

作为一种个人资源，生成式人工智能（GenAI）是否能提升员工的工作绩效 和工作投入（敬业度）？

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摘要。本研究探讨生成式人工智能（GenAI）能否作为一种个人资源，通过强化用户体验、信任与工作投入来提升员工绩效，并检验信任是否在 GenAI 用户体验与工作投入之间发挥中介作用，进而影响绩效。研究采用解释性顺序混合方法设计。研究一对 251 名在工作中使用 GenAI 的印尼职场人士进行问卷调查，并采用基于协方差的结构方程模型进行估计；构念来源于 TRI（乐观、创新性）、TAM（有用性、易用性）、信任、工作投入与员工绩效。研究二邀请 69 名管理学正教授提供专家见解，以解释并丰富定量结果。结果显示：乐观与创新性均正向影响 GenAI 的用户体验，其中乐观的作用更强；用户体验显著提升信任，而信任显著预测工作投入。用户体验对工作投入的直接路径不显著；相反，信任在其中起到完全中介作用。工作投入则显著提升员工绩效。专家进一步印证了信任的核心地位，强调可靠性、透明度与“适配于目的”的使用是实现持续生产率提升的前提。由于采用横截面数据，因果推断受到限制；建议未来开展纵向与跨文化研究。将 JD-R 模型中的“损失循环”（如工作要求、技术压力与耗竭）纳入模型，可更好地理解边界条件。对实践的启示包括：组织应投资于能力建设、明确使用护栏与核验流程；供应商需提升透明度、提供来源可追溯提示与可控性以赢得用户信任；领导者应将 GenAI 定位为辅助性资源，并建立质量把关机制，将使用转化为投入与绩效。本文在 JD-R 视角下整合 TRI 与 TAM，表明信任是把 GenAI 体验转化为投入与绩效的关键机制；GenAI 作为个人资源的价值，只有在有意培养信任的前提下才能真正显现。

关键词：生成式人工智能（GenAI）、信任、用户体验、工作投入（敬业度）、员工绩效、工作要求-资源（JD-R）模型、技术接受模型（TAM）、技术准备度指数（TRI）

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Does GenAI as a personal resource improve employee performance and engagement in the workplace?

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Abstract. This study examines whether generative AI (GenAI) can operate as a personal resource that enhances employee performance by strengthening user experience, trust, and work engagement. It tests if trust mediates the link between GenAI user experience and engagement and, in turn, performance. An explanatory sequential mixed-methods design is used. Study 1 surveys 251 Indonesian professionals who use GenAI at work and estimates a covariance-based structural equation model. Constructs draw on TRI (optimism, innovativeness), TAM (usefulness, ease of use), trust, work engagement and employee performance. Study 2 gathers expert insights from 69 full professors in management to interpret and enrich the quantitative results. Optimism and innovativeness positively influence GenAI user experience, with optimism showing the stronger effect. User experience significantly increases trust, and trust significantly predicts work engagement. The direct path from user experience to engagement is not significant; instead, trust fully mediates this relationship. Work engagement, in turn, significantly improves employee performance. Experts corroborate the centrality of trust, emphasizing reliability, transparency, and fit-for-purpose use as prerequisites for sustained productivity gains. Cross-sectional data limit causal inference; future longitudinal and cross-cultural studies are encouraged. Extending the model to incorporate JD–R “loss cycle” variables (e.g., job demands, technostress, exhaustion) would deepen understanding of boundary conditions. Organizations should invest in capability building, clear guardrails, and verification workflows; vendors should improve transparency, provenance cues and controllability to earn user trust. Leaders play a pivotal role in positioning GenAI as an assistive resource and in instituting quality checks that convert usage into engagement and performance. The paper integrates TRI and TAM within a JD–R lens to show that trust is the decisive mechanism translating GenAI experience into engagement and performance. It reframes GenAI as a personal resource whose value materializes only when trust is deliberately cultivated.

Keywords: generative AI, trust, user experience, work engagement, employee performance, JD–R, TAM, TRI

Introduction

Emerging digital technologies routinely prompt debate about their consequences (Acemoglu et al., 2023). This debate has intensified with the rapid diffusion of generative AI (GenAI) in the early 2020s, particularly following the November 2022 release of ChatGPT-3. Subsequent assessments point to sizable productivity effects and broad, cross-industry disruption (Chui et al., 2023; Wijayati et al., 2022). McKinsey & Company argue that GenAI can reshape task structures by automating a large share of employees’ day-to-day activities, potentially affecting roughly two-thirds of current time use, while also emphasizing that realizing economy-wide productivity gains requires complementary investments to help workers transition and reskill (Chui et al., 2023). Industry transformation envisioned for GenAI can be understood through

the lens of innovation diffusion: during the earliest phase, innovators and early adopters leverage new tools to build advantage (Rogers, 2003). Successful uptake depends on user attitudes including openness, optimism, and perceived benefits, as well as an innovative orientation that shapes whether experiences with new technology yield positive or negative outcomes (Davis, 1989; Parasuraman, 2000; Parasuraman & Colby, 2015).

Empirical evidence from the academic literature reinforces this view. Noy and Zhang (2023) show that GenAI substantially raises output, with particularly strong effects for less-skilled workers, thereby narrowing productivity gaps. Brynjolfsson et al. (2023) report similar patterns and additionally note improvements in on-the-job learning and employee retention associated with GenAI use. Broad, cross-disciplinary commentary likewise highlights sizable productivity potential in sectors such as banking, hospitality and tourism, and information technology, while also flagging meaningful risks, privacy and security threats, workflow disruption, bias, misuse, and misinformation (Dwivedi et al., 2023).

Trust is pivotal for effective technology use and, downstream, for work engagement (Gkinko & Elbanna, 2023; Llorens et al., 2007). Yet AI systems often function as “black boxes” from the user’s perspective: interfaces may be intuitive, but underlying models are opaque and complex. Ease of use, therefore, does not guarantee perceived reliability. Users must exercise judgment when integrating AI-generated outputs into their own work. GenAI can also reshape how employees relate to their work. When perceived as a helpful resource that enables better performance, GenAI may foster engagement; when viewed as unreliable or threatening, it may increase strain and contribute to burnout (Bakker et al., 2023; Demerouti et al., 2001). Against this backdrop, the present study investigates three questions: (1) Does readiness to use GenAI encourage its acceptance and adoption in organizational settings? (2) Does trust in GenAI promote work engagement and, in turn, enhance performance? and (3) Does engagement with GenAI streamline tasks in ways that raise performance or productivity?

