“Generative AI-supported learning and Workplace Creativity in electronic retail”


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# GENERATIVE AI-SUPPORTED LEARNING AND WORKPLACE CREATIVITY IN ELECTRONIC RETAIL

## Abstract

This study examines the relationships among generative AI tool usage for Workplace Learning, Learning Agility, and Workplace Creativity among electronic retail employees in Indonesia. Learning Agility was modeled as a second-order construct comprising developing leadership or growth, seeking feedback, and developing systematically. Data were collected through a cross-sectional survey of 286 employees who actively used generative AI platforms for learning and work-related support. The hypotheses were tested using covariance-based structural equation modeling and bias-corrected bootstrap analysis. The results show that generative AI tool usage was positively associated with Learning Agility ($\beta = 0.738$, $p < 0.001$), while Learning Agility was positively associated with Workplace Creativity ($\beta = 0.484$, $p < 0.001$). Generative AI tool usage also maintained a positive direct relationship with Workplace Creativity ($\beta = 0.408$, $p < 0.001$). The indirect relationship through Learning Agility was statistically significant, with a bias-corrected 95% confidence interval ranging from 0.179 to 0.509. These findings indicate complementary partial mediation, suggesting that Generative AI Use is related to Workplace Creativity both directly and through employees' adaptive learning capacity. The study applies Social Cognitive Theory to generative AI-supported workplace learning by distinguishing AI-enabled learning resources from employees' behavioral engagement with those resources. The findings suggest that Generative AI Use is associated with Workplace Creativity both directly and indirectly through Learning Agility. Practically, electronic retail managers should combine AI adoption with employee development practices that encourage feedback seeking, reflection, experimentation, and systematic learning.

**Keywords** Generative AI Use, Learning Agility, Social Cognitive Theory, Workplace Creativity

**JEL Classification** M53, M12, O33, D83, L81

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## INTRODUCTION

Electronic retail has become a demanding service environment because customers expect fast, accurate, and personalized responses when comparing products, technical features, and purchase options. Employee creativity is therefore not limited to abstract ideas. It is reflected in the ability to translate product knowledge into relevant explanations, adapt service approaches to different customers, and offer practical solutions during daily interactions. Retail research shows that employee performance is linked to customer service quality, problem-solving ability, adaptability, and creative contribution to organizational problems (Widjaja et al., 2024). The growth of consumer technology spending in Indonesia further increases the importance of creative service behavior, as retail firms must differentiate customer experience while responding to changing products and expectations.

At the same time, generative AI adoption has created new learning conditions for employees. AI-based tools can provide explanations, alternative ideas, examples, and immediate feedback that may help employees address work-related problems. However, access to generative AI does not automatically lead to meaningful learning or creative behavior. Employees may use AI only for quick answers without reflecting on information, testing alternatives, or applying learning to new work situations. This creates an important research problem: the relationship between Generative AI Use (GAIU) and Workplace Creativity remains insufficiently explained, especially regarding the learning mechanism that connects AI-supported knowledge with creative work behavior.

Indonesia's electronic retail sector is a relevant setting for examining the relationship among Generative AI Use, Adaptive Learning, and Workplace Creativity. The sector operates in a large digital consumer market, where customers compare specifications, features, prices, warranties, and after-sales services before buying. Indonesian consumers spent IDR 256 trillion on FMCG and consumer technology products in Q3 2024, with consumer technology contributing 19% of total spending, or about IDR 48.6 trillion (NielsenIQ, 2024). Indonesia's e-commerce sector reached USD 65 billion in gross merchandise value in 2024 (Google, 2024). Internet penetration also remains high, with more than 221 million internet users in 2024 according to APJII and 212 million users at the start of 2025 according to DataReportal (APJII, 2024; Kemp, 2025). These figures suggest that Indonesian consumers increasingly search for product information, compare alternatives, and interact with brands across channels.

This digital consumer environment changes the work of electronic retail employees. Frontline employees are no longer responsible only for displaying products or completing transactions. They are expected to explain specifications, translate technical features into customer-relevant benefits, compare brands, respond to objections, and recommend products that match customer needs and budgets. In electronic retail, creativity is closely related to service improvisation, adaptive communication, and practical problem solving. This is consistent with retail research showing that frontline employees shape customer experience, satisfaction, and loyalty (Widjaja et al., 2024). AI and in-store technologies may improve operations and personalization, but their success still depends on human interaction and employees' ability to use technology in context (Gielens, 2024).

The digitalization of customer service further increases the need for employees who can learn quickly and respond creatively. Retailers increasingly use digital tools, AI-based recommendation systems, chatbots, product information systems, and omnichannel platforms to support customer engagement. In Indonesia, Microsoft and LinkedIn reported that 92% of knowledge workers used generative AI at work in 2024, exceeding the global average of 75% and the Asia-Pacific average of 83% (Microsoft, 2024). Although not limited to retail employees, this figure shows that generative AI is becoming a common work-support tool. For electronic retail employees, such tools may provide product explanations, service scripts, response scenarios, and daily learning support.

