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CHAPTER THREE

TRANSFORMATIONAL LEADERSHIP BEHAVIORS AND INNOVATIVE CULTURE: A CROSS-CULTURAL STUDY ON ADOPTION IN HONG-KONG, CHINESE MAINLAND, AND INDONESIA

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Transformational Leadership Behaviors and Innovative Culture: A Cross-Cultural Study on AI Adoption in Hong Kong, Chinese Mainland, and Indonesia

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Abstract

The Government of the People's Republic of China has designated technological progress as a core driver of national development, with strategic partnerships with ASEAN countries identified as a key priority. Amid the rapid evolution of artificial intelligence (AI) technologies, effective leadership and an innovative organizational culture are increasingly recognized as critical enablers of successful AI adoption and implementation. Adopting a sequential mixed-methods design, eight core themes underpinning effective AI adoption were first identified from semi-structured expert interviews with industry leaders and subject-matter specialists. This study then investigates the culturally contingent influence of transformational leadership (TFL) behaviors in fostering innovative cultures across three distinct contexts: Hong Kong, the Chinese Mainland, and Indonesia. Data were collected via an anonymous online survey administered to 757 employees (469 from Hong Kong, 111 from Mainland China, and 177 from Indonesia), designed to examine the relationships between top management's TFL behaviors and innovative culture. Linear regression analyses were conducted using SPSS v. 31 to test these relationships. Findings indicate that none of the seven TFL behaviors exerted a significant influence on innovative culture uniformly across all three contexts; instead, their impacts varied substantially by region. For instance, in Hong Kong, The Top Management Team encourages others to innovate exhibited a moderate positive correlation with the cultural dimension Your organizational culture allows people to take risks and occasionally fail ($B = 0.24$, $\beta = 0.22$, $p < 0.05$); while in Indonesia, The Top Management Team goes beyond self-interest for the good of the group demonstrated the most pronounced influence ($B = 0.19$, $\beta = 0.20$, $p < 0.05$); while no TFL behaviors showed any significant correlation with this innovative culture dimension in Chinese Mainland. These results underscore that no singular TFL

behavior can universally drive innovation across diverse cultural settings. This research offers valuable insights for tailoring leadership strategies to cultivate AI-enabling, innovative cultures, emphasizing the need for context-specific approaches to navigate the complexities of AI integration within the China-ASEAN tech collaboration framework. The findings contribute to the discourse on cross-cultural leadership and AI adoption, providing practical guidance for organizations operating in these dynamic regions.

Keywords: *AI; Transformational Leadership; Innovative Culture; Cross-Cultural; Hong Kong; Mainland China; Indonesia*

INTRODUCTION

Background

The rapid evolution of artificial intelligence (AI) has profoundly transformed modern management practices, reshaping how organizations operate, innovate, and pursue long-term growth. Beyond operational enhancements, AI-driven management practices serve as a critical bridge between innovation, knowledge creation, and sustainable business strategies, enabling organizations to align their short- and long-term objectives while elevating key functions such as human resource management, customer service, strategic leadership, and operational efficiency (Raina et al., 2026). The integration of AI into organizational decision-making has even revolutionized how businesses analyze complex data, forecast future trends, and allocate critical resources, positioning AI as a foundational driver of both modern strategic and operational success. All the three core models, namely AI-assisted, AI-augmented, and AI-autonomous decision-making, can play a distinct role in enhancing decision accuracy, operational efficiency, and strategic alignment, thereby addressing the growing need to balance technological capabilities with human expertise (Owolabi, 2026). AI's importance extends beyond large corporations to small and medium-sized enterprises, as its integration into organizational processes offers transformative potential to enhance competitiveness, operational efficiency, and human-centric productivity in an increasingly digital economy (Ortolano & Gallegos, 2025).

As reported by World Economic Forum and Accenture (2025), the People's Republic of China has firmly anchored technological progress, particularly AI, as a core driver of national development, with a strategic focus on deepening innovation partnerships with ASEAN countries, important partners to China in science and technology (Wu & Liu, 2024), to foster regional digital transformation and shared growth (Zhang & Wang, 2023). This direction is concretely manifested in top-level policy initiatives: the China-ASEAN Free Trade Area 3.0 Protocol, which formally integrates digital economy and AI into regional cooperation frameworks, and the Three-Year Action Plan for AI-Enabled Development and Technological Capacity Building (2025-2027), which outlines actionable measures such as joint AI research projects, specialized application scenarios in key sectors including healthcare, agriculture, and transportation, and the establishment of Sino-ASEAN AI joint laboratories and computing power alliances (Liu, 2025). By prioritizing AI as a general-purpose technology that bridges industrial upgrading, resource optimization, and sustainable development, China aims to not only enhance its own technological competitiveness but also build an inclusive AI innovation ecosystem with ASEAN to promote knowledge sharing, talent exchange, and equitable access to digital dividends. These strategic endeavors reflect China's commitment to leveraging tech collaboration as a

cornerstone of regional economic integration, making AI a linchpin of China-ASEAN mutually beneficial cooperation (Wei & Shen, 2025).

While China's strategic direction underscores the importance of AI-driven collaboration, the success of such initiatives hinges on addressing the cultural contingencies of leadership and organizational culture, where gaps that current research has yet to fully bridge are present. AI adoption is not merely a technological endeavor but a socio-cultural transformation, where effective leadership and innovative culture act as critical enablers to achieve both individual and collective adoption and success (Catta-Preta et al., 2025). However, cultural values, such as power distance, individualism-collectivism, and hierarchy, shape how leadership behaviors resonate and how innovation is nurtured across (Tsui & Farh, 1997). Existing studies confirm that transformational leadership's impact varies across different cultures (Wong, 2024), yet few have systematically examined how culturally adaptive leadership behaviors foster the trust, collaboration, and risk tolerance needed for successful cross-border AI integration. Given that multicultural teams often face amplified challenges in AI adoption, research into context-specific leadership and innovation culture is indispensable. The current study addresses this critical need by investigating Hong Kong, a super-connector between Chinese Mainland and ASEAN (Choo & Jiang, 2023), Chinese Mainland, and Indonesia, a prominent ASEAN economy (Mahaseth & Zainab, 2025), as their distinct cultural landscapes offer a pivotal lens to unpack how leadership can be tailored to nurture AI-friendly innovative cultures, ultimately supporting China-ASEAN's AI adoption and tech collaboration:

- Hong Kong: A global financial hub with a hybrid of Eastern and Western organizational norms and long-term orientation, low power distance, individualistic tendencies, and market-driven innovation (Kelley et al., 2006);

- Chinese Mainland: A hierarchical, state-led innovation system characterized by high power distance, collectivist values, and institutional alignment with national tech priorities (Guo, 2024; Tsui & Farh, 1997);

- Indonesia: ASEAN's largest economy, defined by strong collectivism, relational harmony, and moderate power distance, where group-centric values shape organizational behavior (Tiffany & Rosman, 2024).

Research gap, objectives, and significance

Transformational leadership (TFL), rooted in idealized influence, inspirational motivation, intellectual stimulation, and individualized consideration (Bass, 1985), has dominated the Western leadership theory (Bass, 2003). It has been linked to innovative culture in Western contexts (Wong & Lau, 2025). However, TFL's efficacy is culturally contingent: behaviors that resonate in individualistic settings may fail in collectivist or hierarchical environments. Despite this, few studies have systematically examined how TFL influences innovative culture specifically for AI adoption across Hong Kong, Mainland China, and Indonesia—regions critical to China-ASEAN tech collaboration. However, existing literature suffers from three key limitations. First, most TFL-innovative culture studies focus on Western or single-country Asian contexts, neglecting the China-ASEAN cross-cultural dynamic. Second, few studies link leadership and culture to AI adoption, a gap given AI's unique demand. Third, the mechanisms through which cultural values moderate TFL-innovative culture relationships remain understudied in AI contexts.

The current study employs a mixed-methods design aiming to investigate how seven TFL behaviors influence four dimensions of innovative culture across Hong Kong, Chinese Mainland, and Indonesia, and identify cultural contingencies that shape these relationships for AI adoption. Theoretically, this study advances cross-cultural leadership theory by debunking TFL universalism and integrating AI adoption as a critical contextual variable. In practice, it provides actionable guidance for organizations operating within the China-ASEAN framework, where tailored leadership strategies are essential to unlocking AI's potential.

This paper proceeds as follows: Section 2 reviews the literature on AI adoption, innovative culture, and TFL; Section 3 develops hypotheses; Section 4 details the mixed-methods design; Section 5 presents the results; Section 6 discusses the findings, implications, limitations, and future research; and Section 7 concludes.

LITERATURE REVIEW

Artificial intelligence (AI) adoption and workforce transformation

Empirical evidence demonstrates that AI delivers measurable economic outcomes while acting as a transformative catalyst that enhances human resource management practices and drives strategic workforce transformation (Mohammed, 2026). While organizations stand to gain substantial benefits from AI adoption, boost productivity, and create new employment opportunities, the transformative advancement of AI has also sparked widespread employee anxiety. Employees' primary concerns regarding AI adoption centre on limited adaptability to evolving competency demands, which undermines their openness to organizational change and amplifies fears of uncertainty which include the risk of job displacement as existing roles are restructured and new positions emerge (Dumitrache, 2026). To fully unlock the value of AI, organizations must proactively address workforce concerns by prioritizing reskilling initiatives, ethical AI governance, and humancentric management practices, as the net benefits of AI integration are contingent on mitigating labour market disruptions, supporting employees through skill transformation, and obtaining employees' buy-in (Ritika & Dahiya, 2025).

As AI reshapes and redefines human roles in decision-making and creativity, continuous employee learning stands as indispensable for equipping workforces with the new skills, adaptive mindsets, and foundational knowledge required to leverage AI effectively. Corporate learning serves as the central mechanism for enabling enterprise-wide AI transformation, supporting workforce development, leadership alignment, and business integration of AI technologies, while ensuring employees can continuously adapt to technological shifts and uphold ethical standards in AI deployment to fuel organizational growth and innovation (Moehrle, 2026). AI adoption in human resource management offers meaningful benefits to employees by cultivating a culture of continuous learning and skill development, which strengthens their adaptability in a fastchanging market landscape. Beyond boosting operational efficiency, AIpowered HR practices prioritize longterm employee wellbeing, creating a supportive environment that balances productivity with genuine workforce care. This integration also helps build more agile, inclusive, and socially responsible workplaces, enhancing employee engagement and empowering individuals to flourish within sustainable, digitally transformed organizational systems (Hadwale & Iyengar, 2025).

Innovative culture

The widespread adoption of AI and automation in human resource management serves as a foundational driver in cultivating an innovative organizational culture, as these technologies streamline routine administrative tasks and empower HR professionals to prioritize people-centric initiatives that encourage creativity, agility, and employee engagement. By enabling data-driven decision-making, delivering personalized employee experiences, and enhancing talent development and engagement, AI-powered HR practices create an enabling environment that nurtures continuous learning, proactive problem-solving, and collaborative innovation, which are the core pillars of a robust innovative culture. While ethical considerations, algorithmic transparency, and human oversight remain essential to responsible AI deployment, the strategic integration of AI ultimately strengthens organizational innovativeness by building a more adaptive, empowered, and forward-thinking workforce capable of thriving in an increasingly digital and dynamic business landscape (Modak et al., 2025).

A recent empirical study on Alibaba shows that amid persistent challenges such as employee resistance to technological change and ethical considerations surrounding AI use, the clear positive connection between AI adoption and employee-driven innovation highlights AI's instrumental role in strengthening and sustaining a dynamic innovative culture across modern organizations. AI adoption embedded in organizational workflows acts as a vital catalyst for nurturing a vibrant innovative culture. By boosting employee autonomy, expanding access to actionable information, and supporting continuous learning and skill advancement, AI integration directly fosters the core conditions of innovative culture, encouraging employees to explore creative solutions and drive proactive innovation within the enterprise (Zhang & Ali, 2025).

