

AI Competencies in Determining AI Adaptation among the Communication Professionals in Oman

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AI technologies and competencies are changing work patterns across organizations. Therefore, professionals need to adapt to AI-driven organizational communication practices. In this study, we explored AI competencies among communication professionals in Oman. This study aligns with the role of AI adaptation within Oman Vision 2040. We conducted a survey of 247 communication professionals from the Education, Banking, Telecom, Business, and Construction sectors. We developed scales to measure three major AI Competencies: AI Knowledge, Digital Skills, and Critical Thinking, and empirically examined them using Partial Least Squares Structural Equation Modelling (PLS-SEM). The findings revealed that AI Knowledge (KN) and Critical Thinking (CT) are strong predictors of AI attitude (AT). Moreover, AT is a strong direct predictor of AI Adaptation (AD). Therefore, the study suggests constructive policies aligned with the Digital Transformation goals of Oman Vision 2040 to promote AI knowledge and develop the critical thinking skills of Omani professionals.

Keywords: AI competencies, AI adaptation, critical thinking, digital skills, Oman Vision 2040, communication professionals

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Introduction

Global professionalism is subject to a radical transformation driven by Artificial Intelligence (AI), a pioneering technology of the Fourth Industrial Revolution. It has transitioned from a theoretical discipline to

contemporary business models (Nascimento and Meirelles 2022; Onnen 2024). AI shifts organizational flexibility and adaptation, with the potential to enhance operational efficiency, reduce costs, and facilitate data-driven decision-making (Apostoaie et al. 2025; Eltayib 2024). However, the successful integration of AI is not merely a technical challenge but depends upon the competencies of the human workforce (Baki et al. 2023; Santana and Díaz-Fernández 2023). In the Sultanate of Oman, this transition is framed within the Oman Vision 2040. The Oman focuses on digital transformation and human resource development to ensure national competitiveness (Oman Vision 2040 Implementation Follow-up Unit 2020; Pervez et al. 2025).

Oman Vision 2040 is Oman's national strategic framework for addressing developmental challenges and keeping pace with global changes (Czornik 2025; Oman Vision 2040 Implementation Follow-up Unit 2020). A primary goal of digital transformation is to make AI a significant contributor to Oman's national GDP (Tyagi et al. 2025). Oman's vision aims to improve Oman's standing among the world's developed countries by transitioning the country from a resource-dependent economy to an innovation- and knowledge-based economy (Oman Vision 2040 Implementation Follow-up Unit 2020). The key part of the vision is Human Resource Development (HRD), which emphasizes nurturing national talent with dynamic, globally competitive skills (Ayed 2022; Pervez et al. 2025). Consequently, the development of AI competencies among Omani professionals is not merely a localized requirement but a strategic necessity aligned with Oman's national priorities for a knowledge-based society (Al-Ansi et al. 2024; Pervez et al. 2025).

Within this strategic framework, communication professionals occupy an important position. They encompass a large variety of knowledge and expertise in marketing, public relations, and telecommunications. The telecommunications sector is one of the major stakeholders that provide a primary environment for the application of AI-driven revolution (Eltayib 2024). In modern AI communication environments, AI-driven tools such as chatbots and virtual assistants enable professionals to manage massive informational complexity (Eltayib 2024; Rengasamy et al. 2025). Despite the advantages of AI, many organizations in Oman continue to rely on traditional approaches. However, a significant proportion of firms in Oman are struggling to leverage AI investments to generate real value (Mikalef et al. 2023; Tyagi et al. 2025).

Between traditional and AI-driven approaches, there is a gap in the effective integration of new technologies, known as the ‘adaptation gap’. This adaptation gap is frequently attributed to a lack of clear understanding of AI’s capabilities and to a shortage of the specialized AI competencies required to navigate digital transformation (Mikalef et al. 2023; Santana and Díaz-Fernández 2023). To address this gap between AI competencies and AI adaptation, this study investigates the role of AI competencies for AI adaptation among communication professionals in Oman.

AI competencies encompass practical proficiency to engage with AI systems in the real world (Chiu 2025; Laupichler et al. 2023). Therefore, communication professionals require competencies in technological, cognitive, social, and emotional skills (Baki et al. 2023). From a technological perspective, higher-order technical skills and AI-powered systems become complementary for professionals (Baki et al. 2023; Tyagi et al. 2025). However, while AI excels at pattern recognition, human judgment remains essential for final decision-making. On the cognitive side, the ability to engage in critical thinking is paramount (Baki et al. 2023; Psyché et al. 2023).

The social and emotional dimensions of AI competency support AI adaptation. In the meantime, the demand for human-centric skills such as leadership is expected to grow significantly (Baki et al. 2023; Onnen 2024). Communication professionals serve as the interface between the organization and its stakeholders and demonstrate adaptive agility in managing psychological resistance within the organizational workforce toward AI adaptation (Baki et al. 2023; Song et al. 2025). It is argued that high levels of self-efficacy can empower Omani professionals to overcome technical and organizational challenges associated with AI adaptation. Hence, they can also catalyze the adaptation of innovative initiatives that align with Vision 2040’s sustainability goals (Abdelfattah et al. 2025).

Moreover, the business environment and management structure significantly influence AI investment and adaptation in Oman, a process that involves factors such as the perceived relative advantage and compatibility of AI innovations (Al-Haji and Bakar 2024; Klopčič et al. 2020). Furthermore, existing organizational practices play an important role in technology acceptance and adaptation in Oman (Al-Haji and Bakar 2024; Badghish and Soomro 2024), and government support through policy reforms is decisive in facilitating this transition. Funding opportunities for digital infrastructure and specialized training are part of AI transformation goals in Oman (Al-Haji and Bakar 2024; Pervez et al. 2025). The cur-

rent literature on AI adaptation focuses on the specific competency needs of communication professionals (Eltayib 2024; Tyagi et al. 2025), and on the other hand, Oman Vision 2040 provides a clear roadmap for AI adaptation in Oman, which provides the actual mechanisms that enhance successful organizational AI adaptation (Al-Ansi et al. 2024; Czornik 2025).

This study addresses the knowledge gap regarding the role of AI competencies in the AI adaptation process among communication professionals in Oman. The study highlights the nexus between technological readiness and psychological factors, such as self-efficacy and risk perception. While previous research focuses on how Omani enterprises can achieve sustainable business performance (Abdelfattah et al. 2025; Badghish and Soomro 2024), the present study aims to offer actionable insights for policymakers and industry leaders seeking to align the digital transformation of the Omani workforce with the strategic goals of Oman Vision 2040.

The following are the objectives of the study: to explore AI competencies among Omani communication professionals and to empirically measure the relationship between these competencies and their adaptation to AI. Based on the discussed objective, this study makes three key contributions. First, it develops a cognitive–attitudinal pathway which links AI competencies to AI adaptation. Second, it provides empirical evidence from Oman using a multivariate statistical approach, Partial Least Squares Structural Equation Modelling (PLS-SEM). Third, it offers policy-relevant insights aligned with Oman Vision 2040 and emphasizes cognitive competencies rather than technical training.

The organization of this paper is as follows. The second section provides insights into literature reviews related to AI competencies. The third section outlines the theoretical framework, while the fourth section presents the study's methodology. The fifth section presents the results and discussion, including an empirical analysis. Finally, the sixth section offers a conclusion and policy implications of the study along with directions for future research.