However, access to AI does not automatically create better learning or creative service behavior. AI can provide information, examples, and recommendations, but employees still need to assess whether AI-generated suggestions are accurate, relevant, and suitable for specific customer situations. Inaccurate product explanations may affect customer trust, purchase decisions, and after-sales satisfaction. Therefore, the practical value of generative AI depends not only on technology availability, but also on employees' ability to process information, seek feedback, adapt explanations, and transfer learning across customer cases. This makes learning agility relevant for understanding how generative AI-supported learning is associated with workplace creativity.

Despite Indonesia's digital economy growth and workplace AI use, limited empirical attention has examined how Generative AI Use relates to creative behavior among electronic retail employees. Existing studies discuss AI adoption in retail, digital customer engagement, and AI-supported creativity more broadly, but the learning mechanism linking AI-supported workplace learning with employee creativity remains underexplored. This study addresses that gap by examining whether Generative AI Use for workplace learning is associated with Workplace Creativity through Learning Agility among electronic retail employees in Indonesia. Given the cross-sectional design, the proposed relationships are examined as associations rather than evidence of a causal sequence.

# 1. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Social Cognitive Theory provides the theoretical foundation for explaining how employees' engagement with generative AI-supported learning resources is associated with Learning Agility and Workplace Creativity. SCT proposes that human functioning develops through reciprocal interactions among environmental conditions, personal factors, and behavior (Wood & Bandura, 1989). In the present context, generative AI tools provide a technology-enabled environment containing information, examples, feedback, and alternative problem-solving approaches. Employees' use of these tools represents their behavioral engagement with the available environment rather than the environment itself. Learning Agility reflects a personal adaptive factor related to how employees interpret, evaluate, and transfer acquired information, while Workplace Creativity represents a work-related behavioral outcome. The proposed model therefore examines one theoretically relevant sequence within the broader SCT framework rather than testing the complete reciprocal system.

In this study, Generative AI Use refers not to formal intelligent tutoring systems, but to employees' use of generative AI tools, AI chatbots, and AI-supported platforms for workplace learning and job-related support. The tools and the informational affordances they provide form part of the digital learning environment. By contrast, the focal construct captures employees' behavioral engagement with this environment, reflected in how frequently, broadly, and deeply they use generative AI resources. Through such engagement, employees may access alternative explanations, compare possible responses, request feedback, and explore different approaches to work problems. In SCT terms, the technology provides environmental resources, while its actual use represents behavior through which employees interact with and draw upon those resources. This distinction aligns the theoretical interpretation of the construct with its operational measurement.

Learning Agility represents a personal factor within the SCT framework because it reflects an individual's capacity to learn reflectively and adaptively from experience. In this study, Learning Agility is treated as a personal adaptive capacity associated with how employees engage with, evaluate, and learn from AI-generated information. Because the study uses cross-sectional data, the model estimates the statistical relationships specified in the hypotheses without establishing their temporal or causal ordering. It includes the ability to seek feedback, revise existing approaches, respond to unfamiliar situations, and transfer learning across different work contexts. Prior research has emphasized that Learning Agility is closely related to reflection, feedback seeking, adaptability, and self-regulated learning (Bouland-van Dam et al., 2022; DeRue et al., 2012; Vinesian et al., 2023). In the context of generative AI-supported learning, Learning Agility becomes important because employees need to evaluate AI-generated suggestions, select relevant information, and adapt it to specific work situations. Therefore, Generative AI Use may be associated with higher learning agility when employees use AI tools not only for quick answers, but also for exploration, comparison, reflection, and learning transfer.

Generative AI tools may provide employees with additional cognitive resources during daily work. Employees who engage more intensively with these tools may have greater opportunities to obtain explanations, compare alternative solutions, and reconsider their approaches to work-related problems. Such activities are theoretically consistent with feedback-based and reflective learning because employees can explore ideas without relying solely on formal training. This interpretation aligns with research linking Learning Agility with experience, feedback, reflection, and adjustment


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(DeRue et al., 2012; Rigolizzo & Zhu, 2020; Wolor et al., 2025). In electronic retail, these learning opportunities are particularly relevant because employees frequently encounter updated product information, changing technical specifications, and diverse customer situations. Nevertheless, the proposed association does not imply that Generative AI Use necessarily increases Learning Agility.

Generative AI-supported learning may also be related to Workplace Creativity because it provides employees with a broader range of ideas, examples, and perspectives. Workplace Creativity refers to the generation and application of new and useful ideas in the work setting. In electronic retail, creativity may appear when employees explain product features in simpler ways, adapt product recommendations to customer needs, develop alternative service responses, or suggest improvements in service processes. Previous studies suggest that AI can support creativity by expanding access to knowledge, facilitating idea generation, and assisting employees in exploring alternative solutions (Grilli & Pedota, 2024; Hajj et al., 2025; Jia et al., 2024; Lee & Chung, 2024). However, the relationship between AI use and creativity should be interpreted cautiously because AI-generated ideas do not automatically become useful workplace behavior.

