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DOES ARTIFICIAL INTELLIGENCE MATTER? THE ANTECEDENTS AND CONSEQUENCES OF ARTIFICIAL INTELLIGENCE USE IN ORGANIZATIONS

presented by Jill N. Floden

a candidate for the degree of Doctor of Business Administration

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DOES ARTIFICIAL INTELLIGENCE MATTER? THE ANTECEDENTS AND CONSEQUENCES OF ARTIFICIAL INTELLIGENCE USE IN ORGANIZATIONS

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By
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DEDICATION

To my son Soren, who inspires me to be the best version of myself, thank you for your unwavering support and supply of hugs while I worked.

To my husband Ben, my support foundation who spent countless hours as my first reader, listened to me work through my thoughts on research, as well as pretended to understand academic jargon, yet he still champions me.

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Dreams may be achieved when you surround yourself with a network of support that allows you to be your authentic self and relentlessly pursue your goals. It takes grit, long hours, discipline, and, let's be honest, a bit of crazy obsession to go after a doctorate while working full time and maintaining a home and family life. However, it is very rewarding at the same time. Hence, I greatly appreciate and thank all who helped and kept me grounded.

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ABSTRACT

Artificial intelligence (AI) is a technology that uses machine-based intelligence and advanced computing to mimic human cognitive functions to build, create, develop, make decisions, and perform tasks on its own (Jingyu Li. et al., 2021). Prior literature has espoused a wide variety of AI use capabilities, but there is a lack of research on AI outcome factors and its influence on organizational outcomes.

This dissertation aims to help fill these research gaps by examining the aspects of managing AI and its outcomes through two studies. Study 1 examined the influence of perceived risks, controls, and AI connectedness on AI outcomes. I conducted a confirmatory factor analysis and a partial least squares structural equation modeling (PLS-SEM) analysis. The results indicated AI connectedness is an influential mediator and that manual controls have a significant positive influence on AI connectedness. Study 2 reviewed how AI outcomes influence competitive intelligence and organizational outcomes, with strategy orientation and reactionary strategy being moderators of the relationships. Using PLS-SEM analysis methods, results showed that competitive intelligence is a significant mediator between AI outcomes and organizational outcomes and strategic factors have significant main effects on competitive intelligence.

Findings from these studies contribute to academic literature by illustrating the key role of AI controls and AI connectedness in influencing AI outcomes. Further, this dissertation also shows that improvements in AI outcomes can subsequently lead to improved organizational outcomes through competitive intelligence. These findings have important practical significance since managers can leverage AI controls and strategic focus to improve AI outcomes and organizational outcomes.

Keywords: Artificial intelligence, AI outcomes, connectedness, competitive intelligence, risks, controls, strategy

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ABSTRACT

Artificial intelligence (AI) is taking the world by storm as an innovation expansion driven by the extensive opportunities of use capabilities and evolution due to its ability to mimic human-like actions. An example of a popular AI engine to capture the public imagination and use is the generative AI application ChatGPT. Current progress and hype notwithstanding, the empirical research on enterprise use has not received sufficient consideration. This paper applies sensemaking theory to posit that the top management teams' (TMT) AI connectedness is an impactful mediator between perceived risks and AI outcomes. Also, it posits that internal controls moderate the perceived risk relationship with AI connectedness. This study used a cross-sectional survey of information technology managers and higher in organizations that had been using AI for more than one year. The results indicated AI connectedness is a mediator and that manual controls have a main effect on AI connectedness. This study contributes to both information management and management literature and provides better awareness for TMTs.

Keywords: Artificial intelligence, AI, perceived risk, controls, AI connectedness

Essay 1: Does Artificial Intelligence Connectedness Matter? A Risk-Control Perspective on Artificial Intelligence Outcomes

Artificial intelligence (AI) refers to various kinds of technology ecosystems, algorithms, or machine learning using varying levels of autonomy (Dwivedi et al., 2021). Broadly defined, AI includes technologies that use machine-based intelligence and algorithm capabilities to mimic human cognitive functions to search, collect, analyze, and make decisions based on big data (Langley & Simon, 1995; Li et al., 2021). With the rapid evolution, expansion, capabilities, and factors of AI, it has been examined and referred to as an exploratory frontier (Berente et al., 2021; Fosso Wamba, 2022; Teodorescu et al., 2021). Society and business environments have continuously expanded due to AI's dynamic, personal, and customizable capabilities (Østerlund et al., 2021). Organizations use AI for creation and innovative analysis to develop outcomes from human and machine input to perceive and abstract virtual or real environments that increase technological aptitude in a worldwide marketplace (Borges et al., 2021). Thus, new business models have emerged to leverage AI capabilities, create opportunities, and enhance, scale, and capitalize performance in new ways (Dong et al., 2023).

Extant literature has suggested that organizational use of AI with semi-autonomous or fully autonomous capabilities requires top management teams (TMTs) to be aware of risks to make better decisions regarding their firm's capabilities and controls (Berente et al., 2021; Dwivedi et al., 2021). This is important for TMTs as research has found costly impacts for organizations due to the unintended risks and consequences of AI development (Taeihagh, 2021). For example, generative AI used by individual employees may inadvertently or incorrectly impact decisions and create unintended challenges or consequences for TMTs (Berente et al., 2021). Because of this, academics, regulators, and other stakeholders have called for improved transparency, ethics, and frameworks for decision-making regarding organizational AI use (Bonsón et al., 2021; Dwivedi et al., 2021). In spite of this, little empirical research has covered the risk-control relationship or the influence of AI connectedness on AI outcomes.

In this study, I extend the current literature on AI development to AI outcomes (post-adoptive use, AI maturity, AI orientation) with a specific focus on the influence of AI connectedness. The definitions of AI by Li et al. (2021) and Langley and Simon (1995) were adapted to state that AI outcomes stem from an organization's use of technologies that utilize machine-based intelligence and algorithm capabilities to mimic human cognitive functions to explore, gather, evaluate, and make decisions. Prior research has focused on the creation of capabilities and implementation, but few articles have focused on how AI matures or how firms work to align towards AI orientation (Dong et al., 2023; Dwivedi et al., 2021; Li et al., 2021). Drawing on sensemaking theory, I postulated that the perceived risks negatively influence AI connectedness, and AI connectedness acts as a (partial) mediator between perceived risks and AI outcomes, positively influencing AI outcomes. Additionally, internal controls were posited to positively moderate the relationship between perceived risks and AI connectedness.

This study empirically examined the aforementioned concerns through these overarching research questions:

1. What influence do TMT perceptions of AI, in terms of perceived risks and controls, have on AI outcomes in organizations?
2. Does AI connectedness play a mediating role on the influence of TMT perceptions on AI outcomes in organizations?

The following sections will present an overview of extant literature on AI and connectedness, AI and human interaction, and perceived risks and controls. This is followed by the theoretical framework and hypotheses development section, which describes the construct and the corresponding hypotheses. This is followed by the methods section, which describes survey sample design, the collection of data from TMTs, the conceptual and operational definitions of variables, and procedures. I conclude with the potential implications for research and practice from this study.

Research Background

Artificial Intelligence and Connectedness

Novel and innovative AI has been rapidly overtaking six decades of prior AI development (Duan et al., 2019). As stated previously, the definition of AI by Li et al. (2021) and Langley and Simon (1995) was adapted to state that AI outcomes result from an organization's use of technologies that utilize machine-based intelligence and algorithm capabilities to mimic human cognitive functions. Currently, AI has been hyped or popularized due to its varied capabilities and the significant changes in how people or organizations function and further development opportunities in the years to come (P. T. Kim & Bodie, 2021). Research by Borges et al. (2021) indicated that decision support, stakeholder engagement, automation, and new products or services all help with scaling and enhanced business capabilities and strategies. Ogbanufe (2023) stated that TMTs support firm technology and sustainability through their commitment to organizational strategy. Additionally, extant literature has pointed to anthropomorphism, where the traits of humans' behaviors applied algorithm-based agents happen to impact human behaviors and perceptions, such as amplified trust and connectedness between chatbots and humans (Seeger et al., 2021). No existing research was found on the influence or relationship between the TMT and AI connectedness.

Increasingly, AI use in organizations has been a focus of researchers, and the TMT's connectedness to AI may be an important factor in the overarching integration of AI outcomes in future work. This study uses the psychological term connectedness adapted from Watts et al., (2022) to refer to a state of feeling connected to self, and others, and the wider world. The terminology on connectedness extends beyond psychology; for example, it includes research highlighting innovative social influence roles (Rangus & Černe, 2019) and connectedness with chatbots or intelligent assistants (Seeger et al., 2021). Additionally, connectedness research covers many disciplines to help investigate a connection or relation between things, for example, networks (Abubakre & Mkansi, 2022), mathematics (Deepak et al., 2019), environment (Barrows et al., 2022), and medical networks (So et al., 2020). Research has also found that connectedness helps sustain relationships like cross-divisional firm initiatives (Kelley, 2009). Further consideration of various organizational AI use of technological contexts, challenges, risks and the potential impact on decision-making has been solicited in the extant literature (Dwivedi et al., 2021). No current or past research was found during this study regarding TMTs' perceptions on how AI connectedness relates to AI outcomes in their organizations.

Artificial Intelligence and Human Interaction

With the brisk progression of AI, human interaction with AI has become a significant factor for TMTs that need to allocate the appropriate level of resources and people in an organization (McBride, 2021; Melville et al., 2023; Samuel et al., 2022). Researchers have found numerous challenges like transparency, knowledge, and confidence in overriding the algorithm that could negatively impact human interaction with AI (Berente et al. 2021; Möhlmannn et al. 2023; Tarafdar et al. 2023). Contrary to the challenges though are numerous combinations of properly defined hybrid human–computer teams that optimize work environments by implementing use of structured and well-defined separation of decision-making by AI and operational decisions by humans (Bayrak et al., 2021; Melville et al., 2023). Bayrak et al. (2021) utilized game theory to investigate human–computer teamwork and observed that a human review of the output increased overall performance. Seeger et al. (2021) oversaw an experiment with humans and chatbots which showed that trust impacts human decision-making. A comparison study by Bayrak et al. (2021) reviewed human–multiple computer agents utilizing portioned problem solutions that outperformed human–single agents, showing sizable complex problems perform better with a multi-agent plus a human in the decision-making. Consequently, human interaction with AI is a valid component for TMTs to lead and orient correctly to manage risks in their organizations (Berente et al., 2021; Namvar et al., 2023).

AI–human interaction in extant literature is summarized in Table 1.

Table 1

References for Artificial Intelligence–Human Interaction

Authors	Theories (Method)	Contribution
Möhlmannn (2022)	Enactment theory & Sensemaking theory (opinion)	Introduced model of algorithm sensemaking by tying together enactment, selection, and retention.
McBride (2021)	Agency theory (opinion)	Observed that humans lead and mold the science behind research and refocused the notion that humans in the loop are inevitably agency-driven from humanistic social norms and rituals, learned and practiced rather than non-conscious software.
Melville et al. (2023)	Affordance theory (scoping review)	Focused on the social outcomes, with humans back in the loop.
Samuel et al. (2022)	Cognitive fit theory (experiment)	Showed that AI can augment the humanistic side of human work, becoming an extension of capabilities.
Berente et al. (2021)	Sensemaking theory (opinion)	Review encourages AI management by both social and technical components and their interaction to push scope and capabilities of AI.
Seeger et al. (2021)	Psychological theory of anthropomorphism (experiment)	Found conversational agents such as chatbots show an element of human connectedness and trust that affect human behavior.

Note. AI = artificial intelligence

Perceived Risks and Potential Liabilities

Regardless of the benefits of AI use, there may be catastrophic events if an organization via the TMTs fails to pre-plan or fully understand the potential risks of decision-making (Dwivedi et al., 2021; X. Zhang et al., 2022). Previous research has delved into the potential impacts of perceived risks of AI if not managed and has sorted risks into data risk (e.g., data bias, dataset shift, out-of-domain data risk, adversarial attacks), and model risk (e.g., model bias, model misspecification, model uncertainty) that should be reviewed and managed (X. Zhang et al., 2022). Due the rapid speed of innovation, both opportunities and challenges abound for TMTs tasked with balancing rewards with all of the perceived risks of organizational AI use (Rana et al. 2022; X. Zhang et al. 2022). Since AI may generate or act autonomously, similar to human cognition, it can create unforeseen outputs or outcomes, which increase overall perceived risks if controls are not wisely applied (Rana et al. 2022).

The TMTs need to be vigilantly aware of risks based on the complexities of AI use in their organizations for decision-making (Dwivedi et al., 2021). Often, AI is aligned to each organization's complex and customized business model, so researchers have debated the black-box AI design and deemed that models and algorithms in many scenarios should be openly viewable, open to interpretation and explainable for independence and human agency (Ashok et al., 2022; Venkatesh, 2021). Additional research on black-boxed AI tools has showcased how model learning takes time, and potential model errors may result in users' bad faith, trust, and judgement being altered to disregard algorithms (Venkatesh, 2021). Further research has shown that humans may skew decisions regarding AI based upon their biases, uncertainty, or lack of understanding, impacting organizational efficiency (Chong et al., 2022; Kordzadeh & Ghasemaghaei, 2022; Venkatesh, 2021). Thus, the TMTs need to be aware that the influence of perceived risks of complex AI may affect decision-making through people's thoughts about the technology and their usage of automated decision-making or a hybrid computer–human combination (Araujo et al., 2020).

Extant research on the nature of human–technology interaction or joint collaboration has called out use behavior as a perceived risk and liability to organizations (Canhoto & Clear, 2020). This is manifested in various ways, such as in the stereotypes between stakeholders and AI agents (Ahn et al., 2022), challenges with applied use and low understanding of AI (Borges et al., 2021), the level of employee cooperation to use innovative technology (AlSheibani et al., 2018), human choices impacting technology use (von Krogh, 2018), unique risks of biased after-effects (P. T. Kim & Bodie, 2021; Venkatesh, 2021) and people's behavior towards risk management tools (Stone et al., 2018). Prior studies on behavior have highlighted the potential consequences of liability and risks if stakeholders and TMTs are not closely related to and confident in their organization's AI (Dwivedi et al, 2021). However, there are few researchers who have specifically examined the TMT's perceptions of perceived risks around organizational AI outcomes.

Prior studies have recently examined the challenges of perceived risk factors towards AI adoption, development, and use (Dwivedi et al., 2021). Table 2 covers the main contributions of extant literature on the perceived risks of AI use.

