LEADERSHIP IMPACT ON ACCOUNTANTS' COMPETENCE AND AI ADOPTION READINESS

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A B S T R A C T

***Research Purposes**. This study aims to explore how leadership affects employee competence and organizational readiness to adopt AI in Indonesian firms from the perspective of accountants.*
***Research Methods.** This research collected data through purposive sampling. The model was tested using PLS-SEM methodology from 280+ professional accountants in Indonesia, facilitated by SmartPLS. The result revealed that leadership has a significant influence on affecting Employee Competence, Organizational Readiness and AI Adoption. In addition, Organizational Readiness and Employee Competence have a significant impact on AI Adoption and significantly mediate the Leadership-AI Adoption relationship.*
***Research Results and Findings.** This study is among the few in Indonesia to empirically validate Employee Competence (EC) and Organizational Readiness (OR) as mediators of the relationship between Leadership and AI Adoption. This offers a refined perspective on how Leadership, Employee Competence, and Organizational Readiness drive AI integration in Indonesia's context. The study's findings are beneficial to organizations, providing more in-depth information on the roles of Leadership, Employee Competence, and Organizational Readiness in adopting AI. Especially for companies that are planning to use AI in the future, or are currently integrating AI in their business process.*

A B S T R A K

***Tujuan Penelitian.** Penelitian ini bertujuan untuk mengeksplorasi bagaimana kepemimpinan memengaruhi kompetensi karyawan dan kesiapan organisasi untuk mengadopsi AI di perusahaan-perusahaan Indonesia dari perspektif akuntan.*
***Metode Penelitian.** Penelitian ini mengumpulkan data melalui pengambilan sampel bertujuan. Model diuji menggunakan metodologi PLS-SEM dari 280+ akuntan profesional di Indonesia, difasilitasi oleh SmartPLS. Hasil mengungkapkan bahwa kepemimpinan memiliki pengaruh signifikan dalam memengaruhi Kompetensi Karyawan, Kesiapan Organisasi, dan Adopsi AI. Selain itu, Kesiapan Organisasi dan Kompetensi Karyawan memiliki dampak signifikan terhadap Adopsi AI dan secara signifikan memediasi hubungan Kepemimpinan-Adopsi AI.*
***Hasil Penelitian dan Temuan Penelitian.** Studi ini merupakan salah satu dari sedikit di Indonesia yang secara empiris memvalidasi Kompetensi Karyawan dan Kesiapan Organisasi sebagai mediator antara Kepemimpinan dan Adopsi AI. Hal ini menawarkan perspektif yang lebih baik tentang bagaimana Kepemimpinan, Kompetensi Karyawan, dan Kesiapan Organisasi mendorong integrasi AI dalam konteks Indonesia. Temuan studi ini bermanfaat bagi organisasi untuk memberikan informasi yang lebih mendalam tentang peran Kepemimpinan, Kompetensi Karyawan, dan Kesiapan Organisasi dalam mengadopsi AI. Terutama bagi perusahaan yang berencana menggunakan AI di masa depan, atau saat ini sedang mengintegrasikan AI dalam proses bisnis mereka.*

INTRODUCTION

As of now, artificial intelligence (AI) is a critical 21st-century innovation. According to McKinsey's report on the state of AI, 56% of respondents use AI for at least one function, with this figure rising to 57% in emerging economies such as China, the Middle East and North Africa (Bui et al., 2025Today, organizations strive to improve the efficiency of their operations by redesigning and managing their business processes to become more competitive (Baiod & Hussain, 2024). Companies in all industries have also increased their investments in AI (Rahman et al., 2024). According to the rankings of countries by their AI Capacity at the International level, published on September 19th, 2024, Indonesia lags (AI Index=8.61) compared with countries such as Singapore (32.33), China (53.88), and the United States of America (100). In accounting, the rapid evolution of AI tools in auditing presents an exciting opportunity for transformation (Afifa et al., 2024). However, adoption is fraught with challenges (Al Wael et al., 2024), particularly in emerging markets (Al Wael et al., 2024), particularly in emerging markets (Benhayoun et al., 2025). One of the most well-known use cases of AI in accounting is an AI-empowered Accounting Information System (AIS) with natural language processing (NLP) that analyzes unstructured data, such as emails, financial reports, and online comments, to extract meaningful insights that support decision-making. It also allows auditors to understand the content of documents and reports better and to analyze them comprehensively and meaningfully (Assidi et al., 2025).

AI adoption hinges on three factors: Leadership, Employee Competence (EC), and Organizational Readiness (OR). AI integration requires Leadership, including Transformational Leadership (Hui et al., 2024), Servant Leadership (Mohassel et al., 2024), Adaptive Leadership (Trivellas et al., 2021), and Ethical Leadership (Nejati et al., 2019), among others, to balance human roles with AI integration (Yin et al., 2024). Similarly, EC refers to employees' ability to use AI in accounting, drawing on the knowledge and skills they possess. Employee competence involves mastering AI tools and applying insights to optimize accounting processes (Alghazzawi, 2024). Finally, OR is the extent to which an organization is prepared to adopt AI. OR requires a culture open to innovation, leadership commitment to funding AI initiatives, and training programs to support adoption (Alghazzawi, 2024).

