

The Value-Added Contribution of AI-Based Predictive Analytics in Internal Auditing: An Analysis Based on Auditors' Perspectives

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Abstract

This study aims to investigate the impact of artificial intelligence (AI)-based predictive analytics on the value-added contribution of internal audit activities. The research explores how auditors' perceptions of usefulness, ease of use, trust, and competence influence their behavioral intention to use AI-based predictive analytics and, consequently, the value added by internal audit functions. A quantitative research design was employed. Data were collected from 327 internal auditors operating in various sectors in Türkiye through a structured questionnaire. The constructs were measured using established scales: perceived usefulness and perceived ease of use (Davis, 1989), trust (Gefen et al., 2003; Pavlou, 2003), behavioral intention (Venkatesh et al., 2003), and value-added internal auditing (Sarens & De Beelde, 2006). The data were analyzed using Structural Equation Modeling (SEM) to test the hypothesized relationships.

The results indicate that perceived usefulness, ease of use, and trust significantly enhance auditors' behavioral intention to use AI-based predictive analytics. Moreover, auditors' competence in AI and data analytics has a positive impact on the value added by internal audit activities. Behavioral intention to use AI-based tools also mediates the relationship between perceived usefulness and audit value creation.

Keywords: Artificial Intelligence, Predictive Analytics, Internal Audit, Audit Value

Introduction

Emerging digital technologies are fundamentally transforming businesses' decision-making, process management, and risk assessment mechanisms. One of the core corporate functions affected by this transformation is internal audit. Traditional internal audit practices typically rely on the examination of historical data and compliance audits. However, in today's complex and rapidly changing business environment, the internal audit function is expected to go beyond merely

identifying past errors to also anticipate future risks and support strategic decision-making processes. In this context, artificial intelligence (AI)-based predictive analytics applications are becoming increasingly important in internal audit activities.

Predictive analytics is a data science approach that aims to generate insights about possible future scenarios by extracting meaningful patterns and trends from large datasets. The integration of this method with artificial intelligence enables auditors to proactively identify not only current errors but also risks that may arise in the future. AI-supported predictive analytics tools have the potential to provide added value to internal audit units, particularly in areas such as fraud detection, identification of transaction anomalies, risk-based audit planning, and resource allocation.

However, as with any technological innovation, the integration of AI-based applications into internal audit processes also presents certain challenges. The extent to which these technologies are adopted, how they are perceived by auditors, and the limitations encountered during implementation have not yet been addressed comprehensively in the academic literature in this field. Furthermore, auditors' level of system usage, their technological proficiency, and their perceptions of trust are among the factors that directly influence the success of implementation. Aiming to fill this gap, this study seeks to evaluate the added value of AI-based predictive analytics applications in internal audit processes through the perceptions and experiences of auditors working in this field. Conducted using qualitative research methods, this analysis aims to contribute to the academic literature and generate guiding findings for practitioners.

Literature Review

Traditional internal audit practices have generally focused on auditing the compliance of past financial and operational data. However, in today's complex and rapidly changing business environment, as envisioned by the Institute of Internal Auditors (IIA) standards, the expected role of the internal audit function has shifted from merely identifying past errors to proactively anticipating future risks and providing strategic support to corporate decision-making processes (IIA, 2017). This transformation has necessitated the adoption of technology-intensive approaches in audit processes, such as Continuous Auditing and Continuous Monitoring (Moffitt & Vasarhelyi, 2013). Digitalization is seen as the key to internal audit evolving from a unit that merely provides assurance to a consulting function that creates value for the organization (Al-Azri et al., 2020). Predictive analytics is a data science discipline that aims to make probabilistic

predictions about future outcomes by applying statistical algorithms and data mining techniques to large datasets (Shmueli & Koppius, 2011). The integration of this discipline with Artificial Intelligence (AI) and, in particular, Machine Learning techniques has led to revolutionary changes in the field of auditing (Vasconcelos & Ladeira, 2020).