Materials and Methods

Artificial intelligence (AI) is described from multiple vantage points but is broadly understood as the intersection of computational technologies, statistical/algorithmic models, and large datasets. Through an expanding set of applications, AI seeks to replicate facets of human cognition and, in doing so, helps people push past prior constraints enabling new products, services, and systems that can meaningfully improve life and the environment, including how people engage at work (Samuel et al., 2022). Within AI, generative AI (GenAI) denotes methods that learn patterns in unstructured data to create, refine, summarize, or analyze content. These techniques can produce novel outputs such as text, images, music, or video based on learned representations; in this sense, GenAI comprises computational approaches capable of generating seemingly new, meaningful artifacts from training data (Feuerriegel et al., 2024).

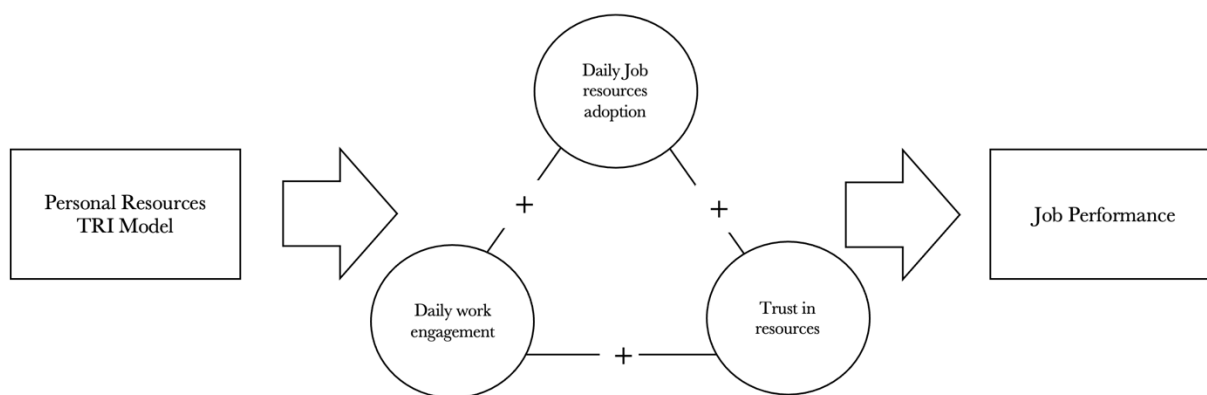
The idea of work engagement has also matured over the past two decades. Early accounts framed engagement as the opposite pole of burnout: energy, involvement, and efficacy contrasted directly with the exhaustion, cynicism, and reduced accomplishment that characterize burnout (Maslach et al., 1997). Subsequent work positioned engagement as a distinct, though negatively related, construct defined by vigor, dedication, and absorption (Schaufeli et al., 2002).

Work engagement is commonly situated within the Job Demands–Resources (JD-R) framework (Bakker et al., 2023; Mazzetti et al., 2023), which posits that any job can be described by two broad classes of factors: demands and resources (Bakker et al., 2023). Job demands are aspects of work that require sustained cognitive or physical effort, whereas job resources are features that alleviate demands, facilitate goal attainment, and support personal growth and development. Engagement and burnout emerge from the dynamic balance between these two classes (Hakanen et al., 2006; Salanova et al., 2005); burnout is

rooted in health impairment processes, while engagement is energized by motivational processes linked to the satisfaction of basic psychological needs including competence, autonomy, and relatedness (Deci & Ryan, 1985). Consistent with this view, support from colleagues and leaders, job control, and task variety have been identified as drivers of engagement (Llorens et al., 2007).

What remains underexplored is how GenAI might function analogously to a “coworker.” From this perspective, the output of these tools must be trusted if they are to serve as true resources for professionals. We therefore argue that confidence in GenAI results can be conceptualized as a job resource within the JD-R model, promoting engagement through motivational pathways (Bakker et al., 2023). In effect, appropriate trust can initiate a “gain cycle” in which engagement builds and, in turn, enhances performance (Bakker et al., 2023). Conversely, trust has a potential dark side: both over-reliance and under-reliance can be counterproductive, undermining effectiveness and yielding adverse outcomes (Levine & McCornack, 1991; Skinner et al., 2014; Xavier Molina-Morales et al., 2011).

A major development in JD-R theory over the past decade is the person-situational approach, which brings the broad constructs of burnout and engagement down to employees’ day-to-day tasks and experiences (Bakker et al., 2023). Unlike earlier formulations, this view posits that personality and personal resources moderate how daily job demands and resources affect well-being and outcomes. Thus, individuals with fewer personal resources are likely to fare worst on days marked by heavy workloads or complex assignments (Debusscher et al., 2016). For instance, workers who lack certain technical skills or who hold pessimistic views about technology may feel a loss of control when required to learn new tools. Our study proposes a model that positions personal resources and trust in GenAI as dual antecedents of work engagement. We explicitly contrast the bright side of trust initiating a JD-R “gain cycle” of sustained daily engagement—with its potential dark side, where misplaced over- or under-trust disrupts that virtuous cycle (Bakker et al., 2023). Figure 1 depicts the relationships among these elements. The next sections develop testable hypotheses and present a research model that integrates these theoretical insights.



Source: Bakker et al. (2023)

Figure 1. Conceptual Framework

Technology Readiness Index (TRI) Model

Around 2014, Parasuraman and colleagues investigated why people are willing to adopt new technologies at a time when mobile commerce, social media, and cloud computing had moved from early experimentation to everyday ubiquity. Their work produced the Technology Readiness Index (TRI), a 36-item instrument with four dimensions (Parasuraman & Colby, 2015). (1) Optimism, the belief that

technology improves control, flexibility, and efficiency; (2) Innovativeness, a tendency to be among the first to try and champion new technologies; (3) Discomfort, feelings of being overwhelmed or losing control when using technology; and (4) Insecurity, skepticism about reliability and concerns about potential negative consequences. The first two dimensions, optimism and innovativeness, capture favorable predispositions toward technology. These positive orientations shape a more rewarding user experience and encourage early uptake, illustrating how a hopeful outlook and a pioneering mindset directly influence how technologies are received and woven into daily routines (Flavián et al., 2022). According to this model, the hypothesis can be constructed as following below:

H₁: Optimism has positive influence on User Experience.