An established and proactive innovative culture acts as a powerful driver of AI adoption, as it nurtures the team innovativeness and technological mindset that enable organizations to embrace AIoriented initiatives with confidence and readiness. Cultivating a culture centred on creativity, continuous learning, and technological preparedness strengthens organizational appetite for AI integration, while reinforcing the positive connection between AI adoption orientation and improved innovation outcomes. By prioritizing the development of an innovative culture and building workforce technology capabilities, organizations not only accelerate the uptake of AI but also maximize its transformative impact on team performance and global competitiveness (Javed et al., 2025). Innovative culture (IC) fosters curiosity and creativity while encouraging employees to embrace calculated risktaking (Watson-Hemphill, 2024). As a core organizational pillar, it is indispensable for enhancing firms' innovation capabilities (Munoz-van den Eynde et al., 2015). Moreover, it accelerates the organizational adoption of AI by streamlining humancomputer interaction and delivers sustainable competitive advantages to organizations that proactively integrate AI technologies (Wong & Lau, 2025).

Transformational leadership

Effective leadership ensures organizations harness AI's productivity gains while supporting employees through role transitions, turning disruptive AI adoption into cohesive, responsible organizational progress. Leadership styles play a pivotal role in navigating the complex paradoxes and inherent tensions of AI adoption, as they directly shape how organizations address temporal mismatches between existing capabilities and future AI-driven goals and relational frictions surrounding human-machine dynamics. Effective leadership approaches can

mitigate organizational hesitation and strategic drift by proactively resolving interwoven temporal and relational tensions, such as establishing clear AI governance, facilitating workforce upskilling, and cultivating collaborative human-AI work models. Transformational leadership (TFL), defined by its four core dimensions, namely idealized influence, inspirational motivation, intellectual stimulation, and individualized consideration, is indispensable to successful AI adoption in human resource management and the pursuit of innovation and sustainable organizational growth (Wong & Lau, 2025).

Idealized influence allows leaders to model visionary, responsible AI integration, setting a benchmark for agile digital adaptation that guides HR professionals and employees alike in moving beyond traditional workforce practices. Leaders who demonstrate idealized influence by serving as exemplary role models and inspiring their teams can significantly elevate performance outcomes (Kayago et al., 2024). The other three core behavioral dimensions of inspirational motivation, individualized consideration, and intellectual stimulation collectively and significantly strengthen organizational creativity and foster sustainable innovation (Piaralal et al., 2026). Inspirational motivation energizes employees by articulating a compelling vision, instilling a shared sense of purpose, and motivating teams to pursue ambitious creative goals (Vu & Hsieh, 2026). Intellectual stimulation drives exploratory thinking by encouraging employees to challenge conventional practices, question existing norms, and generate novel solutions to complex problems (Liu et al., 2021). Individualized consideration nurtures innovation by providing personalized support, recognizing unique employee strengths, and tailoring developmental opportunities to unlock individual creative potential (Change, 2025). Together, these interrelated leadership behaviors create a supportive and dynamic environment that amplifies creative output, stimulates iterative innovation, and lays a foundational foundation for building a proactive, innovation-oriented organizational culture critical for technological advancement and adaptive growth.

Hypothesis Development

Transformational leadership behaviors and innovative culture for AI adoption

TFL, defined by its four core dimensions, namely idealized influence, inspirational motivation, intellectual stimulation, and individualized consideration, is positively associated with the cultivation of innovative organizational culture and continuous innovation (Moparthi & Kopparthi, 2025). Collectively, these four I's of TFL unlock the full potential of AI, building adaptable and resilient workplaces that turn technological innovation into lasting organizational growth (Wong & Lau, 2025).

Idealized influence, a foundational pillar of transformational leadership, enables leaders to cultivate a dynamic innovative culture by articulating a clear strategic vision, encouraging open collaborative communication, empowering employee autonomy, and offering personalized mentorship, which are practices that collectively elevate employee creativity and strengthen organizational innovation (Rahmani et al., 2025).

Inspirational motivation rallies teams around a shared purpose for AI-enabled transformation, linking technological adoption to strategic goals of operational efficiency, employee engagement, and long-term sustainability amid rapid digital evolution. It emerges as one of the most powerful and influential predictors of an organization's continuous innovation capability and fuels sustained organizational innovation by inspiring collective ambition, aligning teams toward a shared innovative vision (Mokoena & Richter, 2026).

Intellectual stimulation empowers employees to challenge conventional workflows, embrace innovative AI-driven tools for talent management and skill development, and foster the continuous learning culture critical to thriving in AI-augmented work environments. As a key pillar of TFL, it acts as a fundamental catalyst for exploratory and exploitative innovation within organizations. By encouraging employees to challenge conventional mindsets, think creatively, and explore novel problem-solving approaches, this leadership dimension nurtures the innovative behaviors that enable organizations to adapt to environmental changes and crises (Bai et al., 2025).

Individualized consideration addresses workforce anxieties surrounding technological disruption, prioritizes employee wellbeing and targeted upskilling, and ensures AI deployment remains human-centric through balancing operational excellence with compassionate people management. It enhances the participation quality of team members and facilitates the exchange of valuable knowledge and innovative ideas (Becker et al., 2022). Under the mediation of employee performance, it also has a positive influence on green innovation (Harasis et al., 2024).

While many executives attribute organizational innovation to heavy research and development investment, scholarly consensus confirms that organizational culture is the foundational driver of holistic and sustained innovation, as innovation is a collaborative, teachable discipline involving cross-personnel cooperation (Drucker, 1993). Grounded in Cameron and Quinn's (2006) Competing Values Framework, which is one of the most influential cultural typologies in organizational research, four core cultural dimensions or types shape an organization's innovative capacity and adaptability to change: first, hierarchy culture, centred on internal integration, stability, and formal control, which supports accountability but stifles innovation and change when overemphasized; second, market culture, focused on external competitiveness and goal achievement, with a results-driven orientation that offers moderate support for innovation; third, clan culture, defined by internal cohesion, collaborative teamwork, and shared values, which fosters the relational foundations for creative collaboration; and fourth, adhocracy culture, the most innovation-conducive type, prioritizing individual flexibility, discretionary autonomy, and external differentiation over rigid control and internal integration.

Openness to new ideas, cross-disciplinary connections, and fluid information exchange further amplifies innovative capacity: its non-hierarchical, boundaryless culture, featuring small interdisciplinary teams, no formal titles or ranks, protected time for exploratory ideation, and acceptance of failure to encourage risk-taking, exemplifies how adhocracy-oriented cultural traits directly fuel continuous innovation, highlighting the critical need to balance innovative flexibility and organizational accountability (Wheatley, 2006).

Hypotheses and research framework

To conclude the development and justification of the four hypotheses for the current study, the theoretical and empirical foundations linking transformational leadership (TFL) to the four dimensions of innovative culture (IC) are synthesized. Rooted in the Competing Values Framework (Cameron & Quinn, 2006) and scholarly consensus on TFL's influence, each hypothesis is grounded in the alignment between TFL's core dimensions, idealized influence, inspirational motivation, intellectual stimulation, and individualized consideration, and the distinct cultural traits that define IC1–IC4. For IC1, adhocracy-oriented flexibility and autonomy, and IC2, clan-based collaborative cohesion, the non-hierarchical, trust-driven environments critical to these cultural dimensions, are believed to be directly nurtured by TFL's emphasis

on vision articulation, collaborative empowerment, and relational support, as strategic vision for innovation is set by idealized influence, while team cohesion and psychological safety are strengthened by individualized consideration and inspirational motivation (Rahmani et al., 2025).

Similarly, IC3, market-driven adaptive innovation, and IC4, balanced hierarchy with innovation enablement, benefit from intellectual stimulation, adaptive problem-solving for external competitiveness is encouraged, and the framework's recognition that even moderately innovation-supportive cultures thrive with TFL's goal-alignment and change advocacy. Each hypothesis thus reflects a targeted connection: the unique values, practices, and norms that distinguish each IC dimension are specifically resonated with by TFL's holistic leadership behaviors, rather than mere general correlation with innovative culture, as validated by prior research linking TFL to organizational adaptability, creative collaboration, and sustained innovation (Bai et al., 2025).

Further justification for H1–H4 is found in the iterative validation of theoretical synergies: the cultural prerequisites for each IC dimension, whether fostering risk-taking (IC1), collaborative ideation (IC2), adaptive goal pursuit (IC3), or accountable flexibility (IC4), are collectively addressed by TFL's four I's. Meanwhile, Drucker's (1993) emphasis on innovation as a collaborative discipline underscores why the nurturing of these cultural traits is dependent on TFL's people-centric leadership. By operationalizing IC through its four distinct dimensions rooted in a widely accepted typology, broad claims are transcended by the hypotheses, which test specific, theoretically grounded relationships to ensure the link between TFL and IC is both measurable and actionable. This approach is reinforced by Wheatley's (2006) observation that boundaryless, failure-tolerant cultures, which are key to IC1–IC4, are cultivated through leadership that balances autonomy and accountability, exactly the duality embodied by TFL, validating why each IC dimension would independently benefit from TFL's multifaceted behaviors. Figure 1 depicts the theoretical model of the current study.

H1: TFL behaviors are positively related to the first IC dimension (IC1)
H2: TFL behaviors are positively related to the second IC dimension (IC2)
H3: TFL behaviors are positively related to the third IC dimension (IC3)
H4: TFL behaviors are positively related to the fourth IC dimension (IC4)

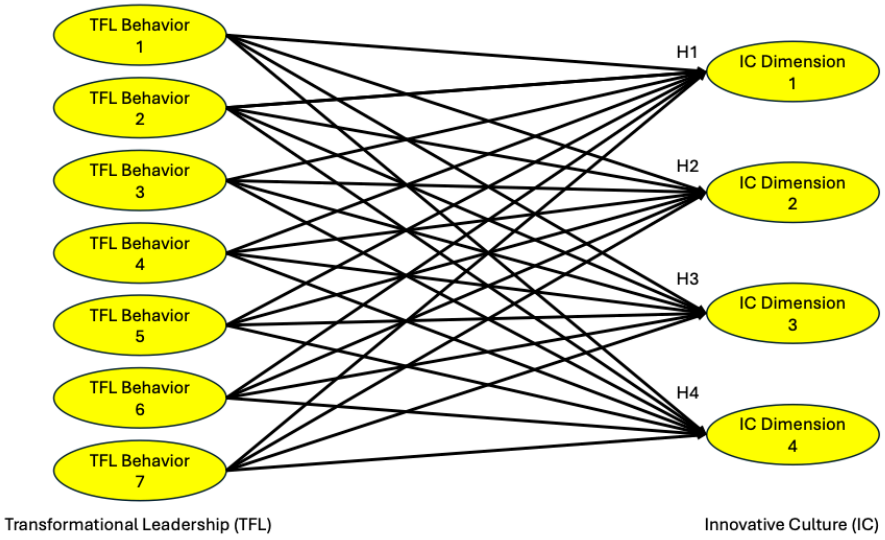

Figure 1. Theoretical Model

Methods

Mixed-methods design

This study adopts a sequential explanatory mixed-methods design (Creswell & Plano Clark, 2018) to investigate the cross-cultural relationships between TFL behaviors and IC for AI adoption, an approach validated in prior research on technology and organizational change (Chen et al., 2026). Phase one of the study employed semi-structured expert interviews to develop and ground the conceptual framework, ensuring alignment with real-world practices and contextual relevance. Purposive sampling was used to recruit ten distinguished experts across diverse sectors, namely logistics, insurance, energy, education, property management, public transport, and social enterprise, and leadership roles including C-suite executives, HR leaders, academic specialists, and industry experts and advisors, including former and current organizational leaders with deep expertise in business management and innovation. Interviews focused on exploring core constructs including critical leadership behaviors, dimensions of innovative culture, and barriers to AI adoption, their hypothesized interrelationships, and cross-cultural nuances in AI-enabled organizational transformation. Thematic analysis of interview data (Braun & Clarke, 2006) identified key variables, refined construct definitions, and informed the selection and adaptation of survey items to ensure the quantitative instrument was grounded in practical insights rather than abstract theory (von Soest, 2022). This phase yielded a testable framework linking specific leadership behaviors to innovative culture outcomes.