The creative value associated with Generative AI Use may vary according to employees' ability to evaluate and contextualize AI-generated input. AI tools may provide suggestions, examples, and alternative responses, but employees still need to judge whether these outputs are accurate, relevant, and suitable for specific workplace situations. This is especially important in electronic retail, where employees must translate technical product knowledge into customer-relevant explanations and practical recommendations. Prior studies have shown that creativity in service and digital work settings requires not only access to ideas, but also adaptive capability, experimentation, and contextual judgment (Byron et al., 2023; Cai et al., 2020; Fischer et al., 2019; Slåtten, 2014; Vredenburg et al., 2024). Therefore, Generative AI Use may provide access to creative resources, while the usefulness of those resources may be associated with how employees evaluate and apply AI-supported knowledge.

Learning Agility is therefore expected to be positively related to Workplace Creativity. Employees with higher Learning Agility are more likely to learn from experience, seek feedback, and adjust their work approaches when facing changing conditions. These behaviors support cognitive flexibility and divergent thinking, which are important foundations for creative behavior (Bouland-van Dam et al., 2022; Jo & Hong, 2022). Learning-agile employees are also more capable of identifying weaknesses in existing solutions and experimenting with alternative approaches. Such reflective and experimental behavior is closely related to workplace creativity because creative ideas usually develop through trial, feedback, refinement, and application (Boerma et al., 2025; Bojinov & Gupta, 2022; Dhanpat, 2025; Mathafena & Grobler, 2020).

The indirect role of Learning Agility is central to the present study. Generative AI tools may provide employees with ideas, explanations, feedback, and alternative approaches to work-related problems. However, access to these resources does not necessarily correspond with creative work behavior. The proposed model therefore examines whether Generative AI Use has a statistically significant indirect association with Workplace Creativity through Learning Agility. In this specification, employees reporting more intensive Generative AI Use are expected to report higher Learning Agility, which is in turn expected to be associated with greater Workplace Creativity. This pattern is theoretically consistent with research emphasizing self-regulated learning and metacognitive engagement in AI-supported learning environments (Ouyang, 2025; Tomisu et al., 2025). Nevertheless, the proposed indirect relationship should not be interpreted as proof of a causal transformation process.

Taken together, previous research suggests that generative AI tools provide informational and learning resources within the digital work environment, whereas employees differ in how actively they engage with those resources. The focal Generative AI Use construct captures this behavioral engagement through the frequency, breadth, and depth of workplace-related use. Within the SCT framework, AI-enabled resources belong to the environmental context, Generative AI Use

Source: Authors' work (2026).

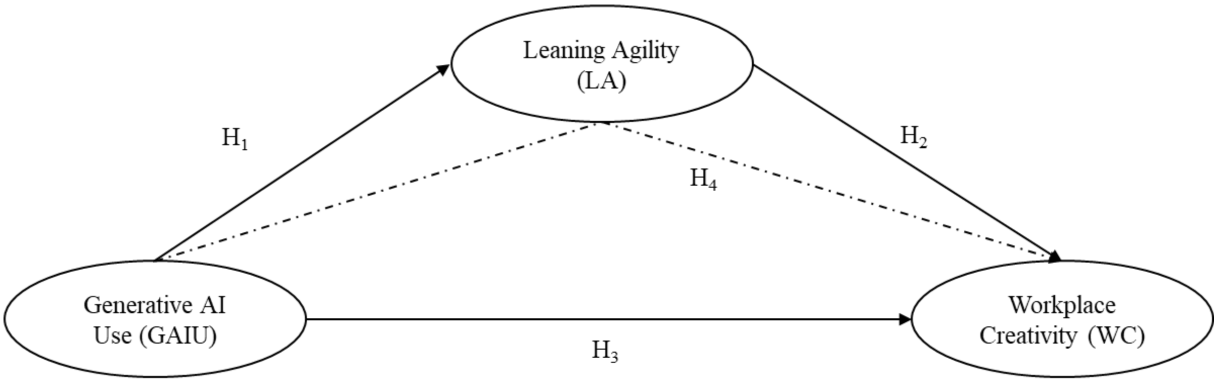


**Figure 1.** Conceptual model

reflects employees' interaction with that context, Learning Agility represents a personal adaptive factor, and Workplace Creativity represents a subsequent work-related behavior. Accordingly, the model proposes that greater engagement with generative AI resources is associated with Workplace Creativity both directly and indirectly through Learning Agility. This specification represents a directional application of SCT and does not claim to test the full reciprocal relationship among environment, personal factors, and behavior.

This theoretical reasoning is particularly relevant to Indonesia's electronic retail sector. Employees in this sector frequently respond to changing product information, customer preferences, and service expectations under time pressure. Generative AI tools may provide information and alternative responses that employees can consider during customer interactions. At the same time, employees with stronger Learning Agility may be more inclined to evaluate, adapt, and transfer AI-supported information across different work situations. The present model therefore examines Learning Agility as an indirect statistical pathway between Generative AI Use and Workplace Creativity, rather than as a necessary condition that causally determines whether AI use produces creative behavior.