H₂: Innovativeness has positive influence on User Experience.

Technology Acceptance Model (TAM)

Davis (1989) advanced the Technology Acceptance Model (TAM) to explain why people adopt and use new systems. TAM centers on two perceptions shaping user experience: perceived ease of use and perceived usefulness. Subsequent work conceptually linked TAM with TRI (Lai & Lee, 2020) and found empirical support for this integration (Flavián et al., 2022). A third pillar frequently complements TAM in uncertain contexts (e.g., e-commerce, mobile payments, autonomous systems): trust in technology. We posit that employees' personal readiness to use GenAI (per TRI) together with TAM's ease-of-use and usefulness beliefs are pivotal for effective workplace integration.

Trust is often defined as a willingness to be vulnerable based on expectations that the other party will act in ways important to the trustor, even without full monitoring or control (Mayer et al., 1995). This notion applies to human–technology relationships, including AI. A review of end-user AI studies identifies trustworthiness. Users' beliefs about a system's honesty, reliability, and proper functioning, as a core user-experience dimension (Laato et al., 2021). Notably, making algorithmic processes more transparent does not automatically raise worker trust or adoption (Bedué & Fritzsche, 2022; Candrian & Scherer, 2022). By contrast, perceived usefulness and low effort expectancy reliably predict favorable attitudes and use across industries (Kelly et al., 2023). Consistent findings show that successful adoption of workplace chatbots hinges on user trust (Chen et al., 2023), and that usefulness and ease of use are positively associated with trust in AI (Zhang et al., 2021). Ease of use, in particular, is critical for improving attitudes and intention to use AI (Chatterjee, Chaudhuri, et al., 2021; Chatterjee, Rana, et al., 2021). Moreover, user-experience beliefs exert stronger effects on AI adoption when trust is present (Kashive et al., 2021). A broader synthesis confirms extensive applications of TAM to the trust–experience–adoption nexus in AI (Yang & Wibowo, 2022). Although much of this evidence concerns AI generally rather than GenAI specifically, we extend these insights to GenAI and, accordingly, derive our hypotheses.

H₃: User Experience has positive influence on Trust.

Trust and Work Engagement

Prior research shows that trust is central to using GenAI effectively. Scholars widely contend that trust-driven behaviors tend to benefit both individuals and organizations (Bachmann & Zaheer, 2006). By lowering the need for oversight, trust reduces information-processing and monitoring costs, facilitates richer intraorganizational communication, and strengthens commitment and work engagement. Extending this logic to AI, treating GenAI as a reliable “coworker” can elevate organizational engagement. In parallel, when GenAI automates routine, administrative activities, employees can reallocate effort to more creative,

challenging work, which can bolster motivation and engagement. It provided they trust the system to execute repetitive tasks competently (Wijayati et al., 2022). That said, trust in GenAI is not uniformly beneficial. A potential dark side exists: over-trust may enable misconduct, degrade the quality of information exchange, or encourage passivity among workers (Gargiulo & Ertug, 2006).

Further, evidence indicates that trust not only supports initial adoption of AI applications but also shapes ongoing user behaviors and interactions, thereby sustaining long-term use (Chen et al., 2023). In the context of AI-based digital assistants, studies report positive links between satisfaction, productivity, and engagement, with trust acting as an antecedent to satisfaction and, subsequently, to engagement (Marikyan et al., 2022). Taken together, these arguments motivate our next step: to formally articulate and test a hypothesis linking trust in GenAI to employee engagement.

H₄: Trust has positive influence on Work Engagement

Work Engagement and Employee Performance

Demerouti et al. (2001), the JD–R model explains employee functioning through the balance between job demands (e.g., workload), which can strain employees, and job resources (e.g., social support), which buffer stress and promote well-being. The framework is widely used in organizational psychology to guide how organizations mitigate stressors and cultivate engagement (Hakanen et al., 2008). Work engagement is commonly described as a positive, motivational state marked by vigor, dedication, and absorption. Vigor reflects high energy, resilience, and sustained effort despite fatigue; dedication captures enthusiasm, meaning, pride, and inspiration; absorption denotes deep immersion in work where time seems to pass quickly and detachment is difficult (Brodie et al., 2011; Llorens et al., 2007). Work engagement operate as proactive agents: they hold strong self-beliefs, generate reinforcing feedback, align personal and organizational values, and persist through challenges. Their engagement often coexists with secure attachment, job satisfaction, and constructive social relationships. Within this context, integrating GenAI can elevate satisfaction by offloading repetitive, low-value tasks and enabling people to concentrate on meaningful, human-centric work, thereby supporting a more fulfilling and productive environment (Rane, 2024).

Although much of the literature examines AI adoption per se (Yang & Wibowo, 2022), fewer studies trace adoption to organizational outcomes. Adoption may influence engagement by enhancing autonomy and improving day-to-day experiences. While prior evidence often addresses AI broadly rather than GenAI specifically, it is reasonable to expect that positive experiences with GenAI will strengthen trust, which in turn fosters work engagement. Supporting this pathway, Picazo Rodríguez et al. (2024) find that firm digitalization raises perceived productivity and engagement, and Chan et al. (2017) show that self-efficacy can heighten engagement via cognitive and emotional routes. In addition, Wijayati et al. (2022) report that AI positively affects both employee performance and engagement, while noting other essential enablers. Among those enablers, leadership is pivotal. Because AI integration is complex, leaders play a central role in championing strategies that translate technology into higher engagement. When leaders encourage GenAI use and frame it as a valuable resource, employees are more likely to view it as supportive, which indirectly elevates engagement. Taken together, these arguments motivate our formal test: we posit a hypothesis linking GenAI adoption and trust to employee work engagement (with leadership support as a key contextual driver).