Phase two translated the qualitative framework into a quantitative study to test hypothesized relationships and cross-cultural generalizability. An anonymous cross-sectional online survey was designed based on interview-derived constructs, with items adapted from validated scales where available and customized to reflect the AI adoption context to measure perceptions of leadership support for innovation, organizational values toward technological change, and AI integration effectiveness, and administered via random sampling to gather employees' perceptions of their top management team's transformational leadership (TFL) and their organization's innovative culture (IC) as it relates to AI adoption, with demographic information also collected through the same instrument.

Data were measured using a 7-point Likert scale anchored at 1 (strongly disagree) and 7 (strongly agree), allowing respondents to indicate their level of endorsement for items assessing core research variables. Specifically, seven items measuring transformational leadership (TFL) were adapted from the classic Multifactor Leadership Questionnaire (MLQ) originally developed by Bass (1985), a widely used instrument for capturing leadership behaviors in organizational research. Four items were employed to evaluate innovative culture (IC), selected from the validated scale proposed by Judge (2012) to capture contextually relevant cultural traits for AI adoption. All items from well-validated, peer-reviewed measurement tools had a Cronbach's alpha value higher than 0.7 to ensure the reliability, construct validity, and conceptual alignment of the survey instrument with the study's theoretical framework. The eleven survey items are:

- TFL1: The Top Management Team goes beyond self-interest for the good of the group.
- TFL2: The Top Management Team considers the moral and ethical consequences of decisions.
- TFL3: The Top Management Team talks optimistically about the future.
- TFL4: The Top Management Team re-examines critical assumptions to question whether they are appropriate.

- TFL5: The Top Management Team helps others develop their strengths.
- TFL6: The Top Management Team makes others feel good to work with them.
- TFL7: The Top Management Team encourages others to innovate.
- IC1: Your organizational culture values innovation and change for the adoption and implementation of AI.
- IC2: Your organizational culture attracts and retains creative people for the adoption and implementation of AI.
- IC3: Your organizational culture provides resources to experiment with new ideas for the adoption and implementation of AI.
- IC4: Your organizational culture allows people to take risks and occasionally fail for the adoption and implementation of AI.

Given that all data were self-reported by survey respondents, the study was susceptible to common source and common method bias, a potential limitation mitigated through multiple procedural remedies: ensuring full respondent anonymity and confidentiality to reduce response distortion, utilizing validated shortened versions of measurement scales to minimize respondent fatigue, randomizing the order of scale items to prevent response set biases, and structuring the questionnaire into distinct, non-navigable pages with which respondents could not revisit prior pages after completing each section. These strategies collectively enhance the reliability and validity of the survey data by addressing key sources of method-related bias.

The survey was available in four languages, English, Traditional Chinese for Hong Kong, Simplified Chinese for Chinese Mainland, and Bahasa Indonesia for Indonesia, administered to 757 employees across these three regions (469 from Hong Kong, 111 from Chinese Mainland, and 177 from Indonesia), ensuring representation of diverse organizational roles and sectors to enhance external validity.

Linear regression analysis was conducted using SPSS v31 to examine the influence of TFL behaviors on the IC dimensions related to AI adoption, with separate models estimated for each region to identify cross-cultural variations. This two-phase design leverages the strengths of qualitative inquiry that enhances the depth of contextual insight and facilitates framework development, and quantitative analysis that ensures statistical rigor and generalizability, mirroring best practices in mixed-methods research on leadership, innovation, and technology adoption.

Semi-structured interviews

Semistructured interviews represent a flexible qualitative method anchored in a predefined interview guide while permitting adaptive probing and open dialogue (Kvale & Brinkmann, 2015). Positioned between structured and unstructured interviewing, this approach ensures consistent coverage of core research topics across participants while enabling deep exploration of contextspecific insights, unanticipated perspectives, and practical industry nuances (Creswell & Plano Clark, 2018). For this study focused on AIdriven workforce transformation, semistructured expert interviews were selected for their ability to elicit grounded, practicebased knowledge from seasoned professionals; this method balances comparability of responses with the depth needed to unpack complex organizational and technological dynamics, making it particularly suitable for exploratory research on emerging digital adoption (von Soest, 2022).

Ten industry and organizational experts were interviewed using a standardized interview guide with eight openended questions to explore two interconnected pillars of AI adop-

tion and organizational change. The first set examined operational and strategic AI integration: how AI is embedded in core workflows rather than pilot projects, optimized endtoend processes, enhanced datadriven decisionmaking, and how organizations measure AI's impact on operational metrics. The second set addressed cultural and talent enablers: how firms build innovationfocused cultures, attract and retain creative employees, support prudent risktaking and acceptable failure, and allocate resources for experimental ideation. This question design ensures comprehensive inquiry into both technical implementation and humancultural dimensions of workforce transformation. The eight questions are:

1. How is AI embedded in the core workflows (e.g., customer service, supply chain, HR), not just experimental pilots, in your organization/industry?
2. How is AI used to optimize end-to-end processes (e.g., from recruitment to customer retention) , not isolated tasks?
3. How does AI enhance decision-making (e.g., predictive analytics for resource allocation) in your organization/industry?
4. How does your organization/industry measure AI's impact on operational metrics (e.g., productivity gains, cycle-time reduction)?
5. How does your organization/industry create a culture that values innovation and change?
6. How does your organization/industry attract and retain creative people?
7. How does your organization/industry allow people to take risks and occasionally fail?
8. How does your organization/industry provide resources to experiment with new ideas?

Interview notes and verbatim transcripts were systematically analyzed using reflexive thematic analysis following the sixphase framework of Braun and Clarke (2006). Initial coding was applied to label meaningful segments of expert responses, after which coded data were grouped into cohesive, recurring themes aligned with the study's conceptual interests. Key emergent themes, including AI workflow integration, data-enabled decision-making, innovation culture building, talent retention, and risk-tolerant resourcing, were refined, named, and mapped to form a structured research framework. This inductivedeductive analytical process distils practical expert insights into testable theoretical dimensions, ensuring the framework is empirically grounded in realworld contexts and provides a robust foundation for subsequent quantitative inquiry (Creswell & Plano Clark, 2018).

Results

Expert interviews

Interview with the advisor of the current study – Mr. KT Lai

Mr. Kam Tong (KT) Lai—a highly respected veteran in human resource management, former President of the Hong Kong Institute of Human Resource Management, seasoned program director and lecturer for human resource management and development educational programs, current chair of multiple human resource committees and advisory panels at universities and non-governmental organizations, and independent director across diverse industry sectors, offers systematic, research-driven insights to guide this leadership study of AI adoption in organizations. Moving beyond a narrow focus on operational implementation, his guidance centres on establishing a rigorous analytical framework, clarifying the boundary between technological disruption and organizational continuity, and identifying high-potential industry sectors for empirical investigation and expert interviews.

At the core of his advisory is a structured analytical lens designed to frame research on AI-driven organizational change. He emphasizes that any meaningful transformation must be examined across three interlocking dimensions: organizational leadership and governance, the job positions being reshaped, and the updated competencies required for those roles. The success and impact of such changes should then be evaluated against his established Three Es framework: Effectiveness, Efficiency, and Economic Value Creation. This holistic, sequential model ensures research does not isolate technology as a standalone variable but instead integrates leadership direction, role redesign, capability building, and measurable outcomes into a coherent inquiry, avoiding fragmented or superficial analysis.

Mr. Lai further articulates a critical conceptual distinction for both academic and practical understanding: while AI is fundamentally redefining the nature of work, automating repetitive tasks, reallocating responsibilities, and reshaping how functions deliver value, it does not, and should not, alter an organization's core vision, mission, and values (VMV). Technology transforms how work is performed, but the foundational purpose, ethical principles, and stakeholder commitments that define an organization remain constant. AI thus acts as an enabler of organizational identity rather than a replacement for it, a distinction that must be explicitly reflected in research design and analysis to avoid overstating technology's role as a disruptor of core organizational purpose.

To deepen the empirical rigor of the study, Mr. Lai recommends researchers focus on industries with illustrative AI adoption practices, sectors where real-world cases vividly demonstrate the interplay between leadership, roles, competencies, and the Three Es. These include education, insurance, public utilities, social services, transportation, and conglomerates, each exhibiting distinct patterns of AI implementation, workforce restructuring, and leadership governance. He advises the research team to conduct expert interviews across these industries to compare how diverse organizational contexts adapt to AI, upskill their workforces, and sustain performance while safeguarding core values, uncovering transferable insights that transcend sector-specific boundaries.

In sum, Mr. Lai's guidance provides a clear roadmap for the research: anchor analysis in the leadership–position–competence framework; measure impacts through the lenses of effectiveness, efficiency, and economic value; recognize that AI transforms work processes but not organizational VMV; and investigate targeted industry cases to generate robust, cross-sectoral findings. This approach ensures the study remains theoretically grounded, empirically rich, and relevant to both human resource practice and organizational strategy in an AI-enabled workplace, bridging academic rigor with practical applicability.

Following the advice and direction of Mr. Lai, the following ten expert interviews were conducted:

Expert interview with Professor KC Li

Professor Kam Cheong Li, a leading expert in open and distance education and a popular keynote speaker on educational technology, served as the Dean of the School of Open Learning and Director of the Institute for Research in Open and Innovative Education at Hong Kong Metropolitan University before his retirement last year. With numerous accolades, including the Prize of Excellence from the International Council for Open and Distance Education, his insights on how leaders can drive the adoption of AI technologies in the education sector were sought.

During this interview, Professor Li discussed the critical role of data analytics and AI in enhancing educational effectiveness and learning outcomes. He emphasized that these tools are essential for navigating the increasingly complex landscape of education. He highlighted the potential of big data, when combined with AI, to predict the performance of students in study programs, noting that exam results and online records serve as valuable indicators for guiding students toward appropriate university majors, as well as assisting universities in selecting students likely to succeed in their studies. Analyzing students' behavioral data and course results can help identify those who may need extra support, allowing educators to tailor assistance based on individual progress and needs. Additionally, such technologies can aid students in their career planning and job seeking.

Professor Li further elaborated on the impact of big data and AI in improving performance assessments for both teaching and non-teaching staff. By incorporating behavioral data and evaluation inputs, institutions can achieve more precise assessments, leading to better-informed decisions regarding staff development and resource allocation. However, he pointed out that successful adoption of these technologies requires prioritization from top management. While engaging various stakeholders is important, the decisive factor lies in the vision and commitment demonstrated by leadership. Every organization and individual experiences some level of resistance to change. Therefore, leadership priority is crucial in overcoming this friction and directing employee focus and energy toward the adoption and implementation of AI across the organization. The way management leads is pivotal to effectively implementing data analytics and AI, ultimately leading to meaningful educational improvements.

In conclusion, Professor Li's insights underscore the transformative potential of big data and AI technologies in the education sector, emphasizing the need for strategic leadership to drive these initiatives toward success.

Expert interview with Professor James S. Tsien

Professor James S. Tsien is a distinguished expert in global logistics, a respected business leader, and a dedicated educator. He currently serves in leadership roles at prominent educational institutions, contributing to the advancement of education. As an influential figure in logistics, he has played a pivotal role in redefining local, regional and global container terminal industry and its operations, significantly advancing the sector through his visionary approach. Professor Tsien's insights have been sought to explore how AI could revolutionize logistics, education, and human resource management.