Therefore, the present study addresses the research gap by examining the statistical relationships among Generative AI Use, Learning Agility, and Workplace Creativity among electronic retail employees in Indonesia. Specifically, this study investigates whether Generative AI Use is associated with Workplace Creativity and whether a statistically significant indirect association exists through Learning Agility. Based on the literature review and SCT-based reasoning, the following hypotheses are proposed:

*H1:* *Generative AI use is positively associated with Learning Agility.*

*H2:* *Learning Agility is positively associated with Workplace Creativity.*

*H3:* *Generative AI use is positively associated with Workplace Creativity.*

*H4:* *Generative AI use for workplace learning has a positive indirect association with Workplace Creativity through Learning Agility.*

The proposed model positions Generative AI Use for workplace learning as the predictor, Workplace Creativity as the outcome, and Learning Agility as the mediating construct. Within the broader SCT framework, generative AI tools and their learning affordances form part of the digital work environment. The measured Generative AI Use construct represents employees' behavioral engagement with those environmental resources, while Learning Agility represents a personal adaptive capacity and Workplace Creativity represents a work-related behavioral outcome. The model therefore examines whether engagement with generative AI resources is associated with Workplace Creativity directly and indirectly through Learning Agility.


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# 2. METHODOLOGY

## 2.1. Research design

This study employed a quantitative cross-sectional survey design to examine the relationships among Generative AI Use, Learning Agility, and Workplace Creativity. A survey design was considered appropriate because the study aimed to measure employees' perceptions and behavioral tendencies related to AI-supported learning and creativity in the workplace. The research model was tested using covariance-based structural equation modeling (CB-SEM), which allows simultaneous assessment of the measurement model and the structural relationships among latent constructs.

## 2.2. Population and sample

The population of this study consisted of employees working in Indonesia's electronic retail sector. Respondents were selected using purposive sampling because the study required participants who had direct experience using generative AI platforms for learning or work support. The inclusion criteria were:

a) currently working in electronic retail;

b) having direct involvement in store operations, sales, customer service, product explanation, or related retail activities; and

c) having used generative AI tools such as AI chatbots or AI-based learning platforms to support work-related learning or problem solving.

A sample size of 200-500 is commonly regarded as a reasonable benchmark for estimating moderately complex CB-SEM models, particularly when indicators have acceptable reliability, factor loadings are sufficiently strong, and the data do not exhibit severe distributional problems (Kline, 2023). Nevertheless, sample-size requirements are not universal because they depend on model complexity, the number of estimated parameters, factor loadings, path coefficients, missing data, and the estimation method employed (Jackson, 2003; Wolf et al., 2013).

## 2.3. Measurement

Data were collected using a structured questionnaire adapted from previously validated instruments. All items were measured using a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. Table 1 shows that Generative AI Use (GAIU) was measured using eight items reflecting frequency, feature breadth, and depth of AI use, adapted from Burton-Jones and Straub (2006), Doll and Torkzadeh (1998), and Venkatesh et al. (2012). Learning Agility (LA) was measured using eighteen items covering growth orientation, feedback seeking, and systematic development, adapted from Bouland-van Dam et al. (2022). Workplace Creativity (WC) was measured using thirteen items representing creative work behavior, adapted from Zhou and George (2001). The items were adjusted to the context of electronic retail and AI-supported workplace learning while preserving the conceptual meaning of the original scales.

The measurement model distinguishes between first-order and second-order constructs based on the conceptual structure of each variable. Learning Agility was specified as a reflective second-order construct because it represents a broad adaptive learning capability manifested through three related but conceptually distinguishable first-order dimensions: Developing Leadership/

**Table 1.** Variable measurement

| Variable | Indicators | Item | Source |
|---|---|---|---|
| Generative AI Use (GAIU) | Frequency, feature breadth, and depth of use | 8 | Burton-Jones and Straub (2006), Doll and Torkzadeh (1998), Venkatesh et al. (2012) |
| Learning Agility (LA) | Developing leadership, seeking feedback, and developing systematically | 18 | Bouland-van Dam et al. (2022) |
| Workplace Creativity (WC) | Unidimensional creative work behavior | 13 | Zhou and George (2001) |

Source: Authors' work (2026).

Growth, Seeking Feedback, and Developing Systematically. The 18-item scale developed by Bouland-van Dam et al. (2022) was designed to capture these interconnected aspects of Learning Agility. Modeling Learning Agility at the second-order level preserves the specific meaning of each dimension while allowing the structural model to examine employees' overall adaptive learning capacity. This specification is consistent with multidimensional construct theory, which recommends a higher-order representation when several distinct dimensions reflect a broader theoretical concept (Edwards, 2001; Law et al., 1998).

