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Modeling the pathway from transformational leadership to innovative work behavior via AI readiness: advancing SDG 4 and SDG 8 in Indonesian higher education

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Abstract: Drawing on a cross-sectional survey of 250 lecturers and administrative staff from Indonesian higher education institutions (HEIs), this study examined the statistical relationships among transformational leadership, AI readiness, and innovative work behavior (IWB) using partial least squares structural equation modeling (PLS-SEM). The findings showed that transformational leadership was positively associated with AI readiness ($\beta = 0.654$, $p < 0.001$) and IWB ($\beta = 0.322$, $p < 0.001$), while AI readiness was positively associated with IWB ($\beta = 0.451$, $p < 0.001$). The indirect effect of transformational leadership on IWB through AI readiness was also significant ($\beta = 0.295$, $p < 0.001$), indicating partial statistical mediation. The structural model explained 56.4% of the variance in IWB, suggesting substantial explanatory power for innovation-related behavior within the sampled HEIs. These findings indicate that transformational leadership and employees' readiness to adopt AI are meaningfully associated with higher levels of innovative work behavior in Indonesian higher education institutions. However, because the study employed a cross-sectional design, the results should be interpreted as evidence of statistical associations rather than causal relationships. The study discusses the implications of these findings in the context of SDG 4 (Quality Education) and SDG 8 (Decent Work and Economic Growth), while acknowledging that SDG outcomes were not directly measured in the empirical model.

Keywords: artificial intelligence; organizational readiness; digital transformation; SDG 4 (Quality Education), SDG 8 (Decent Work).

1. Introduction

Higher education institutions worldwide are undergoing a period of rapid technological transformation driven by the proliferation of artificial intelligence (AI) tools in teaching, research, and academic administration. Faculty perspectives on this shift remain decidedly mixed: surveys of university lecturers report simultaneous optimism about AI's potential to personalize learning and improve efficiency, alongside persistent concern over inadequate training, ethical risk, and threats to academic integrity (Buele & Llerena-Aguirre, 2025; Mah & Groß, 2024). Even where institutional enthusiasm is high, actual classroom and research use of AI frequently lags behind awareness, with faculty members gravitating toward low-risk applications such as chatbots and translation tools while more transformative applications adaptive learning systems, AI-assisted research design remain underused (Rahiman & Kodikal, 2024). This gap between AI's technical availability and its meaningful organizational uptake is, at its core,

a readiness problem rather than a purely technological one (Jöhnk et al., 2021; Makarius et al., 2020).

Indonesia illustrates this tension clearly. The government has signaled a clear intent to position AI as a national priority through the Strategi Nasional Kecerdasan Artifisial (National AI Strategy) 2020–2045, the Ministry of Communication and Informatics' Circular Letter No. 9 of 2023 on AI Ethics, and, most directly relevant to higher education, the Ministry of Education, Culture, Research, and Technology's 121-page guidebook on the use of Generative AI in higher education learning, released in October 2024 to guide students and lecturers on ethical, literate, and risk-aware AI use (Kusumawardani et al., 2024). Yet Indonesia's underlying technological capacity to support this ambition is uneven: in the Oxford Insights Government AI Readiness Index, Indonesia ranked 42nd of 193 countries assessed in 2023, with an overall score of 61.03 out of 100, and its weakest performance was recorded specifically on the technology-sector pillar the dimension capturing the supply of AI tools, talent, and infrastructure available to support adoption (Oxford Insights, 2023). The combination of strong top-down policy signaling and comparatively modest technological and human-capital foundations suggests that successful AI integration in Indonesian higher education institutions (HEIs) cannot be assumed to follow automatically from policy issuance alone; it depends substantially on what happens inside individual institutions, departments, and teams.

A growing body of research argues that the most decisive barriers to AI adoption are organizational and human rather than purely technical: employees' beliefs, anxieties, and change readiness shape whether AI tools are embraced or resisted, often more than the sophistication of the technology itself (Park et al., 2024; Suseno et al., 2022). Leadership behavior is one of the most consistently cited levers for shaping these beliefs. Among leadership styles, transformational leadership characterized by idealized influence, inspirational motivation, intellectual stimulation, and individualized consideration (Bass & Avolio, 1994) has been specifically linked to higher organizational AI adoption and readiness, with leaders' vision-articulation and individualized support emerging as particularly influential mechanisms (Patnaik & Bakkar, 2024). A parallel and far more extensive literature connects transformational leadership to innovative work behavior (IWB), the deliberate generation, promotion, and implementation of new ideas by employees (Janssen, 2000), with multiple systematic reviews confirming this relationship across industries and cultures (Bhatia, 2023; Sueb & Sopiah, 2023).

IWB carries particular weight in the university setting. Indonesian higher education operates under sustained institutional pressure accreditation cycles, Scopus-indexed publication targets, and curriculum reform under the Merdeka Belajar (Freedom to Learn) agenda that makes lecturers' capacity to generate and implement new ideas in pedagogy, research, and service a matter of institutional priority rather than a discretionary extra. Indonesian studies confirm that IWB among lecturers is shaped by a constellation of organizational and leadership factors, including transformational leadership, knowledge sharing, work motivation, and organizational culture (Nugroho, 2023; Suhana et al., 2019), with knowledge-sharing behavior emerging as a particularly important driver of innovation among academic staff.

Despite these parallel literatures, three gaps remain unresolved. First, although transformational leadership's link to IWB is well established overall, evidence from Indonesian HEIs specifically is more inconsistent than the broader literature suggests: some studies find a direct, significant effect of transformational leadership on lecturers' IWB (Istikhoroh et al., 2023; Jadmiko et al., 2026), while at least one recent study among female lecturers found

no significant direct effect, with the relationship fully carried by knowledge sharing (Jadmiko et al., 2025). Second, the literature connecting transformational leadership to AI readiness is still nascent and concentrated outside the education sector in German enterprises (Frick et al., 2021), multinational firms surveyed across Southeast Asia (Tehrani et al., 2024) and Saudi organizations (Alharbi, 2025) and findings are not uniformly positive: one of the few empirical tests of empowering leadership and AI readiness found no significant effect, despite qualitative expert interviews suggesting one should exist (Frick et al., 2021). Third, research linking AI readiness itself to IWB is newer still, and what exists indicates a conditional, double-edged relationship: AI's positive effect on employee innovation behavior strengthens when organizational AI readiness is high but can reverse into a negative effect when readiness is low (Yin et al., 2024), while AI adoption predicts IWB only when paired with adequate training and individual innovativeness (Vandana et al., 2026). No identified study integrates all three constructs transformational leadership, AI readiness, and IWB into a single model, and none situates this triad within Indonesian higher education, where the policy-versus-capacity tension described above makes the question especially salient.