Literature Review

AI ADAPTATION AND OMAN VISION 2040

The strategic mandates of Oman Vision 2040 drive AI within the Sultanate of Oman. This mandate serves as the nation's primary roadmap, focusing on innovation and knowledge (Oman Vision 2040 Implemen-

tation Follow-up Unit 2020). One of Oman's strategic goals is to increase AI's contribution to 10% of national GDP (Pervez et al. 2025). This is one part of a strategic shift designed to overcome developmental challenges in the modern AI landscape and ensure that Oman keeps pace with rapid global changes (Czornik 2025). Within this paradigm, AI adaptation is viewed as a critical mechanism for achieving economic diversification, and the integration of AI is essential to maintain competitiveness (Al-Ajmi et al. 2025).

In Oman, studies indicate that AI adaptation has the potential to impact various economic sectors. These sectors include hydrocarbons, telecommunications, and banking. In the hydrocarbon industry, AI technologies are widely used and offer multiple advantages, including enhanced decision-making, reduced operational costs, and improved effectiveness (Al-Haji and Bakar 2024). Similarly, the telecommunications sector provides comprehensive insights for an ideal environment for AI-driven management. Numerous AI tools are enabling professionals to manage information complexity and deliver personalized customer experiences (Eltayib 2024; Antončič and Zorn 2004). Additionally, in the banking sector, AI adaptation supports fraud detection, risk management, and round-the-clock customer service, aligning with international practices (Rengasamy et al. 2025). Other than the corporate sector, AI technologies are also playing a role in the development of small and medium-sized enterprises (SMEs) in Oman. Therefore, Vision 2040 necessitates a robust focus on Human Resource Development and on empowering SMEs through the effective implementation of AI competencies (Al-Ansi et al. 2024; Tyagi et al. 2025). However, previous research indicates that while SMEs contribute to job creation and economic diversification, an 'adaptation gap' remains due to limited digital infrastructure and a shortage of specialized AI skills (Ayed 2022). This gap requires efforts to promote technical and cognitive skills and a culture of AI adaptation among Omani leaders and professionals (Abdelfattah et al. 2025).

AI COMPETENCIES AND AI ADAPTATION

The integration of AI literacy and competencies into organizations ensures successful technological adaptation (Chee et al. 2025). AI literacy provides the conceptual understanding of intelligent systems, and AI competency refers to the practical capacity to use tools in specialized professional contexts (Psyché et al. 2023). Empirical evidence suggests that a high level of AI knowledge is a primary driver of adaptation in-

tention to AI (Apostoaie et al. 2025). Conversely, a lack of fundamental understanding remains a pervasive social barrier, leading to unrealistic expectations or psychological resistance to AI adaptation (Cubric 2020; Nascimento and Meirelles 2022).

In theoretical conceptualization, AI competency is considered a multidimensional construct, with machine learning and data analytics as essential components (Ng et al. 2023). Further, scholars emphasize that 'hard' skills are insufficient without 'soft' competencies such as critical thinking and ethical judgment (Baki et al. 2023; Onnen 2024). For instance, the ability to evaluate AI-generated outputs is important to maintaining organizational trust (Ikwu and Ifediorah 2025; Song et al. 2025). Furthermore, the demand for human-centric skills is projected to grow significantly. These skills include leadership, empathy, and social intelligence. These are beyond the current capabilities of automated agents (Myszak and Filina-Dawidowicz 2025).

Organizational adaptation of AI technologies is contingent upon Human Resource Development (Hassan 2025). Research indicates that the successful implementation of AI models depends on an organization's internal readiness, which is characterized by a skilled workforce and proactive management (Badghish and Soomro 2024). In many instances, the 'adaptation gap' in SMEs is attributed to a critical deficit in digital skills. It may also be because of limited access to formal training (Popa et al. 2025). To mitigate these barriers, previous research suggests that organizational leaders must promote a culture of continuous learning and innovation. They need to encourage employees to engage in upskilling programmes. These programmes must align with professional capabilities of the Fourth Industrial Revolution and AI transformation (Myszak and Filina-Dawidowicz 2025). AI adaptation is not a one-time event but a dynamic process that provides individuals and organizations with a platform where professionals can consistently recalibrate their skills and leverage the potential of human-AI collaboration (Psyché et al. 2023).

Despite the growing body of literature on AI and digital transformation, several limitations remain. First, most studies focus on technology adoption frameworks, while giving limited attention to AI adaptation processes. AI adaptation is characterized by the effective integration and sustained use of AI in real-world socio-economic contexts. Second, existing research often examines technological competencies in isolation without considering the relationships among AI knowledge, digital skills, and higher-order cognitive abilities such as critical thinking. Third, empiri-

cal evidence from developing or transitional economies remains scarce, limiting the generalizability of existing research findings. Therefore, the present study addresses these gaps by proposing a comprehensive framework that integrates technological competencies and cognitive factors, and it contributes both theoretically and in context to the literature.

Theoretical and Conceptual Framework

AI KNOWLEDGE (KN)

AI knowledge (KN) is a cognitive competency that goes beyond basic digital literacy. It encompasses a conceptual and technical understanding of artificial intelligence (Ng et al. 2021). It involves foundational principles, such as machine learning (ML) and natural language processing (NLP), and distinguishes general and narrow AI systems (Long and Magerko 2020). KN is a framework for technological pedagogical content knowledge (TPACK) and is often categorized as content knowledge, addressing the essential role of data quality in AI systems' information processing (Kim and Kwon 2023). This competency allows professionals to interpret the 'black box' nature of AI, making it easier to understand how these systems function and make decisions (Laupichler et al. 2023).

The role of KN in AI adaptation (AD) is decisive. Both serve as critical functions in a psychological context (Popa et al. 2025; Song et al. 2025). Higher proficiency with AI concepts reduces user uncertainty and anxiety and creates a 'self-reflective mindset' that empowers individuals to integrate AI tools into their professional workflows (Baki et al. 2023). In the context of the Technology Acceptance Model (TAM), KN significantly enhances the perceived value of technological interventions (Baroni et al. 2022). This knowledge base provides the necessary scaffolding for 'Critical Appraisal' and enables users to evaluate AI-generated outputs to support sustainable human-AI collaboration (Annasureddy et al. 2025; Russell et al. 2023).

CRITICAL THINKING (CT)

CT is a higher-order cognitive AI competency that involves analyzing complex information. It deals with relevant insights and translates them into well-reasoned professional actions (Myszak and Filina-Dawidowicz 2025). Within the 'TUCAPA' framework, CT serves as the 'Critical Appraisal' dimension, generating user-friendly AI outputs on accuracy, algorithmic biases, and appropriateness (Laupichler et al. 2023). Unlike

KN, CT competency requires a self-reflective mindset focused on conceptual awareness (Annapureddy et al. 2025; Chiu 2025).

The role of CT in AI adaptation acts as a bridge between technological readiness and institutional integration. AI adaptation is not merely a matter of technical mastery, but also mitigates the risks of over-reliance on automated systems. Therefore, CT serves as a navigation tool for the ‘personalization-privacy paradox’ (Long and Magerko 2020; Popa et al. 2025). Previous research suggests that organizations can strategically delegate tasks to professionals with critical-thinking skills, which are essential to maintaining human agency while enabling enhanced decision-making. (Baroni et al. 2022; Song et al. 2025). CT also plays an important role in ensuring that AI adaptation remains sustainable and compatible with a knowledge-based economy (Santana and Díaz-Fernández 2023; Zhou et al. 2025).

DIGITAL SKILLS (DS)

Digital skills constitute a foundational dimension of AI competency. Both the basic and higher-order technical proficiencies are required for professional landscape (Baki et al. 2023; Onnen 2024). This DS competency is a prerequisite for AI literacy, which involves the ability to use AI-powered hardware and software platforms. In addition, DS also manages the digital infrastructure necessary for AI systems (Chiu 2025; Long and Magerko 2020). Beyond traditional computer literacy, digital skills in the AI era involve specialized competencies in forms such as the ability to troubleshoot algorithmic systems, interpret digital outputs, and ensure data security (Baki et al. 2023; Onnen 2024). DS enables the systematic implementation of new technologies and transforms passive consumers into active interpreters, leading toward organizational workflows and work culture (Santana and Díaz-Fernández 2023; Song et al. 2025).