Previous research in Delhi (Divya et al., 2025) stated that AI Adoption impacts employee engagement through leadership mediation, based on senior management perspectives. The research found that AI can positively influence employee engagement, including mediating Leadership. Another study in Jordan (Alghazzawi, 2024) found that high EC and OR, alongside AI Adoption, can increase accounting efficiency. The research targeted accountants' perspectives on EC, OR, and Leadership. Similarly, the research found that a high level of AI adoption, along with EC and OR, is associated with accounting efficiency.

Common limitations in both research on AI Adoption as the independent variable, where it could in fact impact accounting efficiency, employee engagement, and Leadership; however, it needs to be researched further in other roles as dependent variables. Although other studies by (Benhayoun et al., 2025; Bui et al., 2025; Roszelan & Shahrom, 2025) already tested AI adoption as dependent variables, their diminishing roles for other variables and limited sample sizes suggest the need for further research. Another common limitation is the lack of specificity regarding companies' and accountants' intentions to adopt AI. There is also a limitation in Jordan's research regarding the use of Employee Competence and Organizational Readiness (Vo et al., 2024) as Independent variables. However, they may impact accounting efficiency; they need to be further researched in other roles as mediating variables.

Current research gaps highlight overreliance, where most studies use AI Adoption as an independent variable, neglecting its measurement by other factors. Furthermore, there is a lack of studies in Indonesia linking it to Leadership, EC, and OR. Addressing prior limitations of small samples, this study targets Indonesian accountants across industries. Most studies treat EC and OR as Independent variables; hence, both need to be tested in other roles as mediating variables to explain the indirect relationship between Leadership and AI Adoption. This study contributes by redefining EC and OR as mediators, making this one of the few in Indonesia. The study's main objective is to evaluate the impact of Leadership in AI Adoption in Indonesia's Firms by redefining Leadership's role, testing its indirect influence on AI adoption through mediators, and advancing theories of organizational innovation. This entails examining the extent to which Leadership affects EC and the OR's ability to adopt AI, using the variable as the measure.

Given the constraints identified in prior research, this study aims further to explore key questions about AI adoption in Leadership. Hence, the research question in this study is as follows: (1) How does leadership influence AI adoption?; (2) Does OR and the EC have a mediating role between Leadership and AI?; and (3) Do accountants and their firms in Indonesia have the intention to adopt AI technology at their workplace? Our research contributes to the body of literature on the use of AI in accounting. The results of this study rely on quantitative data collected through a survey targeting the perspectives of professional accountants working in Indonesian firms. From this study, companies will have a clear vision of what is needed and should be done to improve employees' competence and their readiness to influence AI adoption.

LITERATURE REVIEW

Resource Based View

The Resource-Based View was first introduced by Birger Wernerfelt in 1984 and later further developed by Jay Barney in 1991. Since then, it has been widely utilized as a management model to highlight essential resources for organizations. The Resource-Based View (RBV) is a strategic management framework that posits that the key determinants of competitive advantage and performance are an organization's internal resources (Barney, 1991). The RBV contributes to a richer analysis of the role that a firm's intangible and tangible resources play in achieving and maintaining competitive advantage (Zahra, 2021). Unlike other perspectives, this theory focuses on leveraging a firm's uniqueness, value, and inimitable resources to sustain long-term success. Within the RBV framework, technological readiness and leadership vision are conceptualized as strategic resources. Technological readiness encompasses the infrastructure and competencies necessary for AI deployment, while leadership vision reflects senior managers' ability to align digital transformation with strategic objectives. In the 1990s, this theory gained prominence. However, its origins can be traced to earlier work by Penrose (1995), which highlighted the role of the firm's specific assets in organizational growth.

According to RBV, resources are divided into tangible and intangible assets: human capital, organizational culture, technological capabilities, and intellectual property (Wernerfelt, 1984). The resource-based view views AI as a key transformative resource in digital business competition (Zhao et al., 2026). Furthermore, over the past 7 years, RBV theorists have developed a strategy for enhancing firm performance by leveraging available resources to attain a sustainable competitive advantage (Adnan et al., 2018; Pereira & Bamel, 2021; Collins, 2021). It has also been utilized across different research streams, such as mergers & acquisitions (M&A), strategy, innovation, alliances, internal business and knowledge management (Cooper et al., 2023). Companies gaining a sustained competitive advantage must fulfill the four criteria of the VRIO framework -Valuable, Rare, Inimitable, and Organized- (Barney, 1991). This framework helps distinguish ordinary capabilities from strategic resources in increasing firm performance.