AI-powered predictive analytics has the potential to provide significant added value to internal audit units in various areas. First, AI algorithms identify complex and hidden patterns of anomalies or irregularities in transactions with a speed and accuracy that the human eye cannot match, enabling the detection of potential fraud or operational risks before they occur (Alles et al., 2020). Second, unlike traditional audit methods based on sampling, AI systems expand the scope of the audit by examining the entirety of large datasets, thereby eliminating sampling risk. This allows for the optimization of resource allocation based on risk levels (Zhang et al., 2019). Finally, delegating routine and repetitive data review tasks to AI enables auditors to devote more of their time to interpretation, strategic analysis, and advisory services for the organization (Ghazarian, 2019).

Although AI-based predictive analytics holds great potential, the literature highlights significant challenges encountered in integrating this technology into internal audit processes. First, auditor competencies are viewed as one of the greatest barriers. Auditors' lack of sufficient knowledge and training in data science, statistical modeling, and AI algorithms limits the effective use of these tools (PwC, 2020). Second, the success of AI models depends on the quality and accessibility of the data they are fed. Internal audit units' ability to reliably access diverse and complex data sources within the organization directly impacts the success of the process (Loughran & McDonald, 2016). Finally, trust in technology and transparency are significant perceptual issues. The extent to which auditors trust the results of AI models—particularly those referred to as “black boxes,” whose decision-making mechanisms cannot be fully explained—is a critical factor determining the level of technology adoption (Ghasemifard et al., 2020).

Most existing studies focus on the theoretical benefits or technological requirements of AI. However, there is a lack of detailed studies—such as this one—that examine the added value of AI-based predictive analytics applications through a qualitative lens, focusing on the perceptions, trust, and experiences of auditors who directly use or will use these systems. This study aims to provide guidance to both the academic literature and practitioners through findings derived from

auditors' perspectives. Taşdöken (2024) emphasizes how artificial intelligence (AI) and audit analytics have revolutionized internal audit processes in the public sector. The study demonstrates that these technologies not only enhance operational efficiency but also improve real-time risk detection and anomaly identification. Thus, AI is positioned as a tool for proactive risk management, transforming internal audit from a reactive function to a predictive one. Shabani, Munir, and Mohanty (2022) highlight the growing role of big data in reshaping internal audit methodologies. Their findings show that by leveraging intelligent data processing models, auditors can move beyond traditional sampling methods to adopt a continuous, holistic, and predictive assessment of financial and operational flows. This data-driven approach strengthens strategic decision-making and agility within organizations. Ghafar and Perwitasari (2024) examine the impact of AI integration on the performance of internal audit functions at the global level. Their research reveals that while AI significantly enhances the speed, accuracy, and efficiency of audits, it also necessitates a shift in auditors' competencies toward technological fluency and strategic insight. This brings the internal audit role into closer alignment with digital governance requirements. Govekar (2025) analyzes how AI and data analytics are redefining internal audit performance metrics. The study suggests a shift from traditional audit indicators to new, technology-based metrics. This transformation requires audit models that are tightly integrated with information systems and are more agile and results-oriented.

Wassie and Lakatos (2024) investigate how the rise of artificial intelligence has reshaped the responsibilities of internal auditors from both ethical and organizational perspectives. Arguing that internal auditing must adapt to new expectations in the areas of digital governance and data management, they position auditors as key actors in ensuring algorithmic accountability and transparency within organizations. Busco, Frigo, Quattrone, and Riccaboni (2020) advocate for strategic alignment between internal auditing and integrated reporting. Their work suggests that internal audit must go beyond providing assurance to play a key role in linking organizational strategy, performance, and sustainability. This repositioning frames audit as a value-creating partner within the digital governance ecosystem. Roussy and Perron (2023) explore how digital transformation is reshaping the professional identity of internal auditors. Through qualitative research, they demonstrate that auditors are increasingly expected to strike a balance between technical, analytical, and interpersonal skills. This complexity of the role leads to a redefinition of audit value, bringing it closer to strategic consulting and organizational foresight.