The role of DS serves as a psychological mitigator. Empirical evidence indicates that a lack of specialized digital expertise remains a barrier to AI adaptation, creating an adaptation gap that leaves AI investments under-leveraged (Apostoaie et al. 2025; Mikalef et al. 2023). Conversely, higher levels of digital competency enhance self-efficacy and reduce cognitive load among working professionals experiencing AI anxiety and fear (Hassan 2025; Popa et al. 2025). The technical ‘know-how’ regarding the AI capabilities with DS is necessary to facilitate the integration of digital tools (Badghish and Soomro 2024; Santana and Díaz-Fernández 2023).

Therefore, DS bridges the gap between human intelligence and machine processing (Myszak and Filina-Dawidowicz 2025; Onnen 2024).

AI ATTITUDE (AT)

A central cognitive construct of our study, AT determines an individual's internal evaluation and sensemaking of AI systems (Hassan 2025; Song et al. 2025). It has been studied using two models: the Technology Acceptance Model (TAM) and the Attitude Towards Use (ATU). Both models represent the extent to which positive or negative professional feelings affect the specific behaviour of integrating AI into workflows (Hassan 2025). In TAM, AT is related to perceived usefulness and perceived ease of use (Hassan 2025; Marikyan and Papagiannidis 2022), which encompass broader psychological factors, such as the perceived usefulness and ease of use of AI technologies (Baroni et al. 2022; Popa et al. 2025). Furthermore, AT is deeply linked to 'affective competencies', including the individual's interest and self-reflective mindset. Aligning AI with evolving societal and professional standards is also part of these affective competencies (Chee et al. 2025; Ng et al. 2021).

AT represents a behavioural intention to engage in AI adaptation in real-world contexts (Hassan 2025; Song et al. 2025), which is facilitated by lowered psychological barriers and reduced technology-related anxiety (Song et al. 2025; Tambe et al. 2019). Professionals willing to engage in 'human-in-the-loop' can actively contribute to AI adaptation (Baroni et al. 2022; Popa et al. 2025). Conversely, a negative attitude leads to an 'adaptation gap' which may be caused by the fears of job displacement or high perceived risk (Hassan 2025; Lada et al. 2023). Therefore, to promote an innovation-friendly culture, a positive attitude is necessary for AI adaptation in organizations (Popa et al. 2025; Song et al. 2025).

AI ADAPTATION (AD)

Integrating AI and intelligent agents within an organization is considered AD. It enhances operational efficiency and sustains organizational growth (Apostoaie et al. 2025; Mikalef et al. 2023). AD is also compatible with the Technology-Organization-Environment (TOE) framework, which suggests that successful institutionalization depends on the interplay between a firm's technological readiness and external environmental pressures (Apostoaie et al. 2025; Badghish and Soomro 2024). Adaptation represents a dynamic evolution rather than a static implementation and is considered a pivotal component of contemporary business mod-

els, reconfiguring workflows, resource allocation, and traditional labour relations (Mikalef et al. 2023; Santana and Díaz-Fernández 2023). In response to volatile market conditions, AD can optimize decision-making and reduce human workload (Apostoaie et al. 2025; Song et al. 2025).

The successful adaptation to AI in organizations represents a significant shift toward a culture of continuous learning and collaborative intelligence (Baki et al. 2023; Myszak and Filina-Dawidowicz 2025). This adaptation requires individuals to move beyond merely using passive tools and to integrate their cognitive skills with machine efficiency (Baroni et al. 2022). On the other hand, the ‘adaptation gap’ can complicate the development of essential AI competencies among professionals (Baki et al. 2023; Santana and Díaz-Fernández 2023). Therefore, adaptation leads to changes in the professional attitudes of the workforce (Baroni et al. 2022; Popa et al. 2025) and, in turn, transforms technological potential into a lasting competitive advantage in organizations (Apostoaie et al. 2025; Badghish and Soomro 2024).

HYPOTHESES AND CONCEPTUAL MODEL OF THE STUDY

Based on the theoretical discussion, this study assesses the extent of AI technology adaptation in professional practice. It is based upon the Technology Acceptance Model (TAM) and competency-based perspectives of AI literacy. The following hypotheses are therefore developed to empirically test these relationships.

AI knowledge can strengthen professionals’ ability to critically evaluate AI technologies and their implications. Thus, AI knowledge becomes a fundamental component of AI competency. Professionals with knowledge of AI technologies are better equipped to evaluate algorithmic processes and assess the reliability of AI-generated outputs. Meanwhile, digital skills interact with digital technologies and AI tools in professional settings. Individuals with strong digital skills are better equipped to explore AI applications. It is hypothesized that professionals with higher levels of digital skills are more likely to develop stronger critical thinking regarding AI technologies.

H1A AI Knowledge will be more likely to influence critical thinking among communication professionals.

H1B Digital Skills will be more likely to influence critical thinking among communication professionals.

For developing hypotheses, it is assumed that critical thinking shapes individuals' perceptions and attitudes toward emerging technologies. Professionals with strong analytical and evaluative abilities can effectively assess the opportunities and risks associated with AI systems. This leads to greater trust and confidence in AI technologies, rather than relying on emotional reactions such as anxiety and fear. It can be stated that critical thinking promotes balanced attitudes toward AI adaptation. Therefore, we hypothesize H2 as follows:

H2 Critical Thinking will be more likely to influence AI Attitude among communication professionals.

Attitude toward technology determines behavioral intention in the TAM. Individuals who hold positive attitudes toward AI are more willing to integrate AI tools into their professional tasks. This leads to a favourable perception of AI, thereby reducing psychological resistance to AI adaptation while encouraging experimentation with AI-driven systems. Therefore, hypothesis H3 is based on the assumption that professionals with positive attitudes toward AI are more likely to adapt effectively to AI technologies.

H3 AI Attitude will be more likely to predict AI adaptation among communication professionals.

Methodology

The present study is based on a quantitative survey methodology. Data collection is purposive, where 247 communication professionals were selected from Oman. All the respondents were approached through a referral sampling strategy. A research questionnaire was developed in Google Forms and shared with the target participants. In the questionnaire, we developed five scales concerning AI Competencies and Adaptation (table 1). All the ethical guidelines were followed, and data were collected after formal institutional ethical approval.