Building on these gaps and the cross-sectional survey design, this study examines the statistical relationships among transformational leadership, AI readiness, and IWB among university employees in Indonesia using PLS-SEM. The study asks whether transformational leadership is positively associated with AI readiness and IWB, whether AI readiness is positively associated with IWB, and whether the indirect effect of transformational leadership on IWB through AI readiness is consistent with statistical mediation. These questions are relevant to SDG 4 (Quality Education) and SDG 8 (Decent Work and Economic Growth), while the paper treats these SDGs as policy-relevance frames rather than outcomes directly measured in the dataset. Specifically, the paper aims to: (1) test the association between transformational leadership and AI readiness (H2) and between transformational leadership and IWB (H1); (2) test the association between AI readiness and IWB (H3); (3) test the indirect effect of transformational leadership on IWB through AI readiness (H4); and (4) discuss implications for HEI leadership, AI-readiness development, and SDG-aligned institutional policy.

This study makes two contributions. Theoretically, it brings together leadership, AI-readiness, and IWB literatures that have largely developed in parallel and examines AI readiness as an intervening mechanism in the transformational leadership–IWB relationship within Indonesian higher education. Practically, the findings identify leadership development and staff AI-readiness development as potentially complementary priorities when universities implement AI-related initiatives.

2. Literature review

2.1. Transformational leadership

Transformational leadership originates in Burns's distinction between transactional leadership, which exchanges rewards for compliance, and transforming leadership, which raises both leader and follower to higher levels of motivation and morality (Burns, 2012). Bass (1985) operationalized this distinction for organizational settings, and subsequent work by Bass and Avolio consolidated it into the Full Range Leadership Theory (FRLT), which positions transformational, transactional, and laissez-faire leadership along a continuum of leader engagement and effectiveness (Antonakis et al., 2014; Bass & Avolio, 1994; Gazi et al., 2025; Iskandar et al., 2024; Suhana et al., 2019). Within FRLT, transformational leadership is conceptualized as a multidimensional construct

comprising idealized influence (attributed and behavioral charisma, through which leaders earn followers' trust and identification), inspirational motivation (the charismatic articulation of a compelling vision that reduces ambiguity and motivates followers), intellectual stimulation (encouraging followers to question assumptions and approach problems creatively), and individualized consideration (attending to followers' individual developmental needs) (Abbas et al., 2012), drawing on Bass and Avolio (1994).

A large meta-analytic literature confirms that transformational leadership reliably predicts follower performance outcomes through several distinct psychological mechanisms. Ng's meta-analysis of more than 600 samples identified five mediating mechanisms affective, motivational, identification, social exchange, and justice enhancement through which transformational leadership influences task performance, citizenship behavior, and innovative behavior, with leader-member exchange playing a central integrating role (Ng, 2017). A systematic literature review of 608 empirical studies on leadership and employee creativity similarly found that, despite growing interest in newer leadership styles suited to digitalization, transformational and transactional leadership remain the most studied paradigms in relation to innovative behavior (Mursaleen et al., 2024).

2.2. Artificial intelligence readiness

AI readiness refers to the extent to which an organization, or an individual within it, possesses the assets, capabilities, and psychological disposition necessary to adopt and productively use AI (Jöhnk et al., 2021). Although still a young construct, it has been approached from at least two complementary angles: organizational readiness and individual or employee-level readiness.

At the organizational level, Jöhnk et al. (2021) derived five categories of AI readiness factors from in-depth interviews with 25 AI experts, while Tehrani et al. (2026), drawing on interviews with managers from 52 multinational corporations operating in Southeast Asia, identified eight dimensions of AI readiness: informational, environmental, infrastructural, participant, process, customer, data, and technological readiness. Holmström (2022) similarly frames AI readiness as a precondition for successful digital transformation, arguing that readiness depends jointly on data quality, technological infrastructure, and organizational alignment rather than on the AI technology itself. These frameworks converge on a key insight: AI readiness is not a binary state determined by technology procurement, but a multidimensional, organizationally embedded capacity that must be deliberately cultivated.

At the individual level, AI readiness is closely related to employees' attitudes, beliefs, and psychological preparedness (Pansuwong et al., 2023). In higher education, readiness to use emerging technologies also needs to be accompanied by critical evaluation and critical thinking as part of educational innovation (Alwali, 2011). Suseno et al. (2022), studying human resource managers in China, found that managers' beliefs about AI positively predicted their change readiness for AI adoption, while AI-related anxiety negatively predicted it with high-performance work systems buffering the negative effect of anxiety. Pansuwong et al. (2023) developed and validated a 25-item scale capturing employees' multidimensional attitudes toward AI at work, encompassing perceived human likeness, perceived adaptability, AI-use anxiety, job insecurity, and personal utility, underscoring that readiness is as much a psychological and emotional state as a skills-based one.

In higher education specifically, faculty-level evidence suggests that AI readiness remains uneven and frequently ambivalent. A study of 122 faculty members identified four distinct AI-readiness profiles optimistic, critical, critically reflected, and neutral with self-efficacy moderating the link between profile

and actual AI use (Mah & Groß, 2024). A narrative review of faculty perceptions similarly found persistent ambivalence: educators acknowledge AI's usefulness but report ethical concern, technical insecurity, and fear of professional displacement, with limited training and institutional support cited as the most common barriers (Buele & Llerena-Aguirre, 2025). Structural equation modeling research in Indian higher education further confirmed that AI adoption depends on a constellation of acceptance-related factors consistent with the Unified Theory of Acceptance and Use of Technology (UTAUT) (Chatterjee & Bhattacharjee, 2020). Together, this literature indicates that university employees' AI readiness is shaped jointly by organizational support structures and individual psychological factors both of which leadership behavior has the potential to influence directly.