Generative AI Use was modeled as a first-order construct. In this study, the term refers operationally to the use of generative AI tools for workplace learning and job-related support rather than to formal intelligent tutoring systems. The construct does not measure the availability, technical quality, or organizational provision of generative AI as environmental conditions. Instead, it measures employees' enacted use of these resources. Accordingly, its theoretical role is defined as behavioral engagement with an AI-enabled learning environment rather than as the environmental factor itself. Frequency, feature breadth, and depth of use were treated as content domains used to develop the eight indicators, rather than as separate latent dimensions. Burton-Jones and Straub (2006) argued that system usage should be conceptualized according to the nature and extent of users' interactions with a system in a specific nomological context. Similarly, Doll and Torkzadeh (1998) demonstrated that system use can be captured through multiple activities reflecting how extensively technology is employed in organizational work, while Venkatesh et al. (2012) positioned technology-use behavior as an overall behavioral construct. Accordingly, the indicators were specified as reflective manifestations of the overall intensity of Generative AI Use for workplace learning, expressed through frequency, feature breadth, and depth of interaction. A first-order reflective specification is appropriate when indicators are viewed as observable consequences of the same latent construct and are expected to covary (Jarvis et al., 2003).

Workplace creativity was also modeled as a first-order reflective construct. Zhou and George (2001) conceptualized employee creativity as an integrated work behavior involving the generation, expression, and application of ideas that are both novel and useful. Although the 13 items describe different manifestations of creative behavior, such as identifying opportunities, proposing new approaches, and developing practical solutions, they do not represent independent dimensions. Instead, they reflect a common underlying tendency to behave creatively at work. Therefore, treating workplace creativity as a single first-order latent variable is theoretically consistent with the original scale and with reflective measurement principles, under which variation in the latent construct is expected to produce corresponding variation across its observed indicators (Jarvis et al., 2003; Zhou & George, 2001).

Overall, the measurement specification balances conceptual breadth and model parsimony. Learning Agility is represented as a second-order construct because its three dimensions capture distinguishable components of a broader adaptive learning capability. In contrast, Generative AI Use and Workplace Creativity are treated as first-order constructs because their indicators are intended to represent unified patterns of technology-use behavior and creative work behavior, respectively. The appropriateness of these specifications was subsequently evaluated through confirmatory factor analysis, standardized factor loadings, internal consistency reliability, and Average Variance Extracted.

## 2.4. Data collection procedure

The questionnaire was distributed online to employees who met the screening criteria. Before completing the questionnaire, respondents were informed about the purpose of the study, the voluntary nature of participation, and the anonymity of their responses. No personally identifiable information was collected. Respondents provided informed consent electronically before proceeding to the survey. The collected data were used only for academic purposes and analyzed in aggregate form.

## 2.5. Data analysis

Data analysis comprised four stages. First, common method bias was assessed using Harman's single-factor test because all variables came from


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one self-report questionnaire. All items were entered into an unrotated principal component analysis. Common method bias was considered unlikely to be serious when the first factor explained less than 50% of total variance. This test was interpreted alongside controls, including anonymity, voluntary participation, neutral wording, and separation of predictor, mediator, and outcome items.

Second, the measurement model was evaluated through standardized factor loading, Cronbach's Alpha, and Average Variance Extracted. Indicators were considered valid when standardized loadings exceeded 0.70. Internal consistency was acceptable when Cronbach's Alpha was at least 0.70, while convergent validity was supported when AVE exceeded 0.50. Generative AI Use and Workplace Creativity were modeled as first-order constructs. Learning Agility was modeled as a second-order construct consisting of Developing Leadership/Growth, Seeking Feedback, and Developing Systematically.

Third, overall model fit was assessed using Chi-square, degrees of freedom, probability value, CMIN/DF, GFI, AGFI, RMSEA, TLI, and CFI. Chi-square was interpreted cautiously because it is sensitive to sample size and model complexity. A CMIN/DF below 3.00 indicated acceptable fit. GFI and AGFI of at least 0.90 were preferred. RMSEA values below 0.08 indicated acceptable fit and values below 0.05 indicated close fit. TLI and CFI values above 0.90 were considered acceptable.

Data analysis was conducted using IBM SPSS Statistics version 26 and IBM SPSS AMOS version 22. IBM SPSS Statistics 26 was used to assess potential common method bias through Harman's single-factor test, in which all measurement items were entered simultaneously into an unrotated principal component analysis. The remaining analyses, including confirmatory factor analysis, measurement model evaluation, overall model-fit assessment, structural path testing, and mediation analysis, were performed using SPSS AMOS 22. Model parameters were estimated using the maximum likelihood estimation method. The significance of the indirect relationship between Generative AI Use and Workplace Creativity through Learning Agility was assessed using bias-corrected bootstrapping with 5,000 resamples and a 95% confidence interval. An indirect relationship was considered statistically significant when the bootstrap confidence interval did not include zero. The structural coefficients reported in the hypotheses-testing tables are standardized estimates, together with their standard errors, critical ratios, and p-values. Standardized estimates were used to evaluate factor loadings and to compare the relative strength of relationships among constructs.

# 3. RESULTS

## 3.1. Respondent demographic profile

Table 2 presents the demographic and professional characteristics of 286 respondents. Male employees represented 65.0% of the sample, while female employees accounted for 35.0%. The respondents were predominantly young, with 54.9% aged between 20 and 26 years and 35.0% aged between 27 and 32 years. Only 10.1% were older than 32 years. Regarding educational background, 60.1% had completed senior high school, 30.1% held a diploma, and 9.8% held a Bachelor's degree.