The selection of communication professionals is justified both theoretically and contextually. Communication professionals occupy a strategic position, responsible for managing information flows and digital engagement. In the context of AI, their role becomes critical as they interact directly with AI-enabled tools. This makes them particularly suitable for examining AI competencies and adaptation processes. Furthermore, the selection is aligned with the national priorities of Oman Vision 2040. By

TABLE 1 Scales and Measures of Study

Scale Name	Item Code	Statement
AI Adaptation (AD)	AD1	I am familiar with Generative AI tools (i.e., ChatGPT, Gemini, Online Translators, Work Automation, etc.).
	AD2	I often use GenAI (i.e. ChatGPT, Gemini, etc.) in my workplace.
	AD3	I am confident in my ability to use and interact with GenAI applications.
	AD4	I am comfortable with GenAI applications being part of my daily life.
	AD5	I enjoy using GenAI applications for various professional purposes.
AI Knowledge (KN)	KN1	I can define and explain what GenAI (i.e. ChatGPT, Gemini, etc.) is and how it works.
	KN2	I know the different types of GenAI applications and their features and functions.
	KN3	I can understand the benefits and limitations of GenAI for various domains and professional tasks.
	KN4	I can understand and recognize the common applications and examples of GenAI (i.e. ChatGPT and Gemini) in everyday life, such as voice assistants, social media analytics, online translators, etc.
	KN5	I can assess the accuracy and quality of AI applications and their outputs, such as predictions, recommendations, classifications, etc.
Digital Skills (DS)	DS1	I can use GenAI (i.e. ChatGPT, Gemini, etc.) applications effectively and efficiently for my personal and professional needs.
	DS2	I can utilize reliable and valid GenAI applications (i.e. ChatGPT and Gemini) to achieve my professional outputs.
	DS3	I can troubleshoot and solve problems when using GenAI applications (i.e. ChatGPT and Gemini etc.).
	DS4	I can select and use appropriate data sources and formats for GenAI (i.e. ChatGPT, Gemini, etc.) applications.
	DS5	I can easily learn new digital and technological skills to achieve AI proficiency in my workplace.
	DS6	I can effectively craft prompts for GenAI applications (i.e. ChatGPT and Gemini, etc.).
AI Attitude (AT)	AT1	I am interested in learning more about GenAI and its applications.
	AT2	I am optimistic about the future of GenAI and its impact on society.
	AT3	I trust GenAI applications to perform their tasks reliably and safely.
	AT4	I appreciate the benefits and opportunities that GenAI applications offer me.

Scale Name	Item Code	Statement
Critical Thinking (CT)	AT 5	I feel responsible for using GenAI applications ethically and responsibly.
	AT 6	I respect the rights and interests of other users and stakeholders of AI applications.
	CT 1	I can critically evaluate the ethical principles and values that guide the development and use of GenAI applications (i.e. ChatGPT and Gemini, etc.) .
	CT 2	I can critically evaluate the potential risks and harms of AI applications (i.e. ChatGPT and Gemini, etc.) for individuals and groups.
	CT 3	I am aware of the legal and regulatory frameworks that govern the use of AI applications (i.e. ChatGPT and Gemini, etc.).
	CT 4	I can critically evaluate the social and cultural implications of AI applications for diversity and inclusion.
	CT 5	I am aware of the opportunities and benefits of AI applications (i.e. ChatGPT and Gemini etc.) for society and humanity.
	CT 6	I am aware of the current and future trends and developments of AI systems and their applications.

NOTE All items were measured on a five-point Likert scale.

focusing on communication professionals, the study provides policy-relevant insights into workforce readiness for AD. Thus, the sample selection makes AD multidimensional by integrating professional relevance, sectoral diversity, and national strategic alignment.

In pursuit of a self-reported survey design, procedural remedies were employed to minimize common method bias. Respondent anonymity was assured. None of the identifying information was collected to reduce evaluation apprehension. The questionnaire items were carefully structured and made clear and concise to avoid ambiguity. Furthermore, the study employed well-established, conceptually distinct constructs to reduce the likelihood that common method variance would influence the results.

Table 2 presents the descriptive statistics for all measurements. The items include AD, AT, CT, DS, and KN, based on responses from communication professionals in Oman (the details of each acronym are provided in table 1). The measures of central tendency show the overall mean and the sub-factor values. This value range between 3.06 and 3.78 indicates a moderate to moderately high level across all constructs. AI Adaptation items show variability.

The dispersion (standard deviation) ranges from 0.899 to 1.260, which is acceptable for survey-based social science research. While

TABLE 2 Descriptive Statistics

	Mean	Median	Observed min	Observed max	Standard deviation	Excess kurtosis	Skewness	Number of observations used	Cramér-von Mises test statistic	Cramér-von Mises <i>p</i> -value
AD2	3.061	3.000	1.000	5.000	1.260	-0.969	-0.005	247.000	1.182	0.000
AD5	3.640	4.000	1.000	5.000	1.115	-0.283	-0.593	247.000	1.747	0.000
AT2	3.595	4.000	1.000	5.000	1.075	-0.201	-0.553	247.000	1.820	0.000
AT3	3.206	3.000	1.000	5.000	1.099	-0.716	-0.178	247.000	1.561	0.000
AT4	3.470	4.000	1.000	5.000	0.934	0.114	-0.436	247.000	2.378	0.000
AT5	3.713	4.000	1.000	5.000	0.945	0.041	-0.670	247.000	3.116	0.000
AT6	3.636	4.000	1.000	5.000	0.946	0.365	-0.597	247.000	2.413	0.000
CT1	3.555	4.000	1.000	5.000	0.920	0.396	-0.507	247.000	2.489	0.000
CT2	3.498	4.000	1.000	5.000	1.041	-0.163	-0.547	247.000	2.122	0.000
CT3	3.478	4.000	1.000	5.000	0.939	-0.394	-0.231	247.000	2.153	0.000
CT4	3.522	4.000	1.000	5.000	1.083	-0.072	-0.654	247.000	2.165	0.000
CT5	3.583	4.000	1.000	5.000	0.986	0.461	-0.718	247.000	2.512	0.000
CT6	3.753	4.000	1.000	5.000	1.072	0.083	-0.684	247.000	1.876	0.000
DS1	3.781	4.000	1.000	5.000	0.914	1.076	-0.834	247.000	2.863	0.000
DS2	3.486	4.000	1.000	5.000	0.921	0.237	-0.552	247.000	2.648	0.000
DS3	3.413	4.000	1.000	5.000	0.909	0.145	-0.521	247.000	2.677	0.000
DS6	3.534	4.000	1.000	5.000	0.899	0.562	-0.693	247.000	3.071	0.000
KN2	3.255	3.000	1.000	5.000	0.920	-0.488	0.005	247.000	2.177	0.000
KN3	3.547	4.000	1.000	5.000	0.898	1.247	-0.866	247.000	3.204	0.000
KN4	3.437	4.000	1.000	5.000	0.950	-0.115	-0.603	247.000	3.016	0.000
KN5	3.356	3.000	1.000	5.000	1.007	-0.259	-0.451	247.000	2.170	0.000

NOTE AT: AI Attitude; AD: AD Adaptation; KN: AI Knowledge; CT: Critical Thinking; DS: Digital Skills

considering the distribution shape, skewness values are predominantly negative, indicating that responses are skewed toward higher levels of agreement. This is particularly evident for two key constructs: DS and AT items. Excess kurtosis values are mostly negative or close to zero. Such distributions are typical for Likert-scale data in applied research. For Normality Assessment, the Cramér–von Mises test yields statistically significant results for all items, indicating deviations from normality.

The result is not problematic for the study because Likert-scale data are inherently ordinal. Meanwhile, a large sample size, such as $n = 247$ in this study (see demographic characteristics in table 3), increases the

TABLE 3 Demographics of the Study

	Frequency	Percent	Valid Percent	Cumulative Percent
Gender				
Male	148	59.9	59.9	59.9
Female	99	40.1	40.1	100.0
Total	247	100.0	100.0	
Profession				
Banking Sector	12	4.9	4.9	4.9
Business	24	9.7	9.7	14.6
Corporate Sector	24	9.7	9.7	24.3
Education Sector	90	36.4	36.4	60.7
Energy Sector	8	3.2	3.2	64.0
Government Services	16	6.5	6.5	70.4
Health Sector	16	6.5	6.5	76.9
Other	49	19.8	19.8	96.8
Private Job	8	3.2	3.2	100.0
Total	247	100.0	100.0	
Education				
Diploma	76	30.8	30.8	30.8
Bachelors	130	52.6	52.6	83.4
Masters	32	13.0	13.0	96.4
Doctorate	9	3.6	3.6	100.0
Total	247	100.0	100.0	

sensitivity of normality tests. This makes the data fully suitable for subsequent structural modelling.

