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ARTICLE

Psychology of Leadership: Understanding AI Adoption, Self-Efficacy, Green Creativity, and Risk Perception Among Oman's Business Bosses

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ABSTRACT
Artificial intelligence (AI) is at the forefront of transformative changes in organizational innovation. This study examines the social psychology underpinning AI adoption among Oman's top business leaders, including CEOs, founders, and senior executives, to explore how green creativity, positive mental well-being, and risk perception converge with self-efficacy as a critical moderating force. Significant positive correlations were identified between most variables in the data set of 214 prominent Omani leaders using structural equation modeling and SmartPLS 4 software. The findings illustrated how Oman's business leaders harnessed AI to align technological capabilities with deeply ingrained cultural values and communal aspirations. By situating these insights within Oman's strategic vision of economic diversification and sustainability, this study underscored AI's potential to catalyze organizational performance and environmentally conscious innovation. In addition, the moderating role of self-efficacy highlighted the

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importance of leadership confidence in navigating the complexities of AI integration. These discoveries have important implications for scholars, policymakers, and industry practitioners in Oman and other collectivist and emerging markets. By combining technology and human psychology, this study accentuates the need for thoughtful integration of AI, ensuring that rapid digital transformations remain culturally resonant, ethically grounded, and person-centered in an era of continuous change.

KEYWORDS
top management, artificial intelligence adoption, self-efficacy, green creativity, Structural Equation Modeling, Oman

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Introduction

In a world redefining itself in the wake of technological progress and global upheavals, such as the COVID-19 pandemic, integrating artificial intelligence (AI) into organizational operations is no longer a novelty but a necessity (Salah et al., 2023). Although the adoption of AI promises innovation and competitive advantage, the broader implications of this technology are multifaceted, affecting not only the economic and technological spheres but also the domains of psychology and culture. With a blend of traditional wisdom and modern ambition, Oman's context presents an intriguing landscape for exploring these dynamics (Puthukulam et al., 2021).

Despite AI's growing significance, a critical gap remains in understanding how Omani business leaders psychologically perceive and integrate such technology, particularly regarding self-efficacy, risk perception, green creativity, and positive mental well-being. Oman's Vision 2040 underscores economic diversification and technological advancement, aligning AI adoption with national strategic priorities (Oman Vision 2040 Implementation Follow-up Unit, n.d.). However, the existing literature offers limited insights into the psychological impacts of AI adoption on top business leaders in Oman, leaving an opportunity to examine how collective cultural values, leadership beliefs, and organizational goals intersect.

Addressing this gap is vital, since such psychological constructs as self-efficacy, risk perception, ecological creativity, and mental well-being play a key role in shaping leadership behavior and making technology-related decisions. In emerging economies, e.g., Oman, the relationship between technology adoption and leadership psychology remains insufficiently explored, particularly within conservative

or collectivist cultures (Hassan et al., 2023; Saxena & Al-Tamimi, 2018). By bridging technology adoption research with leadership psychology, this study examines how AI can be integrated seamlessly into business strategies while resonating with traditional values and communal norms.

To achieve this aim, we focused on 214 CEOs, founders, and top management personnel in Oman to investigate the interplay between AI adoption and key psychological dimensions. The study's unique emphasis on self-efficacy as a moderating variable reflects leaders' ability to achieve goals and overcome barriers to AI adoption. Self-efficacy can amplify or dampen how leaders perceive AI-related risks, engage in green creativity initiatives, and maintain positive mental health, making it central to understanding effective AI integration.

The cultural considerations intrinsic to Oman, which emphasize communal goals and traditional norms, formed an essential backdrop to this study. These collective cultural elements significantly shape leaders' risk tolerance, creativity, and receptivity to AI-driven changes. Thus, analyzing how AI adoption interacts with these cultural nuances sheds light on technology acceptance at the highest managerial level.

This study contributes to the geographic diversity of studies on AI adoption by drawing on Bandura's theories of self-efficacy and acceptance and use of technology. It explored the confluence of technology, psychology, and culture, shaping organizational behavior and strategic decision-making within Oman's unique context (Bandura, 1986; Williams et al., 2015). The subsequent sections present a comprehensive literature review, define the theoretical foundations, and outline the research questions and hypotheses. We responded to the pressing need for culturally situated insights by explicitly linking these constructs to the Omani context.

This study addresses the limited understanding of the psychological dynamics of AI adoption in Oman and illuminates how leaders navigate technology, human values, and societal norms during an era of rapid change. By examining AI adoption through the distinctive lens of social psychology in Oman, we offer actionable insights for practitioners, policymakers, and academics seeking to harmonize technological ambitions with deeply ingrained human and cultural factors. Thus, this study contributes to broader international discussions on how emerging economies can leverage AI for sustainable innovation and strategic growth.

Therefore, this study addresses an empirical gap and sets the stage for a deeper exploration of regions where technology adaptation and leadership psychology are intertwined.

Literature Review

AI has revolutionized the global business landscape and transformed various sectors with unparalleled potential. This study explores three dimensions of AI adoption in business: global trends, adoption barriers, and the intersection of sustainability and green creativity (Salah, Al Halbusi, et al., 2024). In addition, it integrates psychological frameworks, notably Bandura's theory of self-efficacy and unified theory of acceptance and use of technology (UTAUT), to contextualize how leadership beliefs and organizational culture shape AI adoption.

Theoretical Foundations: Bandura's Theories of Self-Efficacy and Technology Acceptance Model

Theory of Self-Efficacy. Bandura's theory of self-efficacy, rooted in social cognitive theory, plays a pivotal role in the present study. This theory emphasizes an individual's belief in their ability to achieve specific goals (Bandura, 1977). Moreover, according to this theory self-efficacy influences the challenges that people undertake, the effort they expend, and the persistence and resilience they display in the face of obstacles (Stajkovic & Luthans, 1998).

In the context of technology adoption, Compeau & Higgins (1995) revealed that self-efficacy significantly affects technology acceptance and usage behaviors. By shaping an individual's confidence in using new technological tools, self-efficacy determines their willingness to explore, learn, and utilize them to their fullest potential (Venkatesh & Davis, 1996). Recent studies in emerging markets suggest that high self-efficacy can bolster readiness to embrace innovative platforms, even when cultural or infrastructural barriers exist (Gharib et al., 2016; Ghouse, Barber, & Alipour, 2024).