Table 2

References for Perceived Risks

Authors	Theories (Method)	Contribution
X. Zhang (2022)	No theory (systematic risk analysis)	Reviewed source of AI model prediction risks and uncertainty to press for a risk analysis and management framework specifically for AI systems.
Ashok et al. (2022)	Stakeholder theory (systematic literature review)	Found numerous ethical implications for the use of AI in digital technologies using an ontological framework.
Rana et al. (2022)	Contingency theory (survey)	Extended explainable AI by examining the integration of AI into business analytics. Found unintended consequences of adoption may impair competitive advantage.
Chong (2022)	No theory (experiment)	Showed that humans' confidence in themselves directs decision-making more than humans' confidence in AI, as credit or blame is based on prior human experience.
Canhoto & Clear (2020)	No theory (opinion)	Created a framework to identify and manage AI risks that may hinder value creation or create value-destruction.

Note. AI = artificial intelligence.

Controls

Organizations set internal controls for AI use to mitigate or entirely remove perceived risks (Borges et al., 2021; Boudreau & Robey, 2005). Tech giants such as Google, Amazon, and Microsoft have developed data-driven AI as a service (AIaaS) that may suit simple or complex organizations due to their customizable control functions and integration capabilities (Borges et al., 2021; Cobbe & Singh, 2021). However, stakeholders, researchers, and policymakers have debated over suitable controls for AI overall, which is difficult as AI has been primarily a company-led revolution (Østerlund et al., 2021). For example, a survey of managers in India by Rana et al. (2022) suggested that AI has a negative impact on performance due to a lack of structure or controls, poor data quality, and ineffective training. These issues may leave organizations with sizeable internal control gaps that may become expensive or potentially catastrophic regulatory difficulties (Taeihagh, 2021). Few empirical studies have reviewed the role of internal controls' influence on perceived risks since private corporations are not very transparent, with no overarching industry risk and control framework and only the AI ethics principles (B. Kim et al., 2020).

The TMTs are challenged with managing internal controls in their organizations due to the evolution of business, society, or the environment (AlSheibani et al., 2018; Dwivedi et al., 2021). It is possible for AI to function with various levels of human interaction or completely autonomously, so TMTs should comprehend what AI is used for and how the human role integrates business processes, algorithms, models, mechanisms, and functions to lead proper controls (G. Zhang et al., 2021). Extant literature has highlighted how influential developer bias may unintentionally pervade AI applications or models, which may become compliance issues (Ashok et al., 2022; Araujo et al., 2020). Research by Chong et al., (2022) suggested humans' confidence in themselves impacts decision-making on setting infrastructure governance of intelligent systems. There is a complex relationship between human values or beliefs and technology use, as both under- and over-reliance is suggested with technology such as AI (Chong et al., 2022; Hoffman et al., 2013). Thus, performance may be influenced, dependent upon the focal points of fit, by task-technology and behavioral theory (Goodhue, 1995). Although TMTs are involved in AI decision-making on behalf of their organizations, there is scant prior empirical research on their perceptions regarding AI outcomes and their use of controls of AI, which could greatly impact their organizations.

Organizations faced with governance of vital AI controls, both human and technological, require TMTs to understand great complexities of AI use to make decisions (Osmundsen & Bygstad, 2022). Thus, the central extant literature used for this study is displayed in Table 3.

Table 3

References for Controls

Authors	Theories (Method)	Contribution
Kokshagina et al. (2022)	Institutional theory (case study)	Found stakeholder influence controls to form the process and outcome of regulations
Osmundsen & Bygstad (2022)	Digital infrastructure theory (longitudinal case study)	Identified basic interaction trends between sense-giving and sense-making, enabling governance continuous infrastructure controls
Østerlund et al. (2021)	No theory (opinion)	Purposeful design can offset other machine learning issues, changing how humans work
Alsheibani et al. (2018)	Innovation theory (mixed methods)	Promotes a readiness framework for companies when adopting AI
Borges et al. (2021)	No theory (literature review)	Reviewed extant literature on AI business strategy and proposed framework guide for management and organizational practices
Rana et al. (2022)	Contingency theory, resource-based view (survey)	Found that operational inefficiencies impact sales growth negatively
Chong et al. (2022)	No theory (experiment)	Research showed that AI–human interaction impacts results since human self-confidence influences the acceptance or rejection of AI suggestions

Note. AI = artificial intelligence.

Overall, a great deal of research on AI has looked at a variety of behavioral theories to dig into decision-making interactions between humans and technology, but few to date have investigated empirically the TMT's decision-making with controls or the influence of connectedness on AI outcomes.

Theoretical Background

Sensemaking Theory

For this study, I drew upon sensemaking theory to help comprehend the impact of TMT dynamics on organizational AI use and decision-making. Sensemaking theory posits that organizational members make sense of unexpected events or situations through a process of action, selection, and interpretation (Cristofaro, 2022; Weick, 1995; Weick et al., 2005). Prior research has suggested sensemaking theory and AI decision-making are intently allied (Osmundsen & Bygstad, 2022; Østerlund et al., 2021; Berente et al., 2021).

Extant management literature on sensemaking has shown that a posture of progression towards higher levels of information with less uncertainty may offer improved sense of a situation to make better overall decisions (Christianson & Barton 2021; Weick et al. 2005). Prior research has also framed sensemaking as a sense of power for TMTs that have decision-making capabilities towards stimulus for organizational performance (Christianson & Barton 2021; Weick et al. 2005). Therefore, it is important to understand the cognition and perceptions of TMTs, their core mental model used in decision-making, how leaders make sense of things, in order to make sound decisions on behalf of their organization (Cristofaro 2022; Berente et al. 2021; Weick et al. 2005). Management personnel act as agents to take wins and losses both inside and outside of their organizations and attempt to make sense of their experiences (Cristofaro, 2022; Weick, 1995). Hence, sensemaking uses current knowledge and applies meaning-making, incorporating prior experience, comprehension, and understanding of information the individual has to rationalize decisions (Christianson & Barton 2021; Weick et al. 2005). Prior research has suggested that TMTs enact a mental process of perpetual brokering for firm resources for their teams and their own ambitions to achieve their goals (Cristofaro, 2022). Thus, the encompassing environment is part of their continual cognitive progression to take in new information by observing, interpreting, and ascribing meaning to decisions and subsequent actions (Christianson & Barton, 2021; Cristofaro, 2022; Sandberg & Tsoukas, 2020). The result is that TMTs directly apply their sensemaking to any actions which require decision-making, such as AI outcomes.

Applying sensemaking to technology helps to close in on the unknown where individuals infuse their own discernments and interpretations about technology use and its capabilities (Weick, 2000). Prior research has suggested managers attempt to figure out innovate tech from their own prior use and their own comprehension that shapes their behavior towards adoption and use for themselves and their organization (Cristofaro, 2022; Techatassanasoontorn et al., 2023). Venkatesh et al. (2023) considered the relationship of individual humans as agents and technology use as a signal to predict behavior and intent towards technology use.

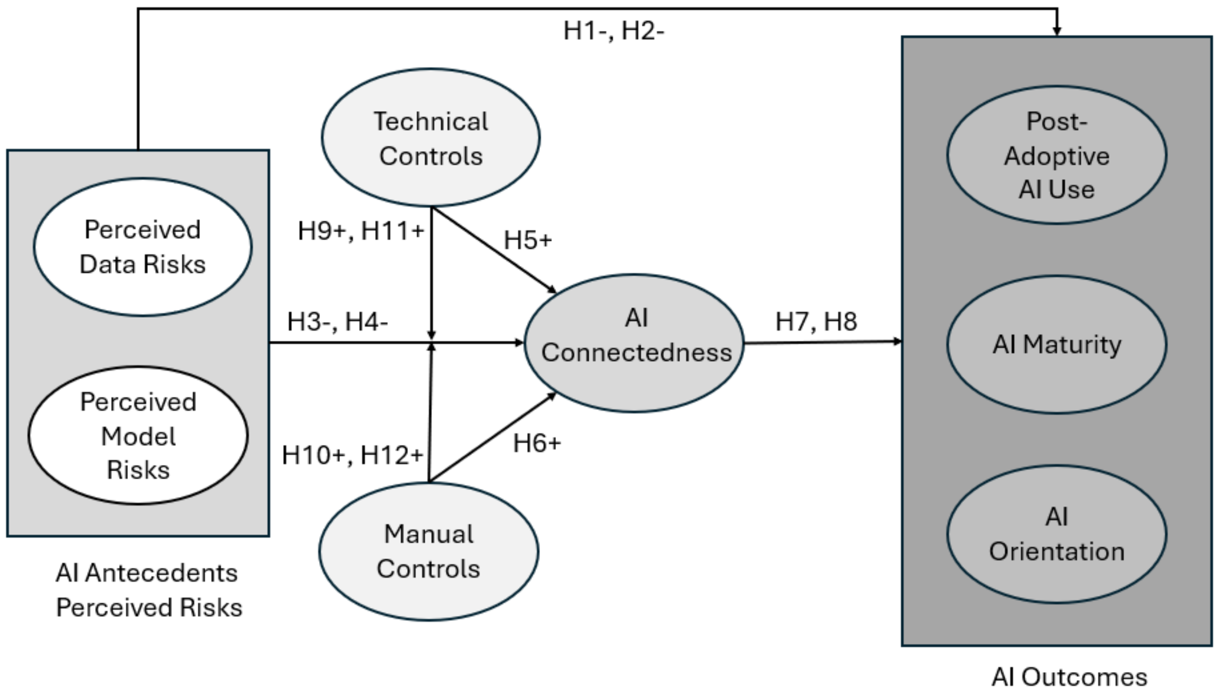
Extant literature has considered that AI surpasses prior technology in that it may behave like humans, expanding capabilities of the decision-making entity within the organization (Berente et al. 2021). Due to the uniqueness of AI decision-making autonomy from earlier technologies, organizations need to be aware of how human users directly or indirectly interact with AI and their level of use (Pelau et al., 2021). The TMTs are tasked to manage and supervise AI systems for their perpetual maturation in their organizations (Berente et al., 2021). Therefore, higher awareness is required for TMTs to better understand AI capabilities, plus the corresponding opportunities (e.g., intelligence, analytics, generativity, scalability) and challenges or limitations (e.g., biases, accuracy, robustness) of tools, integrations, and systems (Berente et al., 2021; Østerlund et al., 2021). Thus, the TMT's sensemaking is a significant component as humans figure out and interact with AI to rationalize and process information relevant to AI outcomes, perceived risks, controls, and feelings of AI connectedness.

Research Model and Hypothesis Development

Portrayed in Figure 1 is the research model hypothesized. This study posits that AI risks, including data and model risks, have a negative influence on AI connectedness. It is posited that AI controls, including technical controls and manual controls, positively influence AI connectedness. It was also posited that AI connectedness is a partial mediator between perceived risks and AI outcomes. Additionally, this study posited that controls positively moderate the relationship between risks and AI connectedness, as well as between the perceived risks and AI outcomes.

Figure 1

Research Model One



Note. AI = artificial intelligence; + denotes a positive association; - denotes a negative association

Dependent Variable: Artificial Intelligence Outcomes

Traditional technology use in organizations was conceptualized through a broadly utilized model that highlights favorable reception and adoption. It conceives that a person's intention is an indicator for use that shapes ease of use and perceived usefulness (Venkatesh et al., 2023). Expanding on this legacy, AI use has abstracted this clarity, of individual intelligibility regarding use of AI logic and algorithms (Glikson & Woolley, 2020; Martin & Waldman, 2022). Thus, it is deemed important for organizations using intelligent systems to decide which innovative aspects of AI to mature, integrate, or distribute (Zapadka et al., 2022).

For this study, I increased AI conceptualization and concentrated on AI outcomes (post-adoptive AI use, AI maturity, and AI orientation) as dependent variables. I altered the definition of post-adoptive AI use from by Li et al. (2021) to be the organization's use of enhanced technologies that utilize machine-based intelligence and algorithm capabilities to mimic human cognitive functions, such as identifying, searching, collecting, detecting, and analyzing big data to generate, integrate, or make decisions. As AI is perpetually flexible, organizations ought to have regular examination, supervising, and analysis to further upgrade or fix problems in order to reach greater levels of maturity (Dong et al., 2023). Altering Becker et al. (2009), I defined AI maturity as any AI enhancement, or any combination of enhancements, which shows measurable improvement, scaling, transfer, or combination of structures, added strengths, functionality, content, or new or updated model or design that organizations implement after initial development and adoption. Additionally, I expanded upon the Li et al., (2021) definition to state AI orientation is an organization's overall strategic direction and goals or objectives associated with managing AI use. Organizations may vary in how they focus on AI, so this study reviewed the impact of AI outcomes (post-adoptive AI use, AI maturity, and AI orientation).

Influence of Perceived Risks on Artificial Intelligence Outcomes

Prior literature, as stated previously, has specified perceived risks as related to AI decision-making (Karwatzki et al., 2022; X. Zhang et al., 2022; Rana et al., 2022). This study used an updated definition of perceived risks from Karwatzki et al. (2022) regarding the extent to which a person perceives or believes that negative or adverse outcomes may arise from specific actions or inaction toward AI.

Extant literature has posited that an AI-specific systematic risk structure is required since AI has distinct challenges, so X. Zhang et al. (2022) took steps by separating and sorting perceived risks into two categories, data and model. Similarly, research on the unintended consequences of AI has pointed out that deficient governance, weak data integrity, and meager training have restrained the overall usefulness of AI (Rana et al., 2022). These perceived risks may foster a dark uncertainty due to things like fraud, identify theft, privacy, and unapproved secondary utilization that create difficult financial costs (Cheng et al., 2022). This study drew upon sensemaking theory to relate TMT experiences, conceptions, and opinions to comprehension of the perceived risks that ultimately impact behavior and AI decision-making (Østerlund et al., 2021). Specifically, TMTs may struggle with comprehension of the generative and autonomous capabilities of AI, as well as the complexity of algorithms or models that impact organizations (Berente et al., 2021). Overall, as stated previously, TMTs may not trust, be certain of, or understand AI, which can have a negative impact on decision-making, use, or improvements to AI (Pelau et al., 2021). Hence, as TMTs perceive AI risks, there may be less chance a manager decides to improve or assign resources to organizational AI outcomes. Thus, this study posits that:

H_1: Perceived data risk negatively influences AI outcomes.

H_2: Perceived model risk negatively influences AI outcomes.

Influence of Perceived Risks on Artificial Intelligence Connectedness

The TMTs may perceive risks of AI and have a feeling of AI connectedness that could sway significant decisions made for the organization. The definition of the psychological construct connectedness is adapted from Watts et al., (2022) as a state of feeling connected to self, and others, and the wider world. This study broadened the definition to define AI connectedness as the perceived state of feeling connected via human emotion, feeling of belonging, relatedness, linking, being interconnected with, and having a cognitive awareness or transparent knowledge about AI. Previous AI research has highlighted individual relationships formed with AI chatbots due to their impressive behavior to mimic human cognitive capabilities (Song et al., 2022). Therefore, I argue that a TMT may form a sense of AI connectedness that assists rationalizing and motivates decisions. This examination excludes the quality or procedure of decision-making.