Findings and Discussion

Table 4 presents the direct structural relationships among the latent constructs and reports standardized path coefficients, standard deviations, *t*-statistics, *p*-values, and bootstrapped confidence intervals.

AT → AD: The path from AI Attitude to AI Adaptation is strong and highly significant, with a coefficient value of 0.659. This indicates that professionals with a more positive attitude toward AI are more likely to adapt it, suggesting that AI use in professional activities is higher than usual. The model's core behavioural mechanism justifies this relationship. These results are consistent with the Technology Acceptance Model (TAM) model. TAM suggests that attitude toward use is a direct antecedent of actual technology use (Hassan 2025; Song et al. 2025). A positive

TABLE 4 Path Coefficients

Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics	P values
AT → AD	0.6590	0.6603	0.0465	14.1677	0.0000
KN → CT	0.7264	0.7293	0.0541	13.4234	0.0000
CT → AT	0.7770	0.7766	0.0329	23.6162	0.0000
DS → CT	0.1070	0.1059	0.0658	1.62510	0.1041
Confidence intervals		Confidence intervals bias corrected.			
	2.5%	97.5%	Bias	2.5%	97.5%
AT → AD	0.5607	0.7435	0.0012	0.5536	0.7382
KN → CT	0.6236	0.8377	0.0029	0.6188	0.8329
CT → AT	0.7077	0.8349	−0.0003	0.7059	0.8326
DS → CT	−0.0277	0.2326	−0.0011	−0.0278	0.2323

NOTE AT: AI Attitude; AD: AD Adaptation; KN: AI Knowledge; CT: Critical Thinking; DS: Digital Skills

attitude toward AI serves as a psychological enabler, which contributes to lower resistance and enhances willingness to institutionalize AI tools in the workplace. The magnitude of the coefficient indicates that attitudinal acceptance is not a marginal influence. However, it can be considered a behavioural mechanism that translates cognitive readiness into actual adaptation. This approach has strategic relevance for Oman Vision 2040. The vision focuses on digital transformation, innovation, and human capital development and further includes national strategies compatible with psychological readiness and cultural acceptance of AI. Thus, a positive attitude toward AI has a multiplier effect on AI adaptation (Al-Ansi et al. 2024; Hassan 2025).

KN → CT: The relationship between AI Knowledge and Critical Thinking is very strong and is statistically significant, with a coefficient of 0.726. This demonstrates that AI knowledge significantly enhances professionals’ ability to evaluate various externalities critically. These externalities include ethical, social, and practical implications of AI, as discussed in hypothesis H1a. The finding is aligned with contemporary AI literacy and competency frameworks. CT is considered an advanced stage of AI competency (Laupichler et al. 2023; Chiu 2025). This stage emerges after foundational knowledge. The phrase suits in this context: *one cannot critically evaluate what one does not conceptually understand*. Therefore, the KN impact on CT is particularly crucial for communication professionals. Their work directly affects public perception and ethical accountability.

CT → AT: The path from Critical Thinking to AI Attitude is the strongest in the model and significant, with a coefficient of 0.777. This direct relationship suggests that critical thinking is the primary driver of positive attitudes toward AI. This supports hypothesis H2. This path highlights that critical thinking is the central cognitive mechanism in AI adaptation. Attitudes toward technologies are formed through reflective evaluation (Chee et al. 2025; Myszak and Filina-Dawidowicz 2025) and are assessed against professional and societal norms. CT is likely to develop informed trust rather than blind acceptance. Hence, AI attitude, followed by critical thinking, is shaped by reasoned judgment and ethical awareness.

DS → CT: Digital Skills to Critical Thinking is found to be weak and not statistically significant, although the path coefficient DS → CT is positive, having a coefficient value of 0.107. This implies that digital proficiency alone does not translate into higher-order critical thinking about AI. The findings of this direct relationship lead to the rejection of H1b. This result elaborates a conceptual distinction between *‘doing AI’* and *‘thinking about AI’*. If digital skills for using AI tools cannot detect algorithmic bias or evaluate societal consequences, then mere digital skills are insufficient for meaningful critical thinking. Therefore, efficient users of AI tools who lack a critical understanding are considered at risk (Russell et al.

TABLE 5 Total Indirect Effect

Path	Original Sample mean		Standard deviation	T statistics	P values
	sample (O)	(M)	(STDEV)		
KN → AD	0.372	0.375	0.046	8.130	0.000
KN → AT	0.564	0.566	0.048	11.737	0.000
CT → AD	0.512	0.513	0.049	10.480	0.000
DS → AD	0.055	0.055	0.035	1.555	0.120
DS → AT	0.083	0.083	0.052	1.594	0.111
Confidence intervals			Confidence intervals bias corrected.		
	2.5%	97.5%	Bias	2.5%	97.5%
KN → AD	0.287	0.466	0.003	0.282	0.461
KN → AT	0.474	0.661	0.002	0.472	0.659
CT → AD	0.414	0.602	0.001	0.409	0.600
DS → AD	-0.013	0.125	0.000	-0.013	0.125
DS → AT	-0.020	0.185	0.000	-0.020	0.185

NOTE AT: AI Attitude; AD: AD Adaptation; KN: AI Knowledge; CT: Critical Thinking; DS: Digital Skills

2023; Ayed 2022). Critical thinking requires domain-specific conceptual knowledge, enriched by ethical reasoning, rather than mere exposure or practice. Therefore, the weak relationship of $DS \rightarrow CT$ path explains why digital skills fail to exert meaningful indirect effects on AI attitude and adaptation.

Table 5 reports the total indirect effects of mediating constructs in the model. The indirect effect of AI Knowledge on AI Adaptation is positive.

$KN \rightarrow AD$: This has a coefficient value of 0.372, which is statistically significant. This indicates that AI Knowledge does not influence adaptation directly, but through mediating mechanisms. The effect is exerted entirely through both factors, CT and AT. This confirms that conceptual understanding of AI enhances adaptation only (Laupichler et al. 2023; Popa et al. 2025). It is further translated into evaluative reasoning and positive attitudinal orientation.

$KN \rightarrow AT$: AI knowledge shows a strong and significant indirect effect on AI Attitude 0.564. This demonstrates that AI Knowledge substantially shapes professionals' attitudes toward AI. The main role of CT is to mediate between KN and AT. It reflects the cognitive–affective transmission mechanism embedded in the model (Laupichler et al. 2023; Song et al. 2025).

$CT \rightarrow AD$: The indirect effect of Critical Thinking on AI Adaptation is large and highly significant at 0.512. This confirms that CT primarily affects AI adaptation through AT. AT plays a mediating role and serves as an immediate behavioural antecedent to AI adaptation (Hassan 2025; Song et al. 2025).

$DS \rightarrow AD$: A statistically non-significant relationship is found between Digital Skills and AI Adaptation. It indicates that Digital Skills do not meaningfully contribute to AI Adaptation. It is therefore verified through the proposed cognitive–attitudinal pathways.

$DS \rightarrow AT$: The indirect effect of Digital Skills on AI Attitude is also non-significant. This suggests that operational or technical proficiency alone does not contribute to AI attitude (Chee et al. 2025; Ikwu and Ifediorah 2025; Onnen 2024) unless it is accompanied by AI knowledge and critical evaluation.