2.3. Innovative work behavior

Innovative work behavior (IWB) is most commonly defined, following Janssen (2000), as the intentional creation, introduction, and application of new ideas within a work role, group, or organization, in order to benefit role performance, the group, or the organization. As synthesized by Abbas et al. (2012), Astuti et al. (2023), Anzarwati and Rahayu (2024), drawing on this and related work, IWB is best understood as a multi-stage process comprising idea generation (producing novel and useful ideas), idea promotion (building coalitions of support for an idea), and idea implementation (translating the idea into practice). This staged conceptualization distinguishes IWB from simple creativity, since promotion and implementation require political and execution skills beyond ideation alone.

A substantial body of work has examined IWB's antecedents. Muchiri et al.'s conceptual review proposes a framework linking transformational leadership, leader-member exchange, and employees' fairness perceptions to IWB, arguing that the quality of the supervisor-subordinate relationship is central to whether innovative potential is realized (Muchiri et al., 2020).

Within Indonesian higher education specifically, IWB among lecturers has attracted sustained empirical attention given its institutional importance. Recent evidence further highlights the role of leadership in fostering employee innovation. Wang et al. (2025) found that digital leadership positively influences employee innovative performance through indirect psychological and organizational mechanisms, reinforcing the importance of leadership in promoting innovative behavior in technology-driven work environments. At a larger scale, Nugroho (2023) surveyed 2,277 teaching staff across Indonesian HEIs and found that knowledge sharing functioned as a key driver of and significant mediator in the relationship between job stress, transformational leadership, and IWB. Fiernaningsih et al. (2023), studying vocational lecturers in East Java, linked organizational support and transglobal leadership characteristics to proactive work behavior and, ultimately, IWB.

2.4. Transformational leadership and IWB

The relationship between transformational leadership and IWB is among the most thoroughly documented in the organizational behavior literature, with recent work also emphasizing the role of intervening psychological resources and contextual conditions (Alwali, 2024). A systematic review based on Scopus-indexed publications concluded that transformational leadership consistently fosters employees' creativity, problem-solving capacity, and innovative output, operating through both direct and indirect pathways (Bhatia, 2023). A PRISMA-guided review of 31 journal articles published between 2017 and 2023 similarly confirmed transformational leadership as an important antecedent of innovative behavior, while identifying a wide range of mediating mechanisms across studies, including organizational support, innovation-oriented

culture, meaningful work, digital literacy, team-work quality, and psychological empowerment (Sueb & Sopiah, 2023).

Evidence from the Southeast Asian context shows that transformational leadership enhances employee performance partly through organizational culture as a mediating mechanism in Malaysian organizations, using a PLS-SEM design comparable to the present study (Vasudevan et al., 2025). Sector-specific evidence reinforces this pattern: in a PLS-SEM study of 314 executives in the Malaysian telecommunications industry, Piaralal et al. (2026) found that the inspirational motivation, individualized consideration, and intellectual stimulation dimensions of transformational leadership significantly enhanced organizational creativity and innovation, which in turn mediated their effect on organizational performance underscoring that transformational leadership frequently shapes innovation-related outcomes through intervening capabilities rather than through uniform direct effects. Complementing these survey-based findings, a science-mapping review of 441 Web of Science documents by Hasan et al. (2026) confirmed that transformational leadership is among the most effective leadership styles for fostering employees' creativity, innovation capability, and knowledge-sharing behavior, with knowledge sharing repeatedly emerging as the mechanism linking leadership to innovative outcomes.

Within Indonesian higher education, however, the picture is more nuanced than the global literature might suggest. Istikhoroh et al. (2023), studying 96 department-head lecturers at private universities in Surabaya, found that transformational leadership both directly influenced IWB and amplified the positive effect of human capital on IWB. Jadmiko et al. (2026), surveying 150 lecturers in Padang, similarly found a significant direct effect of transformational leadership on IWB, with knowledge sharing providing partial mediation (motivation to learn was not a significant mediator). Yet a related study by overlapping authorship, focused specifically on 108 female lecturers, reported that transformational leadership had no significant direct effect on IWB; the relationship was instead fully carried by knowledge sharing, which both mediated the leadership–IWB link and was itself predicted by transformational leadership (Jadmiko et al., 2025). At a national scale, Nugroho (2023) found a significant direct effect of transformational leadership on IWB across 2,277 respondents, again with knowledge sharing playing a significant mediating role.

2.5. Transformational leadership and AI readiness

Research linking transformational leadership to AI readiness is considerably newer and thinner, and it has so far developed almost entirely outside the education sector. Patnaik and Bakkar (2024), combining diffusion of innovation theory with transformational leadership in a structural equation model of 250 companies, found that transformational leadership was a crucial driver of AI adoption, with the vision-articulation and individualized-assistance dimensions of transformational leadership proving especially important for building employees' intention to adopt AI. Alharbi (2025), surveying 71 digital leaders in Saudi Arabia, similarly reported a positive correlation between transformational leadership and AI implementation, moderated by the broader pace of technological advancement within the organization. Within the education sector, emerging evidence suggests that transformational leadership is likewise consequential for managing technology-mediated change: in a PLS-SEM study of 250 early childhood educators in Malaysia, Shorouk et al. (2026) found that transformational leadership significantly shaped children's digital (cyber) behavior and mental well-being, positioning educational leaders as central actors in governing the safe and productive integration of digital technologies a finding that lends preliminary, education-sector support to the broader claim that transformational leadership can influence readiness for technology adoption.

Frick et al. (2021) examined whether empowering leadership conceptually adjacent to transformational leadership through its emphasis on autonomy and developmental support reduced employee resistance to AI-driven change and increased AI readiness in German enterprises. While qualitative expert interviews suggested empowering leadership should be favorable for navigating AI-related change, the accompanying quantitative test found no significant effect of empowering leadership on either resistance to change or AI readiness, leading the authors to suggest that employees may instead value the stability and consistency leaders provide more than autonomy-granting per se. This null finding is an important caution: the theoretical case for a leadership–AI readiness link is stronger than the empirical evidence currently supporting it, and the relationship may depend heavily on how both leadership and readiness are operationalized, as well as on contextual and cultural factors not yet well explored including the higher education sector and the Indonesian context, neither of which appears to have been examined in this specific pairing to date.

A related conceptual literature considers whether the relationship may also run in the opposite direction that AI tools could help leaders become more transformational by improving data-driven decision-making, communication, and individualized employee support (Estherita & Shanmugam, 2024).