As AI is dynamic, the TMTs' awareness or relatedness to its components, factors, concepts, technical aspects, methods, and process progression as part of their infrastructure or systems help to adequately manage risks (Stahl, 2022). Prior research has examined the uncertainties of perceived risk and touched on significant outcomes that call for AI and machine learning structured risk frameworks (X. Zhang et al., 2022). Although progress has been made by researchers, the perpetual changes, along with the complex nature of innovative AI ecosystems, make it difficult for TMTs to be trained on the technology's overarching risks; thus, an uncertainty gap may exist, and interpretation of perceived risks may differ.

Organizations looking to get the greatest benefit from AI use have to trade off a certain level of risk, which may be swayed by individual inclinations instead of efficiencies (Tofangchi et al., 2021). Prior research has suggested that AI mimics human cognition with perpetual change and there is also a similarity in the risks identified (Ashok et al., 2022). Extant literature has examined a broad spectrum of the perceived risks, for example, dignity and well-being (Formosa et al., 2022), accountability (B. Kim et al., 2020), fairness (Dolata et al., 2022), trust in algorithmic grading (Jackson & Panteli, 2023), and other human biases that can impact AI maturity (Akter et al., 2021). Thus, TMT sensemaking impacts decision-making as personal experience, and knowledge may alter perceptions towards AI and any level of interaction with the technology (Berente et al., 2021). This makes TMT awareness of relatedness and understanding of how capabilities and complex intelligence systems function, as well as their limitations, highly important to managing perceived risks (Østerlund et al., 2021). Therefore, I argue that leaders' perceived risks of AI will discourage favorable attitudes toward AI connectedness. This suggests the following:

H_3: Perceived data risk negatively influences AI connectedness.

H_4: Perceived model risk negatively influences AI connectedness.

Influence of Controls on Artificial Intelligence Connectedness

Overall, organizations have many competing areas for resources that make it challenging for TMTs to discover and set proper internal controls (Li et al., 2021). I updated the definition of organizational internal AI controls from Kautish and Khare (2022) as the perceived level of adaptive controls or efficiencies of controls that TMTs think or believe they have to manage their organization's AI use. Since AI may act through a continuing metamorphosis, there is a need and a push by regulators for proper controls with a review mechanism that allows for swift modification and enhancements as AI changes (Stahl, 2022). Unfortunately, no general controls standards for AI exist since many organizations develop their own AI ecosystem, which makes standardization difficult (Kokshagina et al., 2022). Recent research has suggested that a human in the loop and program auditing lessens trust perceptions of algorithm legitimacy, but clear governance and a human formal appeal to the algorithmic decision-making boosts perceived trust of algorithm legitimacy (Martin & Waldman, 2022).

Since scant AI regulatory governance exists, organizations may develop their own level and type of controls based on their jurisdiction (Labadie & Legner, 2023). Controls mechanisms such as improved infrastructure may positively impact AI connectedness through perpetual improvements, procedure, nurturing, and integration, which help sustain an organization as it discovers both opportunities and weaknesses (Osmundsen et al., 2022). Organizations through their TMTs often attempt to align decision-making with organizational outcomes, although their success may vary dependent upon type or level of agency interaction (Borges et al., 2021). As a leader, the TMT is tasked with mechanisms to control both technical systems and level of human characteristics to metamorphose integrations, infrastructure, perceived risks, development, and control mechanisms (Rana et al., 2022). A TMT is so intimate and related to organizational success that they develop a feeling of AI connectedness. Thus, I propose that:

H_5: The TMT's perception of AI technical controls will have a positive influence on AI connectedness in an organization.

H_6: The TMT's perception of AI manual controls will have a positive influence on AI connectedness in an organization.

Mediating Role of Artificial Intelligence Connectedness

As explained previously, AI connectedness refers to the TMTs' perceived state of feeling connected with AI (Dwivedi et al., 2021). Research by Song et al. (2022) suggested that humans form relationships and feelings of love, intimacy, connectedness, passion, and commitment with their chatbots or intelligent assistants via repetitive interactions over time or a one-time interaction. Arguably, many see AI as opportunistic since it adds capabilities and proficiencies that would be considered an enhancement (Dwivedi et al., 2021). This view may be a false positive since individual humans may form AI connectedness dependent on their prior experience and understanding of AI risks and controls that may skew their rationale. Due to this, I argue that TMTs form a feeling of AI connectedness established through use of AI and their individual cognition, belonging, awareness, and relatedness. Thus, the TMT's AI connectedness will positively influence views and subsequent decision-making regarding AI. Hence, I postulate that:

H_7: The relationship between perceived data risks and AI outcomes is mediated by AI connectedness.

H_8: The relationship between perceived model risks and AI outcomes is mediated by AI connectedness.

Moderating Role of Controls

As shown in Figure 1, this study conceptualized controls in reference to enterprise internal controls that TMTs manage through their decision-making and comprehension of perceived risks and AI outcomes. Prior research has found that TMTs develop and manage their internal controls to help run a highly capable organization (Kautish & Khare, 2022). For example, specifically detailed design and visual framing implemented for users makes stronger control actions concerning human decision-making (Kummer & Mendling, 2021). By utilizing sensemaking theory, TMTs form decisions centered on their sense of the perceived risks and their knowledge of the organization's needs, requirements, and capabilities to manage controls. Notably, human attachment to intelligent technologies may be due to cognitive capabilities

(Song et al., 2022). Echoing prior research, this feeling of connectedness to AI may be grounded in the continuous aspects of AI that mimics humans, in that it is capable via algorithms or systems to develop, enhance, learn, find and output relatedness, and the ability to manage its own risks via ecosystem controls or layering of algorithms (Berente et., al., 2021). However, fear, trust, uncertainty, perceived risks, costs, or other reasons may be prohibitive factors in adoption, use, or enhancement of AI (Dwivedi et al., 2021). Consequently, as stated previously, these parts highlight the importance for the TMT, which is tasked with making judgements and successive actions to manage the relationship between perceived risks, controls, and AI connectedness. Thus, this study hypothesizes that:

H_9: Technical controls positively moderate the influence between perceived risks and AI connectedness.

H_{10}: Manual controls positively moderate the influence between perceived risks and AI connectedness.

According to sensemaking theory, AI continuously changes but has often been fully integrated into organization procedures, so TMTs work to align risk with the ever-changing AI use (Østerlund et al., 2021). Operating through agile thinking may benefit organizations quickly instead of requiring the previous long-cycle technology buildouts, so it is important that TMTs actively design their AI infrastructures (Osmundsen & Bygstad, 2022). Moreover, organizations may monitor boundaries, risks, and possible obligations to manage them through machine learning models to counter the biases of other machine learning models so the controls can be constantly enhanced to align to the business evolution (Østerlund et al., 2021). The conclusion is that perceived risks may impact AI outcomes moderated by controls that TMTs may establish for their organizations. Thus, this study hypothesizes:

H_{11}: Technical controls positively moderate the relationship between perceived risks and AI outcomes.

H_{12}: Manual controls positively moderate the relationship between perceived risks and AI outcomes.

Research Methods

Sample Design

Extant literature has examined survey data to investigate individuals' perceptions and AI use (Fosso Wamba, 2022; Song et al., 2022). As an example of this, Pelau et al. (2021) examined psychological anthropomorphic characteristics via AI utilizing a student survey. Song et al. (2022) inspected individual love for intelligent agents by surveying consumers who use chatbots. Fosso Wamba (2022) surveyed supply chain executives on AI assimilation. Therefore, this study extends previous research in the endeavor to gather insight on the relationship between perceived risks and controls from the TMT's stance on AI outcomes. In addition, this study reviews AI connectedness. Furthermore, AI connectedness and its associated constructs are in the decision-making realm of an organization that it is practicable to examine (Abubakre & Mkansi, 2022; Coombs et al., 2021). Prior strategic management literature has utilized TMTs to get a survey sample for studying constructs and relationships dealing with decision-making (Fosso Wamba, 2022). Therefore, the TMT in a company is an appropriate sample for this study.

This study conducted theory testing rather than theory conception, a survey instrument that was deemed appropriate as it provided a standardized data collection to test existing theory (Aguinis et al., 2021). Based on Yin (2013), a cross-sectional survey was considered suitable to do theory testing for this study as this study sought to assess a research model.

This study adapted the constructs post-adoptive AI use (Fosso Wamba, 2022), AI maturity (Chen & Lin, 2021; Fosso Wamba, 2022; Hauptman et al., 2023), AI orientation (Ravichandran, 2018), technical controls (Amoo et al., 2019; Nguyen et al., 2021; Otley & Pierce, 1996), manual controls (Amoo et al., 2019; Nguyen et al., 2021), data risk (Amoo et al., 2019; Ravichandran, 2018), model risk (Pelau et al., 2021; Ravichandran, 2018; Skulimowski & Köhler, 2023; Song et al., 2022), and AI connectedness (Song et al., 2022; Hussein et al., 2021; Pelau et al., 2021) and supplemented new questions. Perceptions and feedback were received first by running the draft survey questions by three practitioners who work in an information technology role with more than a year of organizational AI use. The survey draft was amended based on their critique and suggestions. Next, the survey was reviewed by three professors with AI experience to ensure each of the questions was understandable. The survey was amended based on their expert feedback. Afterwards, the study was piloted via Qualtrics to ensure the survey was functioning as expected. To increase common understanding, AI was specifically defined at the beginning of the questionnaire, as stated in the theory section. Also, CI was defined and stated to be used in relation to the CI questions.

The following control variables were included: firm size (number of employees), firm age, industry, and AI investment were all voluntary questions. Additional optional demographic data was also obtained, including age, gender, education, role, years of work experience, and AI expertise (Fosso Wamba, 2022; Kranz, 2021; Nguyen et al., 2021). Firm age and firm size were included as prior studies have linked this information to firm innovation. Based on pilot study feedback, AI investment was added.

The survey instrument was shaped by amending scales from prior studies using a 7-point Likert scale (1 = *strongly disagree*, 7 = *strongly agree*). This study followed the literature guidance on data collection (Aguinis et al., 2021; Nwafor et al., 2022). In addition, the study utilized ethical guidelines to ensure the collected data is generalizable, of good quality, and secure (Aguinis et al., 2021). Using an online statistical power calculator from Soper (n.d.), the minimum sample size was found to be 151 (effect size 0.15, desired statistical power level 0.8, eight latent variables from the research model, probability level of 0.05).

A structured online Qualtrics survey was administered that gathered 260 completed survey responses. Participants were obtained and compensated via Centiment for giving a complete and valid survey. The survey used inclusion criteria specifying the respondent be role equivalent to an information technology manager or higher, has used AI in their organization or has been the decision-maker on AI for their organization for more than one year, and be 18 years of age or older. The survey responses were voluntary and anonymously gathered with detailed instructions explaining that there were no right or wrong answers. Survey responses were screened to exclude flawed responses such as failure of the attention check, straight lining, and rapid response (taking less than three minutes to complete the survey). Respondents were only able to complete the survey once to make certain that each response was distinctive. A pilot study (n = 29) was collected from an initial set of respondents from the Qualtrics online survey pool based on the study inclusion criteria. The pilot sample was reviewed for average duration to make sure it could be completed in around 10 minutes. The pilot sample was examined to see if factors loaded separately, as well as means and standard deviation were in line for the research model. The finished online survey was then further distributed to gather the remainder of participants, and pilot study responses were included in the final sample.

Data Collection

Data was gathered from respondents who were in an information technology manager or higher role, with one year of organizational AI use or AI decision-making authority as a proxy for TMTs. SmartPLS software was used to conduct a confirmatory factor analysis, structural equation modeling (SEM), and hypothesis testing.

Since this study assessed all variables at the same time, having used a sole online panel platform survey tool, common method bias was a concern (Podsakoff et al., 2003). A marker variable was used to control for possible contaminating effects that were not related to a minimum of one variable in this study to observe relationships between it and any of the other variables which may be assumed to contribute to common method bias (Podsakoff et al., 2003). This study's validity is important to consider as prejudice may have an adversarial impact on constructs and beta-weights (Podsakoff et al., 2003). Therefore, this study scrutinized common method bias by separating factor loading of dimensions and conducting a single-factor test (Podsakoff et al., 2003).

Procedures

A Qualtrics survey was used via the online panel platform Centiment to recruit respondents who were paid after a valid full survey completion. At the opening of the survey, respondents were asked to attest informed consent. Respondents were given instructions that they may complete the survey in one or more sessions, offering options to complete it anonymously via mobile phone or computer. Concise and easy questions were used in the survey to control for possible challenges with non-response bias and to appeal to higher involvement. Respondents received reminders from the system if only part of the survey was completed to promote completion and enhance contribution. To control social desirability bias, the survey was collected via anonymous response, and all data was kept confidential, with no personal information shared with others. The final gathered data set (N = 260) was completed via a Qualtrics online survey and combined with the pilot sample, then reviewed and cleaned for SEM analysis.

Measures

The scale items were carefully selected to benefit from prior measure validity since extant literature was available on the designated variables. In contrast to prior research practices, this study focused on a practical technique of measuring the presence of AI connectedness with AI outcomes by surveying information technology managers (or those in higher positions) specifically. Additionally, a multi-select AI use index was added in Part I, which was subsequently used to select their most familiar AI. The questions were then framed to answer subsequent questions regarding this most familiar AI. No less than 0.70 for each construct was targeted for Cronbach alpha indices. This is central to reasonably gauge the construct measurements (Al-Ansari et al., 2013; Dalakoura, 2010). The number of items and sections of the survey are displayed in Table 4. Table 5 shows the demographics data collected. Table 6 shows the sample respondent characteristics.

Prior research using these variables has measured relationships using a 7-point Likert scale (1 = *strongly disagree*, 7 = *strongly agree*). To assess the construct measurements, Cronbach's alpha indices of no less than 0.70 for each construct were allowed. Table 7 shows the variable items that were used via 7-point Likert scale.

Table 4

Questionnaire Items

Subjects	# of items	References
Data Risk	9	Amoo et al., 2019; Ravichandran, 2018
Model Risk	6	Pelau et al., 2021; Ravichandran, 2018; Skulimowski & Köhler, 2023; Song et al., 2022
Technical Controls	5	Amoo et al., 2019; Nguyen et al., 2021; Otley & Pierce, 1996
Manual Controls	5	Amoo et al., 2019; Nguyen et al., 2021
AI Connectedness	5	Hussein et al., 2021; Pelau et al., 2021; Song et al., 2022
Post-Adoptive AI Use	5	Fosso Wamba, 2022
AI Maturity	5	Chen & Lin, 2021; Fosso Wamba, 2022; Hauptman et al., 2023
AI Orientation	5	Ravichandran, 2018
Control Variables	4	Fosso Wamba, 2022; Kranz, 2021; Nguyen et al., 2021
Total Items:	49	

Note. AI = artificial intelligence.