Most respondents worked in frontline positions. Sales employees represented 75.2% of the sample, while cashiers and supervisors or managers each accounted for 10.1%. Back-office employees represented the remaining 4.5%. In terms of work experience, 39.9% had worked for less than one year and 35.0% had between one and three years of experience. Therefore, 74.9% of the respondents had no more than three years of work experience.

The respondents also reported relatively frequent use of AI at work. Half of the sample used AI daily, while 35.0% used it several times per week. A further 10.0% used AI weekly, and only 5.0% used it less than once per week. Geographically, 80.1% of respondents worked in Jakarta, 15.0% in Tangerang, and 4.9% in Depok. Regarding the main AI tool used, 75.2% reported using Gemini/Google Cloud AI, 19.9% used ChatGPT, and 4.9% used other platforms. Overall, the sample primarily represented young, early-career frontline employees who used AI frequently in their workplace activities.

**Table 2.** Respondent characteristics

Source: Authors' work (2026).

| Characteristics | Category | Frequency | Percentage |
|---|---|---|---|
| Gender | Male | 186 | 65.00% |
| | Female | 100 | 35.00% |
| Age | 20-26 years | 157 | 54.90% |
| | 27-32 years | 100 | 35.00% |
| | > 32 years | 29 | 10.10% |
| Education | Senior high school | 172 | 60.10% |
| | Diploma | 86 | 30.10% |
| | Bachelor's degree | 28 | 9.80% |
| Position | Sales | 215 | 75.20% |
| | Cashier | 29 | 10.10% |
| | Supervisor/manager | 29 | 10.10% |
| | Back office | 13 | 4.50% |
| Work experience | < 1 year | 114 | 39.90% |
| | 1-3 years | 100 | 35.00% |
| | 3-5 years | 43 | 15.00% |
| | > 5 years | 29 | 10.10% |
| AI usage at work | Daily | 143 | 50.00% |
| | Several times per week | 100 | 35.00% |
| | Weekly | 29 | 10.00% |
| | Less than weekly | 14 | 5.00% |
| Location | Jakarta | 229 | 80.10% |
| | Tangerang | 43 | 15.00% |
| | Depok | 14 | 4.90% |
| Main AI tool | ChatGPT | 57 | 19.90% |
| | Gemini/Google Cloud AI | 215 | 75.20% |
| | Others | 14 | 4.90% |

## 3.2. Common method bias

Common method bias was assessed using Harman's single-factor test because all study variables were collected from the same respondents through a single questionnaire at one point in time. All 39 measurement items were entered simultaneously into an unrotated principal component analysis. The results showed that the first extracted component had an eigenvalue of 17.536 and explained 44.965% of the total variance. Because this proportion was below the conventional threshold of 50%, no single factor accounted for the majority of the variance in the observed indicators (Fuller et al., 2016). This finding suggests that common method variance was unlikely to dominate the relationships among Generative AI Use, Learning Agility, and Workplace Creativity.

## 3.3. Measurement model

Table 3 presents the results of the validity and reliability assessment for the first-order and second-order constructs. All standardized factor loadings exceeded the recommended minimum value of 0.70, indicating satisfactory indicator reliability and convergent validity. For Generative AI Use, the loading factors ranged from 0.711 to 0.780, with GAIU1 showing the highest loading and GAIU5 the lowest. Although GAIU5 had the smallest loading, its value remained above the acceptable threshold, meaning that all eight indicators adequately represented the GAIU construct. Workplace Creativity also demonstrated satisfactory indicator reliability, with standardized loadings ranging from 0.713 to 0.807. WC10 had the strongest contribution to the construct, whereas WC1 showed the lowest loading. Since all WC indicators exceeded 0.70, no indicator needed to be removed based on factor loading.

Learning Agility was modeled as a second-order construct consisting of Developing Leadership/Growth, Seeking Feedback, and Developing Systematically. The three first-order dimensions loaded strongly on the higher-order Learning



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**Table 3.** Convergent validity and reliability test

Source: Authors' work (2026).