In the Omani context, applying self-efficacy theory to understand the moderating effect of this construct on the relationship between AI adoption and other dependent variables, such as risk perception, green creativity, and positive mental health, presents a novel research avenue. Oman's Vision 2040, which underscores digital transformation, makes leaders' self-beliefs particularly relevant for navigating technological complexities and cultural expectations within organizations.

Unified Theory of Acceptance and Use of Technology. This study primarily relied on the principles stemming from the technology acceptance theory as presented by Venkatesh et al. (2003). The theory consolidates various technology adoption models (TAM), thus having become a widely recognized framework for understanding user acceptance and utilization. The model posits that performance expectancy, effort expectancy, social influence, and facilitating conditions influence technology acceptance. The theory provides insights into the interplay between user perceptions, organizational culture, technological attributes, and the broader business landscape (Alsheddi, 2020). Given Oman's Vision 2040 goals, aligning AI adoption with national strategic goals adds another layer to this dynamic, making the TAM a relevant theoretical framework.

Recent adaptations of the TAM have considered additional variables such as self-efficacy and risk perception (Upadhyay et al., 2022), highlighting the evolving nature of technology adoption theories and their relevance to contemporary challenges such as AI integration in diverse cultural and economic contexts. By merging Bandura's self-efficacy theory with the UTAUT perspective, this study investigates how organizational leaders in Oman balance cultural expectations, personal beliefs, and strategic objectives when adopting AI.

Bandura's self-efficacy theory and the technology acceptance model offer comprehensive frameworks to explore the multifaceted relationships between AI adoption, self-efficacy, risk perception, green creativity, and positive mental health within the unique Omani context (Ghouse & Chaudhary, 2024). Drawing on these well-established theories, this study contributes to the ongoing dialogue on how technology shapes organizational strategies, leadership beliefs, and cultural considerations.

Global Trends in AI Adoption

The rise of AI in various industries reflects its expansive application and potential for a transformative impact. Rather than improving operational efficiency or automating routine tasks, AI is now a strategic tool that provides a competitive advantage. AI further enables the creation of innovative products and services, as well as the personalization of customer experience. Leading organizations leverage AI to enhance decision-making processes and forecast market trends (Davenport & Ronanki, 2018).

Government-driven initiatives in emerging markets often spur AI integration by emphasizing technological readiness and skill development. Oman's Vision 2040 exemplifies this trend by cultivating technologically proficient industries that compete globally. However, the speed and depth of AI adoption can vary dramatically across organizations depending on leadership orientation, cultural norms, and infrastructure.

Challenges and Barriers to AI Adoption

Despite its promises, AI adoption faces several challenges that impede its seamless integration into organizational practices. Its technological complexity requires a substantial understanding of data science and related technologies. This complexity often translates into high implementation costs, including investments in hardware, software, and training (Ransbotham et al., 2019). The scarcity of skilled AI professionals further compounds these challenges (Accenture, 2024).

Additionally, cultural resistance within organizations and misalignment with corporate objectives can hinder fully embracing AI, particularly in more conservative contexts (Ghouse, Shekhar, et al., 2024). Ethical considerations, including data privacy, security, and legal compliance, add further complexity (Salah et al., 2023). Business leaders in Oman must navigate these technical and ethical complexities while aligning AI adoption with national goals, a delicate balance that underscores the psychological dimensions of adoption decisions.

AI and Sustainability: The Path to Green Creativity

The intersection of AI and sustainability is an emerging critical area of interest. AI has been identified as a vital tool for promoting green creativity by designing products and processes that minimize environmental impact (Kumar et al., 2022). In addition, AI algorithms contribute to energy optimization in various sectors, thereby reducing carbon footprints (Delanoë et al., 2023). AI applications extend to environmental monitoring, threat prediction, and conservation efforts (Salah, Al Halbusi, et al., 2024).

Recognizing the role of AI in achieving social responsibility aligns with global sustainability efforts such as the United Nations' Sustainable Development Goals (Di Vaio et al., 2020). In Oman, where preserving ecological balance forms part of the national development vision, green creativity facilitated by AI can drive innovation that merges economic objectives with environmental stewardship. Such a dual emphasis also resonates with leaders with high self-efficacy, who may be more willing to explore AI-enabled sustainable solutions.

Psychological Aspects of AI Adoption

Psychological factors often play a significant though overlooked role in AI adoption. This section examines three vital psychological aspects influencing AI adoption: positive mental health, self-efficacy, and risk perception (Simons & Peterson, 2000; Yap et al., 2021).

Positive Mental Health. The mental well-being of top management, including CEOs and founders, is crucial to an organization's success (Shipman et al., 2023). As the importance of AI grows in modern business, aligning AI adoption with personal and organizational goals can enhance leaders' mental well-being. Resilience and optimism developed by successfully navigating AI's complexity can positively influence overall organizational morale and effectiveness. Galluch (2015) suggested that mental well-being may be closely tied to how technological adoption aligns with personal aspirations and corporate strategies. In Oman, leaders who interpret AI as a strategic opportunity rather than as a disruptive force may experience reduced stress and higher satisfaction.

Self-Efficacy in Overcoming Barriers to AI Adoption. Self-efficacy, which is the belief in one's capability to achieve goals, is the cornerstone of understanding human behavior and motivation. Bandura's (1977) self-efficacy theory has been applied in various contexts, including technology adoption. In AI, high self-efficacy can amplify a leader's ability to overcome barriers such as technical complexity, financial costs, and organizational resistance (Compeau & Higgins, 1995). According to these findings, fostering self-efficacy among leaders and key stakeholders can lead to more effective decision-making, implementation, and utilization of AI technologies. In conservative cultural settings such as Oman, leaders with robust self-beliefs may also galvanize employee support and improve adoption outcomes.