Professor Tsien drew upon his extensive experience in logistics, banking, and HR, emphasizing the evolution of AI from basic data analysis to practical implementations in various applications. He illustrated AI's transformative impact on logistics, particularly in optimizing container movements and location assignments at ports and on vessels. By analyzing expected container dwell times, managing sequences for vessels, and anticipating vessel and container schedules, AI can significantly reduce handling movements and operating times, improve safety, enhancing overall efficiency and productivity, hence making significant contributions to the bottom-line.

While recognizing the increasing trend toward automation, Professor Tsien noted that the reliance on skilled manual labour has, at times, proven more effective than complete automation. Achieving total automation faces several technical challenges, including the diverse designs of ships, which complicate AI integration. Nevertheless, he remains optimistic that these challenges can be addressed. Although the use of big data and AI in the container port industry is not new, having begun three decades ago, the substantial investments in these technologies require careful consideration of their return on investment and payback periods. As such, strong leadership and a clear vision are essential for successful AI adoption and implementation.

Addressing the implications of AI for employment and education, Professor Tsien indicated that many repetitive roles, such as those in clerical work, basic accounting and financial analysis, and legal documentation tasks, are increasingly at risk of automation. He expressed concerns about the diminishing value of qualifications, noting that knowledge can quickly become obsolete and requires constant updating. Advocating for educational reform, he cautioned that the current emphasis in universities on research often overlooks the importance of practical and vocational skills. He proposed that future educational programs should strive for a balanced approach, integrating both research and applied learning, with a strong focus on applying AI technology in real-world scenarios. Furthermore, he stressed the need to cultivate brain power and interdisciplinary skills among emerging talent, ensuring they can adeptly leverage AI technologies across various fields. This adaptability will be crucial for individuals seeking to excel in a rapidly evolving job market.

In conclusion, Professor Tsien's insights underscore the profound implications of AI in HR and logistics, highlighting the urgent need for organizations to embrace these innovations while advocating for educational reforms that prepare future professionals for an AI-driven landscape.

Expert interview with Professor Wing-Mo Leung

Professor Wing-Mo Leung, former Assistant Director of the Hong Kong Observatory, renowned meteorologist, Adjunct Professor, and Fellow and Spokesperson of the Hong Kong Meteorological Society, shared human-centric leadership strategies for fostering innovative cultures and responsible AI adoption. These insights are rooted in his cross-sector expertise integrating AI into weather forecasting and climatological services, where trust, accuracy, and public accountability are paramount.

At the core of his philosophy is prioritizing people as the engine of AI-enabled innovation. He emphasized that fostering psychological safety is foundational: leaders must cultivate environments where teams feel secure taking calculated risks, such as testing AI models or experimenting with new tech-driven workflows, and sharing failures openly. By framing missteps as collective learning opportunities rather than punitive repercussions, leaders alleviate fears of technological displacement, unlocking intrinsic motivation to innovate. To ensure inclusivity, Professor Leung stressed tailoring AI upskilling to diverse skill sets, from PhD-level scientists refining complex climate models to undergraduates building practical AI literacy, so no stakeholder is left behind in technological transition.

Professor Leung advocates for purpose-driven AI adoption: technologies thrive when tightly linked to clear, mission-aligned goals, for example, accelerating short-term weather forecasts, analyzing climate change trends, and predicting tropical cyclone tracks, rather than being pursued for tech's sake. A critical principle he underscored is that AI should augment, not replace, human expertise, especially in high-stakes fields like meteorology. For instance, while AI streamlines global data processing and automates routine calculations, subjective judgment based on sound theoretical reasoning and knowledge of local climatology remain indispensable for scenarios where AI struggles, such as sudden heavy rain or rare phenomena like water tornadoes or waterspouts. Leaders, he advised, must first validate existing workflows, retain proven methods, and embrace an iterative, adaptive process rooted in continuous accuracy verification to keep AI aligned with core missions like public safety.

Regarding technology itself, Professor Leung highlighted the need to deploy AI that is functional, grounded in real-world needs, and transparent. His leadership lesson is unambiguous: innovative cultures and successful tech adoption hinge on centering people, balancing psychological safety, purpose-driven technology, inclusive upskilling, and iterative improvement. AI's greatest value, he concluded, lies in freeing human experts to focus on high-judgment tasks, creative problem-solving, and public good, all guided by leadership that prioritizes accountability, collaboration, and unwavering commitment to serving communities.

Expert interview with Mr. Peter Crewe

Mr. Peter Crewe is an independent non-executive director, board member, insurance expert, senior strategic advisor, board member and independent consultant, and formerly a chief executive officer with decades of leadership experience across the panAsian insurance sector. Drawing on some 30 years of specialized expertise, he outlined a stakeholdercentric framework for advancing technology adoption and sustainable innovation across the industry. His insights reflect leading largescale organizational transformation, navigating legacy system modernisation, aligning with diverse regulatory environments, and fostering crossfunctional collaboration across multiple markets, contexts in which governance, empathy and incremental progression are indispensable. With extensive experience in strengthening distribution networks, deepening strategic partnerships and leading digitalisation initiatives to enhance customer and stakeholder value, Mr. Crewe's perspective reconciles innovation imperatives with the inherently riskaverse nature of insurance.

Mr. Crewe proposed four foundational pillars for successful AI implementation: quality data, fitforpurpose technology, robust governance and engaged people, emphasising that efforts should prioritise solving specific business problems rather than pursuing technology for its own sake. He advocated targeted, highimpact use cases, for example, claims triage, underwriting efficiency, callcentre automation, fraud detection and customer selfservice, over largescale endtoend overhauls. Refined through work with established insurers operating longstanding workflows and legacy systems, his framework emphasises that innovation fails when it's disconnected from business needs. AI tools should eliminate repetitive backoffice work, such as document processing, and improve customer interactions, for example, realtime claims support, freeing human professionals to focus on highjudgement tasks like complex risk assessment and personalized advisory. He reported measurable results from this problemled approach, including operational workflow improvements of 20–40% and 30% reduction in repetitive tasks after organizationwide scaling.

Governance and regulatory alignment are nonnegotiable foundations of AI leadership, a view shaped by Mr. Crewe's experience across diverse regulatory regimes in the AsiaPacific and global markets. He stressed that insurers operate in heavily regulated ecosystems, requiring careful balance between innovation and compliance. Leaders should establish comprehensive AI governance frameworks covering model inventory, formal approval procedures, ongoing monitoring and integration with enterprise risk management, to mitigate risks such as algorithmic bias, privacy violations and unexplained adverse decisions. Proactive engagement with regulators is essential: Regulators are on the same steep learning curve as industries, he noted, urging leaders to track developments across the EU, UK, North America, Hong Kong and other jurisdictions, and to participate in collaborative initiatives such as regulatory sandboxes. Hong Kong's joint AI sandbox was highlighted as an example that allows insurers to test solutions in a controlled setting while building trust with supervisors. ResponsibleAI safeguards, fairness testing, transparent decision processes and complete audit trails, were presented as both compliance measures and trustbuilding mechanisms with customers and employees.

For practical implementation, Mr. Crewe underlined incremental rollout and crossfunctional collaboration to balance innovation with organizational stability. He recommended piloting AI in lowrisk backoffice areas before expanding to customerfacing functions to avoid

disrupting core operations and legacy systems. Crossfunctional teams including business, finance, actuarial, IT, risk, compliance and legal are essential: You can't let IT build a customer retention platform in isolation. They lack customer insights and regulatory context. He also emphasized the role of external ecosystems: most insurers lack sufficient inhouse AI capability at scale, so partnering with thirdparty vendors with thorough due diligence, clear contractual terms and performance monitoring accelerates innovation without overstretching internal teams.

Mr. Crewe's leadership principle for innovationready cultures centres on people, psychological safety and collective learning through experimentation. To overcome fear of failure and resistance to change, leaders should build basic AI literacy, show curiosity and technical understanding, and invest in targeted upskilling that links AI to daily duties and career development. Cultivating psychological safety involves encouraging lowrisk experimentation with clear governance safeguards, early intervention protocols and realtime project monitoring to limit errors while framing setbacks as shared learning. Inclusive crossdepartmental collaboration breaks down silos, positions innovation as a collective effort, and enables peer learning that builds organizational momentum.

Mr. Crewe concluded that AI's greatest value is to enhance, not replace, human expertise: Millennials may prefer selfservice apps for routine tasks, but ageing populations and complex needs still demand human interaction. Leaders must balance techdriven efficiency with personalized service. Drawing on nearly three decades in the industry, Mr. Crewe argued that successful AI transformation is a shared architectural project involving leaders, employees, regulators and partners. We're all on this learning curve together. Clarity on goals, governance and peoplecentricity will determine who thrives, he observed.

Expert interview with Mr. Joseph Law

In the exploration of the intersection between leadership and AI adoption, Mr. Joseph Law, Managing Director of CLP Power Hong Kong, was interviewed. His insights illuminate the strategies employed within his organization to effectively harness AI technologies, focusing on a comprehensive People-Process-Technology framework.

Mr. Law emphasized the critical role of people in driving AI initiatives. He articulated the importance of understanding the why behind actions to foster an environment conducive to technological change and innovation. According to him, intrinsic motivation is essential in this context. In an ever-evolving landscape, it is vital to comprehend the real purposes and intentions behind both organizational goals and employees' behavior. He recognized that the pursuit of job security and success can evoke both enthusiasm and apprehension regarding the adoption of new technologies.

To facilitate a smooth transition, Mr. Law discussed CLP's initiative to make learning about AI technologies enjoyable and accessible. By bringing large language models (LLMs) in-house and integrating them into their platforms, employees can engage in safe experimentation with AI applications. This strategy aims to scale learning throughout the organization, enhancing familiarity and comfort with AI technologies over time. Additionally, Mr. Law described an innovative 4 trails approach to training that makes AI learning both engaging and trendy, and employees are encouraged to explore external AI technologies that cater to various organizational needs.

In discussing the process, Mr. Law outlined the significance of validating existing workflows before incorporating AI solutions. He highlighted that organizations should emphasize automating functions where AI can add value and it is essential to thoroughly analyse each process step beforehand. If certain steps may no longer add value, they should be eliminated rather than automated. Mr. Law advocates for a proactive approach to change, asserting that AI adoption should not be implemented rigidly; instead, it must evolve organically over time. He emphasized that effective leadership involves not only setting a clear direction and vision for AI implementation but also sustaining employees' motivation and curiosity throughout the transition.

Regarding technology, Mr. Law underscored the need to equip employees with appropriate resources for trial. CLP is committed to providing technologies that facilitate innovation, exemplified by surveillance cameras designed to monitor the power system and by AI systems that identify potential risks and abnormalities in real time. These technologies not only fulfil operational purposes but also engage employees by demonstrating the practical applications of AI in their daily work environment. Mr. Law concluded that technologies should not merely be functional; rather, they ought to inspire and facilitate employees, thereby cultivating a culture of AI adoption within the organization.

Expert interview with Miss Queenie Man

Miss Queenie Man, Founder and CEO of The Project Futurus, a social enterprise dedicated to community programmes and catering services, shared practical, on-the-ground insights into AI adoption within small and resource-constrained organizations. Her perspectives reflect a pragmatic, problem-centred approach to technological integration, prioritising workflow optimisation, cost-effectiveness and team alignment over indiscriminate digital adoption. Drawing from her experience leading a compact and agile team, she outlined how her organization has applied lightweight AI and automation tools to resolve operational inefficiencies, while navigating the unique challenges of balancing innovation with real-world operational constraints.