The mediation results reveal a clear hierarchical mechanism in AI adaptation: *AI Knowledge* $\rightarrow$ *Critical Thinking* $\rightarrow$ *AI Attitude* $\rightarrow$ *AI Adaptation*. In conclusion, digital skills are necessary for interacting with AI tools. However, they fail to generate meaningful indirect effects on either AT or AD. This finding resonates with cognitive and evaluative compe-

TABLE 6 Specific Indirect Effects and Total Effects of AI Competencies on AI Adaptation

Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics	P values
DS → CT → AT → AD	0.055	0.055	0.035	1.555	0.120
CT → AT → AD	0.512	0.513	0.049	10.480	0.000
DS → CT → AT	0.083	0.083	0.052	1.594	0.111
KN → CT → AT → AD	0.372	0.375	0.046	8.130	0.000
KN → CT → AT	0.564	0.566	0.048	11.737	0.000
Total Effect					
AT → AD	0.659	0.660	0.047	14.168	0.000
KN → AD	0.372	0.375	0.046	8.130	0.000
KN → AT	0.564	0.566	0.048	11.737	0.000
KN → CT	0.726	0.729	0.054	13.423	0.000
CT → AD	0.512	0.513	0.049	10.480	0.000
CT → AT	0.777	0.777	0.033	23.616	0.000
DS → AD	0.055	0.055	0.035	1.555	0.120
DS → AT	0.083	0.083	0.052	1.594	0.111
DS → CT	0.107	0.106	0.066	1.625	0.104

NOTE AT: AI Attitude; AD: AD Adaptation; KN: AI Knowledge; CT: Critical Thinking; DS: Digital Skills

tencies. Critical thinking skills drive sustainable AD among communication professionals, rather than technical or digital skills alone.

Table 6 deals with both specific indirect effects and total effects. The specific effect highlights the model's cognitively driven mediating role.

The indirect path CT → AT → AD is strong and highly significant, with a value of 0.512. This implies a sequential pathway leading to cognitive–attitudinal mechanisms that drive AI adaptation. Professionals adapt to AI not because they think critically per se, but because they think critically to stay informed and maintain a positive attitude toward AI tools and technologies (Baroni et al. 2022; Laupichler et al. 2023; Popa et al. 2025). Therefore, this attitude triggers genuine adaptive behaviour.

Further, it confirms that CT affects AD primarily through AT. Likewise, the mediation KN → CT → AT → AD is statistically significant, with a value of 0.372. It indicates that knowledge contributes to adaptive behaviour only after it has been transformed into higher-order critical thinking. It is then subsequently transformed into a favourable attitude. The indirect

effect $KN \rightarrow CT \rightarrow AT$ is also large and significant, with a value of 0.564. This suggests that *CT* serves as a key cognitive conduit between *KN* and *AT*. In contrast, mediation paths involving *DS* ($DS \rightarrow CT \rightarrow AT$ and $DS \rightarrow CT \rightarrow AT \rightarrow AD$) are non-significant. This suggests that digital skills do not meaningfully trigger attitudinal or behavioural outcomes through cognitive mechanisms (Ikwal and Ifediorah 2025; Onnen 2024).

The results of total effects report the overall magnitude of relationships and therefore confirm the dominance of attitudinal and cognitive factors in the model. *AT* shows a strong total effect on *AD*, with *AT* considered the most proximal determinant of adaptation. *CT* also exhibits a substantial total effect on *AD*, having a coefficient value of 0.512. Critical thinking is largely operated through attitude. As *CT* is a distal cognitive driver rather than a proximal behaviour, it shapes the individual's thinking about evaluation, judgment, and the development of a sense of *AI*. *CT* transforms risk–benefit evaluations into informed trust and reduces irrational fear. *KN* demonstrates significant total effects on *CT* (0.726), *AT* (0.564), and *AD* (0.372). *AI Knowledge* is a foundational upstream competency that drives *AI* adaptation and serves as the channel for enhanced critical thinking and for shaping positive *AI* attitudes. Conversely, *DS* exhibits weak and non-significant total effects on *CT*, *AT*, and *AD*. Technical proficiency alone is insufficient to drive *AI* adaptation. It must be accompanied by cognitive and attitudinal development (Chee et al. 2025; Ikwal and Ifediorah 2025).

Table 7 confirms the robustness and statistical adequacy of the measurement model. Both outer loadings and outer weights for all indicators are reported. All indicators load strongly and significantly on their respective constructs. The recommended threshold for the outer loading generally exceeds 0.70. This condition is satisfactory in terms of reliability and convergent validity. For example, the *AD* indicators exhibit particularly high loadings (≥ 0.87). It is considered as a strong representation of the latent construct.

Other indicators, such as *AT* and *CT*, also show consistently high and significant loadings. This makes the construct measurement more coherent and well-defined, although a few indicators (e.g., *AT*₂, *DS*₁) show relatively low loadings. However, they remain statistically significant and within acceptable limits. The literature suggests that when outer weights are positive and highly significant, it confirms that each indicator contributes meaningfully to its construct (Hair et al. 2019). However, it is essential to be considered jointly with other indicators. Notably, the bal-

TABLE 7 Measurement Model Assessment: Outer Loadings and Outer Weights

Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics	P values
Outer Loading					
AD2 → AD	0.874	0.873	0.019	45.208	0.000
AD5 → AD	0.930	0.931	0.009	99.731	0.000
AT2 → AT	0.682	0.680	0.047	14.465	0.000
AT3 → AT	0.802	0.801	0.021	37.652	0.000
AT4 → AT	0.875	0.874	0.017	52.101	0.000
AT5 → AT	0.827	0.827	0.027	31.148	0.000
AT6 → AT	0.875	0.874	0.020	43.223	0.000
CT1 → CT	0.760	0.760	0.030	25.419	0.000
CT2 → CT	0.833	0.832	0.022	37.909	0.000
CT3 → CT	0.835	0.834	0.022	38.418	0.000
CT4 → CT	0.859	0.859	0.018	46.692	0.000
CT5 → CT	0.837	0.836	0.022	38.354	0.000
CT6 → CT	0.756	0.755	0.043	17.676	0.000
DS1 → DS	0.735	0.731	0.069	10.688	0.000
DS2 → DS	0.782	0.781	0.035	22.630	0.000
DS3 → DS	0.812	0.811	0.031	26.304	0.000
DS6 → DS	0.848	0.847	0.032	26.377	0.000
KN2 → KN	0.816	0.816	0.027	30.130	0.000
KN3 → KN	0.881	0.881	0.017	51.468	0.000
KN4 → KN	0.834	0.834	0.017	48.255	0.000
KN5 → KN	0.801	0.800	0.035	22.756	0.000
Outer weight					
AD2 → AD	0.475	0.474	0.023	20.413	0.000
AD5 → AD	0.629	0.629	0.025	25.052	0.000
AT2 → AT	0.210	0.210	0.013	16.451	0.000
AT3 → AT	0.241	0.241	0.009	26.394	0.000
AT4 → AT	0.272	0.273	0.013	20.246	0.000
AT5 → AT	0.253	0.253	0.010	26.495	0.000
AT6 → AT	0.247	0.247	0.009	26.384	0.000
CT1 → CT	0.210	0.210	0.009	24.639	0.000
CT2 → CT	0.205	0.205	0.008	24.942	0.000
CT3 → CT	0.197	0.197	0.009	22.785	0.000
CT4 → CT	0.204	0.204	0.009	23.226	0.000
CT5 → CT	0.217	0.217	0.011	19.012	0.000
CT6 → CT	0.197	0.197	0.010	19.367	0.000
DS1 → DS	0.263	0.263	0.043	6.159	0.000
DS2 → DS	0.269	0.268	0.032	8.426	0.000
DS3 → DS	0.360	0.359	0.024	14.872	0.000
DS6 → DS	0.358	0.358	0.033	10.751	0.000
KN2 → KN	0.295	0.295	0.013	22.466	0.000
KN3 → KN	0.349	0.349	0.015	22.564	0.000
KN4 → KN	0.316	0.317	0.014	22.052	0.000
KN5 → KN	0.235	0.235	0.015	15.444	0.000

NOTE AT: AI Attitude; AD: AD Adaptation; KN: AI Knowledge; CT: Critical Thinking; DS: Digital Skills

anced magnitude of weights suggests that no single indicator dominates construct formation. If any differentiation is found, it reflects multidimensionality within the constructs.