Risk Perception in AI Adoption Decisions. Perception and risk evaluation are essential components of the decision-making process for technology adoption. Risk perception significantly influences technology acceptance (Ahmed et al., 2022). Adopting AI, its inherent complexities and unknowns, is fraught with various perceived risks, including financial investments, ethical dilemmas, and sociocultural impacts (Salah, Al Halbusi, et al., 2024). Although studies on leaders' risk evaluations of AI adoption are emerging, the research remains limited. Understanding how risk perception shapes AI adoption can reveal why specific organizations are more receptive to AI, and how these risks can be mitigated or managed. Risk perception can significantly sway organizational consensus on AI projects in Oman, where leadership decisions may be influenced collectively.

These psychological aspects (positive mental health, self-efficacy, and risk perception) offer a richer understanding of the human factors guiding organizational technological integration. Organizations can build a robust and resilient framework for successful AI adoption by prioritizing mental well-being, encouraging self-efficacy, and carefully managing risks.

AI Adoption in Oman: Economic Diversification, Cultural Considerations, and Government Policy

Adopting AI in the Omani business landscape presents a multifaceted challenge that intertwines with Vision 2040, cultural norms, and government policies. This section explores these dimensions, illustrating how AI aligns with Oman's broader strategic objectives and shapes leadership behavior in a culturally rich setting (Abdelfattah, Dahleez, et al., 2025).

Oman's Vision 2040 strongly emphasizes economic diversification and technological advancement as key pathways for sustainable development (Al Balushi et al., 2019). Seeking to reduce reliance on oil revenues, the Vision champions innovation in various sectors, including healthcare, education, finance, and logistics. AI is critical for this transformation as it offers improved efficiency, predictive analytics, and data-driven decision-making solutions.

Despite this strategic emphasis, empirical studies examining how AI concretely aligns with Oman's development goals remain limited, creating a research gap in understanding the potential impact of AI initiatives on national growth and organizational performance (Ghouse, Shekhar, et al., 2024). Moreover, top management in Omani firms may weigh risk perceptions and cultural considerations differently from leaders in other regions, thus affecting AI uptake. Addressing these gaps could illuminate the synergy between technology-driven policies and Oman's vision of a knowledge-based economy.

The cultural context of Oman is characterized by communal goals, respect for tradition, and adherence to social norms. These collective values influence how AI is perceived, adapted, or resisted in the Omani business environment (Al-Azri, 2012). Aligning AI initiatives with cultural values may foster smoother acceptance and integration (Dwivedi et al., 2021). Conversely, technological solutions perceived as clashing with traditional norms or lacking cultural sensitivity could face significant pushback, hindering their widespread implementation (Salah, Abdelfattah, & Al Halbusi, 2024).

Business leaders' self-efficacy and risk perceptions further shape this cultural dynamic. When leaders feel confident in their ability to navigate cultural sensitivities, they may champion AI to enhance communal well-being, thus garnering organizational and societal support.

Alternatively, if leaders perceive a high risk to social harmony or cultural heritage, they may delay or limit their adoption of AI. Understanding these cultural undercurrents is essential for tailoring AI strategies to resonate with local values and gain broader acceptance.

The Omani government has demonstrated a strong commitment to nurturing AI innovation, as reflected in its investments in education, digital infrastructure, and regulatory frameworks (Ordoñez de Pablos, 2023). Government-led initiatives like national AI strategies and start-up incubators aim to catalyze technology adoption across sectors. For instance, programs targeting data literacy and STEM education ensure a skilled workforce, while policies encouraging public-private partnerships can accelerate AI diffusion (Al Harrasi et al., 2021).

However, government policies must align with the business community's needs and societal expectations for success. Misalignment or a lack of clear regulations may create barriers, leading to confusion regarding data governance, ethical usage, and legal responsibilities (Salah, Al Halbusi, et al., 2024). Thus, the pace and success of AI integration in Oman significantly depend on cohesive strategies involving government agencies, private enterprises, and academic institutions (Al Zadjali, 2020). This collaboration ensures that AI-driven advancements align with Vision 2040, cultural imperatives, and leadership perspectives in the Omani context.

Research Gap and Hypothesis Development

AI adoption in Oman is a complex and multifaceted process that requires careful consideration of Vision 2040, cultural values, and government policies. When AI strategies align with Omani economic goals and cultural ethos, they can catalyze innovation and growth. Simultaneously, neglecting cultural or policy dimensions can hamper local relevance and acceptance of AI initiatives.

The literature review unveiled essential themes shaping the understanding of AI adoption, its psychological correlates, and the specific dynamics within Oman (Abdelfattah, Salah, et al., 2025). Although extensive global research exists, studies exploring AI adoption in Oman are relatively sparse. Therefore, this study examines how AI adoption interacts with green creativity, mental well-being, risk perception, and self-efficacy among top Omani business leaders. Since the cultural and economic context of Oman introduces unique considerations, studying leadership behaviors in this environment adds a fresh lens to the broader discourse on technology–human interaction.

Based on these gaps and conceptual frameworks, the following hypotheses were proposed:

Hypothesis 1 (H1): A positive relationship will be observed between AI adoption and green creativity among business leaders in Oman.

Hypothesis 2 (H2): AI adoption will correlate positively with the mental health of Oman's top management, founders, and CEOs.

Hypothesis 3 (H3): A positive relationship between AI adoption and risk perception in Omani organizations' leadership will be observed.

Hypothesis 4 (H4): Self-efficacy will moderate the relationship between AI adoption and green creativity, making the relationship more robust when self-efficacy is higher.

Hypothesis 5 (H5): Self-efficacy will moderate the relationship between AI adoption and positive mental well-being, strengthening the relationship when self-efficacy is higher.