Table 5

Demographic Variables

ID	Question	Choices
Age	Age	18–25, 26–30, 31–35, 36–40, 41–45, 46–50, 51–55, 56–60, 61–65, >65
Gender	Gender	Write in Text
Race	Race (Please choose all that apply or write in)	Caucasian, African American, Asian, Native Hawaiian or Other Pacific Islander
Education	Highest level of education completed	8^{th} grade or less, Some high school but did not graduate, High School graduate or GED, Some College or 2-year degree, 4-year college graduate, More than 4-year college degree
Role		Staff, Manager, Director, C-level or higher, Other
Years Experience	How many years of experience do you have either a) using AI in your job or b) in a decision-making role involving AI in your organization?	<1, 1–2, 3–5, 6–10, 10+
AI Expertise		Expert, High, Medium, Novice

Note. AI = artificial intelligence.

Analysis

Based on the perceptions of TMTs, this study focused on AI outcomes. Respondents voluntarily provided demographics, as shown on Table 6. This study utilized the desktop-based software tool SmartPLS, version 4.1.0.6 for a full analysis using the partial least squares (PLS) SEM method. A two-part formulation method for PLS algorithm statistical modeling (measurement model) and bootstrapping (structural model) via SmartPLS was used to analyze the proposed relationship between model factors. The PLS-SEM results such as path coefficients, outer weights, Cronbach's alpha, and R-squared values were reviewed via testing the statistical significance via bootstrapping. This was accomplished with the recommended subsample amount (5,000) to analyze the model's posited relationships (Hair et al., 2017). Further review of the discriminant validity of the factors, outer loadings, and general model fit was done in line with the suggested technique by SmartPLS (n.d.) as the manufacturer of the software.

Results: Measurement Model

Initially, to examine the factors, all items from the eight latent constructs were loaded together, and factors were analyzed to ensure the quality of the loadings. Items with factor loadings of less than 0.70 were dropped from the assessment. The recommended benchmark of 0.70 was used, which indicates reliability (Fornell & Larcker, 1981; Zaman et al., 2020). A total of 34 items remained for inclusion in the model. A confirmatory factor analysis was used via SmartPLS to examine the influence of the factors and the relationship between them via the suggested model.

The model suggests a moderate fit result. The normed fit index (NFI = 0.74) indicated a moderate fit but is below the recommended threshold of 0.90. Standardized root mean square residual (SRMR =0.085) was considered a reasonable fit. All the average variance extracted values for the constructs well exceeded Fornell and Larker's (1981) convergent validity criterion of 0.50. R-squared, which measures the proportion of variance in the dependent variables explained by the independent variables, also demonstrated acceptable results of post-adoptive AI use (AIU) = 0.458, AI maturity (AIM) = 0.535, and AI orientation (AIO) = 0.566.

As shown in Table 7, all factors have loadings above the suggested guidelines of 0.70. Table 8 shows scale reliability using Cronbach's alpha, which showed results ranging between 0.812 to 0.929, which is greater than 0.70, and therefore reliability was established (Nunnally, 1978). Table 9 presents the study's composite reliability for all measures used. Table 10 states the results of discriminant validity to validate construct correlations (Fornell & Larcker, 1981).

Table 6

Sample Respondent Characteristics

Demographics	Count	%
Age		
18–25	11	5
26–30	12	5
31–35	37	16
36–40	54	23
41–45	42	18
46–50	18	8
51–55	26	11
56–60	10	4
61–65	15	7
Over 65	6	3
Gender		
Male	159	70
Female	62	27
Non-Binary	1	0
Undisclosed	9	3
Education		
8th grade or less	0	0
Some High School	0	0
High School Graduate	11	5
Some College	30	13
College Graduate	106	46
More than College	80	35
Undisclosed	4	1
Role in Organization		
Manager	124	54
Director	94	41
Undisclosed	13	1
Years in Organization		
0–2 years	3	1
3–5 years	54	23
6–10 years	82	36
10+ years	92	40
AI Expertise		
Expert	45	20
High	113	49
Medium	66	29
Novice	5	2
Undisclosed	2	0
Race **-**		
Caucasian	181	
African American	23	
Asian	15	
American Indian or Alaska Native	6	
Other	18	

Note. AI = artificial intelligence.
- respondents chose any, combination or write in text

Table 7

Measurement Model Assessment

Construct	Item	Loadings
Perceived Risk Data (PRD)[a]		
This AI is more consistent at working with data than human beings.	PRD1	0.935
This AI is more dependable at working with data than human beings.	PRD2	0.915
Perceived Risk Model (PRM)[b]		
Our organization adequately tracks this AI algorithms that predict learning needs of the platform users.	PRM5	0.909
This AI use is consistently monitored, and fine-tuned for our systems, databases, networks, and infrastructure.	PRM6	0.925
AI Connectedness (AIC)[c]		
When I interact with AI, I feel like I am interacting with another human being.	AIC1	0.806
When I interact with AI, I feel that this AI has free will.	AIC3	0.899
When I interact with AI, I feel a sense of closeness.	AIC4	0.932
When I interact with AI, I feel a sense of relatedness.	AIC5	0.907
When I interact with AI, I feel a sense of emotional connection.	AIC6	0.869
Controls Technical (CT)[d]		
Our organization has strong technical controls for this AI that frequently identify errors.	CT1	0.799
Our organization has strong technical controls for this AI that are, in general, effective at detecting inconsistencies.	CT2	0.861
Our organization has the capacity to control the technical aspects of this AI.	CT3	0.846
Our organization has strong technical controls for this AI that are generally effective.	CT4	0.855
Our organization has the right technical controls in place for this AI.	CT5	0.867
Controls Manual (CM)[e]		
Our organization has strong manual controls for this AI.	CM1	0.832
Our organization has manual controls for this AI that can frequently identify errors.	CM2	0.789
Our organization has manual controls for this AI that are, in general, effective at detecting inconsistencies.	CM3	0.848
Our organization has manual controls for this AI that are generally effective.	CM4	0.836
Our organization has the right manual controls in place for this AI.	CM5	0.804
Post-Adoptive AI Use (AIU)[f]		
This AI is used extensively in our organization.	AIU1	0.880
This AI is used across all our business units.	AIU2	0.836
This AI is used for decision-making across all our business units.	AIU3	0.851
This AI is used to support the development of new products and services.	AIU4	0.787
This AI is used to enhance our organization.	AIU5	0.771

Construct	Item	Loadings
AI Maturity (AIM)[g]		
This AI tool has been taught (trained / realigned) to enhance AI maturity.	AIM1	0.772
This AI in our organization continues to mature through repetitive use.	AIM2	0.832
This AI in our organization has changed and improved over time.	AIM3	0.831
This AI in our organization continues to improve through training or realignment.	AIM4	0.853
This AI in our organization has become more efficient over time through training or realignment.	AIM5	0.849
AI Orientation (AIO)[h]		
We have a well-established philosophy around using this AI.	AIO1	0.782
We are creative and innovative with using this "leading edge" AI.	AIO2	0.866
We quickly follow the lead of innovators in adapting new and emerging capabilities for this AI.	AIO3	0.842
We critically evaluate this AI investment to assess business value.	AIO4	0.830
We experiment with new and emerging aspects of this AI.	AIO5	0.827

Note. AI = artificial intelligence.
[a]Cronbach’s alpha = 0.833; Composite reliability = 0.922; Average variance extracted = 0.856.
[b]Cronbach’s alpha = 0.812; Composite reliability = 0.914; Average variance extracted = 0.841.
[c]Cronbach’s alpha = 0.929; Composite reliability = 0.947; Average variance extracted = 0.781.
[d]Cronbach’s alpha = 0.90; Composite reliability = 0.926; Average variance extracted = 0.715.
[e]Cronbach’s alpha = 0.885; Composite reliability = 0.916; Average variance extracted = 0.684.
[f]Cronbach’s alpha = 0.883; Composite reliability = 0.915; Average variance extracted = 0.682.
[g]Cronbach’s alpha = 0.885; Composite reliability = 0.916; Average variance extracted = 0.686.
[h]Cronbach’s alpha = 0.887; Composite reliability = 0.917; Average variance extracted = 0.689.

Table 8

Construct Reliability and Validity

Construct	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	Average Variance Extracted
AI Connectedness	0.929	0.931	0.947	0.781
AI Maturity	0.885	0.886	0.916	0.685
AI Orientation	0.887	0.887	0.917	0.689
Post-adoptive AI Use	0.883	0.888	0.915	0.682
Controls Manual	0.885	0.887	0.916	0.684
Controls Technical	0.900	0.901	0.926	0.715
Perceived Risk Data	0.833	0.843	0.922	0.856
Perceived Risk Manual	0.812	0.817	0.914	0.841

Note: AI = artificial intelligence.

Table 9

Composite Reliability (RHO_C) for All Used Measures

Construct	Original sample (O)	*M*	*SD*	T statistics (|O / *SD*|)	*p* values
AI Connectedness	0.947	0.947	0.006	151.547	0.000
AI Maturity	0.916	0.915	0.012	77.025	0.000
AI Orientation	0.917	0.917	0.011	81.801	0.000
Post-adoptive AI Use	0.915	0.914	0.010	90.150	0.000
Controls Manual	0.916	0.915	0.012	77.009	0.000
Controls Technical	0.926	0.926	0.009	104.729	0.000
Perceived Risk Data	0.922	0.922	0.012	74.9364	0.000
Perceived Risk Manual	0.914	0.912	0.017	53.604	0.000

Note: AI = artificial intelligence.

Table 10

Discriminant Validity: Fornell–Larcker Criterion

	AIC	AIM	AIO	AIU	CM	CT	PRD	PRM
AIC	0.884							
AIM	0.446	0.828						
AIO	0.486	0.841	0.830					
AIU	0.588	0.711	0.702	0.826				
CM	0.437	0.499	0.521	0.432	0.827			
CT	0.415	0.651	0.663	0.501	0.722	0.846		
PRD	0.503	0.505	0.511	0.434	0.387	0.376	0.925	
PRM	0.250	0.253	0.238	0.241	0.214	0.371	0.123	0.917

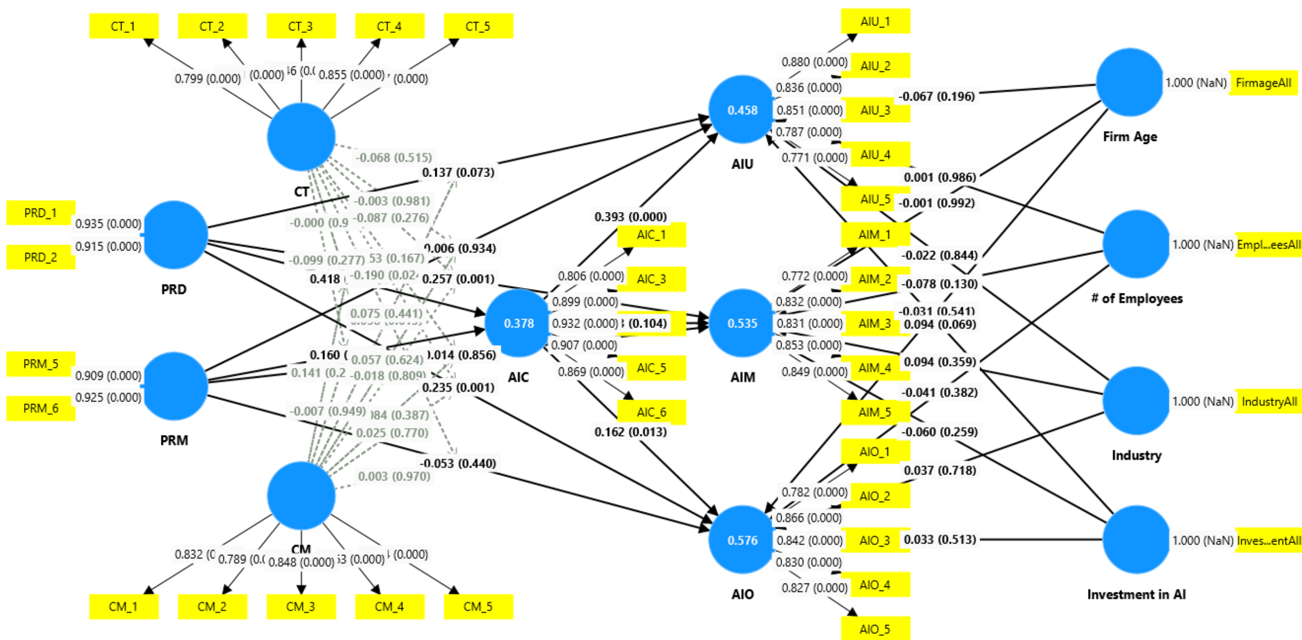
Note: AI refers to artificial intelligence; AIC = AI Connectedness; AIM = AI Maturity; AIO = AI Orientation; AIU = Post-adoptive AI Use; CM = Controls Manual; CT = Controls Technical; PRD =Perceived Risk Data; PRM = Perceived Risk Manual

Results: Structural Model

This study used the SmartPLS PLS-SEM bootstrapping tool to examine the moderating effects of technical controls and manual controls between data risks and model risks and AI outcomes. Table 12 presents the path coefficients from the SEM, examining the relationship between various constructs. The analysis yielded a mixture of results from various pathways as indicated by the variability in path coefficients. The path from AI connectedness (AIC) to post-adoptive AI use (AIU) was significant and positive ($\beta = 0.393$, $t = 4.886$, $p < 0.001$), suggesting a strong influence of AIC on AIU. The variable controls technical (CT) impact on AI maturity (AIM) ($\beta = 0.480$, $t = 4.814$, $p < 0.001$) and AI orientation (AIO) ($\beta = 0.453$, $t = 5.002$, $p < 0.001$) indicated positive effects. The variable perceived risk data (PRD) also showed a consistent positive effect across all its paths, with PRD to AIC ($\beta = 0.418$, $t = 5.371$, $p < 0.001$) being the strongest. A few paths, such as controls manual (CM) to AIM ($\beta = 0.044$, $t = 0.478$, $p = 0.632$) and perceived risk manual (PRM) to AIO ($\beta = -0.053$, t = 0.773, p = 0.440), were not statistically significant, indicating a lack of influence from these constructs on their respective outcomes. Notably, interactions between CM and PRM and also CT and PRM did not yield significant results, with CT and PRM to AIU showing virtually no effect ($\beta = -0.003$, $t = 0.023$, $p = 0.981$).