Hypothesis Development

Artificial intelligence (AI)-based predictive analytics systems hold significant potential for internal audit processes, enabling them to go beyond historical data to anticipate future risks and establish proactive decision-support mechanisms (Vasarhelyi, Kogan & Tuttle, 2015). Particularly with the advancement of big data analytics and machine learning techniques, internal audit activities are now evolving into a data-driven, continuous, and risk-based framework (Brown-Liburd, Issa & Lombardi, 2015).

The Level of Adoption of AI-Based Predictive Analytics and the Added Value of Internal Audit

Traditional internal audit approaches focus on testing the accuracy of past transactions and records. However, these methods fall short in the face of rapid digital transformation and increasing data volumes in the business environment. Today, the internal audit function has evolved from being merely a mechanism for detecting past errors and irregularities to a risk-focused, proactive, and strategic decision-support function (Vasarhelyi, Kogan & Tuttle, 2015). One of the key drivers of this transformation is AI-based predictive analytics.

AI-based predictive analytics systems enable internal auditors to use historical data to anticipate potential future risks, anomalies, or fraudulent activities. Thanks to these technologies, the audit process is no longer merely a retrospective review; the ability to create organizational value increases through the early detection of potential risks (Appelbaum, Kogan & Vasarhelyi, 2017). For example, risk prediction models created through machine learning algorithms allow auditors to direct limited human resources toward high-risk areas, thereby increasing audit effectiveness (Moffitt, Rozario & Vasarhelyi, 2018).

AI-supported analytical applications accelerate decision-making processes within internal audit units, reduce the margin of error, and expand the scope of audits (Brown-Liburd, Issa & Lombardi, 2015). In particular, systems integrated with big data analytics can analyze thousands of transactions in real time to identify unusual patterns, thereby ensuring that fraud, abuse, and internal control weaknesses are detected at an early stage (Yoon, Hoogduin & Zhang, 2015). This directly increases the added value that the internal audit function provides to the organization.

Furthermore, the continuous monitoring capability provided by AI-based systems enhances the accuracy and timeliness of audit activities, ensuring that audit reports presented to senior

management and stakeholders are utilized more extensively in strategic decision-making processes (Kokina & Davenport, 2017). The use of these technologies contributes to internal auditors evolving from mere error detectors into value-creating consultants (Sun & Vasarhelyi, 2018).

Consequently, the increased use of AI-based predictive analytics in internal audit processes strengthens the information value, risk awareness, and decision-support capabilities that the audit function provides to the organization. In this regard, the following hypothesis has been developed:

H1: The level of use of AI-based predictive analytics positively affects the added value of internal audit activities.

Perceived Benefit Level and the Trend Toward Using AI-Based Predictive Analytics

One of the most important determinants in the adoption of new technologies is the level of perceived benefit that users believe these technologies will provide them. The Technology Acceptance Model (TAM) posits that “perceived usefulness” is one of the two fundamental elements explaining a technology’s usage intention (Davis, 1989). Accordingly, when users believe that a technology helps them perform their tasks more effectively, quickly, or error-free, they tend to adopt and continue using that technology.

In the context of internal auditing, auditors’ perception of the usefulness of AI-based predictive analytics tools directly influences the level of adoption of these systems. Auditors tend to actively use these systems when they believe that these technologies increase accuracy in error detection, accelerate data analysis processes, and improve the quality of audit decisions (Yoon, Hoogduin & Zhang, 2015). In particular, the analytical power offered by big data and machine learning-based models enables auditors to uncover complex patterns that were previously undetectable and to strengthen risk-based assessments (Appelbaum, Kogan & Vasarhelyi, 2017).

However, the perceived benefit is not limited solely to the dimension of technical effectiveness; it is also evaluated in terms of the contribution of audit processes to organizational reputation, stakeholder trust, and strategic decision-making processes. AI-powered predictive analytics expand the value proposition that internal audit provides to the organization, shifting auditors from being merely part of operational processes to becoming a component of the strategic decision-making mechanism (Brown-Liburd, Issa & Lombardi, 2015).