2.6. AI readiness and IWB

Yin et al. (2024) provide the clearest evidence that this relationship is conditional rather than uniform. Using two scenario-based experiments, they found that AI-assistant intelligence had a positive indirect effect on employees' AI-enabled innovation behavior through creative self-efficacy, and that this positive effect was significantly stronger when organizational AI readiness was high; conversely, the same AI assistance produced a negative indirect effect on innovation behavior operating through employees' awareness of being replaceable by smart technology, AI, robotics, and algorithms (STARA awareness) when organizational AI readiness was low. This “double-edged sword” finding suggests that AI readiness functions less as a simple predictor of IWB and more as a boundary condition determining whether AI exposure helps or harms employees' innovative behavior.

Vandana et al. (2026), surveying 278 employees and managers in IT companies and grounding their model in UTAUT, found that AI adoption itself driven by performance expectancy and training, and moderated by personal innovativeness positively predicted IWB. Zhang et al. (2025), surveying 339 employees across 13 Chinese manufacturing enterprises, similarly found that AI usage was positively associated with employee innovation behavior via self-efficacy, with the relationship strengthened by employee openness and job complexity. No study identified in this review examines the AI readiness–IWB relationship specifically among university employees or within an Indonesian setting, which, combined with the conditional nature of the relationship documented by Yin et al. (2024), suggests this pairing remains an open and contextually under-examined question one to which leadership behavior, by shaping the underlying readiness level, may be directly relevant.

2.7. The Indonesian higher education and AI policy context

Indonesia has signaled a clear top-down commitment to AI integration in higher education over the past two years. The Ministry of Education, Culture, Research, and Technology, through its Directorate of Learning and Student Affairs, released a 121-page guidebook on the use of Generative AI in university learning in October 2024, covering opportunities for GenAI use by students and lecturers, AI literacy, ethical principles (academic integrity, equity and transparency, data security, and environmental impact), risk-mitigation strategies,

and criteria for selecting among generative AI tools (Kusumawardani et al., 2024). This guidebook builds on the broader Strategi Nasional Kecerdasan Artifisial (National AI Strategy) 2020–2045 and the Ministry of Communication and Informatics' Circular Letter No. 9 of 2023 on AI ethics, which establishes national principles around ethical values, their implementation, and accountability in AI use and development (Kementerian Komunikasi dan Informatika Republik Indonesia, 2023).

This policy infrastructure, however, is being layered onto a higher education system whose underlying AI-readiness foundations remain only moderate by global standards: Indonesia's 42nd-place ranking (of 193 countries) and below-average score on the technology-sector pillar of the Oxford Insights Government AI Readiness Index indicate that the supply of AI tools, technical talent, and infrastructure lags behind the government's policy ambition (Oxford Insights, 2023). This mirrors patterns documented in comparable settings, where faculty awareness and stated willingness to use AI routinely outpace actual, sophisticated classroom and research use (Buele & Llerena-Aguirre, 2025; Rahiman & Kodikal, 2024). Comparable evidence from elsewhere in Southeast Asia further indicates that educational quality and student outcomes in the region's higher education systems are shaped by a range of institutional and socio-economic conditions (Krishnan et al., 2023), reinforcing the relevance of SDG 4 to the regional higher education context. In this environment, the role of institutional and departmental leadership rather than policy or technology alone in translating national AI guidance into actual readiness and innovative practice among university employees becomes a question of direct practical relevance to Indonesian HEI leaders, and one this study is positioned to address.

2.8. Conceptual framework and hypotheses

This study proposes a conceptual framework in which transformational leadership operates both directly and indirectly through AI readiness to shape university employees' IWB (**Figure 1**). The framework reflects three considerations grounded in the preceding review: (1) the well-established but Indonesia-specific sensitivity of the transformational leadership–IWB link to mediating mechanisms; (2) the more nascent and not uniformly positive evidence for a transformational leadership–AI readiness link; and (3) emerging, conditional evidence that AI readiness shapes whether AI exposure helps or harms innovative behavior. Accordingly, the following hypotheses are proposed for empirical testing:

H1: Transformational leadership has a positive and significant association with the IWB of university employees.

H2: Transformational leadership has a positive and significant association with the AI readiness of university employees.

H3: AI readiness has a positive and significant association with the IWB of university employees.

H4: The indirect association between transformational leadership and IWB through AI readiness is statistically significant among university employees.

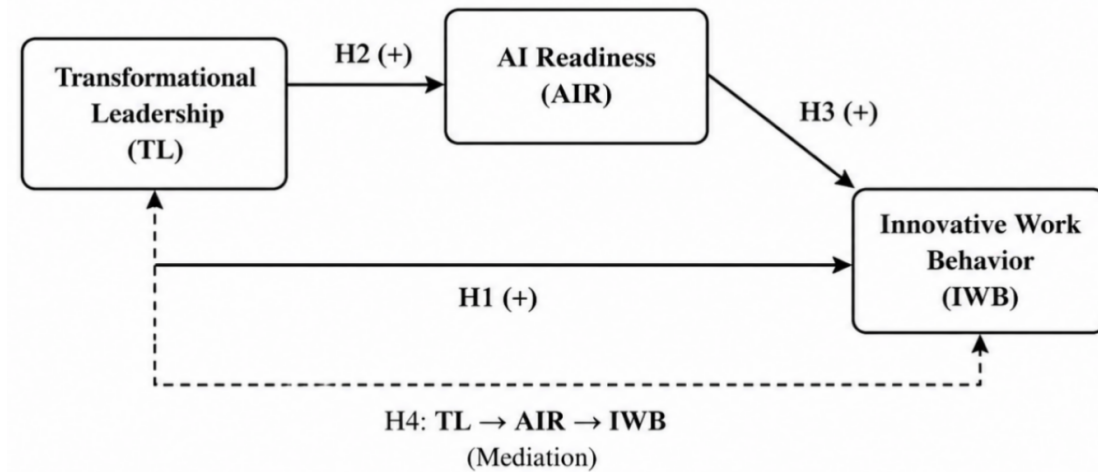


Figure 1. Conceptual framework

3. Materials and methods

This section describes the research design, population and sampling strategy, measurement instruments, data collection procedure, and analytical approach used to test the hypothesized model on data collected from university employees in Indonesia.