Miss Man stressed that AI adoption in small organizations must start with the identification of concrete operational gaps, rather than pursuing technology as a standalone goal. Her team's core focus has been optimising internal workflows including client enquiry handling, quotation generation, payment tracking and data consolidation, processes that were previously manual, time-intensive and vulnerable to inconsistency. Historically, such work relied on fragmented tools including Excel spreadsheets, handwritten records and disconnected filing systems, resulting in insufficient transparency, uneven information access and excessive administrative load. In response, her organization collaborated with an external consultant to implement a streamlined management framework using Airtable, supported by AI-enabled automation to unify data management across departments. This system established a centralized single source of truth, delivering real-time visibility of client enquiries, quotation statuses, payment reconciliation and project milestones, reducing duplication and ensuring consistent cross-team alignment.

While acknowledging the potential of advanced AI applications, Miss Man advocates a start small and validate value mindset, particularly for organizations with limited resources.

Her team has explored AI-powered solutions such as workflow automation platforms and AI chatbots to manage enquiries across Instagram, Facebook, WhatsApp and other digital channels, which would reduce reliance on manual response handling. However, such tools were deferred following cost–benefit analysis: a proposed AI chatbot with customised knowledge libraries required significant investment that was deemed unjustified given the organization's current enquiry volume. She noted that small organizations must evaluate not only direct financial costs but also the learning burden imposed by new systems; her team already used multiple platforms and avoided unnecessary complexity unless clear operational value can be demonstrated. Instead, existing tools such as Airtable have proven sufficient to fulfil current needs, enabling structured data tracking, including analysis of popular catering items and client preferences, that was previously unachievable through manual record-keeping.

In driving organizational change and overcoming resistance to new technology, Miss Man identified two critical success factors: shared team recognition of pain points and tailored system design. Her team embraced the new workflow system because all members directly experienced the inefficiencies of manual processes, creating genuine internal buy-in. For colleagues with lower technological familiarity, such as catering staff focused on core service delivery, the system was intentionally simplified to present only essential information and avoid data overload. Furthermore, the external consultant conducted structured stakeholder interviews to capture individual challenges, ensuring the final solution responded to specific team needs rather than imposing a generic model. This human-centred design approach reduced resistance and strengthened collective ownership of the new workflow.

Miss Man maintained that human connection remains irreplaceable for mission-driven organizations built on service, craftsmanship and community engagement. For the Project Futurus, which prioritises personalized client experience and community trust, AI serves strictly as a behind-the-scenes efficiency enabler, rather than a replacement for human interaction, cultural delivery or hands-on service quality. Her overarching insight for small organizations pursuing AI adoption is unambiguous: technology should solve specific problems, not represent an end in itself. Successful digital integration requires clear operational diagnosis, cost-conscious and scalable tool selection, and team alignment around shared benefits. The greatest value of AI for small enterprises lies in streamlining workflows, centralising information and reducing administrative burden, allowing teams to focus on their core mission. By avoiding premature or unvalidated investment and prioritising practical, user-friendly solutions, small and social organizations can leverage AI to enhance efficiency without compromising agility, authenticity or human-centred service.

Expert interview with Miss Lucy Chen

Miss Lucy Chen, corporate strategy leader and private equity (PE) investor, entrepreneur, profit and loss (P&L) leader, and former management consultant with extensive cross-sector experience, shared actionable strategies for formulating metric-driven strategies and driving technology adoption, and sustainable innovation. These insights are rooted in her hands-on track record: integrating data and AI into operational workflows, evaluating investments, and leading cross-functional innovation initiatives, all contexts where problem-solving, empathy, and agility stand as paramount pillars.

At the core of her philosophy is prioritizing problems over technology to unlock meaningful innovation. She emphasized that successful tech adoption begins with rejecting shiny object syndrome: leaders must first immerse themselves in frontline challenges to ensure tools solve real, human-centric needs. Her work integrating AI into a telecom firm's sales processes exemplifies this approach: instead of deploying technology for abstract efficiency, she spent weeks observing store operations, listening to hundreds of telesales calls, and gaining a deep understanding that sales teams relied on commissions. The AI tool she championed was tailored to address their specific pain points, identifying customer objections in real time, streamlining follow-up workflows, and boosting conversion rates to protect their livelihoods. This human-centric strategy, she stressed, builds unshakable trust and buy-in: Teams don't resist change when they see you're fighting with them, not dictating to them. Innovation fails when it's tech-driven, not problem-driven.

Miss Chen advocates for hands-on empathy as the foundation of tech adoption leadership. She underscored that leaders cannot drive innovation from boardrooms. They must embed themselves in operational teams to earn credibility. Despite not speaking Cantonese, she spent hours alongside frontline sales teams, learning their workflows, listening to their frustrations, and breaking down the corporate vs. operations divide. For AI and tech initiatives, this empathy translates to three critical actions: clarify where technology augments human expertise, for example, AI identifies high-potential leads, but humans nurture customer rapport and navigate complex negotiations; invest in accessible upskilling and avoiding jargon-heavy training in favor of practical, on-the-job learning; and frame failures as collective learning opportunities. AI pilots will stumble, that's inevitable, she noted. But leaders who celebrate small wins, solicit team feedback, and iterate turn setbacks into progress.

Regarding technology itself, Miss Chen highlighted the need to deploy AI that is functional, integrated, and tightly aligned with core business goals. She advised leaders to adopt three pragmatic practices: start small, pilot tech in focused teams or workflows to test, learn, and de-risk before scaling company-wide; break down silos, collaborate cross-functionally with IT, finance, and operations to ensure seamless integration with existing systems; and measure tangible outcomes such as commission growth, reduced administrative workload, or improved customer satisfaction over vanity metrics like number of AI tools deployed. As a former P&L leader, she also emphasized the importance of dual advocacy: You can't give someone an AI tool without equipping them to use it. Leaders must fight for both the technology and the training, resources, and support their teams need to succeed.

Miss Chen's leadership lesson is unambiguous: innovative cultures and successful tech adoption hinge on centering empathy, curiosity, and problem-solving. AI's greatest value lies in freeing human experts to focus on high-judgment tasks and meaningful work, all guided by leadership that prioritizes humility, admitting gaps in tech knowledge and learning alongside teams, agility, adapting to rapid technological shifts, and resilience, persevering through setbacks. She concluded with a powerful reminder: Technology is a tool, not a solution. Leaders who focus on the 'who' behind the tech, including frontline teams, customers, stakeholders, will always outperform those fixated on the 'what.'

Expert interview with Mr. Alvin Lee

Mr. Alvin Lee, Executive Director, Chairman of the Risk Management and AI Steering Committees of FSE Lifestyle Services Limited (FSE Lifestyle), and a recipient of the Directors of the Year Awards 2025 by The Hong Kong Institute of Directors (HKIoD), shared his strategic vision on the adoption of AI, robotics and other advanced technologies to enhance internal operations, business functions, and service delivery across the diversified sectors of FSE Lifestyle. His perspectives embody a holistic approach to innovation, focus on operational efficiency, cost effectiveness, employee wellbeing and the delivery of humancentric services, while positioning modern technologies as strategic initiatives that streamline workflows, reduce operational risks and enhance service quality. Drawing on FSE Lifestyle's ambition to scale these tools across more than 300 property assets and a workforce of over 26,000 staff, he illustrated how AI and robotics can minimize repetitive, lowvalue tasks while preserving the interpersonal human touch essential to service excellence.

Mr. Lee stressed that the FSE Lifestyle's internal integration of AI is deliberately targeted at removing tedious and repetitive administrative tasks, allowing teams to concentrate on highvalue responsibilities. A prominent application lies in tender processing where the traditional review of lengthy tender documents required substantial time and manpower; now, with AIenabled analytics, executive summaries can be generated in a much shorter lead time following targeted and effective training, significantly accelerating management decisions. In accounting, FSE Lifestyle has implemented AIpowered robotic process automation integrated with Optical Character Recognition (OCR) for invoice processing, currently piloted across several business units to manage the large volume of invoices previously handled manually. Expectedly, the system will continue to improve its accuracy, easing administrative burdens and lowering the risk of human errors. In human resource management, the deployment of a customized AI assistant supports HR staff by responding to inquiries concerning complex policy and benefit arrangements, improving response efficiency and assuring consistent support to the large workforce. Mr. Lee reiterated that these internal AI applications are designed to reduce employee fatigue caused by monotonous work, enabling staff to dedicate more energy to responsibilities requiring emotional intelligence and interpersonal engagement.

Beyond internal operational enhancements, Mr. Lee highlighted the transformative impact of AI and robotics on external service delivery and client experience. In building repairs and property maintenance, drones are deployed for high-level and aerial inspections, particularly for detecting water seepage and external wall cracks, with AI analyzing visual data to identify maintenance requirements. This approach enhances safer and delivers more costefficient inspection processes. For resident services, AI chatbots manage routine tenant inquiries, alleviating pressure on frontline staff while gathering data to monitor satisfaction levels and proactively address recurring issues. FSE Lifestyle also deploys robotic devices, such as robotic dogs, to assist staff in confined space inspections, night patrols and heavy or repetitive duties. Guided by human supervision, these robots undertake physically demanding tasks, and reducing strain on staff. Such applications demonstrate how AI and robotics strengthen service reliability, operational safety and productivity, key competitive advantages in the property service and management industry.

To address the primary challenge of technological adoption, employees' anxiety over potential job replacement, Mr. Lee promotes a bottomup approach grounded in comprehensive training, cultural alignment, and clear demonstrations of technology as an enabler rather than a threat. The Human Resources Department maintains regular workshops to upskill employees in the use of AI and robotic tools, consistently emphasizing that technology is meant to assist rather than replace workers. The robotic dog initiative offers a compelling example: operational staff quickly recognized that the robots performed strenuous tasks under their direction, reinforcing the perception of technology as a supportive tool. Meanwhile, residents responded positively to seeing robots guided by approachable and attentive staff, who were now better able to deliver emotional value and interpersonal warmth. Mr. Lee also noted that FSE Lifetstyle's corporate culture fosters calculated risktaking, permitting iterative implementation without demanding total perfection. Central to this approach is the preservation of human touch, he highlighted that FSE Lifestyle is highly labour-intensive and, by outsourcing administrative and logistical work to AI and robotics, staff gain greater capacity to interact with residents and customers through attentive greetings, care and personalized engagement, which cannot be replicated by technology. Instead, AI serves to improve occupational safety and health by taking over hazardous, physically demanding, or repetitive tasks, thereby reducing workplace injuries and strain on staff. The ongoing challenge, he acknowledged, lies in balancing higher levels of automation with the maintenance of frontline service quality and motivation.

Mr. Lee underlined that the adoption of AI and robotics is deeply embedded in the FSE Lifestyle's core value of innovation, which forms a cornerstone of its strategic plan. Management maintains that stagnation leads to market obsolescence, and the organization invests significantly in technology to drive sustainable growth, favouring practical, scalable solutions over symbolic gestures. His overarching insight concerning technological adoption is clear: successful digital transformation depends on aligning AI, robotics and related tools with employee needs and customer expectations. Their greatest value resides in streamlining operational inefficiencies, strengthening workplace safety and boosting productivity, while empowering employees to deliver the humancentric service that defines highquality operational management. By adopting a bottomup implementation model, nurturing a learning culture and focusing on practical, taskspecific applications, organizations can leverage technology to drive growth, improve services and establish industry benchmarks. As FSE Lifestyle's experience demonstrates, AI and robotics represent more than efficiency tools—they act as catalysts for developing smarter, more productive and peoplecentred operational models.

Expert interview with Mr. Jonathan Liu

Mr. Jonathan Liu, Chief Executive Officer of AIA Company (Trustee) Limited, brings extensive leadership experience and deep expertise to the pension and employee benefit landscape. During the interview for the current study, he shared actionable insights on the practical implementation of AI within a large-scale insurance organisational context, offering illustrative examples of AI implementation that reflect his experience rather than formal, groupwide mandates or uniform practices across all AIA entities, and reflecting a top management commitment to bal-

ancing technological advancement with human-centric leadership, psychological safety, and cultural shifts that embrace digital tools, all within the highly regulated insurance context.