This framework explicitly shows performance differentials across resources within firms and emphasizes that the heterogeneity of resources across firms is central to explaining these differences. For instance, organizations with highly competent employees, innovative leadership, or robust IT infrastructure are better positioned to adapt to dynamic environments and capitalize on new opportunities (Grant, 1996). Furthermore, it has been widely applied in various domains, including information systems, strategic human resources, and operations management.

Unlike other strategic theories that emphasize external factors such as industry competition or market trends, RBT focuses primarily on internal resources (Human Capital, Organizational Culture, Intellectual Property) and capabilities (Technological Capabilities) (Sazly et al., 2025). However, despite its influence in explaining sustained competitive advantage, RBV has received some criticism. Scholars argue that it lacks precise mechanisms for resource development and overlooks external factors such as industry dynamics and institutional constraints (Priem & Butler, 2001). Nonetheless, RBV remains a foundational theory in understanding how firms can internally cultivate resources to build capabilities and achieve sustained competitive advantage.

Organizational Information Processing Theory (OIPT)

Organizational Information Processing Theory (OIPT) explains how firms develop their capacity to meet their information-processing requirements (Belhadi et al., 2024). Improving our organizational data processing capabilities will help us navigate the unpredictable environment and enhance performance (Wong et al., 2020Organizational Information Processing Theory (OIPT) provides a framework for understanding how organizations process information to cope with uncertainty and align information needs with processing capacities (Galbraith, 1973). The theory posits that as uncertainty within an organization increases -due to external environmental complexity or internal structural ambiguity- there is a greater demand for information processing mechanisms. It is indeed centered on these three: the demands, capabilities for information processing, and the harmonization to achieve the optimal performance (Yang et al., 2025). Organizations can address this by either reducing the need for information processing (e.g., through slack resources or self-contained tasks) or increasing their capacity to process information (e.g., through vertical information systems and lateral relations) (Daft & Lengel, 1986). In this context, decision-making structures, communication channels, and coordination methods are crucial for enhancing organizational performance, particularly in dynamic, complex environments. This reflects the need for the right "leadership" skills in communicating information from top-down management to employees.

Recent studies emphasize the applicability of OIPT in contemporary contexts, such as digital transformation and the adoption of artificial intelligence. For instance, Premkumar et al. (2005) demonstrate that the success of technology implementation depends not only on adopting digital tools but also on the organization's ability to manage the increased flow and complexity of information. Similarly, Leischnig et al. (2020 find that organizations that align their information processing mechanisms with the complexity of their operational environment are more likely to respond effectively to market shifts. Therefore, this theory proposes that an organization's continued existence and success depend on the effectiveness of its leadership in managing information from within and outside the firm. In summary, OIPT highlights three foundational elements: information processing demands, the skills to manage information, and the degree to which these match (Jia et al., 2025). These findings reinforce the importance of OIPT in guiding managerial decisions on structure, communication, and technological integration, particularly amid rapid innovation and change.

Hypothesis Development

Leadership is a company's approach to guiding its employees to achieve its main objective. It is, in fact, important that every company assess its leadership foundation to serve the team's goals rather than those of individuals (Ahmed et al., 2017). Meanwhile, a good leader would boost their employees through benefits that improve their performance/competence (Asencio & Mujkic, 2016). For an employee to fulfill the organization's goals, training is one of the most important aspects. Therefore, the need for an intentional, authentic, and durable approach extends beyond leadership practices for learning (Richardson et al., 2021). Leadership involves a dynamic interaction between leaders and followers to achieve shared goals. While definitions vary, most conceptualizations highlight influence, vision, and interpersonal relationships as key components (Avolio & Bass, 2004). According to Ul Haq et al. (2025), to effectively operationalize leadership vision in AI adoption, companies must strategically invest in aligning leadership with institutional readiness.

H_1: Leadership positively affects AI Adoption

H_2: Leadership positively affects Employee Competence

H_3: Leadership positively affects Organizational Readiness

Organizational readiness requires developing a strong organizational culture. It is another decisive determinant. Cultures that promote flexibility, collaboration, and trust will enhance both AI integration and the effectiveness of remote work (Choudhury et al., 2020). Organizational readiness refers to an organization's collective preparedness, willingness, and ability to implement a particular change or innovation (Armenakis et al., 1993; Holt et al., 2007). It is not merely about having resources or plans in place, but also about the psychological commitment of employees and leadership toward the change effort. According to Weiner (2009), organizational readiness is a framing readiness as a shared psychological state in which members feel committed to implementing a change and confident in their collective ability to do so. When the company's members feel confident in their abilities, the company will flourish to its full potential. Therefore, effective strategies have a significant impact on a company's sustainability.