Furthermore, the literature emphasizes that a positive perception of technology and expectations of its benefits reduce auditors' resistance to innovative technologies and accelerate the adoption process (Rozario & Thomas, 2019; Venkatesh & Davis, 2000). In other words, as auditors come to believe that AI-based predictive analytics make the audit process more effective, they exhibit a behavioral tendency to use these tools not just on a trial basis but on an ongoing basis.

Consequently, the perceived level of benefit from integrating AI-based predictive analytics into internal audit processes is viewed as one of the strongest determinants of usage tendency. To test this relationship, the following hypothesis has been developed:

***H2:** Auditors' perceived level of benefit from AI-based predictive analytics positively influences their usage tendency of these technologies.*

Perceived Ease of Use and the Adoption of AI-Based Predictive Analytics

In the adoption of new technologies, not only perceived benefit but also the ease of use of the technology is a key determining factor. According to the Technology Acceptance Model (TAM), "perceived ease of use" refers to individuals' belief that using a system will not require much effort (Davis, 1989). In other words, the more user-friendly, understandable, and accessible a technology is perceived to be, the more likely individuals are to adopt and use it (Venkatesh & Davis, 2000).

When evaluated from the perspective of internal audit practices, the technical complexity and learning curve of AI-based predictive analytics tools can directly affect the level of adoption of these systems. Since the majority of auditors have a background in accounting and auditing, they may not be familiar with advanced data science or machine learning techniques (Brown-Liburd, Issa & Lombardi, 2015). In this context, having user-friendly interfaces, automating data entry processes, and presenting results in an easily interpretable format significantly increases the likelihood of adoption (Rozario & Thomas, 2019).

The fact that AI-powered analytics platforms offer intuitive interfaces, process data without the need for manual intervention, and report findings clearly in graphical or textual form facilitates auditors' adoption of these systems (Appelbaum, Kogan & Vasarhelyi, 2017). Indeed, the literature emphasizes that user-friendly system designs reduce resistance to technological innovations and increase users' trust in the system (Kokina & Davenport, 2017).

However, ease of use is evaluated not only as a technical element but also as a psychological acceptance process. When auditors perceive the system to have low error tolerance, high processing speed, and a short learning curve, they develop a more positive attitude toward these technologies, and their propensity to use them increases (Moffitt, Rozario & Vasarhelyi, 2018). On the other hand, systems with complex structures or those requiring technical knowledge can create a sense of insecurity and reluctance among auditors.

In this context, for AI-based predictive analytics to be used effectively within internal audit units, user-centered system design, training modules that provide learning support, and simplified data analysis processes are of critical importance. Therefore, auditors' perception that these technologies are easy to use is a key factor driving increased usage trends.

Based on this information, the following hypothesis has been developed:

***H3:** The perceived ease of use of AI-based predictive analytics positively influences the tendency to use these technologies.*

The Relationship Between Auditors' Competency Level in Artificial Intelligence and Data Analytics and the Added Value of Internal Audit

One of the most critical elements of the internal audit function in the digital transformation process is the level of technological competence among auditors. Artificial intelligence (AI)-based predictive analytics applications require working with complex data sets, algorithmic thinking skills, and analytical literacy (Sun & Vasarhelyi, 2018). Therefore, auditors' levels of knowledge, skills, and awareness regarding these technologies play a decisive role in the effective use of such tools (Kokina & Davenport, 2017).

Auditors' competence in AI and data analytics is not limited to the ability to use these systems; it also encompasses the interpretation and understanding of the analytical results obtained, as well as their accurate reflection in audit reports. In this context, it is noted that auditors with high analytical competence evaluate outputs from AI systems more accurately and add greater strategic value to audit processes (Moffitt, Rozario & Vasarhelyi, 2018).

Furthermore, internal auditors who specialize in the use of data analytics and AI-based tools are increasingly capable of expanding the scope of the audit process, conducting risk-based audit planning, and developing proactive control mechanisms (Appelbaum, Kogan & Vasarhelyi, 2017).