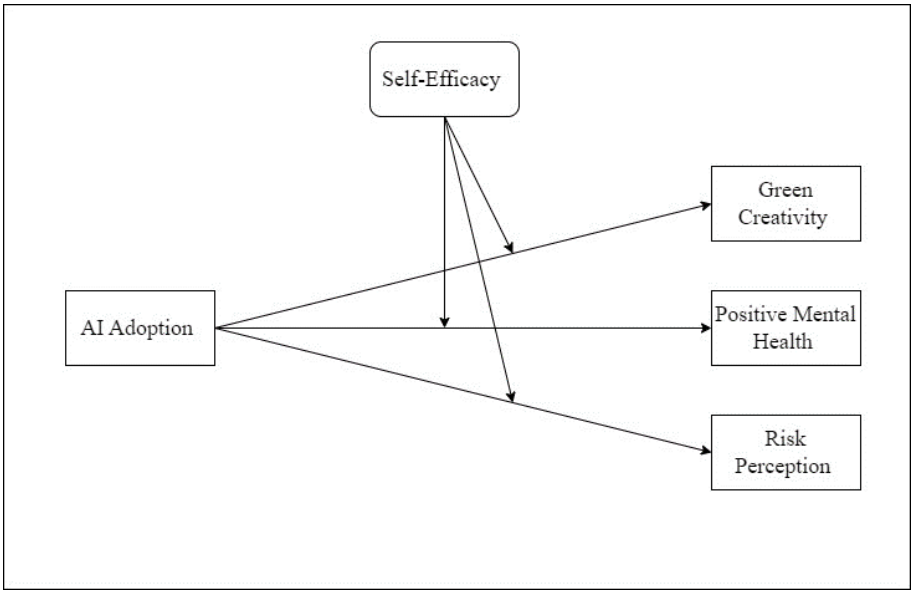
Hypothesis 6 (H6): Self-efficacy will moderate the relationship between AI adoption and risk perception, making the relationship more potent when self-efficacy is higher.

This study aims to address the knowledge gap regarding how AI adoption interacts with leadership psychology in Oman by testing these hypotheses. Research

framework is presented in Figure 1. The study further contributes to strategic insights that can inform policymakers, business leaders, and academics seeking to harness the transformative potential of AI within a culturally grounded framework.

Figure 1

Research Framework



Note. Source: developed by the authors.

Methodology

Sampling and Procedure

The target population consisted of top management personnel from various firms in Oman, including founders, presidents, vice presidents, and other C-level executives. This study involved 214 top management members representing diverse industries and firms. Owing to time and resource constraints, a non-probability convenience sampling method was employed, allowing researchers to access these high-level respondents more efficiently.

Although convenience sampling can expedite data collection and facilitate access to specialized groups, it introduces limitations regarding the generalizability of the findings. Specifically, voluntary participation and the potential exclusion of specific industries or smaller firms may have skewed the sample, rendering it less representative of Omani's top management population. Future research should use probability or multistage sampling to capture a more inclusive perspective of AI adoption across different organizational contexts.

Data was collected through an online survey featuring structured questionnaires designed to measure the constructs of interest (e.g., self-efficacy, risk perception, and

AI adoption). Before initiating the survey, the participants were briefed on the purpose of the study, the voluntary nature of their participation, and the confidentiality of their responses. Informed consent was obtained from all participants to ensure ethical adherence and privacy.

Measurement

The variables under investigation were obtained from previous studies. The concepts of self-efficacy and risk perception were incorporated based on Hassan et al. (2023). The AI adoption construct is adapted from Venkatesh et al. (2003). The concept of green creativity was sourced from Chen and Chang (2013). Finally, the concept of positive mental health was adopted by Lukat et al. (2016). All variables were measured using a five-point Likert scale.

Data Analysis and Results

The research model was analyzed using structural equation modeling (SEM) with partial least squares (PLS) methodology. In line with Ringle et al. (2014), the SmartPLS 4 was selected due to its robustness in dealing with non-normal data, moderate sample sizes, and complex causal relationships including higher-order constructs (Hair et al., 2017). As compared to SEM covariance tools, PLS-SEM does not require strict normality assumptions, making it suitable for exploring the model used in this study.

Following the best-practice guidelines (Hair et al., 2017), we performed a PLS analysis by generating 5,000 bootstrap subsamples to evaluate the statistical significance of the path coefficients (Mohammed et al., 2021a). These subsamples yielded bootstrap *t*-statistics based on *n–1* degrees of freedom (where *n* represents the number of subsamples). This resampling approach enhanced the reliability of our parameter estimates and provided robust confidence intervals, thereby mitigating concerns about non-normal data distributions.

The flexibility and ability of SmartPLS 4 to accommodate first- and second-order constructs made PLS-SEM the ideal approach for analyzing multifaceted relationships in our study. This methodology aligned with the study's objective of examining direct and moderating effects within a culturally nuanced and theoretically rich framework.

Demographic Profiles of Respondents. The age distribution of participants indicated that the majority were between 25 and 50 years old. More than half of the respondents (53.3%, *n* = 114) fell within the 25–30 age bracket, while 41.1% (*n* = 88) were between 41 and 50. A smaller proportion, 5.6% (*n* = 12), were under 25.

The sample was fairly balanced in terms of gender, with male respondents comprising 52.3% (*n* = 112) and females making up 47.7% (*n* = 102).

Concerning professional experience, half of the respondents (50.5%, *n* = 108) reported having between six and 10 years of work experience. Another 29% (*n* = 62) had been in their roles for 11 to 15 years, while the remaining 20.6% (*n* = 44) had three to five years of experience.

Concerning occupational roles, most participants (80.4%, *n* = 172) held senior executive positions such as Chief Executive Officer (CEO), Chief Operating Officer (COO), or Chief Financial Officer (CFO). Additionally, 12.6% (*n* = 27) served as presidents or vice presidents, and 7% (*n* = 15) identified themselves as company founders.

In terms of educational qualifications, 70.1% (*n* = 150) of the respondents had obtained a Bachelor's degree, while the remaining 29.9% (*n* = 64) held postgraduate qualifications, including Master's or doctoral degrees.

Common Method Bias. The potential issue of standard method bias was acknowledged due to the single-source nature of the data, in which both the independent and dependent variables stem from a single survey. Following N. Podsakoff et al. (2003), a twofold approach encompassing procedural and statistical methods was employed to address this concern. For procedural aspects, the survey instrument incorporated multiple measuring scales, and participants were assured that their responses carried no inherent correctness and that their identities would remain confidential, thus reducing social desirability bias. From a statistical standpoint, although standard method bias was deemed unlikely to affect the interaction terms (P. M. Podsakoff et al., 2012), a thorough evaluation was conducted to confirm the absence of bias.

Harman's single-factor analysis examined whether a single factor could account for a significant portion of the covariation among all study items, revealing five factors with eigenvalues exceeding one, collectively explaining 68% of the variance. The most significant factor was 23%, which was well below the 50% threshold (Mohammed et al., 2021b; N. Podsakoff et al., 2003).