Mr. Liu emphasized a pragmatic, efficiencyfocused approach to AI integration, centred on the use of widely adopted enterprise tools to support routine organisational processes. AI is positioned as an assistive capability that enhances information handling and preparatory work rather than automating decisionmaking. This enables teams to reduce time spent on routine tasks and reallocate effort toward highvalue strategic work.

Despite these efficiency gains, Mr. Liu stressed that AI should remain a reference and support tool, not a replacement for human judgment and client relationships. A key concern relates to AI database transparency: limited or incomplete access to uptodate organizational documents may result in inaccurate outputs, necessitating careful human validation. He further explored the potential of AI as an enabler in HR and frontline sales functions. In recruitment, AI tools can assist with preliminary candidate screening by analysing cues, thereby reducing administrative burdens on HR teams; in sales, AI can synthesize client profiles, including background, insurance history, or claims, to significantly optimise consultation time and enhance agent productivity. Human accountability, however, remains irreplaceable; as with the broader financial services industry, legal and regulatory frameworks governing AI accountability continue to evolve.

On leadership and innovation culture, Mr. Liu identifies psychological safety and role-modelling as key to overcoming resistance to change. Leaders must lead by example in AI use to alleviate replacement fears. External factors, for example, Covid-19 or policy change, can catalyze adaptation, but internal change depends on tangible results, sharing AI success cases and training helps employees see time savings and performance gains. An ongoing challenge is shifting mindsets of employees at different stages of digital adoption, addressed via relatable success stories from colleagues with long-established working practices.

Mr. Liu advocates proactive exploration of next-generation AI tools that augment human connection. His core leadership lesson: sustainable AI adoption balances efficiency with human-centric principles, psychological safety, pragmatic value, and unwavering accountability. Leaders must promote and model AI, set clear guardrails, and address transparency and liability upfront. Innovation thrives on tangible benefits, not coercion, and AI's greatest value lies in amplifying human capability, reducing friction, enhancing client insights, and prioritising relationship-building, while keeping humans as ultimate decision-makers, preserving trust in pension and insurance.

Expert interview with Miss Doreen Siu

Miss Doreen Siu, General Manager of Human Resources at MTR Corporation (MTRC), a world-leading public transport operator with nearly 18,000 employees, shared practical, frontline insights on AI adoption and digital transformation within complex, mission-critical operational settings. Her perspectives embody a pragmatic, people-centred approach to technological change, focused on aligning AI integration with operational excellence, employee well-being and leadership accountability, while addressing the unique challenges of a highly regulated, frontline-intensive transport organization.

Miss Siu emphasized that technology is deployed to augment human capabilities rather than replace staff. In station operations, AI-powered platform management tools analyze passenger capacity in train carriages to guide boarding flow, improving crowd control and overall service efficiency. For track maintenance, the organization is phasing out labour-intensive manual night-time track inspections in favour of AI-driven automated monitoring systems. This transition alleviates recruitment difficulties for physically demanding, low-level operational roles. Such initiatives, she stressed, are designed to redirect employees toward higher-value responsibilities including strategic oversight, safety management and customer-focused services, ensuring that technology strengthens rather than diminishes professional expertise.

In human resource management, Miss Siu highlighted how AI and digital tools have elevated employee experience and streamlined administrative workflows. The organization has launched an internal AI chatbot to resolve routine HR enquiries, such as queries concerning medical benefits and workplace flexibility policies, establishing a self-service framework that reduces repetitive call volumes and allows HR professionals to concentrate on strategic talent development. A critical lesson from this deployment, she noted, is the value of incentives in driving digital adoption: the company's wellness platform successfully familiarized employees with mobile applications and digital claims processing, building confidence and comfort before rolling out more advanced AI systems. Going forward, the HR team will review candidate experience frameworks to ensure digital interfaces align with organizational culture, supporting a smooth, people-centred digital transition.

Addressing core barriers to AI adoption, Miss Siu identified infrastructure, psychological safety and process efficiencies as key subjects requiring proactive management. Many frontline employees lack dedicated work devices, creating access gaps; at a psychological level, staff need stronger confidence and digital literacy to keep pace with rapid technological shifts. She highlighted double-work frustration as a critical implementation pain point, where new digital tools are introduced without phasing out legacy manual processes, leading to heavier instead of reduced workloads. To tackle these issues, Miss Siu stressed that leaders must reject AI for AI's sake and prioritize rollouts based on effectiveness and usability, focusing on high-impact, high-value areas rather than fragmented company-wide deployment. Organizations should also conduct skills gap assessments for Future Ready roles, ensuring employees receive targeted support to adapt to evolving job requirements.

On leadership and communication strategy, Miss Siu underlined that successful digital transformation relies on visible leadership buy-in and accessible, relatable communication. To bridge gaps between technical teams and frontline staff, AI initiatives must be framed in plain, non-intimidating language that showcases tangible, role-specific benefits for employees. She further emphasized that leaders must walk the talk by modelling digital adoption and eliminating redundant manual practices, sending a clear signal that digital transformation is an organization-wide strategic priority.

Miss Siu concluded that sustainable digital transformation demands a balance between operational efficiency and employee needs, prioritizing problem-driven technology over trend-chasing and embedding strong leadership and communication into every implementation stage. For MTRC, the greatest value of AI lies in enhancing operational safety, streamlining workflows and empowering employees to focus on high-value, human-centric work, all while upholding the organization's core commitments to reliability, customer service and staff well-being. By placing people at the centre of change, prioritizing practical impact and holding leaders accountable for role-modelling digital adoption, large-scale transport and service organizations can leverage AI to deliver effective, sustainable digital and AI transformations.

Main themes

Through systematic extraction and thematic analysis of recurring focal points, core keywords, and collective insights from the expert interviews, eight overarching themes were identified, each capturing critical dimensions of AI adoption, leadership, and organizational change. These themes, grounded in practitioners' real-world expertise across sectors, served as the foundational basis for developing the current study's conceptual framework.

- ***Human-centric AI adoption and digital transformation***

All experts uniformly emphasized that AI and technology must be designed with a people-first orientation: augmenting, rather than replacing, human expertise, prioritizing employee well-being, and preserving interpersonal and humanistic values, such as customer service quality, community trust, and professional judgment. This theme underpins strategies to alleviate employee fears of displacement, balance automation with meaningful human interaction, and centre stakeholder needs in technological deployment.

- ***Leadership-driven innovation culture for AI integration***

Leadership, encompassing top management vision, role modelling, and behavioral practices, emerged as the cornerstone of successful AI adoption. Key sub-themes included cultivating psychological safety, fostering tolerance for failure, leading by example, communicating AI's value in accessible terms, and driving bottom-up employee buy-in to nurture an innovation-ready organizational culture.

- ***Pragmatic, problem-driven AI implementation (rejecting tech for tech's sake)***

Experts across sectors advocated for targeted, value-based AI deployment: first identifying concrete operational pain points, conducting rigorous cost-benefit analyses, prioritizing high-impact use cases, and adopting incremental, pilot-based rollouts over large-scale, disruptive overhauls. This principle applies universally to organizations of all sizes, from large corporations to resource-constrained social enterprises.

- ***AI-enabled operational efficiency and workflow optimization***

A dominant practical theme centred on AI's role in streamlining repetitive, low-value administrative and operational tasks, such as invoice processing, tender analysis, HR query handling, facility inspection, and logistics scheduling. Technologies like AI, drones, and mechanical robots reduce manual labour, minimize human error, and lower operational costs, while freeing staff to focus on high-judgment, value-added work.

- ***Change management, employee upskilling, and psychological safety***

Addressing organizational resistance to AI was identified as a core priority: mitigating

employee anxiety through tailored upskilling and digital literacy programs, simplifying tech tools for non-technical frontline staff, eliminating double work by phasing out legacy systems alongside new AI implementations, and framing failures as collective learning opportunities to build psychological safety.

- ***Responsible AI governance, compliance, and risk mitigation***

For regulated industries, such as insurance, public transport, and utilities, experts stressed that AI governance, including regulatory alignment, data transparency, and ethical risk management to mitigate algorithmic bias, privacy breaches, and liability, is non-negotiable. Cross-functional collaboration, engagement with regulatory sandboxes, and robust monitoring systems were highlighted as critical to balancing innovation with compliance.

- ***Cross-sector and contextualized AI practices***

AI adoption trajectories vary sharply by industry and organizational scale, underscoring the need for sector-specific, context-aware strategies rather than one-size-fits-all solutions.

- ***Human-AI collaboration and preservation of core organizational values***

Experts emphasized that while AI optimizes workflows, it cannot replace an organization's mission, core values, or high-stakes human judgment. Technology acts as a strategic assistant to amplify human capabilities, with the preservation of organizational purpose and relational trust remaining central to successful AI integration.

Framing the current study and future research priorities

These eight main themes collectively shaped the current study's conceptual framework by highlighting leadership and innovative culture as the linchpin of effective AI adoption, a core insight distilled from Theme 5.2.2 (Leadership-driven innovation culture for AI integration) and reinforced by complementary themes such as human-centric AI adoption (5.2.1), change management (5.2.5), and human-AI collaboration (5.2.8). Specifically, Theme 5.2.2's focus on top management vision, behavioral practices, psychological safety, and failure tolerance directly aligned with the theoretical construct of transformational leadership (TFL), a leadership style defined by inspirational motivation, intellectual stimulation, and individualized consideration, which experts identified as critical to fostering an AI-ready innovative culture (IC). Similarly, IC dimensions (e.g., risk tolerance, bottom-up innovation, and psychological safety) were explicitly foregrounded in Theme 5.2.2 and echoed in Theme 5.2.5, making the relationship between TFL behaviors and IC dimensions the current study's prioritized focus. This prioritization reflects the experts' consensus that leadership and culture are foundational to overcoming AI adoption barriers, as they address the human and organizational dynamics that underpin technical implementation success.

Notably, the expert interviews also uncovered additional factors that intersect with IC but are reserved for future research, as they emerged as secondary but meaningful sub-themes within the eight core focal points. First, transactional leadership and authentic leadership were

identified in Theme 5.2.2: experts referenced leadership role modelling and communicating AI value accessibly, traits aligned with authentic leadership's emphasis on transparency and integrity, while mentions of operational accountability, implied in Theme 5.2.3's pragmatic AI implementation, resonated with transactional leadership's focus on goal-setting and performance feedback. Second, employees' commitment emerged from Theme 5.2.1 (human-centric AI's focus on employee well-being and displacement mitigation) and Theme 5.2.5 (upskilling and buy-in), as experts noted that employees' emotional attachment to their organizations is critical to embracing AI change. Third, employee resilience was highlighted in Theme 5.2.5 (managing resistance and learning from failure) and Theme 5.2.8 (adapting to human-AI collaboration), as experts emphasized the need for employees to cope with technological disruption and skill shifts. While these factors are theoretically and practically relevant to IC, the current study prioritizes TFL-IC relationships to maintain analytical focus, with future research encouraged to explore how transactional leadership, authentic leadership, affective organizational commitment, and employee resilience, all derived from the expert-identified themes, further shape IC in the context of AI adoption.

FINDINGS

This section presents the findings of the current study, which investigates the relationships between seven transformational leadership behaviors and innovative culture for AI adoption. The findings are organized into two thematic subsections: the first outlines the demographic characteristics of the survey respondents, providing contextual insights into the study's sample; the second details the rigorous hypothesis testing conducted to examine the proposed relationships between seven TFL behaviors and four IC dimensions.