Recent studies have extended the relevance of organizational readiness into domains such as AI adoption. For instance, in the context of technology integration, readiness is crucial to mitigate user resistance and enhance adoption success (Ifinedo, 2011Organizations with strong internal communication, adequate training, and clear strategic alignment are more likely to exhibit high readiness levels, fostering a smoother transition during change (Bertram et al., 2015). Therefore, evaluating and developing organizational readiness is increasingly recognized as a prerequisite for sustainable organizational change and innovation within a company.

H_4: Organizational Readiness positively affects Artificial Intelligence Adoption

Employee competence plays a vital role in enhancing organizational performance and achieving strategic goals. According to Diwanti et al. (2021), Human resource competence plays a significant role in shaping the organizational cultural climate. Organizational culture originates from the founder's vision and mission, which serve as fundamental guiding principles. The successful realization of these visions and missions requires competent human resources capable of translating strategic objectives into effective organizational practices. Competence in "Employee Competence" encompasses the knowledge, skills, abilities, and other characteristics that employees need to perform their tasks effectively, thereby improving workplace performance (Alfes et al., 2013; Aima et al., 2017; Parry, 1996). Competent employees contribute not only through task performance but also by engaging in organizational citizenship behaviors that support team functioning and adaptability. As organizations face increasingly dynamic environments, the need for adaptable, skilled, and self-directed employees becomes essential (Muduli, 2015). The development and deployment of employee competencies are also central to human capital theories, which posit that investing in employee learning and capability directly improves productivity and innovation. Furthermore, it is quite important to note that the development of competencies in employees has started from the beginning of their recruitment, selection, training and retention practices, which is crucial for increasing the resilience of an organization in any crisis and speeding up recovery (Ngoc Su et al., 2021; Raetze et al., 2021)

In knowledge-based industries, employee competence is a key differentiator and source of sustainable competitive advantage. Employee competence can be enhanced through organizations' provision of appropriate and systematic training. By investing in training, companies are demonstrating their commitment to employee development, which, in turn, increases employee engagement and loyalty (Alvarezy et al., 2025). Hameed & Waheed (2011) found that continuous learning opportunities and training significantly enhance employee competence and job satisfaction, thereby fostering organizational commitment and retention. Moreover, aligning individual competencies with organizational needs is crucial for the successful implementation of technologies and strategic initiatives, including AI adoption (Tzafrir et al., 2004). Therefore, organizations must invest in structured development programs and competency frameworks to ensure that employees are prepared to meet current and future challenges.

H_5: Employee Competence positively affects Artificial Intelligence Adoption

Organizational Readiness and Employee Competence are two important aspects that a company must have to remain competitive and achieve its goals. Both have emerged as critical mediating factors in the successful implementation of organizational change and AI adoption. Studies suggest that organizational readiness mediates the relationship between strategic leadership and performance, as readiness fosters shared commitment and efficacy among members, which is necessary for change to occur (Armenakis et al., 1993).

H_6: Organizational Readiness strengthens the influence of Leadership on AI Adoption

H_7: Employee Competence strengthens the influence of Leadership on AI Adoption

Research Model

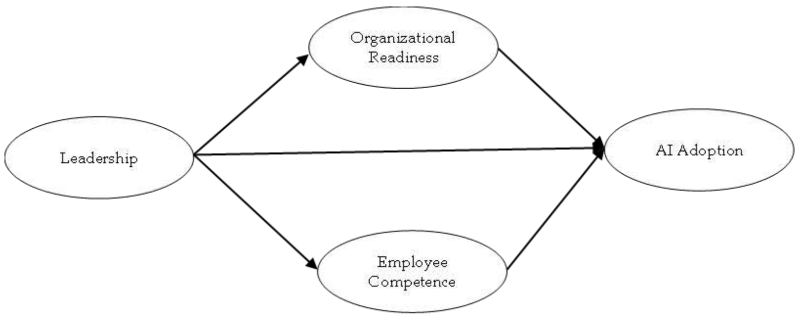

Figure 1. Research Model

RESEARCH METHODS

To rigorously address the research questions posed in this study, a quantitative research design utilizing a cross-sectional survey methodology was employed. This approach is particularly suited to exploring the relationships among organizational constructs such as leadership, employee competence, and organizational readiness across a diverse range of companies. The study targeted a purposive sample of professional accountants currently working in various industrial sectors in Indonesia, a choice driven by Indonesia's status as a rapidly growing emerging economy that currently lags in AI capacity compared to its regional neighbors (Afifa et al., 2024; Tortoise Media, 2024). By focusing on this specific geographical and professional context, the research aims to provide a localized understanding of the "digital gap" in the accounting profession.

The final sample consisted of 282 professional accountants who met the strict inclusion criteria: (1) a minimum of two years of professional experience to ensure a stable understanding of firm culture, and (2) direct exposure to or usage of AI-empowered accounting tools in their daily workflows (such as QuickBooks AI, Xero, SAP S/4HANA, etc). This sample size exceeds the minimum requirements for robust PLS-SEM analysis, providing sufficient statistical power to detect meaningful effect sizes in complex mediating models (Hair et al., 2017). Furthermore, the diversity of industries—ranging from manufacturing to financial services—ensures that the findings represent the broader landscape of digital transformation in Indonesian accounting practices (Assidi et al., 2025).