In addition, variance inflation factors (VIFs) were analyzed to detect vertical and lateral collinearity (Kock & Lynn, 2012). As shown in Table 1, the VIF values for AI adoption (2.113), green creativity (1.221), positive mental health (1.127), risk perception (1.223), and self-efficacy (2.231) were below 3.3, indicating no pathological collinearity or CMV contamination. These results confirm no significant multicollinearity among the variables, corroborating the conclusion that common method bias does not seriously threaten the study's findings (Hair et al., 2022).

Table 1

Measurement Model, Item Loadings, Construct Reliability, and Convergent Validity

Constructs	Items		Loading (> 0.5)	CA (> 0.7)	CR (> 0.7)	AVE (>0.5)
AI Adoption	AI1	A timely AI technical implementation and application migration plan has been developed in our organization.	0.6780	0.834	0.879	0.579
	AI2	Our management has formally endorsed the AI adoption plan.	0.805			
	AI3	A dedicated financial budget and implementation schedule for AI adoption have been approved.	0.836			

Table 1 Continued

Constructs	Items		Loading (> 0.5)	CA (> 0.7)	CR (> 0.7)	AVE (>0.5)
	AI4	Our customers show strong acceptance of our new products and services enabled by AI innovations.	0.784			
	AI5	Our competitive position has improved since adopting AI technologies.	0.758			
Green Creativity	GC1	The members of the green product development project suggest new ways to achieve environmental goals.	0.767	0.843	0.906	0.763
	GC2	The members of the green product development project propose new green ideas to improve environmental performance.	0.803			
	GC3	The members of the green product development project promote and champion new green ideas to others.	0.790			
	GC4	The members of the green product development project develop adequate plans for the implementation of new green ideas.	0.851			
	GC5	The members of the green product development project would rethink new green ideas.	0.727			
	GC6	The members of the green product development project would find out creative solutions to environmental problems.	0.882			
Positive Mental Health	PMH1	I am often carefree and in good spirits.	0.816	0.829	0.911	0.623
	PMH2	I enjoy my life.	0.821			
	PMH3	All in all, I am satisfied with my life.	0.732			
	PMH4	In general, I am confident.	0.841			
	PMH5	I manage well to fulfill my needs.	0.812			

Table 1 Continued

Constructs	Items		Loading (> 0.5)	CA (> 0.7)	CR (> 0.7)	AVE (>0.5)
	PMH6	I am in good physical and emotional condition.	0.823			
	PMH7	I feel that I am actually well equipped to deal with life and its difficulties.	0.871			
	PMH8	I am a calm, balanced human being.	0.818			
	PMH9	Much of what I do brings me joy.	0.731			
Risk Perception	RP1	If we do not adopt AI, our organization may fall behind competitors.	0.823	0.832	0.922	0.747
	RP2	I feel I have limited control over the risks associated with AI adoption.	0.871			
	RP3	Adopting AI could pose serious operational challenges for our business.	0.816			
	RP4	If AI is not implemented properly, it could have major consequences for our organization.	0.850			
	RP5	The risks associated with adopting AI are minor and manageable. z	0.885			
	RP6	AI adoption could significantly disrupt current business processes.	0.784			
	RP7	Poor AI implementation could lead to financial losses for the organization.	0.781			
	RP8	Misuse or failure of AI could negatively affect key stakeholders or customers.	0.755			
Self-Efficacy	SF1	I am confident in my ability to understand and make informed decisions about AI adoption.	0.818	0.835	0.887	0.659
	SF2	I am certain that I will take the necessary actions to implement AI, even if they are difficult or unfamiliar.	0.740			
	SF3	I have the determination to lead my organization through AI-driven change.	0.709			

Table 1 Continued

Constructs		Items	Loading (> 0.5)	CA (> 0.7)	CR (> 0.7)	AVE (>0.5)
	SF4	I am confident that I can overcome challenges associated with integrating AI into business operations.	0.782			
	SF5	I believe I can guide others in using AI tools effectively to achieve strategic goals.	0.731			

Note. CA = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted.

Assessment of the Measurement Model. To evaluate the soundness of the measurement model, an in-depth analysis of internal consistency reliability, convergent validity, and discriminant validity was conducted (Table 2). Most items exceeded the threshold of 0.707, as recommended by Hair et al. (2019), indicating favorable performance.

First, Cronbach's alpha and composite reliability were assessed to examine internal consistency. The results in Table 1 demonstrate values surpassing 0.70 (Hair et al., 2019), affirming the construct's robustness.

Next, the average variance extracted (AVE) was used as the primary metric for convergent validity. Notably, each construct's AVE exceeded 0.50, meeting the prescribed threshold (Hair et al., 2019) and underscoring the convergence of the measures (see Table 1).

Finally, the examination was extended to discriminant validity, which was unblemished. As indicated in Table 2, the AVE values for each construct surpassed the variance shared by other latent constructs (Hair et al., 2017).

Table 2

Descriptive Statistics, Correlation Matrix, and Discriminant Validity

Constructs	Mean	SD	1	2	3	4	5
1. AI Adoption	3.112	0.540	**0.571**	*0.707 [0.612; 0.739]*	*0.321 [0.324; 0.481]*	*0.677 [0.630; 0.741]*	*0.194 [0.147; 0.245]*
2. Green Creativity	3.831	0.441	0.316	**0.841**	0.544 [0.492; 0.609]	0.794 [0.758; 0.827]	0.175 [0.156; 0.239]
3. Positive Mental Health	4.406	0.709	0.339	0.164	**0.446**	*0.570 [0.510; 0.631]*	*0.127 [0.103; 0.203]*
4. Risk Perception	1.374	0.447	0.554	0.292	0.246	**0.675**	*0.180 [0.152; 0.247]*
5. Self-Efficacy	2.711	0.767	0.049	0.074	0.454	0.074	n.a.

Note. AVE values are in bold, Heterotrait-Monotrait values are in italics; n.a. = not applicable.

Furthermore, Heterotrait–Monotrait ratios were below 0.90 and did not enclose 1 within their 95% confidence intervals, reinforcing the distinctness of each pair of variables (Henseler et al., 2015). Table 3 outlines the Heterotrait–Monotrait values in detail.