3.1. Research design and philosophical stance

This study adopts a quantitative, cross-sectional survey design grounded in the positivist philosophical stance, which holds that social phenomena can be measured objectively and that hypothesized relationships between constructs can be tested empirically using statistical models (Hair et al., 2019). Data were collected through a structured questionnaire administered to permanent lecturers and administrative staff at Indonesian higher education institutions (HEIs). This design aligns with the study's objective: to test a PLS-SEM mediation model linking transformational leadership, AI readiness, and IWB, and thereby generate evidence relevant to SDG 4 and SDG 8 in the Indonesian HEI context. The design follows comparable cross-sectional PLS-SEM studies conducted with Indonesian higher education samples (Istikhoro et al., 2023; Jadmiko et al., 2026; Nugroho, 2023).

Theoretical anchor: The study is anchored in Bass and Avolio's Full Range Leadership Theory (FRLT; (Bass & Avolio, 1994)), which provides the theoretical basis for transformational leadership as the independent variable. The Technology Acceptance and Readiness framework (Jöhnk et al., 2021; Suseno et al., 2022) informs the conceptualization of AI readiness, while Janssen's (Janssen, 2000) foundational IWB framework underpins the dependent variable.

3.2. Study population and sampling strategy

The target population comprised permanent lecturers and administrative staff employed at Indonesian higher education institutions (HEIs). Recruitment covered both public and private HEIs and was conducted through institutional email lists and academic networks. The sampling approach was non-probability, purposive/convenience recruitment because participation depended on access to institutional and academic networks and on meeting the study's eligibility criteria.

Eligibility criteria for participation were: (1) employment as a permanent lecturer or administrative staff member at a public or private HEI in Indonesia; (2) a minimum of one year of employment at the current institution; and (3) direct experience with at least one institutional or personal AI tool (e.g., AI-assisted writing, learning management system AI features, or chatbots) in professional work. These criteria mirror sampling approaches in comparable Indonesian HEI

studies (Istikhoroh et al., 2023; Nugroho, 2023; Suhana et al., 2019).

3.2.1. Sample size determination

Sample size was justified using both the model's requirements and a power-oriented sensitivity check. The model contains a maximum of two structural predictors of IWB (TL and AIR) and one predictor of AIR (TL). A conventional multiple-regression approximation using two predictors, a medium effect size ($f^2 = 0.15$), $\alpha = 0.05$, and 80% power requires approximately 68 observations. The final sample of 250 therefore exceeds this benchmark by a wide margin. The earlier 10-observations-per-indicator rule is retained only as a historical rule of thumb rather than as the principal basis for sample-size justification, consistent with current recommendations to emphasize power and model-specific considerations (Cohen, 2013).

The questionnaire was administered online via Google Forms and distributed through institutional email lists and academic networks. Respondents reflected on their immediate supervisor's leadership behavior, their readiness to use AI tools at work, and their IWB. Data collection proceeded over six weeks. Screening excluded responses with more than 10% missing data and straight-lining patterns. A total of 250 complete responses were retained for analysis.

Demographic information (gender, position, institution type, and years of experience) was collected to characterize the respondent profile. All substantive items used a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree).

Demographic variables were collected for sample description but were not entered as control variables in the structural model because the hypotheses were specified around a parsimonious three-construct model, and no a priori theoretical rationale or measurement plan for demographic confounding was established before estimation. To avoid post hoc model expansion, the reported PLS-SEM model therefore focuses on the hypothesized relationships.

3.3. Measurement instruments

All constructs were measured using established scales adapted to the Indonesian HEI context and rated on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). The questionnaire was translated using back-translation from English to Bahasa Indonesia and back to English by two bilingual academics. The instrument comprised 12 transformational-leadership items, 8 AI-readiness items, and 9 innovative-work-behavior items.

3.3.1. Construct operationalization

For transparency, **Table 1** reports the item counts and representative items.

Table 1. Measurement instruments and construct operationalization

Construct	Scale Source	Items	Sample Item
Transformational Leadership (TL)	MLQ-5X from Antonakis et al. (2014), Bass and Avolio (1994)	20 (adapted to 12)	"My supervisor inspires me with new ways of looking at things that used to be a puzzle for me."
AI Readiness (AIR)	Adapted from Jöhnk et al. (2021), Park et al. (2024), Suseno et al. (2022)	8	"I feel confident using AI tools to support my work as a lecturer/staff."
Innovative Work Behavior (IWB)	9-item IWB scale from Janssen (2000)	9	"At work, I generate original ideas for difficult issues."
Control Variables	Demographic items	4	Gender, position, institution type, years of experience

Transformational leadership. Transformational leadership is operationalized following Bass and Avolio (1994) as a four-dimensional construct encompassing

idealized influence, inspirational motivation, intellectual stimulation, and individualized consideration. The MLQ-5X remains the most validated instrument for this purpose (Ng, 2017; Patnaik & Bakkar, 2024), with Antonakis et al. (2014) providing the definitive conceptual elaboration of the Full Range Leadership Theory on which it is grounded.

AI readiness. AI readiness is operationalized at the individual level as the extent to which an employee possesses the psychological disposition, perceived capability, and organizational support necessary to adopt and productively use AI tools at work. This follows Jöhnk et al. (2021), who derived organizational readiness factors from expert interviews, and Park et al. (2024), who validated a 25-item attitudes-toward-AI scale capturing perceived human likeness, adaptability, anxiety, job insecurity, and personal utility. For this study, a parsimonious 8-item individual-level AI readiness scale was used, capturing: (1) perceived AI usefulness, (2) AI self-efficacy, (3) AI anxiety (reverse-scored), and (4) perceived organizational AI support, consistent with Suseno et al. (2022).

IWB. IWB is operationalized using Janssen's (Janssen, 2000) original 9-item scale, which remains the standard instrument in this literature (Istikhoroh et al., 2023; Nugroho, 2023; Udin et al., 2022). The scale captures three sub-dimensions: idea generation, idea promotion, and idea implementation.

3.4. Data collection procedure

Data collection proceeded in three phases. Phase 1 –Instrument validation (Weeks 1–2): A pilot study with 30 respondents, excluded from the final sample, was conducted to assess item clarity, response burden, and preliminary internal consistency. Ambiguous items were revised before the main survey. Phase 2 –Main data collection (Weeks 3–8): The finalized questionnaire was distributed electronically via Google Forms and academic networks. Participation was voluntary and anonymous, and digital informed consent was obtained before respondents could proceed. Participants were informed about confidentiality and their right to withdraw without professional consequence. Phase 3 –Data Screening (Week 9): Incomplete responses (> 10% missing data per respondent) and straight-liners (identical responses across all items) were excluded, and common method bias (CMB) was assessed using Harman's single-factor test and the unmeasured latent factor technique. The CMB checks reported in Section 3.7 indicate that common method bias does not substantially threaten the validity of the findings.