Initially, 300 responses were collected through a survey published on Populix. However, some of these responses were filtered out. 1 respondent was removed because they had only used Gemini AI, which is not considered an accounting-specific tool. Additionally, 12 respondents were excluded because they did not use any AI tools in their work. Lastly, five respondents were filtered out as their role was Operations Manager, not a professional accountant. This concludes the survey results for the Populix survey, conducted with 282 respondents.

The research constructs were operationalized through a 16-item structured questionnaire adapted from established literature to ensure content validity and internal consistency. Each construct was measured using a 5-point Likert scale, ranging from "Strongly Disagree" (1) to "Strongly Agree" (5), allowing for fine-grained measurement of professional perceptions. The choice of these scales was critical to align with the unique information-processing requirements of accounting firms in dynamic environments (Daft & Lengel, 1986).

Specifically, the Leadership construct (6 items) was adapted from Divya et al. (2025 and evaluated three core dimensions: clear strategic vision, technical problem-solving, and open communication. Employee Competence (3 items) and Organizational Readiness (3 items) were adapted from Alghazzawi (2024 whose work specifically targets AI adoption in the accounting sector of emerging markets. Finally, AI Adoption (4 items) was synthesized from Alghazzawi (2024) and Damerji & Salimi (2021), capturing both the institutional intent and the actual level of technical integration (see Table 1).

Prior to full-scale data analysis, the dataset underwent preliminary screening procedures, including assessments of missing values, outliers, and normality. Common method bias was evaluated using full collinearity variance inflation factors (VIF), ensuring that all values remained below the recommended threshold. The measurement model was assessed before testing the structural relationships to establish convergent and discriminant validity. Only after confirming satisfactory reliability and validity indicators was the structural model evaluated to test the proposed hypotheses.

This study used a validity test to ensure that the measurements accurately reflect the research objectives. To do this, we used the Average Variance Extracted (AVE), a measure that shows how much of the variance in the items is explained by the construct itself. We used SmartPLS software (version 4.1.1.1) for this calculation. AVE is used to measure the amount of variance in items that the construct explains. Data are considered valid if the AVE exceeds 0.5 (Hair et al., 2017). A high AVE figure indicates that the questionnaire indicators explain a significant relationship with the indicators of the measured construct variable.

The Reliability test is a measurement process that assesses whether an existing instrument yields consistent, reliable results. This study used Composite reliability, which indicates how consistent and stable the construct is across indicators, with a value greater than 0.7 (Hair et al., 2021). We prioritized Composite Reliability for this test because it provides a more accurate and robust assessment of consistency compared to Cronbach's alpha. While Cronbach's alpha is a common reliability measure, it assumes that all indicators have equal loadings, which is often not the case in real-world research. Violating this assumption, which is common in many research contexts, can result in lower reliability values than those produced by Composite Reliability (ρc). Therefore, for a more accurate and robust assessment of construct reliability, particularly given the potential for varying indicator loadings, this study prioritizes Composite Reliability (Hair et al., 2021).

The SmartPLS software was used to test the hypotheses (1-7) using the PLS-SEM (partial least squares-structured equation modeling) method. The PLS-SEM method is very appealing to many researchers as it enables them to estimate complex models with many constructs, indicator variables and structural paths without imposing distributional assumptions on the data (Hair et al., 2017). PLS-SEM was selected over covariance-based SEM (CB-SEM) due to several methodological advantages. First, PLS-SEM is highly effective for exploratory research to explain the variance of key target constructs (Hair et al., 2017). Second, it is robust against non-normally distributed data—a common characteristic of survey results (Hair et al., 2019). Most importantly, the technique is exceptionally capable of handling complex models with multiple mediation paths, as seen in the mediating roles of OR and EC in this study (Hair et al., 2021).

P-values and T-values were used to test the hypothesis. P-value indicates how likely the observed result is to occur if the null hypothesis (H0) is true. This value provides a quantitative measure of evidence against H0; a lower p-value indicates stronger evidence against H0. If the p-value is less than 0.05, we can reject the null hypothesis that there is no relationship between the variables and accept the alternative hypothesis that there is a significant relationship (Hair et al., 2019).