Figure 1 illustrates the estimated PLS-SEM structural and measurement model. Their standardized coefficients are also provided. The measurement model shows strong indicator reliability. All manifest variables load substantially on their respective latent constructs (generally ≥ 0.68). It supports the convergent validity. Additionally, the reliability and convergent validity of constructs are provided in table C in the appendix.

Table 8 shows rigorous estimation and inference settings for the PLS-SEM analysis. The algorithm employs standardized results. These results portray a path-weighting scheme, a high iteration cap (3000), and a stringent convergence criterion (10^{-7}). They are all used as benchmarks for numerical stability. Bootstrapping is configured with a two-tailed test at $\alpha = 0.05$ and parallel processing. The use of a fixed seed enhances reproducibility. On the other hand, the selected complexity setting prioritizes computational efficiency. All of this provides robust insights without compromising the quality of inference. Tables A and B in the appendix provide inner and outer model specifications and cross-loading, respectively.

Conclusion and Policy Insights

CONCLUSION AND POLICY IMPLICATIONS

This study examined how AI competencies shape AI adaptation among communication professionals in Oman. The study covers the strategic context of Oman Vision 2040. Results are presented using PLS-SEM. The findings from the empirical analysis reveal that AI adaptation is not driven by technical capability but rather follows a cognitive–attitudinal pathway anchored in knowledge and critical evaluation. AI Attitude is the most proximal and strongest predictor of AI Adaptation and is compatible with a psychological orientation toward AI. Therefore, AI attitude is the key mechanism through which professionals translate their AI readiness into actual adaptation. The literature also supports the paradox that attitudinal acceptance serves as a behavioural catalyst for the institutionalization of AI tools in professional communication practices.

At the cognitive level, Critical Thinking is the most influential upstream driver. A strong effect on AI Attitude is empirically evident, and a substantial indirect effect of critical thinking on AI adaptation is also examined,

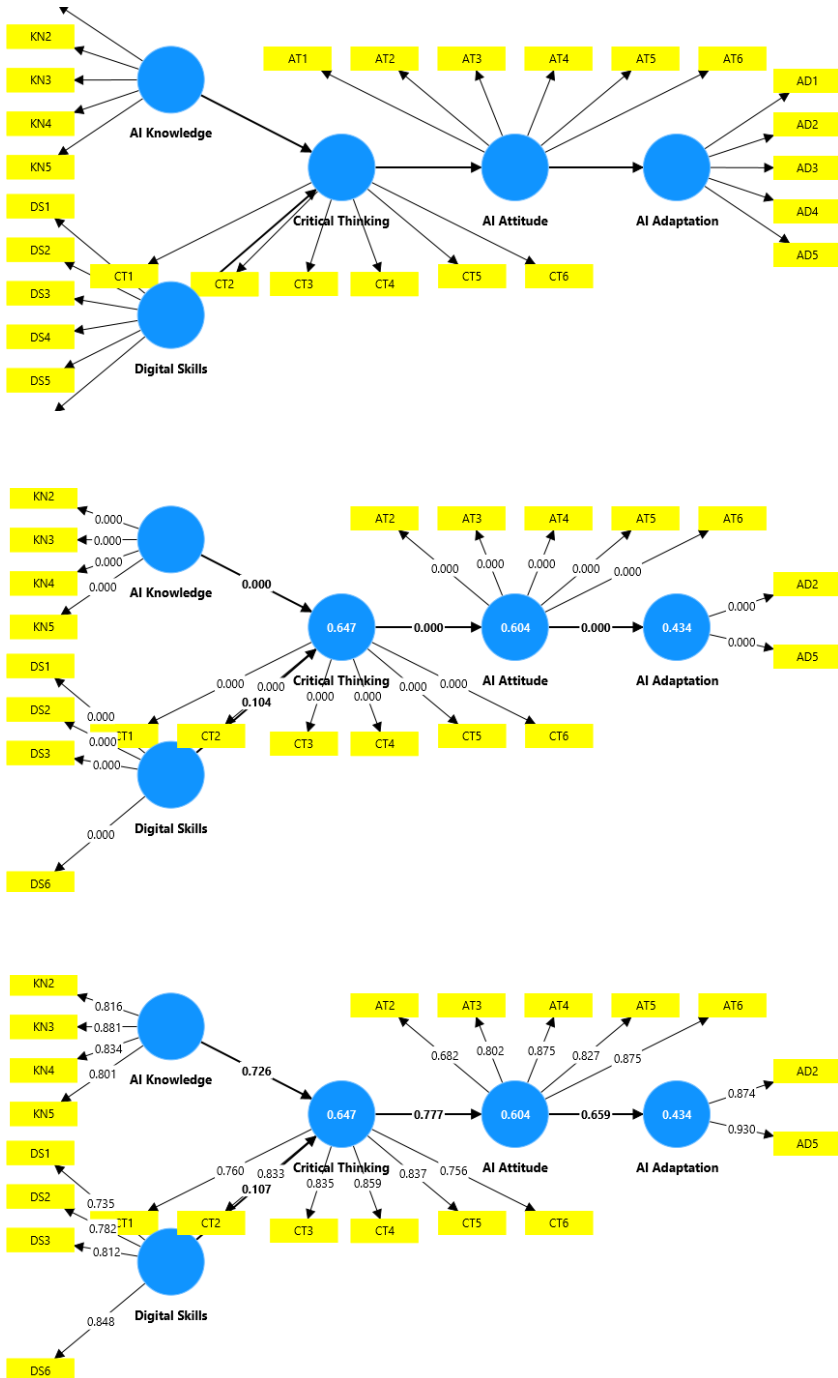


FIGURE 1 Conceptual and Empirical Visualization of AI Competencies

TABLE 8 PLS-SEM Algorithm and Bootstrapping Settings

	Setting
PLS-SEM algorithm	
Initial weights	1.0
Max. number of iterations	3000
Stop criterion	10^{-7}
Type of results	Standardized
Use Lohmoeller settings?	No
Vary copula by binary categories.	Yes
Weighting scheme	Path
Bootstrapping	
Complexity	Most important (faster)
Confidence interval method	Bias-corrected and accelerated (BCa) bootstrap
Parallel processing	Yes
Samples	5000
Save results per sample.	No
Seed	Fixed seed
Significance level	0.05
Test type	Two tailed
Coefficient of Determination (R^2)	
AD	0.75
KN	0.64
DS	0.61
AT	0.58
CT	0.54

showing that critical thinking plays a significant role in promoting positive attitudes toward AI technologies among the communication professionals in Oman. This AI attitude reflects AI's ethical, social, and professional implications. Critical thinking, therefore, operates as a *distal yet decisive force*. It is one of those cognitive mechanisms that shapes informed trust rather than blind acceptance of AI outputs. Additionally, in the adaptation process, the role of AI Knowledge is foundational. A strong empirical path from AI knowledge to critical thinking, with indirect effects on both AI Attitude and AI Adaptation, is confirmed. Thus, AI knowledge must be transformed into positive attitudes to influence behaviour.