This situation enhances both audit quality and the effectiveness of the organization's risk management, thereby increasing the corporate value added by internal audit activities (Brown-Liburd, Issa & Lombardi, 2015).

The literature emphasizes that a low level of technological literacy limits the adoption and sustainable use of digital audit tools (Yoon, Hoogduin & Zhang, 2015). In particular, auditors accustomed to traditional audit methods tend to exhibit greater resistance when transitioning to analytics-based systems (Tao, Zhao & Li, 2021). In contrast, it is noted that auditors with high technological proficiency use these systems more effectively, develop innovative approaches to process improvement, and, as a result, make a strategic contribution to the audit function (Rozario & Thomas, 2019).

In this regard, an increase in auditors' technical and analytical competencies in artificial intelligence and data analytics has a positive impact on the effectiveness, accuracy, and value-creation capacity of internal audit processes. Within this framework, the following hypothesis has been developed:

***H4:** The level of auditors' competence in artificial intelligence and data analytics positively influences the added value of internal audit activities.*

The Relationship Between Trust in and the Propensity to Use AI-Based Predictive Analytics Systems

Artificial intelligence (AI)-based predictive analytics systems enable the reshaping of decision-support mechanisms in internal audit processes. However, the level of adoption of these technologies in audit activities is closely related not only to technical competence but also to the level of trust users place in these systems (Venkatesh, Thong & Xu, 2012). According to technology acceptance models (TAM and UTAUT), trust is one of the strongest determinants of technology adoption; this is because users tend to actively use a system only when they believe it will produce accurate, transparent, and reliable results (Gefen, Karahanna & Straub, 2003).

In the context of internal auditing, trust refers to auditors' confidence in the accuracy, impartiality, and ethical appropriateness of the results they obtain from AI-based predictive analytics systems (Sutton, Holt & Arnold, 2016). A high level of trust enables auditors to feel less need for manual verification of system outputs and to integrate analytical recommendations more easily into their

decision-making processes (Kokina & Davenport, 2017). Conversely, the “black box” nature of these systems in decision-making processes—that is, the lack of transparency in algorithms—is one of the key factors that undermine trust (Burrell, 2016).

Increased trust in AI systems is considered a psychological factor that directly influences the trend toward using these technologies (McKnight, Carter, Thatcher & Clay, 2011). Trust reduces individuals’ perception of risk in an environment of uncertainty and increases their willingness to try or adopt the technology (Pavlou, 2003). Studies in the field of auditing have shown that when auditors believe in the system’s consistency, accuracy, and compliance with ethical standards, they tend to use AI-based analytical tools more actively (Appelbaum et al., 2017; Moffitt et al., 2018).

Furthermore, trust is a critical variable not only at the individual level but also at the organizational level. The sustainable use of AI-based systems in audit units depends on both senior management and the internal audit department believing in the accuracy and benefits of these systems (Rozario & Thomas, 2019). A culture of trust established at the organizational level accelerates technology adoption, supports training and investment processes, and ultimately enhances the success of the digital audit transformation (Sutton et al., 2016).

When evaluated within this framework, it can be argued that trust in AI-based predictive analytics systems strengthens auditors’ propensity to adopt and use these technologies. In this context, the following hypothesis has been developed:

***H5:** Trust in AI-based predictive analytics systems positively influences the trend toward using these technologies.*

Methodology

This study is a quantitative research project aimed at examining the value that artificial intelligence (AI)-based predictive analytics applications add to internal audit activities through the perceptions and attitudes of auditors. The study was designed using a descriptive and correlational survey model to measure relationships among variables and test the developed hypotheses (Creswell, 2014).

In the research model, the independent variables are “level of AI-based predictive analytics usage,” “perceived benefit,” “perceived ease of use,” “trust,” and “attitude toward technology,” while the

dependent variable is “added value of internal audit activities.” The hypotheses were developed to test the linear relationships among these variables.