Figure 2

Structural Model One



Note: AI refers to artificial intelligence; AIC = AI Connectedness; AIM = AI Maturity; AIO = AI Orientation; AIU = Post-adoptive AI Use; CM = Controls Manual; CT = Controls Technical; PRD =Perceived Risk Data; PRM = Perceived Risk Manual

Table 11

Summary of the Structural Model

Hypothesis	Constructs	ß	*t* Values
H_1	PRD → AIU	0.137^{+}	1.795
	PRD → AIM	0.257**	3.482
	PRD → AIO	0.235**	3.374
H_2	PRM → AIU	(0.006)	0.083
	PRM → AIM	$(0.014)^{+}$	0.182
	PRM → AIO	(0.053)	0.773
H_3	PDR → AIC	0.418***	5.371
H_4	PMR → AIC	0.160**	2.595
H_5	CT → AIC	(0.008)	0.071
H_6	MC → AIC	0.241*	2.130
H_7	AIC → AIU	0.393***	4.886
	AIC → AIM	0.113	1.627
	AIC → AIO	0.162*	2.493
H_8	CT x PRD → AIC	0.000	0.003
	CT x PRM → AIC	(0.099)	1.086
	CM x PRD → AIC	0.141	1.238
	CM x PRM → AIC	(0.007)	0.063
H_9	CT x PRD → AIU	(0.068)	0.651
	CT x PRD → AIM	(0.087)	1.089
	CT x PRD → AIO	(0.190)*	2.259
H_{11}	CT x PRM → AIU	(0.003)	0.023
	CT x PRM → AIM	0.153	1.383
	CT x PRM → AIO	0.075	0.770
H_{10}	CM x PRD → AIU	0.058	0.506
	CM x PRD → AIO	0.025	0.292
H_{12}	CM x PRM → AIU	0.057	0.491
	CM x PRM → AIM	(0.084)	0.865
	CM x PRM → AIO	0.003	0.037

$+p < 0.01$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Note: AI refers to artificial intelligence; AIC = AI Connectedness; AIM = AI Maturity; AIO = AI Orientation; AIU = Post-adoptive AI Use; CM = Controls Manual; CT = Controls Technical; PRD =Perceived Risk Data; PRM = Perceived Risk Manual

Discussion

This study finds significance in mediation effects in that AI connectedness acts as a partial mediator on AI outcomes. Although mediation was found, AI connectedness significantly influences AI outcomes (post-adoptive AI use and AI orientation), there was no observed significant mediation on AI maturity. The lack of direct effect supports the mediation role. This result suggests that humans do, in fact, form a feeling of connectedness to AI. The strongest connection was the path from AI connectedness to AI outcomes; this may imply the greater the feeling of AI connectedness, the higher levels of AI outcomes. The strength of the path may indicate AI use is predicated on a feeling of connectedness that may significantly influence integration and use. To the best of my knowledge, this is the first study that has examined AI connectedness based on the perceptions of TMTs.

As this study observed perceived risks, it found both data risks and model risks are antecedents of AI connectedness. Contrary to the negative hypotheses on risks, perceived data risk was found to have a statistically significant relationship with AI connectedness, AI maturity, and AI orientation but no relationship with AI outcomes, which was not statistically significant. Perceived model risk, despite the negative hypotheses, was found to have a positive influence on AI connectedness, suggesting that perceived risks are in fact related to AI connectedness. This may be due to TMTs' awareness of or their attempt to make sense of risks, appropriately aligning risk-based decisions regarding AI for their organizations. This could potentially allude to TMTs' vigilance in keeping a pulse on their organizations' technology aptitude and awareness of AI to provide strategic responses, enhancing their AI overall.

The study did not find support for either technical controls or manual controls in a moderation relationship. This may indicate that the technical and manual controls relationship may not directly impact risk levels or have an impact on the risk versus AI use overall. Even though progress and awareness of AI has increased in recent years, this finding highlights the difficulty that prior researchers have suggested about potential AI use gaps that could negatively affect organizational outcomes (Rana et al., 2022; Taeihagh, 2021; X. Zhang et al., 2022). From a technology standpoint, prior research has suggested that innovation has led ahead of governance or controls (Dwivedi et al., 2021). Additionally, technical controls were not found to have any influence on or relationship with AI connectedness. Therefore, the technical aspects are not sufficient to enhance feelings of connectedness without the conjoined manual aspects.

Surprisingly, manual controls were found to have a main effect (i.e., positive influence) on AI connectedness. This may signal support for prior research, indicating that having a human-in-the-loop, or some level of human interaction, oversight, or collaboration with AI is an important component that allows TMTs to feel connected in managing their organizations' AI (McBride, 2021; Melville et al., 2023). However, no manual controls influenced AI use, AI maturity, or AI orientation. However, technical controls were found to have a positive direct relationship with AI use, AI maturity, and AI orientation. The direct effect may signal trust in the technical aspects of AI, such as their organizational framework or systems. As prior research has eluded to, this may be due to TMT confidence in themselves, leading to over-reliance on technology such as AI (Chong et al., 2022).

Overall, this study demonstrated that AI connectedness mediation exists and has a place in AI research, leading to greater awareness for management teams as they use, mature, and orient their organizations to AI. As researchers and practitioners dig deeper into AI overall, these contributions are vital to further understanding factors that may impact organizational sustainability for the long-term.

Limitations of This Study

This research has a few limitations. First, this research only surveyed information technology management with one year or more organizational AI use; future research may expand to other timeframes or roles. Due to the dynamic nature and evolution of AI capabilities and uses, other qualitative methods may provide deeper causal insights or measures on AI outcomes. Specifically, as this survey was limited in length, it could not capture complex, content-dependent factors relevant to customization, levels of interaction, or other aspects specific to their particular AI or combination of AI used that may impact organizational outcomes. Additional scale development specific to AI outcomes may prove useful to broaden the conceptual framework. Building out additional model constructs, any additional mediators and moderators could broaden the utility of AI connectedness or AI outcomes that were not able to be covered in the scope of this study. Further expansion may give academics and practitioners better answers on how to understand the perceived risks, control frameworks, AI connectedness, and innovative AI for organizational outcomes.

Implications for Research

The challenge for researchers continues due to AI's rapid adoption and innovation in organizations and society (Dwivedi et al., 2021). For instance, AI continues to be seen as complex in terms of both technical and human factors and direct and indirect traits that leaders need to be aware of and manage to obtain optimal firm performance (Mikalef & Gupta, 2021). This study found perceived risks as antecedents. This could be an indicator of increased knowledge and awareness of AI due to the rapid popularity, adoption, and development in recent years. Risk awareness research could be expanded for exploration of pathways with possible mediators or moderators that might influence these relationships. Along with perceived risks, researchers need to continue to explore the paradox between risks and controls and possible combinations including technical and manual controls for a comprehensive governance framework. Future studies could review influencing variables and outcomes to better understand causality.

Finally, as AI connectedness had not previously been examined in relationship to AI, this study helps extend the AI connectedness mediation concept for information management. Further exploration of AI connectedness as a mediator with a larger sample size or additional variables may give further insights. Additional qualitative studies could delve deeper into AI connectedness mediation.

Implications for Practice

Organizations may rely on AI in conjunction with or similar to human employees. AI connectedness may be a key factor for practitioners to improve capabilities and knowledge around AI to improve outcomes. This study gives TMTs better awareness of some overarching challenges that are important in managing AI and allocating resources that may help identify risks, set controls, and empower further maturity. Organizations should be cognizant that perceived data and model risks as antecedents could serve as mechanisms for improving AI connectedness and, potentially, AI outcomes. Strategies should include education on the perceived risks and AI connectedness. For the long term, a clear path aligning strategies using perceived risks, internal controls, and AI connectedness constructs may help to provide improved sustainable management of AI.

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ESSAY 2: OMNI AWARE THROUGH ARTIFICIAL INTELLIGENCE? THE INFLUENCE OF ARTIFICIAL INTELLIGENCE ON COMPETITIVE INTELLIGENCE AWARENESS AND FIRM SUCCESS

ABSTRACT

Organizations of all sizes are looking to extend and enhance capitalization of artificial intelligence (AI) outcomes due to the extensive firm and individual use capabilities. One such advantage may be competitive intelligence (CI) awareness, defined as the top management team's (TMT) ability to understand, articulate, or express their organization's CI or key business intelligence needs, their process, the data gathering, and the analyzing. Applying organizational AI to CI may influence firm outcomes but could depend upon the strategic orientation and reactionary strategy. Extending prior research, this study examined the relationship between AI outcomes and organizational outcomes with the mediating influence of CI awareness. Additionally, the organization's strategic orientation and reactionary strategy were reviewed as potential moderators between CI and organizational outcomes. The study found that TMTs have a significant role; they are tasked with strategically leading CI awareness, strategic orientation, reactionary strategy, and AI decision-making to achieve goals towards their organizational outcomes.

This study adds insight to AI research by studying 260 information technology managers (or higher positions), reviewing their perceptions on the relationship between AI outcomes on organizational outcomes. A confirmatory factor analysis and partial least squares structural equation modeling was conducted, and results showed CI fully mediates the relationship between AI outcomes (AI maturity and AI orientation) and firm performance. The knowledge gained from this study expands upon information management research and provides practitioners with insights on managing AI in their organizations. Although AI and CI have vast histories, they are continuously changing and have not received adequate attention from the TMT's viewpoint. This study imparts results that TMTs may use to enhance their organizational AI outcomes for long-term results.

Keywords: artificial intelligence, AI outcomes, competitive intelligence, reactionary strategy, strategy orientation, organizational outcomes

Essay 2: Omni Aware through Artificial Intelligence? The Influence of Artificial Intelligence on Competitive Intelligence Awareness and Firm Success

Today's top management teams (TMTs) may improve their strategy and innovation through post-adoptive artificial intelligence (AI) use, along with competitive intelligence (CI) awareness to enhance firm performance in their organizations. Defined as technologies that use machine-based intelligence and advanced computing compacity to mimic human cognitive functions, AI extends past conventional technologies as it is similar to human cognitive functions to search, analyze, and make decisions based on large-scale data (Langley & Simon, 1995; Li et al., 2021). Advancements in big data afford AI capabilities such as rapid generative qualities, automated decision-making, and machine learning for organizations (Faraj et al., 2018; Li et al., 2021). Due to the rapid evolution, many uncertainties exist regarding AI systems, algorithms, or tools, which have underlying complexities and transparency. For example, AI can accomplish both autonomous driving and temperature control simultaneously (Dwivedi et al., 2021). Thus, AI enhancement opportunities and efficiencies are a focus for organizations in global competition (Borges et al., 2021). Those TMTs looking to develop and strategize using the current market information may use AI for CI (González-Díaz et al., 2021). Defined by Madureira et al. (2021), CI includes the resources, activities, and capabilities to produce knowledge about the environment or marketplace in a current or forward view for an organization's performance advantage. Often organizations use big data to surveil business and key in on certain aspects via CI, so TMTs need awareness of how AI functions, as well as the associated risks and controls that may influence not only decision-making but ultimately firm performance (Madureira et al., 2021).

The practice of CI encompasses both gathering data and disseminating information to enhance informed decision-making for TMTs and organizations (Ranjan & Foropon, 2021). The TMTs may profit from using AI in various manners due to their ability to reduce information overload for users, as well as conduct deep dive analytics (Saxena & Lamest, 2018). However, receiving AI information alone is not enough, as TMTs need awareness of the underlying algorithm and systems to make decisions (Bartley et al., 2019). Organizations via their TMTs need to continuously review and manage their platforms, systems, and data (Köseoglu et al., 2019). Part of the challenge is that TMTs make sense of CI use and customizations in relation to organizational mission and vision towards performance outcomes (Maungwa & Fourie, 2018). Organizations and TMTs need to decide both how complex AI can be used and its boundaries, integrations, and combinations, directly or indirectly (Dwivedi et al., 2021). However, prior studies have shown little empirical evidence on the impact of AI outcomes and how TMTs use CI to affect firm performance.

Researchers have been able to highlight issues regarding AI development and use—information overload, hallucinations, misinformation, propaganda, and fake news—that challenge the benefits of authentic AI and may affect the TMT's decision-making based on their ability to make sense of everything (Dwivedi et al., 2021; Saxena & Lamest, 2018). This study draws upon sensemaking theory as the art of identifying, labeling, and sorting information to help us comprehend TMT perceptions and have awareness that leads to human behavior or action (Weick, 1995; Weick et al., 2005). For example, making sense of the capabilities and use of AI may help improve TMT awareness for decision-making on innovative market insights, trends, anomalies, and quick adaptation in the society or industry (Verganti et al., 2020).

Affordance theory fits well with AI outcomes and decision-making as TMTs determine technology budgets, staffing, data use, and other resources based on understanding of their objectives and goals (Chatterjee et al., 2021). Furthermore, perceived affordance allows TMTs to decide how to dynamically leverage both technical and manual aspects of AI use (Berente et al., 2021; Blewett & Hugo, 2016). Moreover, CI awareness may impact managing affordances related to technological intelligent systems and costs (Chatterjee et al., 2021). Prior research by Salovich et al. (2021) found that misinformation affects judgement and leads to errors and that system influence outweighs knowledge and ability. This points to the aspects of affordances that may progress in phases as TMTs have awareness of system complexities and customization capabilities, which may be afforded to exclusive groups (Chatterjee et al., 2021).

The complex innovative blend of AI and CI into organizational models or infrastructure may be a vital component in affording TMTs a simplified framework for identifying and strategizing in their competitive markets. This study expands prior research by delivering on the significance of AI outcomes and CI research by exploring their influence on organizational outcomes.

The goal of this study was to refine the research gap by expanding research streams on both AI and CI, inspecting the influence between concepts through the viewpoint of TMTs. Considering the aforementioned aspects, this study aimed to examine these research questions:

1. What influence do AI outcomes have on CI awareness in an organization?
2. What influence does CI awareness have on organizational outcomes?

Research Background

Historically, CI played a part in bartering or trading or in empire military collection and strategy (Madureira et al., 2021). When Porter’s (1980) book on competitive strategy was published, it highlighted the prevalence of CI as a part of overall business strategy for researchers and practitioners. More recently, CI has become its own discipline or business profession; for example, CI professionals work as consultants or strategy practitioners and formed the Strategic & Competitive Intelligence Professionals (n.d.) group. Researchers have utilized characteristics to separate CI professional roles and identities as additional credibility and structure are given to the field (Madureira et al., 2021; Zinn & Goldsby, 2014). Recent research on CI has keyed in on the innovation evolution of smart tools, intelligent and agile technologies that collect, analyze, and distribute information for competitive advantage (Larson & Chang, 2016).