H₅: User Experience has positive influence on Work Engagement

Engaged employees tend to act proactively spotting opportunities, initiating improvements, and contributing constructively to their surroundings (Llorens et al., 2007). By setting ambitious goals, they build a sense of competence that fuels sustained effort and high standards. Their positive affect also enhances cognitive processing, which, in turn, supports better judgment and task execution. Put simply, engagement operates as a driver of superior job performance across multiple domains (Salanova et al., 2006). That said, there are potential side effects: in highly competitive, technology-mediated labor markets, elevated engagement can coincide with technostress, with downstream implications for well-being and productivity (Umair et al., 2023). Even so, evidence from meta-analytic work across diverse contexts indicates that engagement reliably predicts stronger performance (Christian & Slaughter, 2007), a pattern echoed in recent analyses of technology's productivity impacts (Chui et al., 2023).

H₆: Work Engagement has positive influence on Employee Performance

The hypothesis development in this study is shown as following Figure 2.

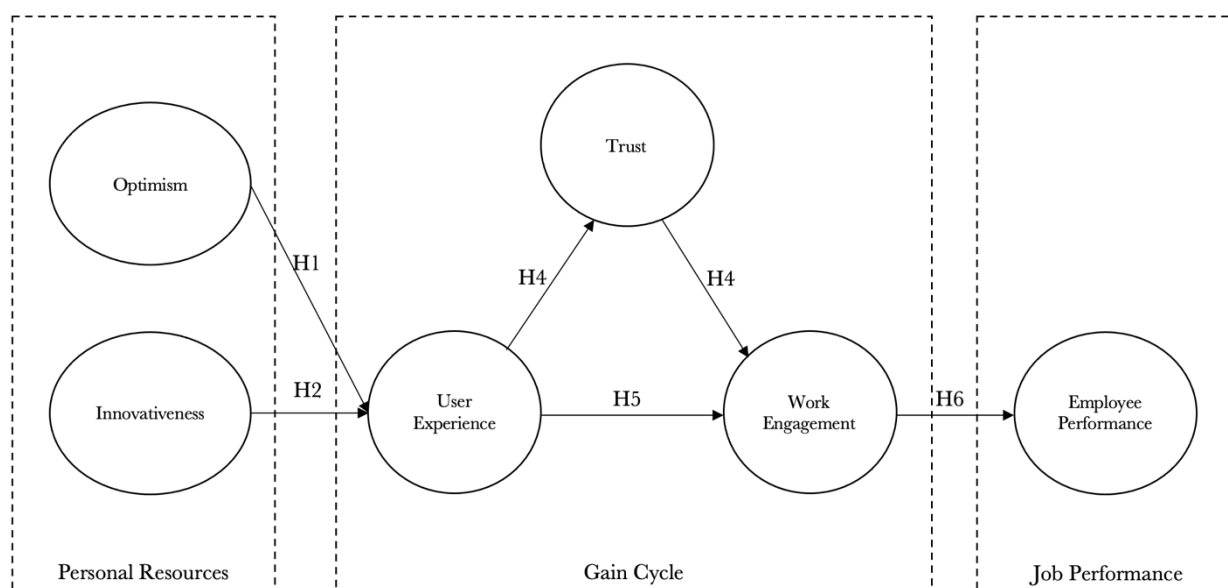


Figure 2. Research Model Proposition

Methods

We adopt an explanatory sequential mixed-methods design. Study 1 uses a quantitative approach, specifically, covariance-based SEM to test the research questions and evaluate the model shown in Figure 2. Study 2 then follows with a qualitative phase: a survey of senior academics (full professors in management) designed to probe the mechanisms behind the quantitative results and clarify why the observed relationships emerge. Consistent with Creswell and Poth (2016), the qualitative evidence is intended to explain and elaborate the initial quantitative findings. The next four subsections detail Study 1 (quantitative) procedures; the final subsection describes the Study 2 (qualitative) methodology. Study 1 tests the research model in Figure 2 by examining how the use of GenAI tools shapes workplace outcomes in a user sample. The survey instrument was designed to span all focal constructs: it first assessed technology readiness, then measured technology acceptance and user experience, followed by trust in GenAI. It also captured work engagement and job performance. To ensure content validity, items for each construct were drawn from or adapted based on established, validated scales in the literature. Table 1 details each construct, its indicators, and the corresponding source references.

Table 1. Variable Indicators

Construct	Code	Item	Adapted from
Optimism	OPT1	GenAI tools contribute to a better quality of my life.	Parasuraman (2000); Parasuraman & Colby (2015)
	OPT2	GenAI tools give me more freedom and flexibility.	
	OPT3	GenAI tools give me more control over my work tasks.	
Innovativeness	INN1	Other people come to me for advice on new GenAI technologies.	Parasuraman (2000); Parasuraman & Colby (2015)
	INN2	In general, I am among the first in my circle of friends to acquire new GenAI technology when it appears.	
	INN3	I can usually figure out new GenAI tools without help from others.	
	INN4	I keep up with the latest GenAI technological developments in my areas of interest.	
Usefulness	USE1	I find GenAI useful in my job.	Davis (1989)
	USE2	Using GenAI makes it easier to do my job.	
	USE3	Using GenAI in my job would enable me to accomplish tasks more quickly.	
Easy to Use	EAS1	I think that GenAI is easy to use.	
	EAS2	Learning to use GenAI was easy for me.	
	EAS3	I find it easy to get GenAI to do what I want it to do.	
Trust	TRU1	In my work, I feel comfortable depending on the information provided by GenAI.	Candrian & Scherer (2022); Frank et al. (2023); Glikson & Woolley (2020); Mayer et al. (1995); McKnight et al. (2002)
	TRU2	I trust that I can rely on GenAI in my work.	
	TRU3	I feel that I can count on the responses of GenAI to help me in my work.	
	TRU4	If I have a challenging problem in my work, I use GenAI.	
	TRU5	I feel assured about data protection on the GenAI-tools.	
	TRU6	I feel adequately protected from problems on the AI-tools used in my company.	
	TRU7	I trust that GenAI-tools used in my company comply with established legal structures.	
Work Engagement	WEN1	Time flies when I am working.	Hakanen et al. (2008); Schaufeli et al. (2002); Wijayati et al. (2022)
	WEN2	I am enthusiastic about my job.	
	WEN3	When I am working, I forget everything else around me.	
	WEN4	At my work, I always persevere, even when things do not go well.	
	WEN5	My job inspires me.	
	WEN6	At my job, I am very resilient.	
Employee Performance	EPE1	My tasks are completed as per the specifications and standards.	Wijayati et al. (2022)
	EPE2	The units of output meet organizational expectations.	
	EPE3	My tasks are generally completed on schedule.	