| Construct | Measurement order | Dimension/indicator | Standardized factor loading | Cronbach's Alpha | AVE |
|---|---|---|---|---|---|
| Generative AI Use (GAIU) | First order | GAIU1 | 0.780 | 0.905 | 0.566 |
| | | GAIU2 | 0.754 | | |
| | | GAIU3 | 0.750 | | |
| | | GAIU4 | 0.751 | | |
| | | GAIU5 | 0.711 | | |
| | | GAIU6 | 0.747 | | |
| | | GAIU7 | 0.771 | | |
| | | GAIU8 | 0.750 | | |
| Learning Agility (LA) | Second order | Developing Leadership/ Growth (DL) | 0.861 | 0.860 | 0.747 |
| | | Seeking Feedback (SF) | 0.908 | | |
| | | Developing Systematically (DS) | 0.822 | | |
| Developing Leadership (DL) | First-order dimension of LA | LA1 | 0.794 | 0.920 | 0.620 |
| | | LA2 | 0.786 | | |
| | | LA3 | 0.778 | | |
| | | LA4 | 0.796 | | |
| | | LA5 | 0.766 | | |
| | | LA6 | 0.790 | | |
| | | LA7 | 0.788 | | |
| | | LA8 | 0.800 | | |
| Seeking Feedback (SF) | First-order dimension of LA | LA9 | 0.822 | 0.867 | 0.631 |
| | | LA10 | 0.777 | | |
| | | LA11 | 0.775 | | |
| | | LA12 | 0.798 | | |
| | | LA13 | 0.798 | | |
| Developing Systematically (DS) | First-order dimension of LA | LA14 | 0.821 | 0.886 | 0.596 |
| | | LA15 | 0.743 | | |
| | | LA16 | 0.748 | | |
| | | LA17 | 0.769 | | |
| | | LA18 | 0.777 | | |
| Workplace Creativity (WC) | First order | WC1 | 0.713 | 0.946 | 0.570 |
| | | WC2 | 0.754 | | |
| | | WC3 | 0.781 | | |
| | | WC4 | 0.732 | | |
| | | WC5 | 0.758 | | |
| | | WC6 | 0.750 | | |
| | | WC7 | 0.754 | | |
| | | WC8 | 0.763 | | |
| | | WC9 | 0.777 | | |
| | | WC10 | 0.807 | | |
| | | WC11 | 0.737 | | |
| | | WC12 | 0.722 | | |
| | | WC13 | 0.764 | | |

Agility construct, with standardized coefficients of 0.861 for DL, 0.908 for SF, and 0.822 for DS. Seeking Feedback was therefore the strongest dimension in representing Learning Agility, followed by Developing Leadership and Developing Systematically. Nevertheless, all three coefficients were substantially above 0.70, providing empirical support for the second-order specification of Learning Agility. At the first-order level, the indicators of DL had loading factors ranging from 0.766 to 0.800, SF from 0.775 to 0.822, and DS from 0.743 to 0.821. These results confirm that the items consistently represented their respective dimensions.

The reliability results also indicate satisfactory internal consistency. Cronbach's Alpha values were 0.905 for GAIU, 0.860 for the second-order Learning Agility construct, 0.920 for DL, 0.867 for SF, 0.886 for DS, and 0.946 for WC. All values exceeded the recommended threshold of 0.70, demonstrating that the indicators within each construct were internally consistent. The relatively high reliability of WC indicates excellent consistency among its indicators, while remaining below the level commonly associated with excessive item redundancy.

Convergent validity was further supported by the Average Variance Extracted values. The AVE values were 0.566 for GAIU, 0.747 for second-order LA, 0.620 for DL, 0.631 for SF, 0.596 for DS, and 0.570 for WC. Since all AVE values exceeded 0.50, each construct explained more than half of the variance in its indicators. The AVE of 0.747 for Learning Agility also confirms that the three dimensions share a substantial amount of variance in representing the higher-order construct. Overall, the results demonstrate that the measurement model satisfies the requirements for indicator reliability, internal consistency, and convergent validity. Therefore, the constructs are considered valid and reliable for subsequent structural model testing.

**Table 4.** Discriminant validity of first-order constructs

Source: Authors' work (2026).

| Construct | GAIU | DL | SF | DS | WC |
|---|---|---|---|---|---|
| GAIU | 0.752 | 0.609 | 0.653 | 0.644 | 0.716 |
| DL | 0.630 | 0.788 | 0.788 | 0.717 | 0.616 |
| SF | 0.664 | 0.782 | 0.794 | 0.733 | 0.691 |
| DS | 0.601 | 0.708 | 0.747 | 0.772 | 0.598 |
| WC | 0.717 | 0.635 | 0.670 | 0.606 | 0.755 |

Discriminant validity was assessed using the heterotrait-monotrait ratio of correlations and the Fornell-Larcker criterion. To present the findings concisely, the square roots of AVE are reported on the diagonal, inter construct correlations are presented below the diagonal, and HTMT ratios are shown above the diagonal. Table 4 shows that at the first-order level, HTMT values ranged from 0.598 to 0.788, remaining below the conservative threshold of 0.85. The highest HTMT value was observed between Developing Leadership/Growth and Seeking Feedback. This relatively strong association was theoretically reasonable because both are related dimensions of the higher-order Learning Agility construct.

**Table 5.** Discriminant validity of second-order constructs

Source: Authors' work (2026).

| Construct | GAIU | LA | WC |
|---|---|---|---|
| GAIU | 0.752 | 0.735 | 0.716 |
| LA | 0.731 | 0.864 | 0.735 |
| WC | 0.717 | 0.737 | 0.755 |

The Fornell-Larcker results also supported first-order discriminant validity because the square root of the AVE for each construct exceeded its correlations with the other constructs. Although the correlation between Developing Leadership/Growth and Seeking Feedback was relatively high at 0.782, it remained below their respective square roots of AVE of 0.788 and 0.794.