Researchers have not always agreed upon a sole definition of CI, causing confusion and resulting in a multitude of names for corresponding concepts (Madureira et al., 2021). Researchers may discuss CI using “coexisting terms like organizational intelligence, business intelligence, business intelligence systems, market intelligence, economic intelligence, national intelligence, organizational intelligence, [and] technology intelligence” (López-Robles et al., 2019, p.22), which cracks the foundation and separates the discipline (López-Robles et al., 2019; Madureira et al., 2021). Utilization by all researchers of a standardized defined field such as competitive intelligence may be viewed as both an art and a discipline as constant changes occur in society and the environment, altering the boundaries of the field (Hoppe, 2016). Madureira et al. (2021) reframed the conversation by building a unified CI definition using five dimensions of purpose, process, product, purview, and practices. However, it was missing direct coverage of innovation, digital transformation, and executive intelligence research, which are key to resource allocation and investment in AI (Appio et al., 2021; López-Robles et al., 2019; Yin, 2018). Separately, the term integrated intelligence has been used by researchers as a robust integration of insights from big data that are identified across the business or social environment and in conjunction with other areas and disciplines that are aggregated to see a comprehensive trends currently and its probable future state Bulger (2016).

In addition, there is a human component and non-technological data that should not be left out of the technological context of intelligent integrated network connections, as organizations need to discern information from all sources. Thus, the definition of CI should incorporate and integrate all information for use by various academics or practitioners to enhance the research stream. This research used CI as one consolidated broad-based term rather than using integrated intelligence or the other various terms. This research defined CI as the leader firm's ability to strategically gather important business information or intelligence to analyze, interpret, understand, articulate, or express the organization’s key intelligence needs to use in a decision-making process.

Aspects of Competitive Intelligence Awareness

Extant literature has validated the importance of CI awareness, particularly related to information overload (Saxena & Lamest, 2018) system design (Tomasura, 2015), bias (Hoppe, 2016), lack of education (Kaur, 2019), and CI failures (Maungwa & Fourie, 2018), which shows the complexity of collecting, analyzing, and distributing key information that may influence firm performance (Madureira et al., 2021). Hence, organizations that culturally display strategic entrepreneurship mindsets might have higher levels of market competition awareness, leading to innovative products and services (Withers et al., 2018). This research aligns with prior competitive dynamic studies that have stated short-term advantages may be garnered in comparison to those with entrepreneurial blind spots that impact outcomes (Withers et al., 2018).

Prior research has determined that CI is positively related to organizational outcomes, signaling that CI influences action and decision-making (López-Robles et al., 2019; Yin, 2018). Thus, it is important for TMTs to have awareness of the ability of AI to engage in human behaviors and oversee intelligent products, services, and experiences (Di Vaio et al., 2020). As AI is evolutionary, there is not comprehension of its full potential, though research has shown competitive business intelligence is a "data driven process that combines data storage and gathering with knowledge management to provide input into the business making decision process" (Larson & Chang, 2016, p2). Utilization of big data is critical for an organization that wishes to identify, analyze, and utilize knowledge as part of their structure and systems (Dwivedi et al., 2021). Organizations that build and adopt CI use cases have found data analytics to be helpful in improving organizational outcomes (Larson & Chang, 2016).

Contrary to the opportunities, the challenges of CI failure may generate significant loss and liability for organizations (Maungwa & Fourie, 2018). At the start, being efficient with quality data and information allows for scaling capabilities that may be operationalized (López-Robles et al., 2019; Maungwa & Fourie, 2018). Thus, boundaries should be required for organizational use of AI that are critical to further development to prevent ineffectiveness, inefficiencies, inaccuracies, or other generative output problems, such as bias or discrimination (Jackson, 2021). Thus, TMT awareness of the technical and human aspects is critical to reach organizational strategic objectives (Madureira et al., 2021). Furthermore, the design and framework to monitor CI information and integrations becomes important to success (Dwivedi et al., 2021; Jackson, 2021). Challenges evolve that directly and indirectly influence CI; however, no known research has inspected how AI influences CI, which then influences organizational outcomes. Table 12 summarizes the extant literature on the CI impacts of AI.

Table 12

References for Competitive Intelligence Awareness

Authors	Theories (Method)	Contribution
Ranjan & Foropon (2021)	Grounded theory (exploratory interviews)	Used grounded theory to explore how the aggregate use of big data and competitive intelligence can be leveraged
Madureira et al. (2021)	Mixed methods (content analysis)	Created a unified perspective of competitive intelligence
Maungwa & Fourie (2018)	No theory (semi-structured interviews)	Showed problems associated with the articulation of key information needed for competitive intelligence
López-Robles et al. (2019)	No theory (bibliometric review)	Found through a 30-year review on intelligence that competitive intelligence is a core model in its own right

Strategy

Organizations use strategy in an opportunistic manner but also to negate harmful effects from specific events that may occur (Breitsohl, 2009; Dwivedi et al 2021). This study's definition of reactionary strategy was expanded from Breitsohl (2009), highlighting the formal or informal deliberate or anticipatory management plan to remedy a situation, problem, issue, or event that may occur in an organization. As such, a reactionary strategy may take various forms that cater to a specific situation; for example, TMTs could use techniques to evade, conceal, defend, appreciate, or accommodate (Breitsohl, 2009).

Prior research on strategy has garnered varied results in that it can have a positive or negative influence on outcomes (Breitsohl, 2009). The main challenge is that strategies must align with overall or specific business planning and information system planning (King & Teo, 2000). Forms of specific reactionary strategies include cybersecurity plans, disaster recovery, pandemic planning, sale of a strategic key partner or vendor, or a key person leaving (Hauptman et al., 2023). Due to the disposition of AI, the autonomous capabilities are challenging to anticipate with an adequate reactionary strategy since the humans coding or monitoring may not be cognizant of the genuine real-life issues and ripple effects (Dwivedi et al., 2021). Strategies are generally custom designs for achieving goals or dealing with challenges, and some may fail the organization (Breitsohl, 2009). For example, strategy actions may poorly influence firm outcomes if TMT comprehension and familiarity with AI is low (Gonzalez et al., 2022). Thus, a strategy may go farther than technology to require education or re-skill of workers, along with the continual testing, monitoring, and education of humans and AI to achieve organizational outcomes (Ren et al., 2023). Importantly, in an organization where technology is important, a reactionary strategy helps protect and diminish negative effects (Hauptman et al., 2023). This highlights the importance of the TMT's perception and role, which can alter resources and strategies that influence organizational outcomes (Foxall & Johnston, 1987). Table 13 summarizes the influence of strategies on AI.

Table 13

References for Strategies

Authors	Theories (Method)	Contribution
Marcazzan et al. (2022)	High reliability theory (secondary)	Found experience did matter in reducing negative effects of pure reactive strategies to adversities
Hauptman et al. (2023)	No theory (survey)	Showed that co-working human–AI teams with a well-defined incidence response procedure adapt and work better together
Short & Pfarrer (2023)	Leverage theory (secondary data)	Leaders can help protect their firms from negative events by using a reactionary strategy
Kamariotou & Kitsios (2022)	No theory (survey)	Research helps align IT goals and explores business strategy planning influence on business performance
King & Teo (2000)	Information system planning theory (survey)	Found the involvement of TMTs creates greater leadership ownership and motivates information systems strategic plan implementation

Note. AI = artificial intelligence; IT = information technology; TMT = top management team

Extant literature has focused on themes of both AI and CI development and capabilities but has paid little attention to certain aspects of the relationship or strategy between AI and CI. No empirical evidence has been found regarding the TMT perspective of AI outcomes, CI, and strategic orientation or reactionary strategy towards organizational outcomes.

Theoretical Background

To arrange a basis for AI outcomes and CI awareness, this study drew on three theories. First, upper echelon theory (UET) aligns with TMTs as organizational decision-makers in strategizing, synchronizing, and allocating resources for their organization's innovative AI outcomes and overarching CI awareness (Hambrick, 2007; Li et al., 2021). The UET infers that TMTs lead organizations through decision-making and strategy based on their own historical experiences, values, and personal knowledge (Hambrick, 2007). Prior studies on technology with a UET lens have focused on characteristics of TMTs (Bromiley & Rau, 2016), black box management and technologies (Brevini & Pasquale, 2020), leadership's cognition of information (Neely et al., 2020), and the damaging facets such as overconfidence and narcissism (Brunzel, 2021). Second, sensemaking theory emphasizes the perception of TMTs in decision-making on AI outcomes and CI awareness (Weick, 1995; Weick et al., 2005). Sensemaking for TMTs is based on real-life experiences, perceptions, history, and overall comprehension, centering on their cognitive process for decision-making, which impacts their performance goals (Berente et al., 2021; Weick et al., 2005). Lastly, affordance theory ties TMT decision-making to AI outcomes and CI awareness (Gibson, 2014; Østerlund et al., 2021; Volkoff & Strong, 2013). Affordance theory delivers insight on the interaction yield proficiencies between technology and users (Herterich et al., 2023). Affordance is the belief and behavior behind what to choose or adapt in human–AI interaction based on awareness (Østerlund et al., 2021). These theories connect TMTs with decision-making on AI, CI awareness, strategic orientation, and reactionary strategy, which ultimately influence outcomes.

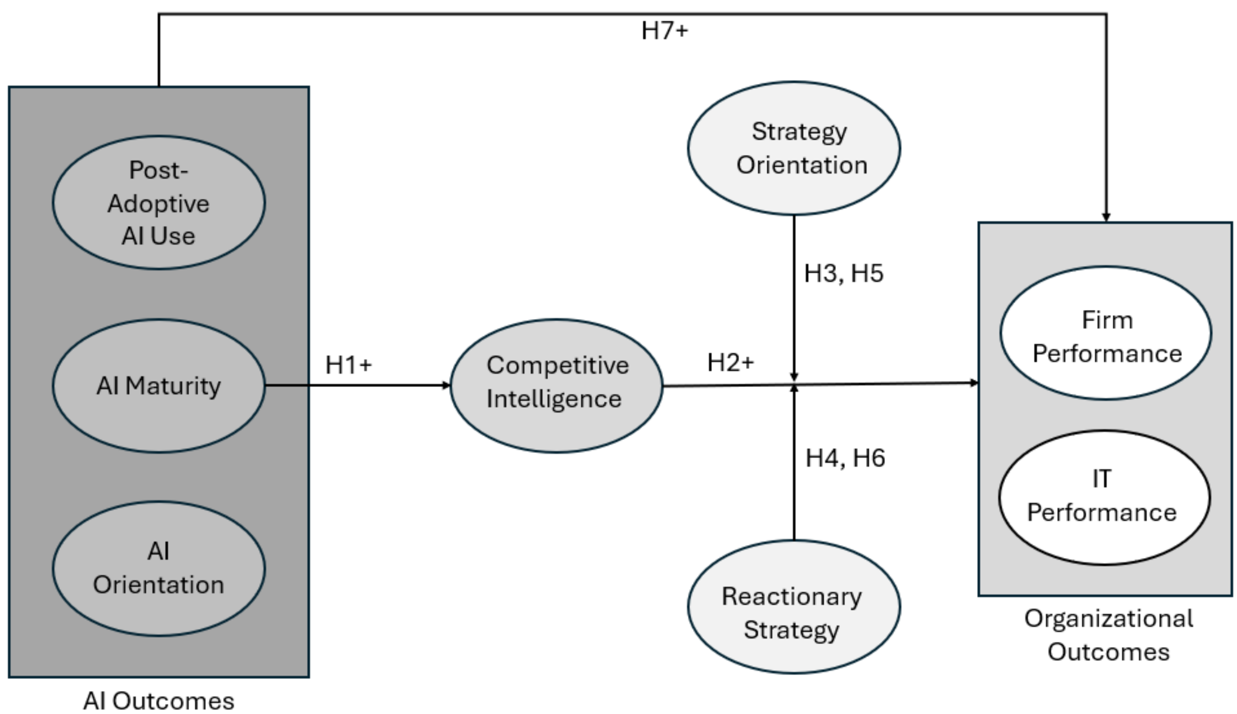
Research Model and Hypotheses Development

Innovation and evolutionary systems such as AI allow organizations to strategize and find competitive market advantage through information management capabilities, placing emphasis on CI awareness through utilization of AI for not only single phenomenon but overall global trends (Dwivedi et al., 2021). Organizations depend upon individual TMTs to use their own history, experience, and expertise to combine with new knowledge to make well informed (Gračanin et al., 2015; López-Robles et al., 2019). Prior research has suggested the power of behavior as a change agent in creation of intelligent technology that impacts organizational outcomes (Larson & Chang, 2016; Maungwa & Fourie, 2018).

The hypothesized model of research is displayed in Figure 3. The purpose of this method is to study the relationship between AI outcomes, mediated by CI. Additionally, this study investigated the strength of moderating effects of strategy orientation or reactionary strategies between AI outcomes, CI, and organizational outcomes.

Figure 3

Research Model



Note. AI = artificial intelligence; IT = information technology; + denotes a positive association

Artificial Intelligence Outcomes

Due to the generative and machine learning aspects of AI, it can function as a business creation, analysis, and intelligence information management tool that makes it an integral component of strategic and tactical decision-making (Gračanin et al., 2015). Due to the broad implications of organizational use of AI overall, this study focused upon AI outcomes (post-adoptive AI use, AI maturity, and AI orientation) as principal factors of organizational growth. I adapted Li et al.'s (2021) definition to state post-adoptive AI use as the organization's use of enhanced technologies that utilize machine-based intelligence and algorithm capabilities to mimic human cognitive functions to identify, search, collect, detect, and analyze big data to generate, integrate, or make decisions. In addition to the basic use capabilities, opportunities, and challenges, with the continuous aspects of self-learning and training of AI, organizations must monitor and supervise its progress and maturity (Dong et al., 2023). Thus, I amended from Becker et al.'s (2009) definition of AI maturity as follows: any AI enhancement, or any combination thereof, that shows measurable improvement, scaling, transfer, or combination of structures, added strengths, functionality, and/or content, which may be new or updated model or design that organizations implement after initial development and adoption. It is also important for organizations to think through how they orient themselves and make decisions through their focus on use, maturing and improving AI, since TMTs attempt to align strategies of use with desirable outcomes (Sun et al., 2024). Therefore, I adjusted Li et al.'s (2021) definition of AI orientation as follows: an organization's overall strategic direction and goals or objectives associated with managing AI use. Extant literature has highlighted AI as a complex intelligent technology, infrastructure, or systems developed by organizations to realize their objectives (Li et al., 2021; Masa'deh et al., 2018; Peterson, 1989). Hence, organizations must continuously align their AI with their overall goals. To address this, this study reviewed the impact of AI outcomes (post-adoptive AI use, AI maturity and AI orientation) on organizational outcomes.