3.5. Analytical strategy: PLS-SEM

Partial Least Squares Structural Equation Modeling (PLS-SEM) was applied to the survey data using SmartPLS 4, which implements the standard Mode A (reflective) path-weighting algorithm. PLS-SEM was selected over covariance-based SEM (CB-SEM) for the following reasons: (1) the model is prediction-oriented as well as theory-testing; (2) the target sample size is moderate ($N = 250$), which is better suited to PLS-SEM's distribution-free bootstrapping approach; (3) the model includes a mediation path that benefits from PLS's direct bootstrapped confidence intervals; and (4) prior studies in this domain with comparable constructs and Indonesian HEI samples used PLS-SEM (Istikhoroh et al., 2023; Jadmiko et al., 2026; Jadmiko et al., 2025; Nugroho, 2023), facilitating future comparability (Hair et al., 2019).

3.5.1. Measurement model assessment (Stage 1)

The measurement model is evaluated for reliability and validity using the criteria and thresholds summarized in **Table 2** (Hair et al., 2019).

Table 2. Measurement model assessment criteria and thresholds

Criterion	Threshold	Purpose
Cronbach's Alpha (CA)	≥ 0.70	Internal consistency reliability
Composite Reliability (CR)	≥ 0.70	Internal consistency reliability (preferred over CA for PLS)
Average Variance Extracted (AVE)	≥ 0.50	Convergent validity
Factor Loadings	≥ 0.70 (outer loadings)	Indicator reliability
HTMT Ratio	< 0.85 (or < 0.90 liberal)	Discriminant validity (Henseler et al., 2015)
HTMT Bootstrapped CI	Does not include 1.0	Discriminant validity confirmation
Fornell-Larcker Criterion	$\sqrt{\text{AVE}} > \text{inter-construct correlations}$	Discriminant validity (traditional)
VIF (inner model)	< 5.0 (ideally < 3.3)	Collinearity assessment

3.5.2. Structural model assessment (Stage 2)

The structural model is assessed for explanatory power and predictive relevance using the criteria and thresholds summarized in **Table 3**.

Table 3. Structural model assessment criteria and thresholds

Criterion	Threshold	Hypothesis Tested
Path coefficients (β)	Significance via bootstrapping (5,000 resamples)	H1: TL $\rightarrow$ IWB; H2: TL $\rightarrow$ AIR; H3: AIR $\rightarrow$ IWB
R ² (endogenous variables)	≥ 0.10 (IWB and AIR)	Explanatory power
f ² (effect size)	0.02 small; 0.15 medium; 0.35 large	Practical significance
Q ² (predictive relevance)	> 0 via PLSpredict/blindfolding	Out-of-sample predictive power
Indirect effect (TL $\rightarrow$ AIR $\rightarrow$ IWB)	Bootstrapped 95% CI excluding zero	H4: AIR mediates TL $\rightarrow$ IWB
VAF	$> 20\%$ partial; $> 80\%$ full mediation	Type of mediation (H4)

3.6. Mediation analysis (H4)

The mediation hypothesis (H4: AI readiness mediates the relationship between transformational leadership and IWB) was tested using bootstrapped indirect effects, following Preacher and Hayes's approach as implemented in PLS-SEM (Hair et al., 2019). Following standard practice, 5,000 bootstrap resamples were drawn, and a 95% percentile bootstrap confidence interval excluding zero constitutes evidence for mediation. Partial versus full mediation was determined by the significance of the direct path (TL on IWB) when the mediator (AIR) was included in the model, complemented by the variance accounted for (VAF) heuristic. This mirrors the analytical approach in comparable Indonesian HEI mediation studies (Jadmiko et al., 2025; Nugroho, 2023).

3.7. Common method bias assessment

Because data for this study were collected from a single source (self-report questionnaire) at a single time point, common method bias (CMB) is a potential concern. The following procedural and statistical remedies were applied:

(1) Procedural: Respondent anonymity was guaranteed, survey items were separated by construct, and data collection was conducted online with no time pressure to reduce evaluation apprehension and consistency motifs (Podsakoff et al., 2003).

(2) Statistical –Harman's single-factor test: All items were loaded onto a single factor; the first (unrotated) factor accounted for less than 50% of the total variance, indicating that CMB is not a dominant concern.

(3) Statistical –Unmeasured latent factor (ULF): A common latent factor was

added to the PLS model; path coefficients changed by less than 0.20 after its inclusion, indicating that CMB is not a serious threat (Podsakoff et al., 2003).

4. Results

All results reported derive from the PLS-SEM analysis of survey data collected from 250 university employees at Indonesian HEIs ($N = 250$), as described in Section 3. The findings reflect the professional experiences of lecturers and administrative staff regarding their supervisors' transformational leadership behaviors, their AI readiness in the workplace, and their IWB on the job. The respondent profile ($N = 250$) is summarized in **Table 4**.

Table 4. Respondent demographic profile ($N = 250$)

Characteristic	Category	n	%
Gender	Male	138	55.2
	Female	112	44.8
Position	Lecturer	178	71.2
	Administrative Staff	72	28.8
Institution type	Public HEI	104	41.6
	Private HEI	146	58.4
Experience	1–5 years	87	34.8
	6–10 years	93	37.2
	> 10 years	70	28.0

4.1. Measurement model assessment

Following the two-stage PLS-SEM evaluation procedure (Hair et al., 2019), the measurement model was first assessed for internal consistency reliability, convergent validity, and discriminant validity.

4.1.1. Reliability and convergent validity

All constructs exceeded the recommended thresholds for Cronbach's alpha (≥ 0.70), composite reliability (≥ 0.70), and average variance extracted (AVE ≥ 0.50), as shown in **Table 5**.

Table 5. Reliability and convergent validity ($N = 250$)

Constructs	Cronbach's α	Composite Reliability (CR)	AVE
Transformational Leadership (TL)	0.928	0.939	0.607
AI Readiness (AIR)	0.901	0.920	0.591
Innovative Work Behavior (IWB)	0.917	0.932	0.603

All AVE values exceeded 0.50, indicating that each construct explained more than half of the variance in its respective indicators on average, and all CR values exceeded the 0.70 threshold, supporting adequate convergent validity and internal consistency reliability.