Survey administration and demographics

Data were gathered by a professional survey firm to ensure reliability and procedural rigor. Fieldwork took place in January 2025 and yielded 251 complete questionnaires from Indonesian professionals with workplace experience using GenAI tools. Descriptive checks showed no notable gender imbalance. As

summarized in Table 2, over half of respondents were younger than 35, while 19.5% were 46 or older. Regarding usage intensity, 13.9% reported heavy use and 21.1% used GenAI at least once per day, suggesting substantial familiarity across the sample. By sector, education was the most active adopter, comprising 27.09% of participants. In terms of specific applications, 51.79% used OpenAI's ChatGPT for text generation and another 8.37% employed other chatbots for similar tasks. In together, about 60% of the sample highlighting the broad diffusion of conversational AI. The next most common application area involved image and video generation tools.

Table 2. Respondent Background

Category	Number	%
Male	129	51.4
Female	122	48.6
Total	251	100.0
Between 18 and 20 years	0	0.0
Between 21 and 25 years	78	31.1
Between 26 and 35 years	62	24.7
Between 36 and 45 years	62	24.7
Between 46 and 55 years	49	19.5
>55	0	0.0
Total	251	100.0
Professional studies	85	33.9
University degree	73	29.1
Master or PhD degree	93	37.1
Total	251	100.0
High Management	15	6.0
Intermediate position	87	34.7
Operational position	71	28.3
Other	78	31.1
Total	251	100.0
Intensively every day	35	13.9
Once per day	53	21.1
Once per week	71	28.3
In very few occasions	92	36.7
Total	251	100.0
Banking/Insurance	14	5.58
High tech	42	16.73
Life-sciences	19	7.57
Entertainment	16	6.37
Education	68	27.09
Manufacturing	17	6.77
Others	75	29.88
Total	251	100.0
Customer operations	52	20.72
Marketing and sales	30	11.95
Software engineering	37	14.74
R&D	29	11.55
Others	103	41.04

Category	Number	%
Total	251	100.0
Less than 10 employees	37	14.74
Between 11 and 250 employees	103	41.04
More than 250 employees	111	44.22
Total	251	100.0
National	190	75.70
International	61	24.30
Total	251	100.0
Chatbot for text generation (OpenAI ChatGPT)	130	51.79
Chatbot for text generation (Google Bard)	21	8.37
Chatbot for text generation (Microsoft Bing AI)	9	3.59
Text generation (e.g., Jasper, Notion AI, Copy.ai, Writesonic, or others)	5	1.99
Generation of presentations (e.g., SlidesAI, Wepik, Tome, or others)	8	3.19
Image generation (e.g., OpenAI DALL·E, Midjourney, Adobe Firefly, Canva AI, or others)	33	13.15
Video generation (e.g., RunwayML, Canva HeyGen, Pictory, Fliki, or others)	6	2.39
GenAI assistants in common programs (e.g., Google Duet AI, Microsoft Copilot, or others)	26	10.36
Another specific tool for department activities	13	5.18
Total	251	100.0

Assessment of the research model

This study seeks to chart the pathway from readiness to use GenAI at work to employee performance, mediated by user experience, trust in GenAI, and work engagement. We implemented a two-stage analytic strategy. First, we ran five separate EFAs (principal components with varimax rotation) to screen and refine indicators for each construct, ensuring that the measures used in the structural analysis were both reliable and conceptually aligned. Next, we tested the research model in Figure 2 using structural equation modeling (SEM). Estimation employed robust maximum likelihood with an asymptotic variance–covariance matrix in EQS. For each construct, we evaluated reliability (Cronbach’s α and composite reliability, CR) and convergent validity (average variance extracted, AVE). Discriminant validity was assessed by comparing the squared AVE for each construct with its inter-construct correlations. Model adequacy was judged using the Bentler–Satorra χ^2 (value, coefficient, and df) together with standard fit indices (e.g., CFI, RMSEA). After establishing acceptable fit, we examined and interpreted the standardized path coefficients to elucidate the relationships among the latent variables.

“Trust” Mediating function

A central feature of our model (Figure 2) is the mediating role of trust in the link between user experience and work engagement. This section examines that mechanism in depth. Our mediation strategy follows classic guidance on indirect effects (Baron & Kenny, 1986; Hayes, 2009; Zhao et al., 2010). These works inform how we test whether trust acts as the intervening construct that transmits (or modifies) the influence of technology acceptance beliefs to subsequent engagement at work. Specifically, we evaluate whether user experience affects trust, whether trust predicts engagement, and whether the indirect path is statistically distinct from zero. Accordingly, this part of the methodology details the procedures used to estimate the full structural model and to quantify the indirect effect via trust, thereby preparing the ground for the empirical results and interpretation that follow.

Survey to academics on business management

After estimating the structural model, we conducted Study 2, a follow-up survey with a panel of senior academics (all full professors) to critically assess and contextualize the quantitative findings from Study 1. The goal was to deepen interpretation by incorporating expert judgment. Guided by the initial results, we invited 69 management professors from Indonesian universities primarily Central Java (58.0%), reflecting the Indonesian sampling frame of Study 1. Additional area represented were Yogyakarta, Jakarta, West Java, East Java, Sumatera, Borneo, Sulawesi, Bali, and Papua. The panel comprised 31.9% women and 68.1% men; 31.9% held tenured full professorships, indicating substantial expertise. The mean age was 48 years ($SD = 7.5$). Ages were approximately evenly distributed: one-third <46 , one-third 46–51, and one-third >51 . Regarding GenAI usage, 46.4% ($n=29$) reported intensive daily use, whereas 31.8% used such tools only on rare occasions.

Experts were asked three focused questions—reframed from the original research questions for clarity:

1. To what extent do optimism and a predisposition to experiment with new technologies shape your subsequent experiences with them?
2. How important is it that the tools' outputs are reliable and consistent enough to use confidently in your work?
3. To what degree do you agree that using these tools improves productivity?

Result

Subsection 1 reports the empirical findings from Study 1, based on the sample of 251 GenAI users. Subsection 2 then presents the results of Study 2, drawn from a follow-up survey of 69 senior management scholars.