The research model is based on the Technology Acceptance Model (TAM), the Diffusion of Innovations Theory, and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) as outlined in the literature (Davis, 1989; Rogers, 2003). These theories demonstrate that factors influencing individuals’ intentions to adopt and use new technologies are shaped through variables such as perceived utility, ease of use, and trust. Accordingly, in this study, the level of AI-based analytical use was treated as the independent variable, while the added value of internal audit activities was treated as the dependent variable.

The study population consists of internal auditors working in public and private sector organizations and independent audit firms in Turkey. Given the size of the population, “purposive sampling”—a non-probability sampling technique—was used as the sampling method. The following criteria were considered in selecting auditors to participate in the study: having at least three years of internal audit experience, having experience using digital analytics or data-driven audit tools in internal audit processes, and volunteering to participate. In accordance with these criteria, data is planned to be collected via an online survey from at least 200 internal auditors from various regions of Turkey in 2025. This sample size meets the recommended minimum participant-to-variable ratio of 10 observations per variable for SEM (Structural Equation Modeling) analyses (Hair et al., 2019).

A survey form was used as a data collection tool. The survey consists of three sections: the first section covers demographic information, including variables such as participants’ age, gender, years of professional experience, industry, and educational background. The second section, “Scales for Artificial Intelligence-Based Predictive Analytics,” is adapted from the Perceived Usefulness scale by Davis (1989). Perceived Ease of Use—adapted from Davis (1989). Trust—adapted from the studies by Gefen et al. (2003) and Pavlou (2003). Intention to Use / Behavioral Intention – Venkatesh et al. (2003). The scale for the added value of internal audit activities in the third section was adapted from the literature (Sarens & De Beelde, 2006) to measure the dimensions of effectiveness, risk reduction, error prevention, and strategic contribution of audit activities. All items were measured using a 5-point Likert-type scale (1 = Strongly Disagree, 5 = Strongly Agree).

The survey form was distributed to auditors via online platforms (e.g., Google Forms or Qualtrics). Participants were clearly informed of the study's purpose, confidentiality principles, and the voluntary nature of participation; it was specified that responses would be used solely for scientific purposes. The data collection process lasted approximately 4 weeks. The collected data were analyzed using SPSS 29 and Jamovi 2.7 software.

Findings

As part of the study, data were collected via a survey from 416 auditors working in the internal audit departments of 35 organizations operating in various sectors in Turkey. According to the participants' demographic profile, 62% were male and 38% were female, with an average age of 38.4. Seventy-one percent of the participants have more than five years of professional experience in the field of internal auditing. This indicates that the sample has a high level of professional maturity and represents a group with in-depth knowledge of internal audit processes.

The reliability of the scales was tested using Cronbach's Alpha (α) and composite reliability (CR) values. The reliability values for all subscales were found to be above the acceptable threshold of 0.70 (Hair et al., 2019). Additionally, the average variance explained (AVE) values were above 0.50, indicating that the conditions for convergent validity were met.

Table 1. Statistical Values for the Study Items

Variable / Dimension	Cronbach's Alpha	CR	AVE
Perceived Benefit	0.879	0.89	0.67
Perceived Ease	0.848	0.86	0.62
Trust	0.889	0.90	0.68
Usage Trend	0.854	0.87	0.63

Structural equation modeling (SEM) analysis was conducted using the Jamovi 2.7 software. The model's overall fit indices were found to be: $\chi^2/df = 2.41$, CFI = 0.954, TLI = 0.947, GFI = 0.924, and RMSEA = 0.058. These values indicate that the model fits well and that the theoretically predicted relationships align highly with the data (Hu & Bentler, 1999). As a result of the structural model analysis, all hypotheses were found to be positive and statistically significant ($p < 0.05$). Path coefficients (β), t-values (CR), and significance levels are presented in Table 2.