Prior research has shown rapid improvement in AI systems' collaboration with or extension of human capabilities that transform the world of work (Li et al., 2021). Due to this work environment transformation, organizations via their TMTs have the power to influence the orientation and interaction between AI and human workers (Østerlund et al., 2021). Some organizations may have an AI autonomous agent as a co-worker, but human workers are inclined to perceive AI agents apart from their human counterparts and with less benevolence (Dennis et al., 2023). Research has highlighted that the perception of stakeholders is important in enhancing technology capabilities (Goodhue, 1995). Therefore, as rapid changes occur, human counterparts hold a deep implication along with AI enhancements for organizational outcomes (Dwivedi et al., 2021).

Organizations may profit from AI use for its numerous capabilities in gathering, organizing, and analyzing huge quantities of data quickly, identifying industry trends, comparing competition information, or engaging in business or industry model changes or other interdependencies that continue to update often (Withers et al., 2018). Utilizing AI for predictive information on market, environmental, or social trends allows businesses to maintain agility, manage risks, signal on important matters, and take advantage of growth opportunities (Withers et al., 2018). Together AI and CI may allow rapid data mining for analysis and predictive analytics to assist in a highly competitive global marketplace (Gračanin et al., 2015).

Competitive Intelligence Awareness

Madureira et al. (2021) defined CI as the resources, activities, and capabilities to create awareness about today's surroundings or to use predictive analytics for an organization's performance advantage. This study expanded upon CI awareness from Acharya et al. (2018), defining the strategic leader's ability to strategically gather important business information or intelligence to analyze, interpret, understand, articulate, or express the organization's key CI needs to use in a decision-making process. The concept of CI awareness encompasses comprehension of an organization's framework, procedures, and strategic vision to utilize the information management databases, which involves non-traditional data to make decisions (Madureira et al. 2021; Ranjan & Foropon, 2021). Organizations highly value quality data but it must be collected, analyzed, and distributed through the appropriate viewpoint, whether narrow or wide, to fit the circumstance and audience (Ranjan & Foropon, 2021). Methodologically, the objective of CI is based upon competitive advantage and strategy orientation through the collecting, analyzing, and distributing of intelligence or knowledge to impact organizational outcomes (López-Robles et al., 2019; Oubrich et al., 2018; Ranjan & Foropon, 2021). In a highly competitive capital marketplace, organizations require current technology to stay competitive or risk losing market share and potentially lagging the new standards set, which could create costly and unsustainable failures (Maungwa & Fourie, 2018). Due to recent business disruptors, newer startups have challenged business models and created an evolution to compete and sustain long-term (Dwivedi et al., 2021). Importantly, this emphasizes the prominence of information management for competitive organizations, requiring them to define what CI means for them and TMTs to have CI awareness for decision-making purposes (Chen & Lin, 2021).

As organizations deal with large quantities of data in complex business models, they strategically look to obtain custom metrics and set up benchmarking, monitoring, automations, and a myriad of other capabilities to align with their goals (Ranjan & Foropon, 2021). Capabilities are afforded by AI that were not available easily in older technologies and have improved efficiency and reliability (De Luca et al., 2021). However, organizations via their TMTs must be secure enough in confidence to strategize via use of intelligent systems (Li et al., 2021). Prior research has investigated beliefs on the technology itself and suggested many factors that give clues on the strength of AI used, such as risk, usefulness, experience, involvement, and stakeholder awareness (Zhang et al., 2021). Therefore, comprehending belief or trust behavior, along with interpretation of information, can improve the probability of success when sensemaking for organizational outcomes (Tan et al., 2020; Weick et al., 2005). Sensemaking viewed via information systems is the theoretical view used to examine frameworks and systems via societal aspects and methodological implementations (Tan et al., 2020). With rapid innovation, sensemaking is a vital aspect to align firm values and direction (Tan et al., 2020). Based on these factors, I posited that:

H_1: AI outcomes will have a positive influence on CI awareness.

Organizational Outcomes

Extant literature has reviewed the impact of innovative technologies on firm performance, such as the value of innovation using big data analytics (Grover et al., 2018). The use of innovative technology alone has not been found to be enough for sustainable performance, so TMTs have to distribute knowledge and implant process improvements in their organizations (Grover et al., 2018). Thus, TMTs that strategize and align their information and technology frameworks may improve long-term outcomes (Wu et al., 2015). Generative or autonomous AI or CI may behave like human workers in their responses, which has transformed authoritative decision-making in organizations (Faraj et al., 2018). Due to this, TMTs should align CI awareness to their organizational objectives for decision-making on strategy and resources that impact firm outcomes (Ranjan & Foropon, 2021). Thus, I proposed that:

H_2: CI awareness will have a positive influence on organizational outcomes.

Strategy

Incorporating business strategies such as using AI to assist with key performance indicators and utilizing actionable generative information and enhanced segmentation may improve organizational outcomes (Borges et al., 2021). As AI agents take on full or partial roles in organizations, strategy becomes vital in how both human and autonomous agents or any combination thereof impact organizational intelligence process outcomes (Hauptman et al., 2023). This study used an adapted definition of strategy orientation from Kamariotou and Kitsios (2022), where strategy orientation is how a firm aligns and orients AI use with its organizational strategy and goals. Additionally, this study added and defined reactionary strategy as a firm's advance planning to manage unforeseen events to improve organizational outcomes. The ability to quickly incorporate new data or information via CI into organizational strategy has become both an opportunity and a challenge but provides value to the decision-making process (Chen & Lin, 2021). For example, a reactionary strategy created for assorted decision-making events may safeguard against any negative kickback, resulting in a better outcome (Berente et al., 2021). On the contrary, a set-in-stone strategy could impair adaptability or innovation, creating challenges that hamper swift corrective action (Bayrak et al., 2021). Drawing upon sensemaking theory, TMTs utilize their own cognition, experience, and unique understanding to act on behalf of their organizations (Weick et al., 2005). Therefore, strategy and reactionary strategy are about making sense of the information at hand to turn it into actionable results. Thus, TMTs have the task of making decisions with known CI with the intent of favorable outcomes. There could be either a positive or a negative moderating effect of strategy on the relationship between CI and organizational outcomes (Bayrak et al., 2021). Hence, as stated previously and with aforementioned continuous changes in CI, I proposed that:

H_3: Strategy orientation will moderate the relationship between CI and organizational outcomes.

H_4: Reactionary strategy will moderate the relationship between CI and organizational outcomes.

Organizational outcomes may be a direct result of strategic planning being impacted by the utilization of AI (Hauptman et al., 2023). Prior research has reported mixed results on the relationship with AI adoption and firm outcomes due to the challenges that often accompany innovation (Dwivedi et al., 2021). Human biases, trust, lack of knowledge, or black-boxed AI can be a detriment to organizations when transparency, comprehension, and lack of distribution are involved with key stakeholders (Berente et al., 2021). However, the use cases also vary by capabilities or type of AI and the level of human–agent interaction, which factor into the mixed results (Bayrak et al., 2021). Prior research has highlighted that strategic AI use improves many organizational processes, products, and service offerings (Chen & Lin, 2021). Enhancements to AI have created a change in how culture orientation may improve outcomes (Li et al., 2021). From this, I posited that:

H_5: Strategy orientation will moderate the relationship between AI outcomes and organizational outcomes.

H_6: Reactionary strategy will moderate the relationship between AI outcomes and organizational outcomes.

A generative tool, AI is used for innovating products and services, with new capabilities evolving that may influence organizational outcomes (Mikalef & Gupta, 2021). Prior research has showcased that technology and AI do impact firm performance (Fosso Wamba, 2022; Kamariotou & Kitsios, 2022). Hence, drawing upon upper echelon theory to signify that organizations imitate the behavior or actions of their leaders, a culture led by TMTs to engage in AI use and innovation may be granted profitable outcomes (Bhandari et al., 2020). Therefore, this study posited the following hypothesis:

H_7: AI outcomes will have a positive influence on organizational outcomes.

Methods

Measures

This study used the same design and collection as the first study but added measures specific to this study from extant literature as shown on Table 14. Strategy and CI questions did not refer to their most familiar AI but were specific to organizational use. The AI outcomes and controls from Study 1 were utilized in this study.

Prior research using AI variables measured relationships using a 7-point Likert scale (1 = *strongly disagree*, 7 = *strongly agree*). To assess the construct measurements, Cronbach's alpha indices of no less than 0.7 were used for each construct. Table 15 shows the variable items used via 7-point Likert scale.

Table 14

Questionnaire Content

Subjects	# of items	References
Competitive Intelligence	5	Chen & Lin, 2021
Strategy Orientation	5	Amoo et al., 2019
Reactionary Strategy	5	Amoo et al., 2019
Firm Performance	5	Fosso Wambo, 2022; Queiroz et al., 2018
Information Technology Performance	5	Nugroho et al., 2022; Dubey et al., 2020
Total Items:	25	

Analysis

This study utilized the desktop-based software tool SmartPLS version 4.1.0.6 for a full analysis using the partial least squares structural equation modeling (PLS-SEM) method. A two-part formulation method for PLS algorithm statistical modeling and bootstrapping via SmartPLS was used to analyze the proposed relationship between model factors. The PLS-SEM results such as path coefficients, outer weights, Cronbach's alpha, and R-squared values were reviewed by testing the statistical significance via bootstrapping. This was accomplished with the recommended subsample amount (5,000) to analyze the model's posited relationships (Hair et al., 2017). Further review of discriminant validity of the factors, outer loadings, and general model fit were reviewed in line with the suggested technique by SmartPLS as the manufacturer of the software (SmartPLS, n.d.).

Results

First, to investigate the factors, all items were loaded collectively, and factors were assessed individually to review the validity of the loadings. Item loadings were removed from the assessment if less than .70, per the recommended benchmark that shows reliability (Fornell & Larcker, 1981; Zaman et al., 2020). The remaining 39 items were used in the model. A confirmatory factor analysis via SmartPLS was used to review the factors and the relationship between them via the suggested model.

The model fit suggested mixed results. The normed fit index (NFI = 0.73) did not suggest a great model fit, but a more moderate fit. The standardized root mean square residual (SRMR = 0.067) was considered a good fit. All the average variance extracted values for the constructs well exceeded Fornell and Larker's (1981) convergent validity criterion of 0.50. The R-squared values, which indicate the proportion of variance in the dependent variable explained by the independent variables, demonstrated good results: Firm Performance (FP) = 0.734 and Information Technology Performance (ITP) = 0.718. As shown in Table 15, all factors had loadings above the suggested guidelines of 0.70.

All constructs were also reviewed for inner consistency (reliability) for all constructs. Cronbach's alpha was statistically significant when greater than 0.7, which shows scale reliability. This study indicated a range of 0.883 to 0.923, as shown in Table 16 (Nunnally, 1978). Table 17 presents the study's composite reliability for all measures used. Table 18 shows the study's discriminant validity and Fornell–Larcker results. The SmartPLS bootstrapping tool was utilized to examine the moderating effects of strategy orientation and reactionary strategy between AI outcomes and organizational outcomes, as shown on Figure 4. Table 19 displays a summary of the structural model results, showing the significance and strength of path coefficients.

Table 15

Measurement Model Assessment

Construct	Items	Loadings
AI Outcomes (AIU)[a]		
This AI is used extensively in our organization.	AIU1	0.881
This AI is used across all our business units.	AIU2	0.830
This AI is used for decision-making across all our business units.	AIU3	0.835
This AI is used to support the development of new products and services.	AIU4	0.787
This AI is used to enhance our organization.	AIU5	0.794
AI Maturity (AIM)[b]		
This AI tool has been taught (trained /realigned) to enhance AI maturity.	AIM1	0.779
This AI in our organization continues to mature through repetitive use.	AIM2	0.835
This AI in our organization has changed and improved over time.	AIM3	0.823
This AI in our organization continues to improve through training or realignment.	AIM4	0.852
This AI in our organization has become more efficient over time through training or realignment.	AIM5	0.848
AI Orientation (AIO)[c]		
We have a well-established philosophy around using this AI.	AIO1	0.773
We are creative and innovative with using this "leading edge" AI.	AIO2	0.867
We quickly follow the lead of innovators in adapting new and emerging capabilities for this AI.	AIO3	0.841
We critically evaluate this AI investment to assess business value.	AIO4	0.831
We experiment with new and emerging aspects of this AI.	AIO5	0.836
Competitive Intelligence (CI)[d]		
Our organization uses competitive intelligence to improve the efficiency of business planning.	CI1	0.879
Our organization aligns competitive intelligence to strategic planning and changes in the business environment.	CI2	0.884
Our organization uses competitive intelligence to identify the business models and operating processes to be improved.	CI3	0.851
Our organization utilizes competitive intelligence to better understand the opportunities or threats in the firm.	CI4	0.786
Our organization uses competitive intelligence to effectively discover the opportunity to raise or improve efficiencies.	CI5	0.846
Strategy Orientation (SO)[e]		
There is a commitment by all members of the organization in implementing AI strategy.	SO1	0.846
Our organization essentially ensures that functions are aligned with AI strategy.	SO2	0.869
Our organization is actively involved in managing change in the implementation of AI strategy.	SO3	0.816

Construct	Items	Loadings
Strategy Orientation (SO)		
Our organization has the right control measures in place to ensure on-going revision of AI strategy.	SO4	0.822
Priority is given to projects/programs that meet the organization's AI strategy when it comes to allocating financial resources.	SO5	0.840
Reactionary Strategy (RS)[f]		
Our organization has well-defined mechanisms to react to unforeseen events of AI use.	RS1	0.817
Our organization allocates time and resources necessary in planning organizational forms of AI use.	RS2	0.833
Our organization essentially ensures that functions are aligned with its strategy of AI use.	RS3	0.799
Our organization gives top priority to managing unforeseen events of AI use.	RS5	0.850
Firm Performance (FP)[g]		
As a result of AI use, we have achieved higher profits.	FP1	0.871
As a result of AI use, we have achieved higher sales.	FP2	0.906
As a result of AI use, we have achieved higher revenue growth.	FP3	0.911
As a result of AI use, we have achieved higher market share growth.	FP4	0.891
As a result of AI use, overall, we have achieved better performance.	FP5	0.791
IT Performance (ITP)[h]		
Our organization's use of this AI to make IT functions more efficient.	ITP1	0.797
Our organization's use of this AI is driven to achieve IT satisfaction.	ITP2	0.826
Our organization's use of this AI contributes to customer value.	ITP3	0.831
Our organization emphasizes the importance of this AI use in allocating resources.	ITP4	0.808
Our IT organizational performance has improved due to this AI use.	ITP5	0.871

Note. AI = artificial intelligence; IT = information technology.
[a]Cronbach's alpha = 0.883; Composite reliability = 0.915; Average variance extracted = 0.682.
[b]Cronbach's alpha = 0.885; Composite reliability = 0.916; Average variance extracted = 0.686.
[c]Cronbach's alpha = 0.887; Composite reliability = 0.917; Average variance extracted = 0.689.
[d]Cronbach's alpha = 0.903; Composite reliability = 0.928; Average variance extracted = 0.722.
[e]Cronbach's alpha = 0.895; Composite reliability = 0.922; Average variance extracted = 0.704.
[f]Cronbach's alpha = 0.854; Composite reliability = 0.902; Average variance extracted = 0.696.
[g]Cronbach's alpha = 0.923; Composite reliability = 0.942; Average variance extracted = 0.766.
[h]Cronbach's alpha = 0.884; Composite reliability = 0.915; Average variance extracted = 0.684.