Subsection 1

Prior to hypothesis testing, we assessed common method bias (CMB) using Harman's single-factor test. An EFA on all 46 items produced eight factors with eigenvalues > 1 ; the first factor accounted for 36.0% of the variance, indicating CMB was unlikely to be a concern. The quantitative phase began with five EFAs. The first, applied to TRI items (optimism and innovativeness), confirmed that these two dimensions are empirically distinct. EFAs for the remaining constructs each yielded a single factor, meeting the standards of Ladhari (2012) and Wolfinbarger & Gilly (2003): (i) primary loadings ≥ 0.70 , (ii) cross-loadings ≤ 0.50 , and (iii) item–total correlations > 0.50 .

Table 3. Principal Component Analysis (PCA)

Item	Innovativeness	Optimism	User Experience		Trust		Work Engagement		Employee performance	
	LF	LF	Item	LF	Item	LF	Item	LF	Item	LF
INN1	0.782	0.261	USE2	0.779	TRU2	0.777	WEN2	0.765	EPE2	0.803
INN2	0.780	0.175	USE1	0.770	TRU6	0.768	WEN5	0.748	EPE1	0.776
INN4	0.764	0.276	USE3	0.743	TRU3	0.741	WEN4	0.715	EPE3	0.773
INN3	0.708	0.268	EAS1	0.740	TRU1	0.727	WEN6	0.703		
OPT3	0.246	0.790	EAS2	0.706	TRU7	0.720	WEN1	0.696		
OPT2	0.280	0.784	EAS3	0.698	TRU5	0.702	WEN3	0.671		
OPT1	0.222	0.783			TRU4	0.623				

Table 3 lists retained vs. dropped items. Two near-threshold cases: EAS3 (0.698) and WEN1 (0.696) were kept due to their substantive relevance. With the final item set established for the model in Figure 2, we estimated a covariance-based SEM.

Table 4. Validity and Reliability Test

Construct	Code	LF	Cronbach alpha	Composite Reliability	AVE
Optimism	OPT1	0.801	0.869	0.968	0.692
	OPT2	0.856			
	OPT3	0.838			
	INN1	0.839			
Innovativeness	INN2	0.791	0.87	0.873	0.632
	INN3	0.736			
	INN4	0.811			
	USE1	0.838			
User Experiences	USE2	0.802	0.878	0.871	0.532
	USE3	0.763			
	EAS1	0.650			
	EAS2	0.627			
	EAS3	0.670			
	TRU1	0.731			
Trust	TRU2	0.786	0.88	0.881	0.553
	TRU3	0.776			
	TRU4	0.664			
	TRU5	0.763			
	TRU6	0.736			
	TRU7	0.731			
Work Engagement	WEN1	0.674	0.878	0.871	0.532
	WEN2	0.760			
	WEN3	0.744			
	WEN4	0.733			
	WEN5	0.929			
	WEN6	0.674			
Employee Performance	EPE1	0.466	0.825	0.828	0.617
	EPE2	0.382			
	EPE3	0.398			

Table 4 reports reliability for the six constructs: both Cronbach's α and composite reliability (CR) exceeded 0.70 (Hair et al., 2010). Average variance extracted (AVE) values were all above 0.50 (Nunnally & Bernstein, 1994), supporting convergent validity.

Table 5. Discriminant Validity

	1	2	3	4	5	6
(1) Optimism	0.832					
(2) Innovativeness	0.505	0.795				
(3) User Experience	0.647	0.524	0.729			
(4) Work Engagement	0.378	0.336	0.392	0.773		
(5) Trust	0.668	0.607	0.728	0.444	0.744	
(6) Employee Performance	0.249	0.280	0.407	0.596	0.374	0.786

Table 5 presents discriminant validity results using the Fornell–Larcker criterion: the square root of each AVE surpassed the corresponding inter-construct correlations (off-diagonal entries), confirming satisfactory discriminant validity. We further evaluated discriminant validity using the heterotrait–monotrait ratio (HTMT). Following Henseler et al. (2015), all inter-construct HTMT values were below 0.85. Estimates ranged from 0.287 (Optimism to Employee Performance) to 0.798 (User Experience to Trust), with a mean of 0.546 and SD = 0.165 across the model's 15 construct pairs. Model fit statistics indicated that the indicators loaded coherently on their intended factors. The Satorra–Bentler χ^2 was 577.75 with 317 df ($p < .001$); $\chi^2/df = 1.82$, under the conventional ≤ 5 threshold. Additional indices showed acceptable fit: RMSEA = 0.057 and CFI = 0.913. Given the known sensitivity of robust χ^2 , the overall fit was judged adequate (Hair et al., 2010).

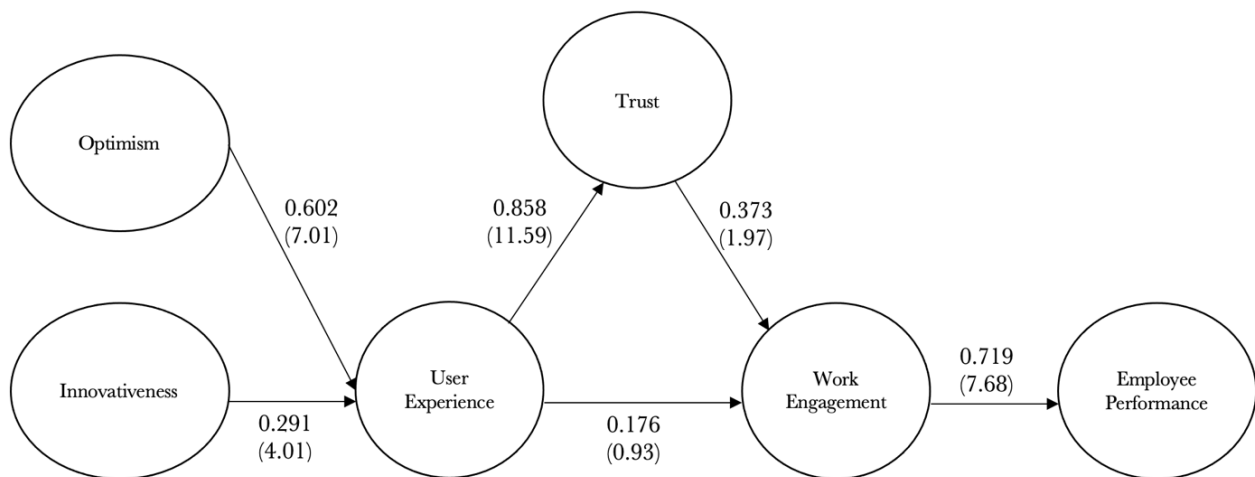
**Figure 3. Research Model Output**

Figure 3 presents standardized paths with t-values in brackets. All paths were significant at .05, except the link from User Experience to Work Engagement. Consequently, six hypotheses were supported, while H5 (positing a positive User Experience to Work Engagement effect) was not. This non-significant direct effect is theoretically salient and warrants deeper examination: User Experience did not directly predict Work Engagement. Notably, Optimism exerted roughly twice the effect on User Experience compared to Innovativeness. In other words, an optimistic disposition is the primary driver of a favorable user experience with GenAI, although an early-adopter tendency still contributes. This pattern aligns with Wang et al. (2023), who, using TAM, show AI can enhance effectiveness and profitability in e-commerce. Accordingly,