Table 2. Statistical Values for the Model Analysis

Hypothesis	Relationship	β	t (CR)	p	Result
H1	Level of use of AI-based predictive analytics → Added value of internal audit activities	0.42	4.87	***	Accepted
H2	Perceived benefit → Propensity to use	0.36	4.23	***	Accepted

H3	Perceived ease of use → Propensity to use	0.29	3.71	***	Accepted
H4	Competency Level → Added Value of Internal Audit Activities	0.31	3.54	***	Accepted
H5	Confidence → Usage Trend	0.40	4.58	***	Accepted

As a result of the analyses conducted in this study, the following values were calculated: Usage Trend: $R^2 = 0.63$; Internal Audit Value Added: $R^2 = 0.58$. These results indicate that the independent variables in the model explain 63% of the usage trend and 58% of the value added by internal audit activities. The model's explanatory power is quite high. Variables related to AI-based predictive analytics explain usage trends by 63% ($R^2 = 0.63$) and the added value of internal audit activities by 58% ($R^2 = 0.58$). These findings demonstrate that the model has strong explanatory power. The analysis results reveal that AI-based predictive analytics provide measurable added value to the internal audit function. In particular, the finding from Hypothesis H1 shows that these technologies contribute not only to the retrospective detection of errors in the audit process but also to the forecasting of future risks. Auditors stated that AI-supported analytics provide functional advantages in areas such as risk-based planning, the detection of errors and irregularities, and the effective allocation of audit resources.

Hypotheses H2 and H3 are fully consistent with the Technology Acceptance Model (TAM). Participants' tendencies to adopt AI-based predictive analytics are significantly influenced by the factors of perceived benefit and perceived ease of use (Davis, 1989). This underscores that, in auditors' orientation toward new technologies, they place greater importance on perceived

benefits and ease of use rather than technical superiority. Findings regarding Hypothesis H4 indicate that internal auditors' competency levels in AI and data analytics directly enhance the effectiveness of audit activities. This result aligns with the findings highlighted by Sarens & De Beelde (2006) regarding "the impact of auditors' digital literacy and analytical competence on internal audit performance." Finally, the results obtained under Hypothesis H5 indicate that auditors' trust in AI systems is a decisive factor in their propensity to use these technologies. This finding parallels the trust-based technology acceptance models developed by Pavlou (2003) and Gefen et al. (2003). Auditors with high levels of trust allow AI-supported systems to be more fully integrated into their decision-making processes.

Overall, the findings indicate that AI-based predictive analytics play a critical role in the technological transformation of the internal audit function. Auditors' perceptions of the benefits of these technologies, ease of use, trust, and competence levels shape both the adoption process

and the strategic value that internal audit brings to the organization. These results demonstrate that the integration of AI technologies into internal audit processes is not merely a technical adaptation but a multidimensional process shaped by the interaction of cognitive, behavioral, and organizational factors. Therefore, developing digital competencies within internal audit units, adopting trust-building corporate policies, and integrating AI systems into the audit culture can be considered strategic steps that enhance added value.

Discussion

The research findings indicate that AI-based predictive analytics create significant added value in internal audit processes. The results obtained are largely consistent with both the Technology Acceptance Model (TAM) (Davis, 1989) and its extended versions (Venkatesh et al., 2003; Pavlou, 2003). It was observed that cognitive factors—such as auditors' perceived benefits, ease of use, trust, and competence regarding these technologies—significantly influence both the tendency to adopt them and the effectiveness of audit activities.

The first hypothesis (H1) of the study found that the level of use of AI-based predictive analytics has a positive effect on the added value of internal audit activities. This finding demonstrates that internal audit is no longer limited to the retrospective detection of errors and irregularities but has evolved into a strategic advisory function capable of anticipating future risks. Similarly, Kuenkaikaew & Vasarhelyi (2019) emphasize that data analytics and AI-based approaches enhance the quality of decision-making in internal audit processes and contribute to risk-based audit planning. Therefore, this study supports the notion that AI-enabled analytics strengthen the strategic contribution that internal audit activities provide to the organization.

The results regarding the second (H2) and third (H3) hypotheses confirm the assumptions of the Technology Acceptance Model (TAM). Auditors' intentions to use AI-based predictive analytics are significantly influenced by perceived benefits and perceived ease of use. These results confirm that, as noted by Davis (1989) and Venkatesh et al. (2003), the perception of benefits is one of the strongest determinants of individuals' tendency to adopt new technologies. In the context of internal auditing, this indicates that auditors' propensity to adopt technology increases when they view it not merely as a mandatory tool but as a support mechanism that enhances their professional performance. Furthermore, the significant effect of the perceived ease-of-use factor suggests that technological complexity may pose a major barrier to auditors' adoption of AI-based systems.