Respondents' profile

A total of 768 respondents completed the survey questionnaires. Eleven responses submitted by individuals based outside Hong Kong, Chinese Mainland, and Indonesia were excluded from this study, resulting in a final valid sample of 757 participants. Tables 1, 2, and 3 present the demographic characteristics of the respondents, including their primary work location, job level, organizational size, and industry sector. In terms of primary work location, 62% of the sample was from Hong Kong, 15% from Chinese Mainland, and 23% from Indonesia. Regarding job level, middle management staff constituted the largest group (43%), followed by senior management (34%) and junior-level employees (23%). For organizational size, the majority of participants worked in large organizations with 1,000 or more employees (35%) and medium-sized enterprises with 50 to 499 employees (33%); the remaining respondents were employed by small organizations with fewer than 50 employees (24%) and medium-large organizations with 500 to 999 employees (8%). In respect of industry distribution, the most heavily represented sectors were Banking, Financial Services, and Insurance Activities (16%), Education (13%), Consulting, Professional Services, and Scientific & Technical Activities (11%), NGO and Non-Profit Activities (10%), and Import/Export, Wholesale, Retail Trades, and E-Commerce (9%). The remaining 41% of respondents were spread across 12 other industry sectors.

Job Level	01. Hong Kong	02. Chinese Mainland	03. Indonesia	Grand Total
01. General Staff or Non-Managerial Position	97	8	66	171
02. Assistant Manager, Manager, Senior Manager or Equivalent	211	59	58	328
03. Senior Executive (CXO, VP, General Manager, Director or Department Head or Equivalent)	161	44	53	258
Grand Total	469	111	177	757

Table 1. Respondent profile by job level

Organizational Size	01. Hong Kong	02. Chinese Mainland	03. Indonesia	Grand Total
01. Below 50	95	15	74	184
02. 50-499	156	30	61	247
03. 500-999	36	14	11	61
04. 1,000 and above	182	52	31	265
Grand Total	469	111	177	757

Table 2. Respondent profile by organizational size

Industry	01. Hong Kong	02. Chinese Mainland	03. Indonesia	Grand Total
01. Accommodation, Food Service Activities, etc.	15	1	8	24
02. Arts, Entertainment, Recreation, etc.	8	1	4	13
03. Banking, Financial Services, Insurance Activities, etc.	82	21	15	118
04. Conglomerate, Multi-industry Organisation, etc.	11	14	4	29
05. Construction	11	3	5	19
06. Consulting, Professional Services, Scientific, Technical Activities, etc.	55	7	22	84
07. Education	57	3	40	100
08. Energy	4	3	5	12
09. Government, Public Administration, etc.	19	6	15	40
10. Healthcare	25	9	7	41
11. Import/Export, Wholesale, Retail Trades, e-Commerce, etc.	46	10	15	71
12. Information, Communications, etc.	25	10	3	38
13. NGO, Non-Profit Activities, etc.	67	2	3	72
14. Real Estate	15	6	1	22
15. Transportation, Storage, Postal, Courier Services, etc.	24	5	4	33
16. Water Supply, Sewerage, Waste Management, etc.	1	---	---	1
17. Manufacturing	4	10	26	40
Grand Total	469	111	177	757

Table 3. Respondent profile by industry

Linear regression analysis

The present study employed linear regression analysis to empirically examine the predictive effects of transformational leadership (TFL) behaviors (independent variables) on innovative culture (IC) (dependent variables). This analytical approach is wellestablished and widely validated in social science research for estimating the directional and quantitative relationships between predictor and outcome constructs (Field, 2024). A core output of linear regression modelling is the Beta (β) coefficient, which quantifies the magnitude and direction of the association between independent and dependent variables; this study applies two distinct interpretive forms of this metric: unstandardized Beta (B) and standardized Beta (β).

The unstandardized Beta coefficient corresponds to the raw slope parameter in the regression equation ($y = \beta\square + \beta\square x$), reflecting the absolute change in the dependent variable tied to a oneunit increase in the independent variable while preserving the original measurement units of the dataset. In contrast, the standardized Beta coefficient is adopted to evaluate the relative predictive importance of distinct independent variables within the same model: it measures the number of standard deviations the dependent variable shifts in response to a onestandarddeviation increase in the predictor, is scaled to a range of −1 to +1, and eliminates unitbased disparities to enable direct comparisons of variables with heterogeneous measurement scales (Wooldridge, 2020).

This dual interpretive framework supports both granular assessments of raw predictive effects and comparative analyses of variable salience, bolstering the analytical rigor and interpretive depth of the study's hypothesis testing. As reported in Tables 4 to 7, the regression analyses identify statistically significant (where $p < 0.05$) relationships between specific transformational leadership behaviors and the four dimensions of innovative culture across the three research contexts: Hong Kong, Chinese Mainland, and Indonesia.

IV	Hong Kong					Chinese Mainland					Indonesia				
	B	Std. Error	Beta	t	Sig.	B	Std. Error	Beta	t	Sig.	B	Std. Error	Beta	t	Sig.
TFL1	-0.02	0.06	-0.02	-0.36	0.722	-0.06	0.11	-0.06	-0.56	0.577	0.04	0.06	0.05	0.69	0.489
TFL2	-0.02	0.06	-0.02	-0.32	0.751	0.12	0.11	0.12	1.09	0.28	**-0.27**	**0.09**	**-0.28**	**-2.93**	**0.004**
TFL3	0.03	0.05	0.02	0.6	0.549	-0.08	0.11	-0.06	-0.7	0.488	0.1	0.07	0.09	1.29	0.199
TFL4	-0.03	0.07	-0.03	-0.45	0.651	-0.03	0.13	-0.03	-0.2	0.841	-0.01	0.09	-0.01	-0.06	0.951
TFL5	0.01	0.07	0.01	0.17	0.868	0.27	0.14	0.27	1.97	0.052	-0.01	0.08	-0.01	-0.17	0.864
TFL6	0.03	0.07	0.03	0.53	0.599	-0.07	0.12	-0.06	-0.54	0.588	0.05	0.08	0.05	0.59	0.554
TFL7	**0.49**	**0.05**	**0.48**	**9.51**	**0**	0.23	0.12	0.21	1.92	0.058	**0.35**	**0.08**	**0.34**	**4.42**	**0**

Table 4. Linear regression analysis – IC1 as dependent variable

IV	Hong Kong					Chinese Mainland					Indonesia				
	B	Std. Error	Beta	t	Sig.	B	Std. Error	Beta	t	Sig.	B	Std. Error	Beta	t	Sig.
TFL1	0.03	0.06	0.03	0.52	0.602	0.13	0.13	0.11	0.97	0.335	-0.01	0.06	-0.01	-0.2	0.839
TFL2	-0.06	0.06	-0.05	-0.95	0.344	-0.03	0.14	-0.03	-0.24	0.809	0.07	0.09	0.07	0.73	0.467
TFL3	-0.06	0.05	-0.05	-1.13	0.26	-0.04	0.14	-0.03	-0.27	0.785	0.01	0.08	0.01	0.12	0.906
TFL4	-0.03	0.07	-0.03	-0.45	0.653	0.2	0.16	0.16	1.21	0.231	0.03	0.09	0.03	0.35	0.725
TFL5	0.07	0.07	0.07	0.94	0.349	0.08	0.17	0.07	0.5	0.62	**0.24**	**0.08**	**0.26**	**3**	**0.003**
TFL6	0.05	0.07	0.05	0.75	0.451	0.23	0.15	0.19	1.51	0.136	0.1	0.08	0.1	1.16	0.247
TFL7	**0.28**	**0.06**	**0.26**	**5.07**	**0**	-0.17	0.15	-0.13	-1.12	0.264	0.03	0.08	0.03	0.38	0.706

Table 5. Linear regression analysis – IC2 as dependent variable

IV	Hong Kong					Chinese Mainland					Indonesia				
	B	Std. Error	Beta	t	Sig.	B	Std. Error	Beta	t	Sig.	B	Std. Error	Beta	t	Sig.
TFL1	0.07	0.06	0.06	1.2	0.23	-0.11	0.13	-0.1	-0.82	0.414	-0.05	0.08	-0.05	-0.58	0.561
TFL2	-0.02	0.06	-0.02	-0.3	0.766	0.18	0.14	0.16	1.29	0.199	0.11	0.12	0.1	0.9	0.371
TFL3	0.05	0.05	0.04	1.04	0.297	-0.13	0.14	-0.1	-0.95	0.345	**-0.23**	**0.1**	**-0.19**	**-2.35**	**0.02**
TFL4	0.07	0.07	0.06	1.05	0.295	0.02	0.16	0.02	0.11	0.915	0.02	0.11	0.02	0.21	0.833
TFL5	**0.14**	**0.07**	**0.14**	**2.08**	**0.038**	0.1	0.17	0.1	0.61	0.543	**0.28**	**0.1**	**0.29**	**2.83**	**0.005**
TFL6	**-0.13**	**0.07**	**-0.13**	**-2.05**	**0.041**	0.29	0.15	0.26	1.87	0.065	-0.05	0.11	-0.05	-0.46	0.645
TFL7	**0.28**	**0.05**	**0.27**	**5.49**	**0**	0.09	0.15	0.08	0.59	0.554	0.19	0.1	0.17	1.87	0.064

Table 6. Linear regression analysis – IC3 as dependent variable

IV	Hong Kong					Chinese Mainland					Indonesia				
	B	Std. Error	Beta	t	Sig.	B	Std. Error	Beta	t	Sig.	B	Std. Error	Beta	t	Sig.
TFL1	0.07	0.06	0.07	1.13	0.258	-0.15	0.11	-0.14	-1.33	0.187	**0.19**	**0.09**	**0.2**	**2.17**	**0.032**
TFL2	-0.01	0.07	-0.01	-0.1	0.921	-0.09	0.11	-0.08	-0.77	0.446	-0.2	0.13	-0.19	-1.53	0.129
TFL3	0.05	0.06	0.04	0.95	0.345	-0.1	0.11	-0.08	-0.86	0.394	-0.11	0.11	-0.09	-1.02	0.311
TFL4	-0.06	0.08	-0.05	-0.77	0.442	-0.11	0.13	-0.1	-0.79	0.429	-0.24	0.13	-0.24	-1.92	0.057
TFL5	0.11	0.08	0.1	1.38	0.167	-0.03	0.14	-0.03	-0.23	0.822	0.09	0.11	0.09	0.83	0.409
TFL6	-0.01	0.08	-0.01	-0.09	0.925	0.13	0.12	0.13	1.06	0.293	0.12	0.12	0.11	0.97	0.331
TFL7	**0.24**	**0.06**	**0.22**	**3.96**	**0**	0.08	0.12	0.07	0.63	0.533	0.19	0.11	0.17	1.69	0.092

Table 7. Linear regression analysis – IC4 as dependent variable

Hypothesis testing

This section presents the results of hypothesis testing for the study's four core hypotheses (H1–H4), which examine the predictive relationships between seven transformational leadership (TFL) behaviors (independent variables: TFL1–TFL7) and four dimensions of innovative culture (IC, dependent variables: IC1–IC4) across three regional contexts: Hong Kong, Chinese Mainland, and Indonesia. Hypothesis testing was conducted using linear regression analysis, with results reported in Table 4 (IC1), Table 5 (IC2), Table 6 (IC3), and Table 7 (IC4). A result was deemed statistically significant if the p-value was less than 0.05, which are highlighted in bold and shaded in green (for statistically significant positive relationships) or pink (for statistically significant negative relationships), with effect sizes interpreted per Cohen's (2013) established guidelines: small ($|\beta| < 0.10$), moderate ($0.10 \leq |\beta| \leq 0.29$), and large ($|\beta| \geq 0.30$). Table 8 shows the hypothesis testing results.