Table 1. Measurement and Development of the Instrument

Construct	Code	Items
Leadership	L_CV	Our department develops a clear vision to achieve objectives.
	L_SBP1	We are able to understand business problems and guide AI to solve them.
	L_SBP2	We can anticipate the future business needs of managers, suppliers, and customers by using AI.
	L_SBP3	Employees in the company demonstrate strong leadership to commit to and support the use of AI.
	L_OC1	I can collaborate with data scientists, other employees, and customers to identify opportunities that AI brings to the organization.
	L_OC2	My company communicates openly, and we are able to resolve employee issues immediately.
Organizational Readiness	OR_1	Our organization has the necessary infrastructure to support the use of AI.
	OR_2	There is a culture of innovation and support for new technologies in our organization.
	OR_3	Management is committed to and supports the use of AI.
Employee Competence	EC_1	Our employees have the necessary skills to use advanced accounting technologies, including analytical and technical skills.
	EC_2	Employees in our accounting department are proficient in AI software.
	EC_3	Training programs in our company have adequately prepared employees for the adoption of the latest technologies.
AI Adoption	AIA_1	Our accounting department extensively uses AI technologies
	AIA_2	We have integrated AI into various accounting processes to facilitate decision making
	AIA_3	The level of AI implementation in our accounting tasks is high, which automates routine ones
	AIA_4	I will use AI technology when performing accounting tasks

RESULTS AND DISCUSSION

Results

The demographic profile of the 282 respondents provides critical context for interpreting the study's findings, particularly regarding the accounting workforce's readiness and competence in Indonesia. As detailed in Table 2, the gender distribution is relatively balanced, with female respondents constituting a slight majority at 54.61% (154 participants) compared to 45.39% (128 participants) males. This relatively even split is advantageous because it minimizes potential gender bias in the results, ensuring that perceptions of leadership and AI adoption are representative of the broader accounting professional community.

In terms of generational cohorts, the sample is heavily dominated by "digital natives." The majority of respondents belong to the Millennial generation (born 1981–1996), accounting for 72.34% of the sample, followed by Generation Z (born in 1997–2012) at 22.34%. Collectively, nearly 95% of participants are under 43 years old. This demographic skew is highly significant for this study; it implies that the workforce surveyed is inherently more familiar with digital technologies compared to older generations. Consequently, the high levels of Employee Competence and AI Adoption observed in the latter analysis may be partially attributed to generational familiarity with technology, suggesting that a youthful, tech-savvy workforce reduces the barrier to AI adoption in Indonesian accounting firms.

Furthermore, the respondents' professional profiles indicate a high level of experience and strategic seniority, which adds credibility to the self-reported data on organizational readiness. Regarding tenure, the vast majority (88.66%) have been with their current organization for 3-10 years, indicating a high degree of organizational stability and deep knowledge of their firm's internal culture. More importantly, the distribution of job positions reveals that this study captures the views of decision-makers and senior professionals. A combined total of 71.98% of respondents hold senior-level positions, comprising Accounting Managers (32.62%), Senior Accountants (31.56%), and Chief Financial Officers (7.80%). Only a smaller fraction are junior staff (28.01%). This high concentration of managerial and senior roles is crucial to the validity of this research, as these individuals possess the "strategic vantage point" necessary to accurately assess complex constructs such as Leadership Vision and Organizational Readiness, which entry-level staff might not fully comprehend.

Table 2. Descriptive Results

Respondent Characteristics	Frequency	Percentage
Gender		
Male	128	45,39
Female	154	54,61
Year Born		
1946-1964	1	0,35
1965-1980	14	4,96
1981-1996	204	72,34
1997-2012	63	22,34
Experience in Organization		
3-5 years	138	48,94
6-10 years	112	39,72
11-20 years	24	8,51
>20 years	8	2,84
Job Position		
Staff	42	14,89
Junior Accountant	37	13,12
Senior Accountant	89	31,56
Chief Financial Officer	22	7,80
Accounting Manager	92	32,62

The validity and reliability of the variables were confirmed using Average Variance Extracted (AVE) and Composite Reliability (rho(c)). First, all latent variables demonstrated good validity, with AVE values ranging from 0.535 to 0.624. Since these values are all above the 0.5 threshold, this indicates strong convergent validity. This means that a significant portion of the variance in the observed items for each variable is successfully explained by the construct itself. Second, the reliability of the constructs was also high. The Composite Reliability (rho(c)) scores for all constructs were well above the recommended threshold of 0.7, with a range of 0.786 to 0.873. This confirms that the constructs are highly consistent and reliable, as their indicators consistently measure the same underlying concept. Because the data has been proven to be both valid and reliable, the study is now ready to proceed with hypothesis testing. A detailed breakdown of each variable's validity and reliability scores can be found in Table 3.

Table 3. Validity and Reliability

Variables	Composite Reliability Rho(c)	Average Variance Extracted (AVE)
AI Adoption	0,869	0,624
Employee Competence	0,790	0,556
Leadership	0,873	0,535
Organizational Readiness	0,786	0,551

Following the validation of the measurement model, the structural model (inner model) was assessed to test the hypothesized relationships between leadership, competence, readiness, and AI adoption. This phase of analysis focuses on the model's explanatory power and the statistical significance of the path coefficients (β). As recommended by Hair et al. (2017), the significance of these paths was determined using a bootstrapping procedure with 5,000 resamples to derive stable t-statistics and p-values.