our first research question is affirmed: readiness to adopt GenAI is associated with a more positive user experience. The output can be shown as following Table 6.

Table 6. SEM Hypothesis Test Output

Hypothesis	Direct effect	P-value	
<i>H₁: Optimism has positive influence on User Experience.</i>	0.602***	7.01	Accepted
<i>H₂: Innovativeness has positive influence on User Experience</i>	0.291***	4.01	Accepted
<i>H₃: User Experience has positive influence on Trust.</i>	0.858***	11.59	Accepted
<i>H₄: Trust has positive influence on Work Engagement</i>	0.373*	1.97	Accepted
<i>H₅: User Experience has positive influence on Work Engagement</i>	0.176	0.93	Rejected
<i>H₆: Work Engagement has positive influence on Employee Performance</i>	0.719***	7.68	Accepted
<i>User Experience has indirect effect on Work Engagement</i>	0.32**	2.08	

Note: *** sig level at < 0.001; ** sig level at < 0.01; * sig level at < 0.05

Because trust is central to our framework, Table 6 reports the decomposition of User Experience's effect on Work Engagement. The core result is that the direct path is not significant, while the indirect path via Trust is significant. As foreshadowed by the rejection of H5, this underscores the strategic role of trust in the model. Using Zhao et al.'s (2010) typology, the pattern indicates full mediation: absent trust in GenAI outputs, User Experience does not translate into engagement and, by extension, cannot lift employee performance. In short, deploying GenAI to foster engagement is not a plug-and-play solution; cultivating trust is essential. This addresses our second research question, supporting the claim that trusting GenAI is pivotal for improving productivity. A further implication is that the JD-R "gain cycle" (Bakker et al., 2023) does not operate through a direct User Experience to Engagement link in our data. Instead, the process is linear, with trust positioned between predisposition to adopt GenAI and employee performance. This accords with findings in other domains such as service recovery where trust frequently mediates key relationships (DeWitt et al., 2008). The sixth hypothesis is also supported: engagement significantly predicts employee performance (the right-hand side of the model). This confirms our final research question that work engagement lies on the pathway to improved performance. We additionally ran a multi-group analysis splitting the sample by gender (men: 129; women: 122). We constrained the structural regressions to equality across groups and evaluated six constraints; for each, the p-value associated with the chi-square increment exceeded .05. Thus, none of the path coefficients differed significantly by gender: the model in Figure 2 functions equivalently for men and women, and the standardized coefficients shown in Figure 3 display no meaningful cross-group differences.

Subsection II

The panel showed strong convergence in their responses to all three questions. For Question 1: "To what extent do a predisposition to try new technologies and optimism about their capabilities shape your future experiences with them? (scale 1–5)". The mean rating was 4.2 (SD = 0.7) on a five-point Likert scale, reinforcing our first research question.

Representative remarks included the following themes:

- Openness rises when perceived capability is high and the tool is not difficult to learn; several experts stressed the trade-off between benefits and adoption costs.
- Some participants admitted that a low personal inclination to experiment reduces their likelihood of trying new tools at all.

- Predisposition, rather than unqualified optimism, was viewed as decisive: willingness to try encourages initial use, but continued use depends on whether the tool delivers on its promise.

Overall, the comments point to a generally positive stance toward new technologies: an initial readiness to experiment tends to promote early adoption, greater tolerance for early imperfections, and a virtuous cycle of exploration and engagement. Optimistic adopters are more likely to try GenAI, use it intensively, and learn realistic expectations, which in turn supports more effective use, better outcomes, and growing trust over time. At the same time, respondents noted caveats. Without some baseline optimism, early experiences may be underwhelming, dampening future engagement. There was also criticism of certain AI tools (e.g., ChatGPT) in tasks where clear source attribution and the most current information are essential, such as academic research.

For Question 2: “How crucial is it that the tools’ outputs are reliable, consistent, and usable with confidence in your work? (scale 1–5)” The panel again showed near-unanimity, with an average rating of 4.4 (SD = 0.8). Illustrative themes from the comments:

- Reliability matters, though a rough, timely answer can sometimes be preferable to none at all.
- Trust is earned through consistent, high-quality results and builds with successful use over time.
- Early, unquestioning reliance on ChatGPT gave way to more careful review after users encountered errors; many now treat outputs as guidance rather than final answers.
- Several respondents emphasized routine verification: if reliability or consistency seems low, they disengage.
- Opaqueness (“black box”) was a recurring concern. Even so, when used judiciously, total time for prompting plus review can be lower than doing the task entirely by hand.

Across responses, experts described a pragmatic workflow: employees evaluate GenAI outputs against their own knowledge and standards, and that judgment calibrates future trust. This aligns with the SEM findings from Study 1: trust is central. Workers generally view GenAI as a productive assistant, but they retain ownership of the work. Trust erodes when outputs contain inconsistencies or factual/mathematical mistakes; conversely, uncritical, wholesale acceptance can produce unreliable deliverables.

For Question 3: “To what degree do you agree that these tools enhance productivity? (Scale 1–5)” The mean rating was 4.3 (SD = 0.8), indicating strong enthusiasm among the academics. Illustrative remarks included:

- “My results improve markedly with use; the more I learn what the tool can deliver, the better the content and formatting of my work.”
- “Repetitive, knowledge-heavy tasks speed up substantially.”
- “Anyone who has examined this closely can see it boosts both productivity and creativity.”
- “Having a quick first draft dramatically increases productivity.”