Table 3

Structural Path Analysis: Direct Effect

Hypothesis	Relationship	SB	*SD*	*t*-value	*p*-value	Bias and Corrected Bootstrap 95% CI [Lower Level; Upper Level]	Decision	VIF
H1	AI Adoption > Green Creativity	0.386	0.060	6.467	.000	[0.275; 0.475]	Supported	1.664
H2	AI Adoption > Positive Mental Health	0.198	0.066	3.019	.001	[0.075; 0.293]	Supported	2.275
H3	AI Adoption > Risk Perception	0.280	0.070	3.990	.000	[0.166; 0.404]	Supported	1.834

Note. VIF = variance inflation factor.

Assessment of the Structural Model

The findings pertinent to **H1–H3** are presented in Table 3. Notably, these hypotheses encountered no complications linked to multicollinearity, considering that the VIF values remained comfortably below the 5.0 threshold established to flag such issues (Hair et al., 2017).

Supporting **H1**, the data revealed a significant and positive relationship between AI adoption and green creativity (β = 0.386, t = 6.467, p < .000, Table 3), offering compelling support for the hypothesis. Regarding **H2**, it became evident that AI adoption significantly impacted positive mental health (β = 0.198, t = 3.019, p < .001). Furthermore, **H3** was supported, with AI adoption exhibiting a positive and substantial correlation with risk perception (β = 0.280, t = 3.990, p < .000). Consequently, all direct predictions associated with these hypotheses were robust, as shown in Table 3.

The moderation analysis (Table 4) represented a pivotal dimension of this study. It aimed to determine whether self-efficacy moderates the relationship between AI adoption (the independent variable) and the three dependent variables: green creativity, positive mental health, and risk perception. With this objective, we closely examined the interaction effects of self-efficacy.

First, when evaluating the interaction of AI adoption and self-efficacy on green creativity, results indicated a substantial interaction (β = 0.142, t = 4.530, p < .000). This outcome supports **H4**, suggesting that high self-efficacy amplified the positive impact of AI adoption on green creativity. In contrast, the second interaction—encompassing

AI adoption, self-efficacy, and positive mental health—yielded an insignificant effect ($\beta = 0.055$, $t = 1.024$, $p = .153$), thereby not supporting **H5**.

The third interaction explored the relationship between AI adoption, self-efficacy, and risk perception; the results revealed a positive and significant interaction ($\beta = 0.089$, $t = 3.166$, $p < .001$). This supports **H6**, indicating that leaders with higher self-efficacy exhibit different and more pronounced risk perceptions in response to AI adoption.

Table 4 provides detailed coefficients and corresponding statistical indicators for a comprehensive summary of these moderation findings.

Table 4

Structural Path Analysis: The Interaction Effect (Moderation)

Hypothesis	Relationship	SB	*SD*	*t*-value	*p*-value	Bias and Corrected Bootstrap 95% CI [Lower Level; Upper Level]	Decision	VIF
H4	AI Adoption × Self-Efficacy > Green Creativity	0.142	0.052	4.530	.000	[0.041; 0.203]	Supported	1.148
H5	AI Adoption × Self-Efficacy > Positive Mental Health	0.055	0.044	1.024	.153	[–0.117; 0.020]	Not supported	1.568
H6	AI Adoption × Self-Efficacy > Risk Perception	0.089	0.046	3.166	.001	[0.027; 0.176]	Supported	1.072

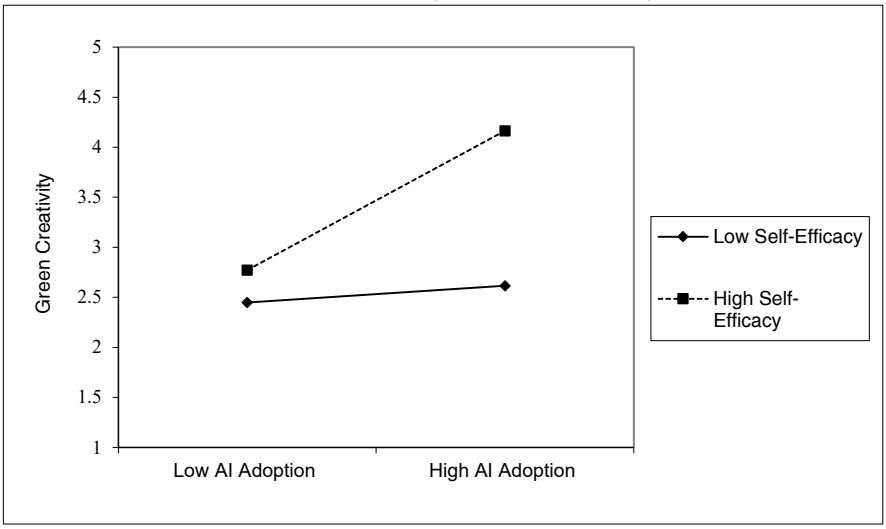
Note. VIF = variance inflation factor.

In line with Dawson's (2014) recommendation, interaction plots were employed to explore how self-efficacy moderates the relationship between AI adoption and the outcome variables. By visualizing the gradient of slopes for each interaction, these plots provided a clearer picture of the differences in effect sizes between high and low levels of self-efficacy.

Figure 2 shows that the first interaction plot highlights the differential slopes of AI adoption and green creativity in the high- and low-self-efficacy groups. Notably, the high self-efficacy line exhibits a steeper incline than the low self-efficacy line, indicating that the positive link between AI adoption and green creativity was more pronounced when self-efficacy is high.