Table 16

Construct Reliability and Validity

Constructs	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted
AI Maturity	0.885	0.887	0.916	0.686
AI Orientation	0.887	0.888	0.917	0.689
Post-adoptive AI Use	0.883	0.885	0.915	0.682
Competitive Intelligence	0.903	0.906	0.928	0.722
Firm Performance	0.923	0.925	0.942	0.766
IT Performance	0.884	0.886	0.915	0.684
Reactionary Strategy	0.854	0.856	0.902	0.696
Strategic Orientation	0.895	0.895	0.922	0.704

Note: AI = artificial intelligence; IT = information technology

Table 17

Composite Reliability (RHO_C) for All Used Measures

Constructs	Original sample (O)	*M*	*SD*	*t* statistics (|O / *SD*|)	*p* values
AI Maturity	0.916	0.915	0.012	77.582	0.000
AI Orientation	0.917	0.917	0.011	81.856	0.000
Post-adoptive AI Use	0.915	0.914	0.010	90.453	0.000
Competitive Intelligence	0.928	0.928	0.010	91.881	0.000
Firm Performance	0.942	0.942	0.008	117.143	0.000
IT Performance	0.915	0.915	0.010	87.191	0.000
Reactionary Strategy	0.902	0.901	0.012	75.985	0.000
Strategic Orientation	0.922	0.922	0.009	102.280	0.000

Note: AI = artificial intelligence; IT = information technology

Table 18

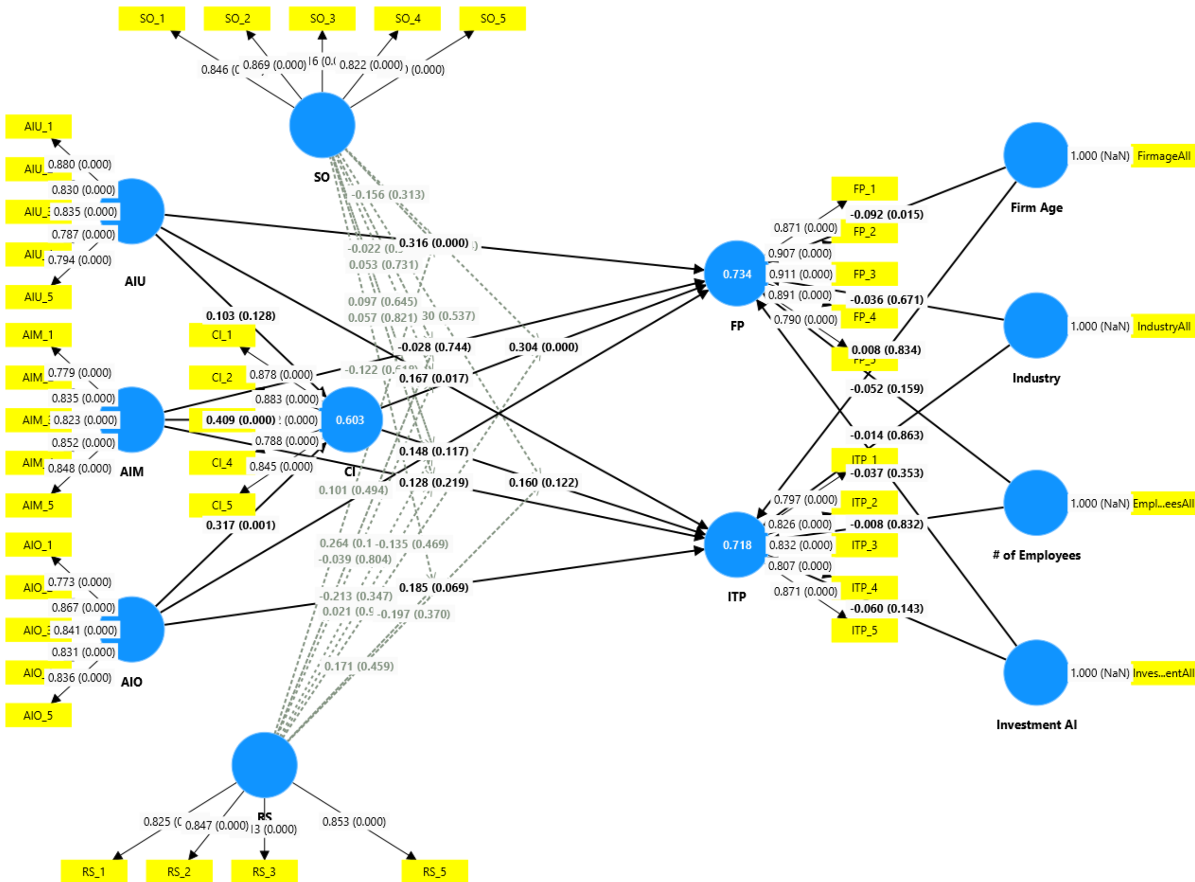
Discriminant Validity: Fornell–Larcker Criterion with Composite Reliability and Average Variance Extracted

	AIM	AIO	AIU	CI	FP	ITP	RS	SO
AIM	0.828							
AIO	0.841	0.830						
AIU	0.715	0.704	0.826					
CI	0.749	0.733	0.619	0.850				
FP	0.699	0.729	0.712	0.761	0.875			
ITP	0.752	0.749	0.671	0.759	0.834	0.827		
RS	0.721	0.732	0.594	0.809	0.713	0.717	0.834	
SO	0.782	0.780	0.645	0.859	0.766	0.784	0.871	0.839

Note: AI refers to artificial intelligence; AIM = AI Maturity; AIO = AI Orientation; AIU = Post-adoptive AI Use; CI = Competitive Intelligence; FP = Firm Performance; ITP = Information Technology Performance; RS = Reactionary Strategy; SO = Strategic Orientation

Figure 4

Structural Model



Note: AI refers to artificial intelligence; AIM = AI Maturity; AIO = AI Orientation; AIU = Post-adoptive AI Use; CI = Competitive Intelligence; FP = Firm Performance; ITP = Information Technology Performance; RS = Reactionary Strategy; SO = Strategic Orientation

Table 19

Summary of the Structural Model

Hypotheses	Constructs	ß	*t* Values
H_1	AIM → CI	0.409***	4.836
H_7	AIM → FP	-0.028	0.326
H_7	AIM → ITP	0.128	1.228
H_1	AIO → CI	0.317***	3.313
H_7	AIO → FP	0.148	1.567
H_7	AIO → ITP	0.185	1.82
H_1	AIU → CI	0.103	1.522
H_7	AIU → FP	0.316***	4.483
H_7	AIU → ITP	0.167*	2.398
H_2	CI → FP	0.304***	3.941
H_2	CI → ITP	0.16	1.548
H_6	RS x AIM → FP	0.264	1.376
H_6	RS x AIM → ITP	0.021	0.107
H_4	RS x CI → FP	-0.135	0.723
H_4	RS x CI → ITP	-0.197	0.896
H_5	SO x AIU → FP	-0.156	1.008
H_5	SO x AIU → ITP	0.053	0.344
H_5	SO x AIM → FP	-0.022	0.109
H5	SO x AIM → ITP	0.057	0.226
H_5	SO x AIO → FP	0.097	0.46
H_5	SO x AIO → ITP	-0.122	0.498
H_3	SO x CI → FP	0.096	0.547
H_3	SO x CI → ITP	0.13	0.618
H_6	RS x AIU → FP	0.101	0.684
H_6	RS x AIU → ITP	-0.039	0.249
H_6	RS x AIO → FP	-0.213	0.941
H_6	RS x AIO → ITP	0.171	0.741

Note: AI refers to artificial intelligence; AIM = AI Maturity; AIO = AI Orientation; AIU = Post-adoptive AI Use; CI = Competitive Intelligence; FP = Firm Performance; ITP = Information Technology Performance; RS = Reactionary Strategy; SO = Strategic Orientation
*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

This study reviewed the relationship between various constructs using SEM path coefficients as shown above in Figure 4 and Table 19. The analysis showed various pathways as presented by the variability in path coefficients. The path from AI maturity (AIM) to competitive intelligence (CI) showed the strongest significant relationship (ß = 0.409, $t = 4.836$, $p < 0.001$). AI orientation (AIO) positively impacted CI (ß = 0.317, $t = 3.313$, $p < 0.001$). Post-adoptive AI use (AIU) positively and significantly affected firm performance (FP) (ß = 0.316, $t = 4.483$, $p < 0.001$) and information technology performance (ITP) (ß = 0.167, $t = 2.398$, $p < 0.05$). Although AIU had a positive impact on CI (ß = 0.103, $t = 1.522$), the relationship was not significant. CI significantly influenced FP (ß = 0.304, $t = 3.941$, $p < 0.001$) but had a weak, non-significant effect on ITP (ß = 0.16, $t = 1.548$). Strategic orientation (SO) and reactionary strategy (RS) moderation pathways were not supported or significant. However, in additional testing SO did have a significant main effect on ITP (ß = 0.322, $t = 2.832$, $p < 0.01$). CI showed a weak, non-significant effect on ITP (ß = 0.16, $t = 1.548$). There was no significant effect of AIO on FP (ß = 0.148, $t = 1.567$) or ITP (ß = 0.185, $t = 1.82$), although the relationships were positive. None of the other pathways examined were statistically significant.

Discussion

This study sought to explore the impact of AI and CI as an integral part of strategy to enhance organizational outcomes. A notable outcome, CI was found to have a strong and significant main effect on firm performance. The results suggested higher levels of CI interaction in the organization will benefit firm performance. Prior research has also demonstrated that CI is positively related to firm performance (López-Robles et al., 2019).

Additionally, the results showed that CI fully mediates the relationship between both AI maturity and AI orientation to firm performance. Prior research has suggested that TMT awareness and knowledge in both AI and CI is influential in how organizations reach strategic objectives (Madureira et al., 2021). Through use of CI, AI maturity and orientation help organizations to identify, analyze, and conduct short- or long-term planning that has a positive strong impact on firm performance. Thus, organizations and TMTs that work to mature and orient their AI culture through infrastructure, tools, and technologies are likely able to enhance their CI and benefit firm performance.

This study found AI outcomes have a significant positive relationship with both firm performance and information technology performance. No mediation existed for post-adoptive AI. Interestingly, even though use of AI had a strong influence, AI maturity and AI orientation had no significant direct relation to firm performance or information technology performance. This may be due to the broader implications of AI maturity and AI orientation, apart from AI outcomes. By itself, AI use may provide an influence on firm performance due to its capabilities and efficiencies.

Strategic orientation only had one positive relationship; its relation to information technology performance was positive and significant. Granted that strategy orientation is managed and led by TMTs, the support of information technology performance coincides with other research that has found technology management and governance are vital components for organizations (Dwivedi et al, 2021). With AI agents acting autonomously, TMTs should be utilizing strategic orientation based on AI to have greater awareness of the impact on information technology performance.

Interestingly, all other strategy items' relations of strategic orientation and reactionary strategy to other factors were not supported or were too weak to be significant. This may be due to the complexity of strategy, other missing factors related to strategy, the variance of strategy, or the varying perceptions across organizations; perhaps this study's mechanisms were not able to capture the data adequately. It may be possible that strategy and AI require a larger sample size or a longer period of time.

Limitations

Based on the broad scope of this study, there are a few limitations. This research focused on a sample of information technology managers and those in higher positions; future studies may look at other groups or a specific geography as this study did not focus on a particular location or area. Additionally, there was no deep dive into particular AI or CI systems or infrastructures. Since CI and AI are customizable, this study chose a broader view as an initial research step without regard to the benefits of one particular AI or CI. This study did not delve into the transformational aspects of AI or CI, as has been covered by prior research (Dwivedi et al. 2021; López-Robles et al., 2019). However, due to the dynamic nature of AI and its interactions with various factors, the impact of dynamic capabilities could be studied further regarding effects on firm performance.

This study was based on a single event panel data analysis, and it is possible to obtain deeper analysis with complete dynamics from other methods such as a time series, case studies, or a mixed methods approach. Therefore, the findings of this study are general in nature and of limited use. Finally, since AI continuously evolves, other methods or measures may give further insights.

Implications for Research

Researchers have been working to examine the benefits of AI, along with the nuances as leaders manage AI with hopes to build sustainability (Berente et al., 2021; Dwivedi et al., 2021). This study contributes to how both AI outcomes and CI awareness impact firm performance.

Additionally, it contributes to the differentiation of AI outcomes, AI maturity, and AI orientation with viewpoints on how to manage AI towards organizational outcomes. To the best of my knowledge, CI awareness has not been an academic focus using AI. Few studies have studied the use of CI via AI capabilities, and none have specifically examined AI outcomes. Having a stronger view of the impact of CI through an AI lens may elucidate the unique characteristics and value of CI awareness.

Future research could extend this study by incorporating innovation to review how organizational research and development, specific to AI outcomes or CI enhancements, may impact mediation or outcomes. Extending this research to the dynamic levels of AI–human interaction by industry or role would be an important key to the evolution of work, and it would be critical to future planning. This would provide insights as to what human and technology resources are needed so that organizations may develop and train in critical areas.

Implications for Practice

This study found that AI and CI positively impact organizational firm performance; thus, TMTs should strategize to orient their organizations to both AI and CI through employee engagement and training and development for improved collaboration and decision-making that may contribute to firm performance. An environment that culturally leans into understanding the characteristics and mechanics of CI by defining it clearly and focusing on developing and integrating CI into their framework could strongly influence their competitive advantage. In a highly adaptive environment, CI awareness through decision-making may be the key to sustainability. This aligns with Li et al.’s (2021) call to orient and use AI to reliably raise the bar in how organizations manage AI.

Reliable information may give leaders better insight and decision-making abilities on behalf of their organizations. This study calls for leaders to strategically define and identify target areas where ongoing AI use, maturity, and orientation may aid organizational outcomes.

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