Overall, respondents agreed that GenAI efficiently absorbs repetitive work, freeing time for more creative, higher-value activities. Common benefits cited were rapid first drafts, concise summaries of large materials, better content quality and presentation, and help with translation and email composition. Many noted time savings and enhanced creativity, which let them focus on more complex or strategic tasks. This, in turn, can elevate job satisfaction. Caveats emerged as well. Some argued the productivity lift may be temporary diminishing once higher output becomes the new baseline. Effectiveness varied by task type and user familiarity, and several cautioned against over-reliance without adequate understanding and review. Additional, unprompted insights surfaced: a number of experts felt GenAI increases their sense of security and autonomy. They can quickly consult a tool that is always available rather than waiting on a colleague. A psychological downside was also mentioned: when outcomes are poor, relying on AI can amplify feelings of guilt compared to doing the task entirely oneself. As noted, the survey’s three questions align closely with the three research questions introduced at the outset. The expert responses clarify and contextualize the

quantitative findings from Study 1, while also surfacing additional insights that were not captured in the initial analysis.

Discussion

This study provides an integrated view of how GenAI is adopted and used at work. By examining technology readiness, user experience, trust, and work engagement together, we clarify how these factors interact to shape employee performance in GenAI-enabled settings. First, optimism emerges as the primary spark for a positive user experience that ultimately supports professional outcomes. Compared with being an early adopter, an optimistic stance toward technology is the stronger predictor of user experience. This aligns with evidence from the General Attitudes towards Artificial Intelligence Scale (GAAIS), where the positive subscale correlates closely with TRI's favorable dimensions (Innovativeness and Optimism) (Schepman & Rodway, 2023). Put differently, cultivating a constructive outlook helps employees engage more fruitfully with GenAI and those who are most optimistic also tend to adopt earlier, gaining an advantage over later entrants.

Second, trust fully mediates the path from user experience to work engagement. The absence of a direct effect from user experience to engagement, coupled with a significant indirect effect via trust, positions trust as the indispensable bridge in this relationship. There is no shortcut: simply deploying or frequently using GenAI is insufficient for engagement and performance gains. Employees must believe in the accuracy, reliability, and validity of GenAI outputs. As that confidence builds, engagement grows and performance follows. Note, too, that trust is not purely calculative; it can be affective, grounded in optimistic feelings about another party's goodwill and competence (Gkinko & Elbanna, 2023). Third, the link from engagement to employee performance is robust, confirming the final hypothesis and reinforcing recent findings in the literature (Babina et al., 2024; Bankins et al., 2023; Czarnitzki et al., 2023; Kellogg et al., 2020; Marikyan et al., 2022). Engagement functions as a catalyst that translates GenAI use into better outcomes.

Managers can strengthen trust in GenAI by acting on three fronts. Inside the organization, build employee competence and confidence through progressive onboarding (from short demos to role-specific sandboxes), peer learning and external benchmarking, and clear guardrails about when GenAI is assistive versus authoritative. Explain how the system works at a practical level. Its typical failure modes and when double-checks are required then institutionalize verification with simple checklists for sources, numbers, bias, and facts. Track quality with light KPIs (accuracy on sample tasks, revision effort, turnaround time, user satisfaction) and encourage incident reporting with quick feedback loops so lessons are shared. On the provider/product side, design for trust and benevolence. Systems should demonstrate "closeness" by acknowledging user goals, adapting to preferences, and signaling understanding; increase transparency with citations or provenance where possible, label generated versus retrieved content, and surface uncertainty. Reduce the black-box feel via model cards or behavior notes, basic "why this answer" cues, and controllable parameters. Align with the benevolence–ability–integrity triad by showing reliability metrics, prioritizing user interests, and enforcing clear safety rails (privacy-by-design, audit logs, easy reporting). Earn trust over time through visible version histories and change logs. At the ecosystem level, institutions and agencies can foster a positive technology culture with awareness campaigns, user education and micro-credentials, transparency standards or voluntary seals, recognition programs for trustworthy deployments, and open forums where regulators, providers, workers, and researchers review evidence and refine norms. In combination, these actions help trust grow from informed use, transparent system behavior, and a supportive environment enabling engagement and, ultimately, stronger performance.

From an academic standpoint, this paper advances three main contributions. First, it proposes an integrated framework that combines TAM and TRI to explain how GenAI affects productivity. We label

this framework “Trusting in trust as an enhancer from experience to work engagement and performance (TTEEWEP),” repeating “trust” intentionally to emphasize its centrality in the model. Second, the study demonstrates that trust is the pivotal mechanism: it fully mediates the relationship between user experience and work engagement, indicating that the JD–R “gain cycle” (Bakker et al., 2023) does not operate through a direct user experience to engagement link in this context. Third, the overall pattern connecting user experience, trust, engagement, and employee performance shows a distinct chain in which trust occupies a critical mediating role.

Conclusions

The positive cycle beginning with user experience operates only in part. Favorable experiences with GenAI strengthen professionals’ confidence in the tool’s outputs; this trust, in turn, fosters engagement. Employees who regard GenAI as a reliable, expert collaborator report higher energy, enthusiasm, and absorption at work. Thus, trust enables good experiences to translate into engagement, even though the direct path from experience to engagement is not significant in our data leaving the loop “open.”

Future work should examine these relationships across different cultural and organizational settings and consider the JD–R “loss cycle,” incorporating job demands and exhaustion to capture strain processes. Longitudinal designs would help reveal how these dynamics evolve as GenAI becomes embedded in day-to-day routines. Additional exploratory studies could test how adjacent constructs such as job satisfaction, life satisfaction, and well-being shape or moderate the pathways in our model. It will also be useful to compare distinct use cases of GenAI (e.g., brainstorming for creativity, proofreading, utilitarian versus entertainment uses; Barrett et al., 2024). Finally, our group comparison suggests similar structural relations for men and women, but future research should probe whether specific factors differentially influence subgroups.

The paper opened with Acemoglu’s observation that technological progress raises productivity while distributing gains unevenly. That broader debate who benefits, and why depends on power, context, and practice. Empirical studies like this one help clarify where and how GenAI can produce value, for whom, and under what conditions (Acemoglu et al., 2023).

Conflicts of Interest: The authors declare no conflicts of interest.

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