remains a crucial need, calling for collaborative efforts among academics, practitioners, and policymakers.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Appendix A

Questionnaire and the related dimensions.

**Introduction**

The determinants of the intention to use visual recognition technology in the external audit environment.

The purpose of the questionnaire:
This questionnaire is part of a research project to study the factors influencing external auditors' intention to adopt visual recognition technology, which is one form of artificial intelligence technology that is currently used and has untapped potential in the field of external audits. The questionnaire will be used as a data collection instrument for my Doctoral degree in accounting. As a questionnaire participant, you will receive the results of this study after I analyze and discuss the data.
Your thoughts and answers will be extremely helpful and valuable for the researcher, in order to obtain a deeper understanding of this topic. The questionnaire should take around ten minutes to complete. If you wish to add further comments, please feel free to do so at the end of the questionnaire.
Statement of privacy and security:
This questionnaire has been approved by the Ethics Committee. All information will be treated in the strictest confidence and will only be used for this research purpose. Your identity will remain anonymous. The results will be combined with other participants' results and analyzed as a group.
If you have any queries or feedback, please do not hesitate to email me.
Visual recognition technology definition:
Visual recognition technology (VRT) is one form of artificial intelligence technology that is used to identify objects, people, places, writing, and actions in images. It can autonomously extract data from images and analyze the data, to perform several audit functions. Functions of VRT include asset assessment, the identification of people, and data extraction from files without the intervention of auditors. Visual recognition technology can assist auditors in performing an audit in many cases. During the COVID-19 period, when physical inventory checking was difficult, auditors were able to use a VRT built-in CCTV system to verify inventory conditions. VRT can also be used to identify people at a conference, analyze facial expressions, and analyze words used during a conference. In addition, drones with built-in visual recognition cameras can assist auditors in verifying the conditions of hard-to-approach asset items.

**Demographic data**

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| What is your gender? | Male | | Female | | | not prefer to say | |
| How old are you? | Under 21 | 21——30 years | 31——40 years | | 41——50 years | | over 50 years |
| What is the highest level of education you have completed? | | Bachelor's Degree | Master's Degree | | Doctoral Degree | | Other |
| Do you have a professional accounting qualification? | | Yes | | | No | | |
| Do you have an IT audit qualification? | | Yes | | | No | | |
| How long have you been working in the field of external audit? | | Less than a year | 1–5 years | 6–10 years | 11–15 years | 16–20 years | Over 20 years |
| What is your position? | | Staff | | Senior Manager | | | |
| What category does your organization belong to? | | Big Four | International firm (not one of the Big Four) | | Regional Firm | | Other |
| **Category** | **Variable** | **Code** | **Question** | | | **Dimension** | |
| 1 | Performance expectancy (PE) | PE1 | I believe VRT will be useful in the field of external audits. | | | Effectiveness | |
| | | PE2 | Using VRT will enable me to accomplish tasks more efficiently. | | | Efficiency | |
| | | PE3 | Using VRT will increase the quality of the output of the audit. | | | Quality | |
| | | PE4 | If I use the VRT, I will spend less time on routine job tasks. | | | Timesaving | |
| 2 | Effort expectancy (EE) | EE1 | Learning and understanding how to work with VRT will be complicated | | | Difficulty of understanding | |
| | | EE2 | VRT will not be flexible to work with. | | | Flexibility | |
| | | EE3 | It will be difficult to make VRT do what I want it to do. | | | Difficulty of use | |
| | | EE4 | It will be difficult for me to become skillful at using VRT. | | | Mastering | |
| 3 | Social influence (SI) | SI1 | The expectation from peers is an important factor for me to use VRT. | | | Expectation of peers | |
| | | SI2 | Clients think that I should use new technologies. | | | Expectation of Clients | |

(*continued on next page*)