In contrast, Digital Skills show weak and non-significant effects on Critical Thinking, AI Attitude, and AI Adaptation. Although digital proficiency is necessary to interact with AI tools, it does not, on its own, generate favourable attitudes. Therefore, there is a critical distinction between *using AI* and *understanding AI*.

To accelerate AI adaptation in line with national digital transformation agendas, several policy-relevant insights are needed. Policies should prioritize cognitive and evaluative competencies for human capital development. They should not only rely on technical training but Also Nationalize AI strategies and embed AI knowledge and critical thinking to gain greater advantages for professionals. There should be professional training programs enriched with AI-related competencies. These competencies are structured learning pathways that link AI knowledge to critical thinking and, in turn, to AI adaptation among communication professionals. Such programs can strengthen informed trust and reduce psychological resistance among communication professionals toward AI adaptation in communication technologies.

Organizations should explicitly address the attitudinal readiness of their workforce, which is one of the strongest predictors of AI adaptation and the resulting organizational change. The organizations need to take steps, including awareness campaigns, participatory AI governance, and human-in-the-loop practices. Professionals' positive attitudes toward AI promote positive perceptions of AI technologies and encourage AI adaptation. In the wake of Oman Vision 2040, it is essential to re-frame AI readiness as a behavioural and cognitive challenge. AI literacy programmes can set a milestone, while AI investments can increase organizational value. Especially, communication professionals should be positioned as AI sense-makers. They can act as intermediaries between technology, institutions, and society. They can interpret AI outputs and shape responsible public narratives around AI use.

LIMITATIONS AND FUTURE DIRECTIONS OF THE STUDY

Despite its contributions, this study has several limitations that should be acknowledged. This study is based on a cross-sectional research design. AI adaptation is dynamic, and causal inferences should therefore be interpreted with caution. The use of data-collection measurements is a form of perceptual inflation. The sample was limited to communication professionals in Oman. This may restrict the generalizability of the findings to other professional groups. The model focuses on individual-level competencies, while other levels, such as organizational factors like leadership support, AI governance, and organizational culture, were excluded. Finally, the study emphasized positive adaptation mechanisms but did not explicitly model negative outcomes.

Given the limitations discussed above, several avenues for future research are recommended. Future studies can benefit from a longitudinal design. AI competencies and attitudes, along with AI systems, evolve and can provide in-depth insights. To address multidisciplinary aspects, researchers can incorporate organizational and institutional variables. Such variables can capture multi-level drivers of AI adaptation. A comparative study across different professional domains or countries can provide contextual robustness. Various other factors, like AI anxiety and technostress that integrate negative psychological constructs, can be considered for future research. Finally, it is necessary to look more deeply into how critical thinking develops and how professionals move from the instrumental use of AI toward human–AI collaboration.

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Appendix

TABLE A Inner and Outer Model Specification in the PLS-SEM Framework

	AI Adaptation	AI Attitude	AI Knowledge	Critical Thinking	Digital Skills
Inner model					
AI Adaptation					
AI Attitude	1				
AI Knowledge				1	
Critical Thinking		1			
Digital Skills				1	
Outer model					
AD2	-1				
AD5	-1				
AT2		-1			
AT3		-1			
AT4		-1			
AT5		-1			
AT6		-1			
CT1				-1	
CT2				-1	
CT3				-1	
CT4				-1	
CT5				-1	
CT6				-1	
DS1					-1
DS2					-1
DS3					-1
DS6					-1
KN2			-1		
KN3			-1		
KN4			-1		
KN5			-1		

Table A presents the model specification matrix for both the inner (structural) and outer (measurement) models used in the PLS-SEM analysis. In the inner model, the entries marked with ‘1’ indicate the hypothesized directional relationships among the latent constructs. This structure is consistent with a sequential mediation framework. In the outer model, the ‘-1’ entries denote reflective measurement relationships. They specify that each indicator loads on its corresponding latent construct.

Table B shows the cross-loadings of the variables and constructs.

TABLE B Cross Loadings

	AI Adaptation	AI Attitude	AI Knowledge	Critical Thinking	Digital Skills
AD1	0.531	0.414	0.583	0.459	0.575
AD2	0.715	0.515	0.478	0.437	0.644
AD3	0.827	0.805	0.581	0.738	0.662
AD4	0.857	0.825	0.655	0.724	0.699
AD5	0.791	0.677	0.604	0.629	0.629
AT1	0.753	0.790	0.523	0.655	0.564
AT2	0.647	0.689	0.505	0.523	0.561
AT3	0.650	0.764	0.602	0.542	0.660
AT4	0.786	0.868	0.684	0.705	0.756
AT5	0.709	0.819	0.607	0.691	0.691
AT6	0.727	0.869	0.637	0.688	0.657
CT1	0.655	0.722	0.583	0.760	0.583
CT2	0.581	0.623	0.670	0.831	0.487
CT3	0.672	0.617	0.639	0.835	0.501
CT4	0.684	0.618	0.686	0.860	0.576
CT5	0.688	0.675	0.701	0.837	0.602
CT6	0.692	0.623	0.603	0.757	0.661
DS1	0.512	0.384	0.516	0.404	0.634
DS2	0.595	0.537	0.623	0.413	0.722
DS3	0.621	0.609	0.633	0.551	0.810
DS4	0.653	0.666	0.577	0.544	0.722
DS5	0.733	0.762	0.650	0.658	0.796
DS6	0.688	0.643	0.555	0.548	0.848
KN1	0.603	0.484	0.703	0.492	0.636
KN2	0.588	0.566	0.816	0.649	0.613
KN3	0.713	0.699	0.882	0.768	0.680
KN4	0.609	0.629	0.807	0.696	0.612
KN5	0.526	0.554	0.784	0.517	0.596
AD2	0.755	0.515	0.478	0.436	0.638
AD4	0.846	0.824	0.655	0.724	0.650
AD5	0.883	0.679	0.604	0.629	0.591
AT1	0.672	0.786	0.523	0.655	0.494
AT2	0.589	0.687	0.505	0.522	0.535
AT3	0.672	0.769	0.602	0.542	0.602
AT4	0.756	0.870	0.684	0.704	0.699
AT5	0.645	0.818	0.607	0.691	0.659
AT6	0.669	0.868	0.637	0.688	0.620

Continued on the following page

	AI Adaptation	AI Attitude	AI Knowledge	Critical Thinking	Digital Skills
CT1	0.588	0.721	0.583	0.759	0.533
CT2	0.548	0.623	0.670	0.832	0.461
CT3	0.631	0.616	0.639	0.835	0.464
CT4	0.601	0.617	0.686	0.860	0.545
CT5	0.633	0.675	0.701	0.837	0.551
CT6	0.615	0.623	0.603	0.756	0.611
DS1	0.410	0.385	0.516	0.403	0.651
DS2	0.520	0.538	0.623	0.412	0.735
DS3	0.588	0.610	0.633	0.551	0.844
DS4	0.691	0.667	0.577	0.544	0.755
DS6	0.633	0.643	0.555	0.547	0.836
KN1	0.588	0.485	0.703	0.492	0.650
KN2	0.531	0.566	0.816	0.649	0.607
KN3	0.665	0.700	0.882	0.768	0.640
KN4	0.552	0.629	0.807	0.696	0.551
KN5	0.500	0.556	0.784	0.517	0.600

TABLE C Reliability and Convergent Validity of Constructs

Constructs	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
AI Adaptation (AD)	0.86	0.84	0.52
AI Knowledge (KN)	0.81	0.85	0.51
Digital Skills (DS)	0.90	0.90	0.69
AI Attitude (AT)	0.71	0.73	0.61
Critical Thinking (CT)	0.89	0.71	0.55