Figure 2

Interaction of AI Adoption and Self-Efficacy on Green Creativity

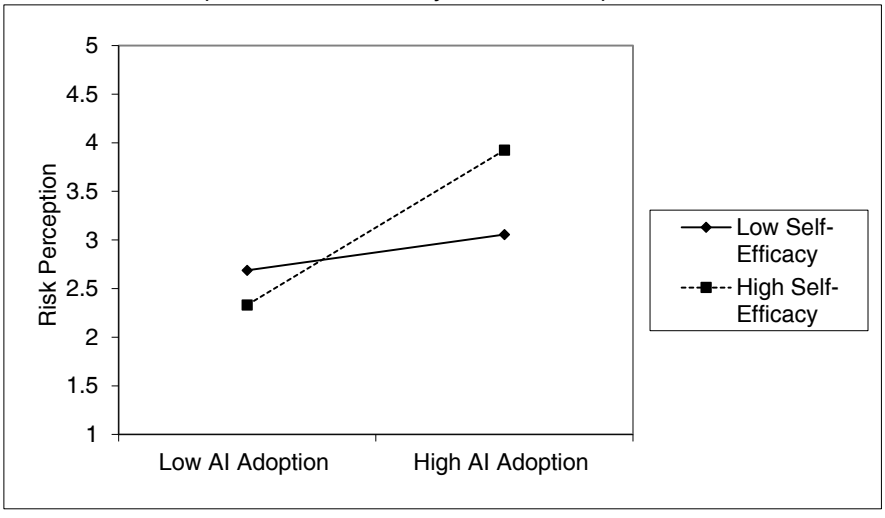


Note. Source: developed by the authors.

As shown in Figure 3, which depicts the second interaction involving AI adoption, self-efficacy, and risk perception, the plot demonstrates that risk perception increased more strongly under high self-efficacy conditions. Specifically, leaders with higher self-efficacy displayed a sharper increase in their perceived risk as AI adoption intensified, suggesting that self-efficacy amplifies their evaluations of uncertainties and potential threats.

Figure 3

Interaction of AI Adoption and Self-Efficacy on Risk Perception



Note. Source: developed by the authors.

Figures 2 and 3 show these interactions, enhancing understanding the nuanced dynamics within the study's framework. They revealed how self-efficacy can shift the direction or strength of AI adoption's impact on green creativity and risk perception, offering more profound insights into the role of leadership beliefs in technology implementation.

Discussion

This study explored the relationships among AI adoption, green creativity, positive mental health, risk perception, and the moderating effect of self-efficacy in 214 CEOs, founders, and top management in Oman. The findings offer valuable insights and contribute significantly to the theoretical and practical discourse on how AI shapes organizational strategies, particularly in collectivist and culturally rich business environments.

AI adoption has emerged as a pivotal factor driving global business strategies in this rapidly advancing technological era. One of its most intriguing dimensions is the positive relationship between AI adoption and green creativity (Tawfik et al., 2023), which is evident in the Omani business context. This finding underscores how embracing AI can spur eco-friendly innovation, which is a priority in many emerging economies that strive to balance economic progress with environmental sustainability (Kulkarni et al., 2025).

In Oman, this synergy has a heightened significance. Vision 2040 explicitly calls for economic diversification beyond traditional oil revenues, sustainability, and responsible resource management (Yigitcanlar et al., 2021). Implementing AI aligns with these objectives, offering data-driven and predictive capabilities that enable companies to minimize waste, optimize energy consumption, and create value consistent with cultural norms that emphasize communal well-being. For instance, AI algorithms help Omani businesses forecast supply chain demand, monitor environmental impacts, and design innovative and eco-friendly products (Gupta et al., 2022).

Moreover, AI-powered creativity drives the development of new green products, materials, and business models, promoting profitability and social responsibility (Ghobakhloo et al., 2021). Nevertheless, organizations face limited AI expertise, cultural alignment, and technical readiness (Allioui & Mourdi, 2023; Salah, Al Halbusi, et al., 2024). Thus, top management must cultivate an innovative-friendly culture that embraces advanced technology while respecting local traditions and collective norms.

From a comparative standpoint, these findings mirror global research linking AI adoption to sustainable initiatives. However, the Omani setting, with its strong emphasis on Vision 2040 and communal values, offers a unique perspective. The positive link between AI adoption and green creativity enriches the international dialogue on how technology can catalyze sustainable development. Local policymakers and business leaders can leverage these insights to incentivize green AI projects, train talent in data science, and promote success stories that highlight environmental stewardship. Doing so may deepen Oman's commitment to responsible innovation and reinforce its trajectory toward a greener, more diversified economy.

Beyond operational efficiency and productivity gains, this study revealed a noteworthy positive correlation between AI adoption and the mental well-being of CEOs and top management (Dwivedi et al., 2021). This insight underscores the human dimension of technological adoption, which is often overshadowed by technical and financial considerations.

This connection stems from leaders' sense of accomplishment and control when AI is leveraged to enhance decision-making, streamline processes, and foster innovation (Tambe et al., 2019). This alignment between organizational goals and personal efficacy fosters psychological fulfillment, manifested as increased mastery over complex issues and greater clarity in strategic direction (Bruch & Vogel, 2011; Salah, Al Halbusi, et al., 2024). Such well-being in the upper echelons often cascades to a broader workforce, cultivating a collaborative and data-driven organizational culture (Zahoor et al., 2022).

In Oman, where collectivism and respect for hierarchical leadership play pivotal roles in corporate culture, the mental well-being of CEOs can significantly influence employee engagement and acceptance of technology-driven changes. Oman's broader vision of economic diversification and social development also emphasize human capital enhancement, suggesting that leaders' psychological health could serve as a cornerstone for effective AI integration. However, challenges exist, such as limited technical training and cultural norms around work stress, and addressing them requires holistic strategies that blend technical readiness with well-being initiatives (Dwivedi et al., 2023).

The positive correlation between AI adoption and mental health represents a new perspective beyond viewing AI as merely a set of tools. Comparatively, research in other collectivist or emerging markets has indicated that technological empowerment can increase leadership morale. However, the Omani setting offers additional nuances given the weight placed on harmony and community values (Zaidan et al., 2019). By recognizing AI's role as a strategic partner rather than as a threat or automation engine, managers can shape a work environment that is conducive to positive mental health and resilience.

In practice, business leaders should invest in skill-development programs, foster AI literacy at multiple organizational levels, and actively encourage open dialogue regarding AI implementation to relieve anxiety. Such measures can sustain a healthier workplace and bolster top management's confidence, as they guide their companies through technological transitions in alignment with Vision 2040.

Integrating AI into business operations entails opportunities and challenges, often accompanied by inherent risks. This study identified a positive association between AI adoption and risk perception, indicating that leaders who engage more deeply with AI do not necessarily perceive fewer risks; instead, they recognize and illuminate them (Rodway & Schepman, 2023).