4.1.2. Discriminant validity (HTMT)

Discriminant validity was assessed using the Heterotrait-Monotrait (HTMT) ratio of correlations (Henseler et al., 2015), with all values required to fall below the conservative 0.85 threshold, as reported in **Table 6**.

Table 6. HTMT ratios (N = 250)

Constructs	TL	AIR
AI Readiness (AIR)	0.742	
Innovative Work Behavior (IWB)	0.781	0.716

The highest ratio was observed for the transformational leadership–IWB pair (0.781), followed by transformational leadership–AI readiness (0.742) and AI readiness–IWB (0.716); all three remained comfortably within the acceptable range, indicating that respondents distinguished the three constructs empirically.

4.2. Structural model assessment

Having confirmed the adequacy of the measurement model, the structural model was assessed for explanatory power (R^2), effect size (f^2), predictive relevance (Q^2), and path significance via bootstrapping (5,000 resamples). As reported in **Table 7**, transformational leadership accounted for 42.8% of the variance in AI readiness ($R^2 = 0.428$), while transformational leadership and AI readiness jointly accounted for 56.4% of the variance in IWB ($R^2 = 0.564$), both representing moderate-to-substantial explanatory power per Hair et al.'s (Hair et al., 2019) PLS-SEM benchmarks. Q^2 values above zero for both endogenous constructs (0.278 and 0.347, respectively) confirm the model's predictive relevance via the blindfolding cross-validation procedure described in Section 3.5.2.

Table 7. R^2 and Q^2 values (N = 250)

Endogenous Variable	R^2	Q^2
AI Readiness (AIR)	0.428	0.278
Innovative Work Behavior (IWB)	0.564	0.347

As summarized in **Table 8**, transformational leadership exerted a large effect on AI readiness ($f^2 = 0.748$), while its direct effect on IWB and AI readiness's effect on IWB were both of medium magnitude ($f^2 = 0.142$ and 0.267 , respectively).

Table 8. F^2 effect sizes (N = 250)

Path	f^2	Effect Size
Transformational Leadership (TL) → AI Readiness (AIR)	0.748	Large
Transformational Leadership (TL) → IWB	0.142	Medium
AI Readiness (AIR) → IWB	0.267	Medium

All three direct hypotheses were statistically supported, as shown in **Table 9**. Transformational leadership showed a positive and significant association with innovative work behavior (IWB) ($\beta = 0.322$, $t = 5.764$, $p < 0.001$), supporting H1. It was also positively associated with AI readiness ($\beta = 0.654$, $t = 14.823$, $p < 0.001$), providing support for H2. In addition, AI readiness demonstrated a positive and significant association with IWB ($\beta = 0.451$, $t = 8.297$, $p < 0.001$), supporting H3.

Table 9. Direct path coefficients and hypothesis testing (N = 250)

Hypothesis	Path	β	t-value	p-value	Decision
H1	TL $\rightarrow$ IWB	0.322	5.764	< 0.001	Supported
H2	TL $\rightarrow$ AIR	0.654	14.823	< 0.001	Supported
H3	AIR $\rightarrow$ IWB	0.451	8.297	< 0.001	Supported

4.3. Mediation analysis (H4)

H4 proposed that AI readiness statistically mediates the association between transformational leadership and IWB. The indirect effect was assessed using PLS-SEM bootstrapping with 5,000 resamples and a 95% percentile confidence interval. The indirect effect was significant ($\beta = 0.295$, $t = 6.912$, $p < 0.001$), which is consistent with partial statistical mediation because the direct TL $\rightarrow$ IWB association remained significant when AI readiness was included.

As shown in **Table 10**, the indirect effect was positive and significant ($\beta = 0.295$, $t = 6.912$, $p < 0.001$). The bootstrapped 95% percentile confidence interval ranged from 0.212 to 0.381 and did not include zero, satisfying the standard criterion for mediation. Following the conventional variance accounted for (VAF) interpretation thresholds (VAF < 20% = no mediation; 20–80% = partial mediation; VAF > 80% = full mediation), a VAF of 47.8% indicates that AI readiness functions as a partial mediator of the relationship between transformational leadership and IWB among the surveyed Indonesian university employees. The continued significance of the direct path (TL on IWB: $\beta = 0.322$, $p < 0.001$) after including the mediator corroborates this classification: AI readiness accounts for a substantial share of the leadership-to-innovation pathway, but the observed leadership–IWB association is not fully accounted for by AI readiness, consistent with the broader literature (Nugroho, 2023; Suhana et al., 2019).

Table 10. Bootstrapped indirect effect with 95% confidence interval

Path	β	t-value	p-value	95% LLCI	95% ULCI	Result
TL $\rightarrow$ AIR $\rightarrow$ IWB (Indirect)	0.295	6.912	< 0.001	0.212	0.381	Significant

5. Discussion

This study examined how transformational leadership relates to IWB among Indonesian university employees, and whether AI readiness mediates that relationship. Drawing on survey data from 250 lecturers and administrative staff, the PLS-SEM analysis supported all four hypotheses. This section interprets those findings in relation to the three literature gaps identified in Section 1, situates them against comparable studies in Indonesian and wider Southeast Asian higher education, and considers their theoretical and practical implications.

5.1. Transformational leadership, AI readiness, and IWB

The findings show a strong positive association between transformational leadership and AI readiness ($\beta = 0.654$, $p < 0.001$; $f^2 = 0.748$). This extends a literature that has previously examined leadership and AI readiness mainly outside higher education (Frick et al., 2021; Patnaik & Bakkar, 2024). The result is also consistent with the broader proposition that leadership can shape employees' perceptions and preparedness during technology-enabled change. However, because the present design is cross-sectional, the result should not be read as evidence that leadership causes AI readiness.

Transformational leadership was also positively and significantly associated with IWB ($\beta = 0.322$, $p < 0.001$), consistent with the substantial Indonesian and international literature linking the two (Astuti et al., 2023; Bhatia, 2023; Garad et al., 2022; Istikhoroh et al., 2023). AI readiness was also positively and significantly associated with IWB ($\beta = 0.451$, $p < 0.001$), providing among the first evidence for this link within a higher education setting, where prior direct evidence had come predominantly from manufacturing and IT contexts (Antonakis et al., 2014; Anzarwati & Rahayu, 2024; Vandana et al., 2026). Together, transformational leadership and AI readiness accounted for 56.4% of the variance in IWB ($R^2 = 0.564$), a substantial level of explanatory power by Hair et al.'s benchmarks (Hair et al., 2019).