(*continued*)

| **Introduction** | | | | |
|---|---|---|---|---|
| | | SI3 | The senior management of my organization will be supportive of the use of VRT. | Expectation of managers |
| | | SI4 | People using VRT will have more prestige than those who do not. | Prestige in general |
| 4 | Facilitating conditions (FC) | FC1 | I have the resources necessary to use VRT. | Resources |
| | | FC2 | I have the knowledge necessary to use VRT. | Knowledge |
| | | FC3 | Using VRT is compatible with other systems I use. | Compatibility |
| | | FC4 | A specific person (or group) is available for assistance with how to use VRT. | External resource |
| 5 | Ethical concerns (EC) | EC1 | VRT will substitute my role in the future. | Substitution |
| | | EC2 | VRT will cause a leak of the client's confidential information. | Confidentiality |
| | | EC3 | VRT will hinder the auditability of the audit process. | Auditability |
| | | EC4 | It will be difficult to control data when using VRT. | Data protection |
| | | EC5 | The automatic performance of routine audit tasks by VRT will negatively affect my professional skepticism and judgment. | Professional skepticism and judgment. |
| | | EC6 | VRT will impair auditor independence. | Auditor independence |
| 6 | Intention to use (IU) | IU1 | I intend to use VRT in the near future. | Future use |
| | | IU2 | I will recommend others to use VRT. | Recommendation of use |

## Appendix B

Descriptive statistics of the variables.

| | | N | Mean | Std. Deviation | Variance |
|---|---|---|---|---|---|
| I believe VRT will be useful in the field of external auditing. | PE1 | 311 | 4.00 | 0.740 | 0.547 |
| Using VRT will enable me to accomplish tasks more efficiently. | PE2 | 311 | 3.94 | 0.748 | 0.559 |
| Using VRT will increase the quality of the output of the audit. | PE3 | 311 | 3.85 | 0.788 | 0.621 |
| If I use VRT, I will spend less time on routine job tasks. | PE4 | 311 | 4.05 | 0.784 | 0.615 |
| Learning and understanding how to work with VRT will be complicated. | EE1 | 311 | 2.85 | 0.925 | 0.855 |
| VRT will not be flexible to work with. | EE2 | 311 | 3.01 | 0.905 | 0.820 |
| It will be difficult to make VRT do what I want it to do. | EE3 | 311 | 2.96 | 0.882 | 0.778 |
| It will be difficult for me to become skilled at using VRT. | EE4 | 311 | 3.35 | 0.940 | 0.884 |
| The expectation from peers is an important factor for me to use VRT. | SI1 | 311 | 3.51 | 0.758 | 0.575 |
| Clients think that I should use VRT. | SI2 | 311 | 3.29 | 0.803 | 0.645 |
| The senior management of my organization will be supportive of the use of VRT. | SI3 | 311 | 3.68 | 0.789 | 0.623 |
| People using VRT will have more prestige than those who do not. | SI4 | 311 | 3.70 | 0.865 | 0.748 |
| I have the resources necessary to use VRT. | FC1 | 311 | 3.09 | 0.967 | 0.936 |
| I have the knowledge necessary to use VRT. | FC2 | 311 | 2.88 | 1.038 | 1.078 |
| Using VRT is compatible with other systems I use. | FC3 | 311 | 3.25 | 0.794 | 0.630 |
| A specific person (or group) is available to assist me in using VRT. | FC4 | 311 | 3.16 | 0.985 | 0.970 |
| VRT will substitute my role in the future. | EC1 | 311 | 3.25 | 0.976 | 0.953 |
| VRT will cause a leak of the client's confidential information. | EC2 | 311 | 3.25 | 1.030 | 1.061 |
| VRT will hinder the auditability of the audit process. | EC3 | 311 | 3.24 | 0.943 | 0.888 |
| It will be difficult to control data when using VRT. | EC4 | 311 | 3.30 | 0.878 | 0.772 |
| The automatic performance of routine audit tasks by VRT will negatively affect my professional skepticism and judgment. | EC5 | 311 | 3.21 | 0.923 | 0.852 |
| VRT will impair my independence. | EC6 | 311 | 3.50 | 0.986 | 0.972 |
| I intend to use VRT in the near future. | IU1 | 311 | 3.60 | 0.840 | 0.705 |
| I will recommend using VRT to others. | IU2 | 311 | 3.61 | 0.805 | 0.648 |
| Do you use VRT in your organization? | AU | 311 | 0.15 | 0.361 | 0.130 |

**Notes:** The actual usage (AU) question, "Do you use VRT in your organization?" is coded 1 if yes and 0 if no.

## Data availability

Data will be made available on request.

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