Table 8. Hypothesis testing results

Hypothesis	Hong Kong	Chinese Mainland	Indonesia
IC1: Your organizational culture values innovation and change for the adoption and implementation of AI.			
TFL1 is positively related to IC1	Rejected	Rejected	Rejected
TFL2 is positively related to IC1	Rejected	Rejected	Rejected
TFL3 is positively related to IC1	Rejected	Rejected	Rejected
TFL4 is positively related to IC1	Rejected	Rejected	Rejected
TFL5 is positively related to IC1	Rejected	Rejected	Rejected
TFL6 is positively related to IC1	Rejected	Rejected	Rejected
TFL7 is positively related to IC1	**Accepted**	Rejected	**Accepted**
IC2: Your organizational culture attracts and retains creative people for the adoption and implementation of AI.			
TFL1 is positively related to IC2	Rejected	Rejected	Rejected
TFL2 is positively related to IC2	Rejected	Rejected	Rejected
TFL3 is positively related to IC2	Rejected	Rejected	Rejected
TFL4 is positively related to IC2	Rejected	Rejected	Rejected
TFL5 is positively related to IC2	Rejected	Rejected	**Accepted**
TFL6 is positively related to IC2	Rejected	Rejected	Rejected
TFL7 is positively related to IC2	**Accepted**	Rejected	Rejected
IC3: Your organizational culture provides resources to experiment with new ideas for the adoption and implementation of AI.			
TFL1 is positively related to IC3	Rejected	Rejected	Rejected
TFL2 is positively related to IC3	Rejected	Rejected	Rejected
TFL3 is positively related to IC3	Rejected	Rejected	Rejected
TFL4 is positively related to IC3	Rejected	Rejected	Rejected
TFL5 is positively related to IC3	**Accepted**	Rejected	**Accepted**
TFL6 is positively related to IC3	Rejected	Rejected	Rejected
TFL7 is positively related to IC3	**Accepted**	Rejected	Rejected
IC4: Your organizational culture allows people to take risks and occasionally fail for the adoption and implementation of AI.			
TFL1 is positively related to IC1	Rejected	Rejected	**Accepted**
TFL2 is positively related to IC1	Rejected	Rejected	Rejected
TFL3 is positively related to IC1	Rejected	Rejected	Rejected
TFL4 is positively related to IC1	Rejected	Rejected	Rejected
TFL5 is positively related to IC1	Rejected	Rejected	Rejected
TFL6 is positively related to IC1	Rejected	Rejected	Rejected
TFL7 is positively related to IC1	**Accepted**	Rejected	Rejected

DISCUSSION

Against the backdrop of global digital transformation, AI implementation is no longer a discretionary choice but a strategic imperative for organizations seeking sustainable competitive advantages through enhanced productivity and efficiency. However, the successful uptake of AI hinges critically on a robust innovative culture. This mixed-methods study investigates the culturally contingent relationships between transformational leadership (TFL) behaviors and innovative culture (IC) for AI adoption across Hong Kong, Chinese Mainland, and Indonesia, complementing quantitative regression findings with practical insights from industry experts, enterprise founders, and subject-matter specialists. The current study further aims to generate empirical evidence for how leadership cultivates innovative culture, thereby strengthening organizations and employees' readiness for AI adoption and implementation. This section synthesizes cross-regional findings, elaborates theoretical and practical implications, addresses research limitations, and proposes future research directions.

Hong Kong

Hong Kong exhibited relatively more consistent pattern of significant TFL-IC relationships, with empirical support for all four core hypotheses across the four IC dimensions (Tables 4–7). Notably, TFL7 (The Top Management Team encourages others to innovate) emerged as the sole universal positive predictor of all IC dimensions, demonstrating strong explanatory power:

- For IC1 (values innovation and change for AI adoption), TFL7 yielded a strong positive effect (B = 0.49, β = 0.48, $p < 0.05$);
- For IC2 (attracts and retains creative talent), IC3 (provides resources for experimentation), and IC4 (tolerates risk and failure), TFL7 showed moderate positive effects (B = 0.28, β = 0.26; B = 0.28, β = 0.27; B = 0.24, β = 0.22, respectively; all $p < 0.05$).
-

This dominant effect aligns with Hong Kong's entrepreneurial, market-oriented, and individualistic cultural context, where explicit leadership advocacy for innovation directly nurtures the psychological and operational conditions for AI adoption. A noteworthy counterintuitive finding was that while for IC3, TFL5 (developing employee strengths) was also a significant positive predictor (B = 0.14, β = 0.14, $p < 0.05$) alongside TFL7, a significant negative effect of TFL6 (The Top Management Team makes others feel good to work with them) on IC3 (B = -0.13, β = -0.13, $p < 0.05$) was observed, suggesting that excessive interpersonal rapport-building may divert organizational focus from resource allocation for experimental AI initiatives, revealing the nuanced and occasionally counterproductive nature of isolated TFL behaviors.

Chinese Mainland

In Chinese Mainland, all TFL-IC hypotheses were fully rejected, as no TFL behavior exerted a statistically significant effect on any IC dimension (all $p > 0.05$). The only marginal results were TFL7 for IC1 ($p = 0.058$), and TFL5 for IC2 ($p = 0.052$), both fell just outside the 0.05 significance threshold. This absence of meaningful relationships can be attributed to the

region's unique institutional and cultural context: high power distance, hierarchical organizational structures, and collectivist norms that prioritize organizational conformity, top-down directives, and institutional alignment over individual or team-driven innovation. Conventional TFL behaviors, rooted in Western individualistic leadership frameworks, fail to resonate in this context, indicating that universal TFL strategies are ill-suited to fostering innovative culture for AI adoption in Chinese Mainland.

Indonesia

Indonesia demonstrated mixed support for all hypotheses, with significant TFL predictors distinct from Hong Kong which may be tightly aligned with the country's strong collectivist cultural values (Tiffany & Rosman, 2024):

- For IC1, TFL7 exerted a large positive effect (B = 0.35, β = 0.34, $p < 0.05$), while TFL2 (ethical accountability) had a significant negative effect (B = -0.27, β = -0.28, $p < 0.05$), reflecting tensions between innovation advocacy and ethical governance in AI adoption;
- For both IC2 and IC3, TFL5 (developing employee strengths) was a significant positive predictor (B = 0.24, β = 0.26; B = 0.28, β = 0.29, both $p < 0.05$), while TFL3 (optimistic future vision) negatively predicted IC3 (B = -0.23, β = -0.19, $p < 0.05$);
- For IC4, TFL1 (group-oriented self-sacrifice) emerged as a significant positive predictor (B = 0.19, β = 0.20, $p < 0.05$).

These findings confirm that collectivist-aligned TFL behaviors, such as prioritizing group interests and developing employee capabilities, drive innovative culture in Indonesia, whereas abstract inspirational messaging or rigid ethical framing may hinder experimental AI initiatives.

Theoretical Implications

The current study makes three key theoretical contributions to cross-cultural leadership, innovative culture, and AI adoption research. First, it addresses the critical scarcity of empirical research linking transformational leadership and organizational innovative culture in the context of AI adoption and implementation. Extending prior literature that confirms TFL's impact on innovative culture (Wong & Lau, 2025) and positive organizational and individual outcomes (Bass, 1985), this study validates the potential of TFL in translating specific TFL behaviors into specific positive innovative culture outcomes.

Second, it advances cross-cultural leadership theory by debunking the universalistic assumption of TFL efficacy. The study's cross-regional divergence, namely relatively more consistent TFL effects in Hong Kong, null effects in Chinese Mainland, and mixed effects in Indonesia, demonstrates that TFL-IC relationships are culturally contingent, responding to variations in individualism-collectivism, power distance, and institutional norms. This responds to calls for contextually grounded leadership research in China-ASEAN digital cooperation.

Third, the study integrates qualitative expert insights with quantitative analysis to ground abstract leadership theory in real-world AI adoption practices. The eight core themes derived from expert interviews empirically validate that leadership and culture are the linchpins of human-centric AI integration, bridging the gap between theoretical leadership frameworks and applied organizational science.

Practical Implications

Translating empirical findings and expert insights into actionable guidance, this study offers targeted practical recommendations for organizational leaders, senior managers, and HR practitioners operating in the China-ASEAN digital economy. First, cross-culturally adaptive leadership strategies are non-negotiable for AI-driven innovation. In Hong Kong, leaders should prioritize explicit innovation advocacy (TFL7) to nurture all dimensions of innovative culture, while balancing interpersonal engagement with resource allocation for AI experimentation; in Chinese Mainland, leaders should demonstrate contextually appropriate leadership practices aligned with hierarchical and institutional norms, such as top-down AI strategic alignment and collective innovation mandates; in Indonesia, leaders should leverage collectivist TFL behaviors (TFL1 and TFL5) to foster group cohesion and employee development and avoid certain TFL behaviors that are counterproductive, framing AI adoption as a collective organizational goal rather than an individual innovation initiative.

Second, leaders must act as role models for human-centric AI transformation, as emphasized by expert interviewees. Executives should step outside comfort zones, communicate a clear AI vision transparently, model ethical risk-taking, and cultivate psychological safety by framing failures as collective learning opportunities. This reduces employee anxiety toward AI displacement and drives bottom-up buy-in for technological adoption.

Third, organizations must adopt pragmatic, problem-driven AI implementation, rejecting tech for tech's sake, and balance innovation with governance. Regulated industries such as insurance and transportation should establish robust AI governance frameworks, while small and medium-sized enterprises should prioritize low-cost, scalable AI tools that resolve concrete operational pain points. HR practitioners play a pivotal role in delivering targeted AI upskilling, eliminating double-work between legacy systems and new AI tools, and centering employee well-being in digital transformation.

Limitations and Future Research Directions

Despite its contributions, this study has several limitations that point to meaningful avenues for future research. First, innovation, AI and digital transformation require leaders to adapt their styles to situational demands, employee competencies, and developmental needs. The current study focuses exclusively on TFL, yet full-range leadership theory (Bass, 1985) emphasizes that transformational and transactional leadership are complementary, with both styles driving positive organizational outcomes. Transactional leadership's focus on accountability and contingent rewards may be particularly relevant for regulated AI adoption, especially in Chinese Mainland, while authentic leadership, rooted in transparency and trust, can enhance diversity, psychological safety, and innovative culture. Transactional and authentic leadership behaviors may correlate with IC, justifying future empirical examination of these styles.

Second, the current study employs a cross-sectional design, which limits causal inferences about the temporal relationships between leadership behaviors and IC. Longitudinal research is recommended to verify causal direction and track changes in culture and other employee outcomes across AI implementation stages.

Third, all quantitative data are self-reported, introducing common method bias despite procedural remedies. Future research may adopt multi-source data collection, for example, leader-rated IC and objective AI adoption metrics, to reduce bias.

Fourth, the sample is restricted to three regions; future studies may expand to other ASEAN member states to enhance generalizability.

Finally, the study prioritizes TFL-IC relationships and does not measure other crucial factors, such as employees' commitment and resilience, which were identified in expert interviews as critical to AI adoption and implementation. Future research is encouraged to formally examine their roles in AI adoption and other employee outcomes.

CONCLUSION

This mixed-methods study confirms that leadership is an indispensable pillar of an innovative culture, serving as the foundational enabler of technological integration. Empirically, transformational leadership behaviors exert context-specific effects on innovative culture, demonstrating varied impact across Hong Kong, Chinese Mainland, and Indonesia. No universal leadership behavior can drive innovation across diverse cultural settings. In practice, industry experts emphasize that successful AI transformation requires human-centric leadership, psychological safety, value-aligned talent management, and cross-culturally adaptive strategies.

As China and ASEAN deepen their AI and digital economic cooperation, the study's findings underscore that technological investment alone is insufficient: culturally adaptive leadership and an inclusive, innovative culture determine whether AI delivers a sustainable competitive advantage. By tailoring leadership practices to local cultural norms, cultivating innovation-friendly organizational climates, and centering employees in digital transformation, organizations can turn AI from a technical tool into a catalyst for holistic, sustainable growth, benefiting both organizational performance and the human capital that underpins long-term China-ASEAN collaborative success.

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