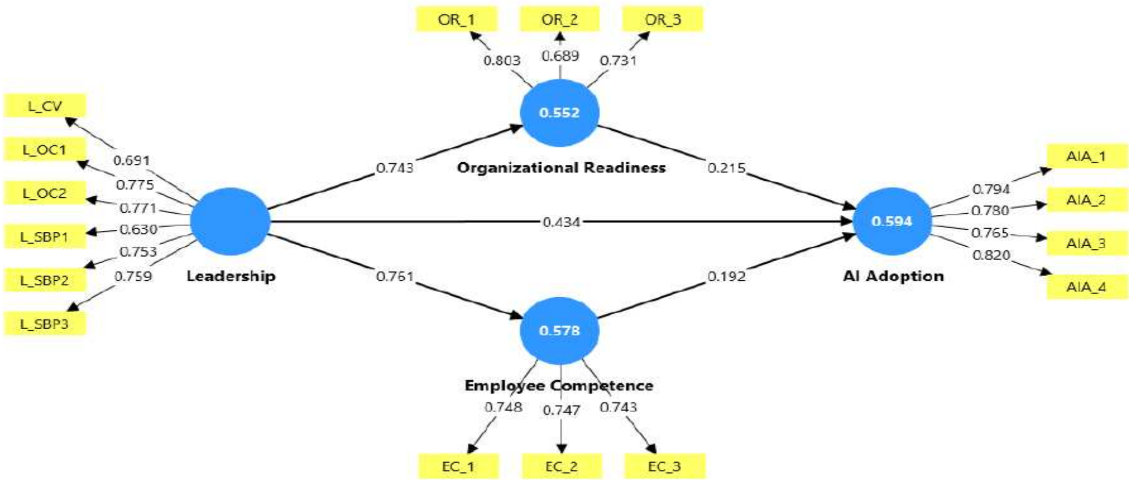

Figure 2. Structural Model Result

The results of the structural model analysis, summarized in Table 4, provide a comprehensive overview of the dynamics of digital transformation within the sample. All structural paths in the model achieved p-values below 0.05, indicating that all hypothesized relationships are statistically supported at the 95% confidence level. This consistency across all pathways suggests that the proposed theoretical framework, grounded in RBV and OIPT, has strong explanatory power for AI adoption in Indonesian accounting firms. The following subsections provide a detailed thematic analysis of these findings, categorized by the direct, indirect, and mediating influences observed.

Table 4. Hypothesis Testing

Hypothesis	Path	Beta	T-Values	P-Values	Decision
Hypothesis 1	Leadership Positively affects AI Adoption	0,434	4,855	0,000	Accepted
Hypothesis 2	Leadership positively affects Employee Competence	0,761	26,704	0,000	Accepted
Hypothesis 3	Leadership positively affects Organizational Readiness	0,743	21,535	0,000	Accepted
Hypothesis 4	Organizational Readiness positively affects Artificial Intelligence Adoption	0,215	2,888	0,004	Accepted
Hypothesis 5	Employee Competence positively affects Artificial Intelligence Adoption	0,192	2,019	0,044	Accepted
Hypothesis 6	Organizational Readiness strengthens the influence Leadership on AI Adoption	0,160	2,867	0,004	Accepted
Hypothesis 7	Employee Competence strengthens the influence Leadership on AI Adoption	0,146	1,981	0,048	Accepted

Discussion

Based on the data analysis results from Table 4, Hypothesis 1, which posits that leadership positively affects AI adoption, was accepted. This finding is highly consistent with Afifa et al. (2024), who demonstrated that transformational leadership serves as a critical catalyst for 'accounting going digital' by providing the strategic vision needed. Beyond direct adoption, leadership shows an even more profound impact on internal organizational factors. Hypothesis 2 (Leadership to Employee Competence) was accepted, while Hypothesis 3 (Leadership to Organizational Readiness) was also accepted. These strong relationships suggest that leadership serves as the primary architect of a firm's digital infrastructure and human capital, mirroring Mohassel et al.'s (2024) findings on leadership's role in fostering professional capabilities through knowledge sharing. Furthermore, while Vo et al. (2024) emphasize that organizational readiness is a prerequisite for Industry 4.0, this study extends their argument by confirming that leadership commitment is the fundamental antecedent that builds such readiness. From a theoretical lens, the Resource-Based View (RBV) categorizes this leadership as a strategic, inimitable resource that orchestrates 'human capital' to build sustained competitive advantage (Barney, 1991; Grant, 1996). Simultaneously, the Organizational Information Processing Theory (OIPT) interprets leaders as mechanisms that reduce uncertainty by clarifying the necessity of complex AI tools (Daft & Lengel, 1986). Ultimately, the acceptance of H1, H2, and H3 confirms that, in the Indonesian accounting sector, leadership is the essential starting point for both the organizational mindset and the technical skill set required for AI integration.