This may seem counterintuitive as one would expect familiarity with AI to reduce perceived risk. However, leaders actively engaging in sophisticated AI technologies often develop greater awareness of their limitations, uncertainties, and potential pitfalls (Wijayati et al., 2022). This heightened consciousness reflects a mature approach to

technological adoption wherein risk is managed rather than avoided. This risk literacy aligns with Featherman and Pavlou's (2003) argument that informed leaders make more resilient decisions.

In Oman, where economic diversification is paramount (Al Zuheimi, 2025), leaders balancing enthusiasm for AI with a cautious assessment of risks can better align investment strategies with the overarching goals of Vision 2040. Culturally, Omani business leaders often exhibit collective responsibility and feel compelled to protect shareholders' interests and societal welfare. This perspective may amplify emphasis on responsible AI deployment, transparency, and ethical considerations.

From a global standpoint, this nuanced view of risk perception fosters a balanced stance on AI adoption, wherein innovation coexists with due diligence (Kaplan & Mikes, 2012). For managers and policymakers, the practical takeaway is clear: educational programs, collaboration, and transparent communication regarding the risks and benefits of AI help build trust among stakeholders. Business leaders in Oman and other emerging markets may thus adopt structured risk assessment frameworks to ensure that optimism regarding AI capabilities is tempered by foresight and robust governance.

Integrating AI into business practices reshapes industries and unlocks innovation frontiers. This study's central contribution is revealing the moderating role of self-efficacy, highlighting how leaders' confidence and beliefs in their capabilities can amplify or temper the effects of AI adoption on green creativity, positive mental health, and risk perception (Marr, 2019).

In Omani organizations, self-efficacy may merge with collective cultural values, such as communal responsibility and respect for hierarchical structures, to influence technology adoption. Highly self-efficacious leaders are more likely to embrace AI's potential, pursue eco-innovations, and constructively address balanced risk concerns. This expanded understanding of Bandura's self-efficacy theory underscores how cultural norms and individual belief systems interlock and shape the trajectory of AI-driven transformations.

By investing in training programs, mentorship, and an organizational climate that encourages experimentation and supports learning, businesses can foster self-efficacy among top management and key stakeholders. This approach resonates with the emphasis of Vision 2040 on human capital development and the positioning of self-efficacy as a strategic asset for sustainable AI integration.

Business leaders in other collectivist societies exhibit similar dynamics in which individual confidence intersects with community-oriented values (Ghouse & Chaudhary, 2024). Thus, the moderating effect of self-efficacy is neither purely individualistic nor merely an organizational concern; it arises from the complex interplay of personal beliefs, social influences, and national objectives.

Ultimately, cultivating self-efficacy offers practical benefits for navigating AI's evolving landscape. It empowers leaders to evaluate the capabilities and limitations of AI realistically, enabling more strategic adoption patterns that capitalize on innovation while managing the associated risks.

Theoretical and Practical Implications

Integrating AI within the business domain poses complex challenges and opportunities that intersect with various organizational and psychological aspects. Situating this integration within the unique Omani context, the present study offers vital theoretical and practical insights that address the gap between the abstract and the tangible, particularly as Oman navigates Vision 2040 and strives for economic diversification and technological modernization.

The theoretical implications of this research extend beyond conventional understanding. By providing empirical evidence supporting Bandura's self-efficacy theory in the context of AI adoption, this study expands this psychological construct to new and relatively unexplored fields. The positive relationships observed between AI adoption, green creativity, positive mental health, risk perception, and the moderating role of self-efficacy paint a multifaceted picture of how technology interfaces with the kaleidoscope of organizational and psychological dynamics.

Moreover, placing the study in Oman's cultural setting adds depth to the theoretical conversation, emphasizing how collectivist norms, respect for tradition, and communal goals influence technology acceptance. This cultural lens underscores the diversity of human behavior within organizational structures, inviting further investigation in emerging markets and other collectivist societies. Scholars may also extend these findings by comparing Omani leadership behaviors to those in different cultural or economic contexts, thereby enriching global research on technology and human interactions.

From a practical standpoint, this study illuminates viable pathways for organizations to realize the benefits of AI. Recognizing the potential to enhance AI integration through targeted training programs will pave the way for innovation, efficiency, and well-being that align seamlessly with Oman's Vision 2040. Companies can foster cultures of resilience, creative experimentation, and sustainable progress by cultivating self-efficacy among CEOs and key stakeholders.

Acknowledging the dynamic relationship between AI adoption and risk perception is equally important to provide a practical roadmap for strategic risk management. Leaders with high self-efficacy are better prepared to identify, assess, and respond to potential pitfalls, thus ensuring that enthusiasm for AI remains anchored in realistic and ethical considerations. As Omani businesses strive to diversify and modernize, this risk-aware approach can support long-term stability and public trust in AI-driven initiatives.

The study finds that AI can promote green creativity and resonate with global imperatives around environmental responsibility. It illustrates how organizations can harness AI's potential in a nurturing environment that cultivates self-efficacy, forming a bridge between creativity and sustainability. This alignment allows companies to innovate in eco-friendly ways, dovetailing with international sustainability goals and Oman's cultural focus on communal welfare and the stewardship of natural resources.

Finally, the link between AI adoption and positive mental health opens a new chapter in organizational support systems. Understanding that AI adoption can

be perceived not as an added stressor but as an empowering tool sets the stage for environments that prioritize employee well-being. This holistic view extends to recognizing how cultural norms can facilitate or hinder the mental resilience of leaders and employees. Consequently, Omani firms seeking to adopt AI may benefit from leadership training, mental health support, and change management strategies that simultaneously engage cultural and psychological elements.

In conclusion, this study revealed the intricate tapestry of technology, individual psychology, organizational strategy, and cultural contexts. Insights drawn from the Omani business landscape are not merely academic contributions but provide key insights for modern businesses seeking to combine technology with cultural sensitivity and human-centered values. Using theory and practice, this study depicts the multifaceted role of technology in shaping organizational success and individual fulfillment. Its implications resonate with academia and businesses alike, offering valuable perspectives on the transformative power of AI, particularly in emerging markets that balance rapid change with a rich cultural heritage.

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