5.2. The mediating role of AI readiness

The mediation analysis showed that AI readiness partially mediates the transformational leadership–IWB relationship (indirect $\beta = 0.295$, $p < 0.001$; VAF = 47.8%). Because the direct path remained significant after including the mediator, AI readiness accounts for a substantial share of leadership's influence on innovation while transformational leadership also continues to operate through channels beyond AI readiness. This finding addresses the first literature gap directly: the inconsistent direct TL on IWB effect observed across Indonesian HEI studies (e.g., the non-significant direct effect reported by Jadmiko et al. (2025) is consistent with a relationship that is substantially transmitted through intervening mechanisms. AI readiness is confirmed as one such mechanism, complementing knowledge sharing, which prior Indonesian work has repeatedly identified (Nugroho, 2023; Suhana et al., 2019). Substantively, the partial-mediation pattern implies that efforts to raise IWB through leadership development are likely to be more effective when they also build employees' readiness to adopt and use AI, rather than treating leadership and technological preparedness as independent levers.

These results also speak to the second and third gaps. By finding a strong, significant TL on AIR path within higher education (second gap), the study extends a thin and previously non-education literature into a new sector and context. By confirming a positive AIR on IWB path among university employees (third gap), it provides context-specific evidence where none previously existed. At the same time, the present cross-sectional, linear-mediation design cannot address the conditional, "double-edged sword" pattern documented by Yin et al. (2024), in which AI readiness operates as a moderator determining whether AI exposure helps or harms innovation.

5.3. Comparison with Southeast Asian higher education studies

The findings align with, and extend, comparable PLS-SEM leadership studies in the region. In Malaysia, transformational leadership dimensions have been shown to enhance organizational creativity and innovation, which in turn mediate effects on performance (Piaralal et al., 2026), and organizational culture has been found to transmit sustainable leadership effects on employee performance (Vasudevan et al., 2025). In Malaysian early childhood education, transformational leadership has been positioned as central to governing safe and productive digital technology integration (Shorouk et al., 2026), and in Thailand, leadership approaches have been linked to inclusive, SDG 4-aligned educational environments (Kongmalai et al., 2023). Consistent with all of these, the present study places an intervening capability between leadership and its distal outcome, but it is distinctive in identifying AI readiness specifically as that mechanism within higher education, and in doing so within the Indonesian policy context of the National AI Strategy and the Kemendikbudristek GenAI guidance.

5.4. Practical and policy implications for SDG 4 and SDG 8

The findings have implications for Indonesian HEI leaders and policymakers, with SDG 4 and SDG 8 used as policy-relevance frames rather than measured outcomes. First, leadership development may be paired with practical AI-readiness support, including institutional vision-setting, staff coaching, and opportunities to develop confidence in AI use. Second, AI-literacy initiatives can be aligned with existing higher-education guidance and with concrete academic workflows such as course redesign and research support. Third, the partial indirect effect suggests that leadership and employee readiness should be considered together when institutions plan AI implementation. The literature on ethical AI also cautions against reducing responsible implementation to procedural compliance alone (Alwali, 2026). These recommendations concern organizational practice; they should not be interpreted as evidence that the present study directly demonstrates improvement in SDG 4 or SDG 8 outcomes.

6. Conclusion

This study examined a PLS-SEM model linking transformational leadership, AI readiness, and IWB among 250 Indonesian university employees. All four hypotheses received statistical support: transformational leadership was positively associated with AI readiness ($\beta = 0.654$) and IWB ($\beta = 0.322$); AI readiness was positively associated with IWB ($\beta = 0.451$); and the indirect effect through AI readiness was significant ($\beta = 0.295$; VAF = 47.8%), with the model explaining 56.4% of the variance in IWB.

The study contributes by integrating Full Range Leadership Theory, AI-readiness research, and Janssen's IWB framework in one empirical model; by providing context-specific estimates for relationships that remain under-examined in Indonesian higher education; and by showing that AI readiness is statistically related to the leadership–IWB pathway. The SDG relevance is interpretive rather than outcome-based: the study links its implications to the aims of SDG 4 and SDG 8.

6.1. Limitations

Several limitations should be borne in mind when interpreting these findings. First, the cross-sectional design precludes strong causal inference; although the hypothesized directions are theoretically grounded, the data cannot rule out reciprocal or reverse relationships, and longitudinal or experimental designs would provide firmer causal evidence. Second, all constructs were measured by self-report from a single source at a single time point, so common method bias is a potential concern; while the procedural remedies and statistical checks reported in Section 3.7 indicate it is not a dominant threat, a multi-wave or multi-source design (for example, supervisor-rated IWB) would be preferable. Third, the sample was drawn from Indonesian public and private HEIs, and although this supports relevance to the study's context, the findings should be generalized to other national settings or to non-higher-education sectors only with caution. Fourth, the model treats AI readiness solely as a mediator and therefore cannot test the moderating boundary-condition role that AI readiness may play in the relationship between AI exposure and innovation (Yin et al., 2024); addressing this would require the moderated-mediation extension outlined in Section 6.2.

6.2. Recommendations for future research

Several directions follow from the findings. First, future studies should add knowledge sharing as a second mediator alongside AI readiness, given its recurring role in Indonesian HEI studies of the leadership–innovation link (Jadmiko et al., 2026; Jadmiko et al., 2025; Nugroho, 2023; Udin, 2023), to establish whether the two mechanisms are distinct or overlapping. Second, the AI readiness construct could be broadened with additional organizational-support and psychological-safety items, in light of Frick et al.'s (Frick et al., 2021)

evidence on the importance of stability and support. Third, and most importantly, future work should extend the present linear-mediation design into a moderated-mediation model retaining the TL on IWB through AIR pathway while testing AI readiness as a moderator of AI-exposure effects on innovation, or comparing high- versus low-readiness subgroups so as to reconcile the mediating role established here with the moderating “double-edged sword” role documented by Yin et al. (2024). Finally, longitudinal or multi-source designs would strengthen causal inference beyond what the present cross-sectional data can support.

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