Hypotheses 4 and 5 were also validated, establishing that organizational readiness and employee competence function as direct drivers of AI implementation. Hypothesis 4 proposes that organizational readiness positively affects artificial intelligence adoption. This indicates that the presence of necessary technical infrastructure (OR1) and a supportive culture of innovation (OR2) directly translates into successful technological engagement. This finding strongly supports Alghazzawi (2024), who argued that readiness is a critical prerequisite for enhancing accounting efficiency in emerging markets. Similarly, Hypothesis 5, which suggested that employee competence positively influences AI adoption. This confirms that the mastery of AI-empowered systems by accountants—specifically their analytical and technical skills (EC1)—is essential. However, the borderline significance of H5 serves as a cautionary note. While competence is a driver, it may be a more fragile factor than organizational readiness, suggesting that skilled employees still require strong management commitment (OR3) to drive adoption effectively. Theoretically, these results reinforce the OIPT perspective, which suggests that organizations must align their internal 'information processing capacity' with the complexity of their environmental demands (Daft & Lengel, 1986). By cultivating both 'human skill' (EC) and 'organizational structure' (OR), firms create the mechanisms needed to handle the high volume of information generated by AI tools. From an RBV standpoint, these competencies and structural readiness represent valuable and rare assets that distinguish high-performing firms from competitors (Barney, 1991).

The acceptance of Hypotheses 6 and 7 provides critical insight into the mediating mechanisms through which leadership influences AI adoption. Hypothesis 6, which posited that organizational readiness mediates leadership's influence, showed a significant indirect effect. This reveals that leadership vision does not automatically translate to adoption; it must first be operationalized into structural preparedness. Hypothesis 7 was similarly validated, confirming that employee competence serves as a critical bridge that transmits leadership's impact into technological integration. These findings demonstrate that digital transformation is a sequential journey in which leadership first translates vision into internal 'will and skill' before those factors manifest in actual adoption. This alignment confirms the theories of Armenakis et al. (1993) and Weiner (2009) on organizational readiness as a 'shared psychological state' that must be cultivated for change efforts to be successful. Within the Resource-Based View (RBV), this reflects the process of transforming potential resources into realized capabilities, in which leaders actively manage human capital to build a competitive advantage (Barney, 1991; Wernerfelt, 1984).

Furthermore, from an OIPT standpoint, the mediating roles of OR and EC act as the 'connecting tissue' linking top-down management with bottom-up operational execution (Daft & Lengel, 1986). By ensuring that accountants have the necessary competencies and that the organization has the structural capacity, leaders effectively set the communication channels required for AI-empowered systems to thrive. Thus, leadership's most transformative role in the Indonesian accounting sector is its ability to build the technical and psychological infrastructure represented by readiness and competence.

CONCLUSION

This study provides significant empirical evidence on how leadership influences AI adoption within Indonesian firms, particularly from the perspectives of professional accountants. The findings affirm that leadership plays a pivotal role not only in directly impacting AI adoption but also in fostering employee competence and enhancing organizational readiness. These mediating factors—employee competence and organizational readiness—serve as crucial bridges through which leadership exerts its full influence on successful AI implementation. This research provides a definitive empirical roadmap for AI adoption within the Indonesian accounting sector. The validation of all seven hypotheses reinforces the Resource-Based View (RBV), demonstrating that leadership is the "strategic orchestrator" that transforms intangible assets into dynamic capabilities (Barney, 1991). Moreover, the study validates Organizational Information Processing Theory (OIPT) by showing that structural readiness and employee skills serve as the "information channels" through which strategy is transmitted (Daft & Lengel, 1986). This research successfully validated seven hypotheses, all of which demonstrated statistically significant relationships. Leadership was found to strongly influence both employee competence and organizational readiness, reinforcing the notion that effective leadership inspires capability development and cultivates a supportive environment for innovation. Moreover, both employee competence and organizational readiness were shown to positively impact AI adoption and strengthen leadership's influence on it, confirming their vital mediating roles.

This study contributes to redefining employee competence and organizational readiness by serving as a mediator in the Leadership-AI Adoption relationship. This nuance adds a novel layer to existing frameworks in innovation adoption and organizational change theories, especially in the Indonesian context, where such empirical studies are limited. Practically, this suggests that organizations seeking to accelerate AI transformation must prioritize leadership development that nurtures both technical competence and organizational infrastructure. While the findings are compelling, the study is not without limitations. This study was conducted among firms in Indonesia, especially those in the accounting sector. In addition, data were collected through surveys, which may introduce bias. Furthermore, future research should consider different regions and industry sectors to experiment with and analyze different scopes. Despite these limitations, this research marks a meaningful advancement in understanding the mechanisms behind successful AI adoption. It emphasizes that digital transformation is not solely a technological challenge, but a human and organizational one. A company must invest in leadership, employee training, and technology readiness. Organizations that understand and act on every development are more likely to achieve sustainable digital integration.

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