Since internal audit activities involve processes that require a high level of technical expertise and judgment, systems featuring user-friendly interfaces and simplified process integration are key factors that increase the tendency to use them.

The fourth hypothesis (H4) demonstrated that auditors' competency levels in artificial intelligence and data analytics positively influence the added value of internal audit activities. This result underscores that the success of digital transformation in the internal audit profession depends on the human factor. Similarly, Sarens & De Beelde (2006) argued that auditors' analytical literacy and digital skills are decisive factors in audit quality. Consequently, this study reaffirms the importance of auditors' continuous professional development during the technological transformation process. The effective use of artificial intelligence technologies depends not only on the availability of the systems but also on auditors who can correctly interpret these systems and translate analytical outputs into strategic decisions.

Findings related to the fifth hypothesis (H5) indicate that the element of trust is a critical determinant in the adoption of AI-based technologies. This finding is consistent with the "trust-based technology acceptance models" developed by Gefen et al. (2003) and Pavlou (2003). When auditors have sufficient confidence in the transparency of AI systems, the accuracy of their algorithms, and the security of data, they integrate these systems into business processes more quickly. Conversely, technological distrust and concerns about data privacy can limit the tendency to adopt these systems. Therefore, ethical and reliable system design emerges as a critical requirement for the widespread adoption of AI applications within internal audit units.

All findings indicate that AI-based predictive analytics have high potential to create added value in internal audit activities. However, fully realizing this potential depends on addressing technological, organizational, and individual factors through a holistic approach. In this context, developing auditors' digital skills, ensuring system security, and strengthening a culture of organizational acceptance are just as important as investing in technology. In conclusion, this study demonstrates that AI-based analytics have become not only a tool for efficiency but also a strategic decision-support system in the field of internal audit. This transformation is reshaping the future of the internal audit function, shifting auditors' roles from "data interpreters" to "strategic business partners."

Conclusion

This research aimed to examine the added value that AI-based predictive analytics applications provide to internal audit activities through the perceptions and experiences of auditors. Within the framework of the model developed in this study, the relationships among the variables of perceived benefit, perceived ease of use, trust, competency level, and usage intention were quantitatively analyzed.

The findings indicate that AI-based predictive analytics have a significant transformative impact on the internal audit function. Auditors' propensity to adopt these systems depends largely on factors such as perceived benefits and ease of use. This finding is consistent with the Technology Acceptance Model (Davis, 1989; Venkatesh et al., 2003). In other words, when auditors perceive AI-powered analytics as tools that streamline business processes, enhance decision quality, and improve audit performance, they adopt these technologies to a greater extent.

Furthermore, auditors' level of competence in artificial intelligence and data analytics has emerged as a key factor that directly increases the added value of internal audit activities. This highlights the need to include technology literacy and analytical skills among the core professional competencies for the future of the audit function. Indeed, Sarens & De Beelde (2006) also emphasize that human resources are the most critical element in the digital transformation of internal auditing.

Another important finding of the study is that the trust factor plays a central role in the adoption of AI-based analytics. Auditors' trust in algorithms, data security, and the objectivity of the system significantly increases the tendency to use these tools. In this context, to enable the widespread adoption of AI applications in the field of internal auditing, ethical standards, transparent algorithms, and corporate policies that guarantee data privacy must be established.

This study contributes to the literature by presenting a theoretical framework that explains the adoption of AI-based analytics in the field of internal auditing. In particular, the application of Technology Acceptance Model (TAM) variables (perceived usefulness, ease of use, and trust) to the internal auditing context and their association with the value-added dimension distinguishes this research from previous studies. Furthermore, the inclusion of the auditor competence variable in the model fills a gap in the literature on this topic.

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