Table 5 shows that at the second-order level, the HTMT values were 0.735 between Generative AI Use and Learning Agility, 0.716 between Generative AI Use and Workplace Creativity, and 0.735 between Learning Agility and Workplace Creativity. Bias-corrected bootstrapping with 5,000 resamples further indicated that none of the 95% confidence intervals included 1.00. The Fornell-Larcker criterion was also satisfied because the square roots of AVE for Generative AI Use, Learning Agility, and Workplace Creativity exceeded all corresponding inter construct correlations. Overall, both assessment methods supported the discriminant validity of the first-order dimensions and the second-order constructs.

## 3.4. Goodness-of-fit

Table 6 indicates that the proposed model demonstrates an overall acceptable to good fit with the empirical data. The Chi-square value was 1,032.893 with 696 degrees of freedom and a statistically significant probability value of less than 0.001. Although a non-significant Chi-square is conventionally preferred, this statistic is highly sensitive to sample size and model complexity. Therefore, the Chi-square result should not be interpreted independently but should be evaluated together with other fit indices. The normed Chi-square value, represented by CMIN/DF, was


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**Table 6.** Goodness-of-fit

Source: Authors' work (2026).

| Index | Value | Cut-off | Evaluation | Source |
|---|---|---|---|---|
| Chi-square ($\chi^2$) | 1,032.893 | Smaller value is preferred | Significant, interpreted with other indices | Hair et al. (2019), Hu and Bentler (1999) |
| Degrees of freedom (df) | 696 | Descriptive information | Adequate | |
| Probability value | < 0.001 | > 0.05 | Not fulfilled | |
| Normed Chi-square (CMIN/DF) | 1.484 | ≤ 3.00 | Good fit | |
| Goodness-of-Fit Index (GFI) | 0.852 | ≥ 0.90 | Marginal fit | |
| Adjusted Goodness-of-Fit Index (AGFI) | 0.834 | ≥ 0.90 | Marginal fit | |
| Root Mean Square Error of Approximation (RMSEA) | 0.041 | ≤ 0.08 | Good fit | |
| Tucker-Lewis Index (TLI) | 0.952 | ≥ 0.90 | Good fit | |
| Comparative Fit Index (CFI) | 0.955 | ≥ 0.90 | Good fit | |

1.484, which is below the recommended threshold of 3.00. This result indicates that the discrepancy between the observed covariance matrix and the model-implied covariance matrix remains within an acceptable range.

The Root Mean Square Error of Approximation value was 0.041, which is below the commonly recommended threshold of 0.08 and also below the more stringent criterion of 0.05. This finding indicates a close approximate fit and suggests that the model has a relatively low level of specification error. The incremental fit indices also demonstrated satisfactory results. The Tucker-Lewis Index was 0.952 and the Comparative Fit Index was 0.955, both exceeding the recommended threshold of 0.90 and the stricter benchmark of 0.95. These values show that the proposed model provides a substantially better representation of the data than the baseline independence model.

However, the Goodness-of-Fit Index of 0.852 and the Adjusted Goodness-of-Fit Index of 0.834 remained below the conventional threshold of 0.90. These indices therefore indicate marginal fit and suggest that the model does not achieve uniformly strong fit across all evaluation criteria. Nevertheless, GFI and AGFI are sensitive to sample size, the number of indicators, and model complexity. Considering the satisfactory CMIN/DF, low RMSEA, and strong TLI and CFI values, the model can be classified as having an acceptable to good overall fit.

Table 7 shows that Generative AI Use was positively and significantly associated with Learning Agility, with a standardized coefficient of 0.738, a critical ratio of 9.625, and a p-value below 0.001. Thus, *H1* was supported. This result indicates that employees reporting more intensive use of generative AI for workplace learning also tended to report higher levels of learning agility. The relatively large critical ratio suggests that this relationship was estimated with considerable statistical precision.

Learning Agility was also positively and significantly associated with Workplace Creativity. The coefficient was 0.484, with a critical ratio of 5.531 and a p-value below 0.001, supporting *H2*. This finding suggests that employees who were more capable of learning from experience, seeking feedback, and systematically adapting their development were also more likely to demonstrate creative behavior in the workplace.

The direct relationship between Generative AI Use and Workplace Creativity was positive and statistically significant, with a coefficient of 0.408, a

**Table 7.** Direct relationships

Source: Authors' work (2026).

| Hypothesis | Structural relationship | Standardized estimate (β) | Standard error | Critical ratio | p-value | Decision |
|---|---|---|---|---|---|---|
| *H1* | GAIU → LA | 0.738 | 0.077 | 9.625 | < 0.001 | Supported |
| *H2* | LA → WC | 0.484 | 0.088 | 5.531 | < 0.001 | Supported |
| *H3* | GAIU → WC | 0.408 | 0.083 | 4.907 | < 0.001 | Supported |

**Table 8.** Direct relationship

Source: Authors' work (2026).

| Hypothesis/indirect relationship | BC 95% CI lower bound | BC 95% CI upper bound | p-value | Decision |
|---|---|---|---|---|
| *H4*: GAIU → LA → WC | 0.179 | 0.509 | 0.002 | Supported |

critical ratio of 4.907, and a p-value below 0.001. Therefore, H3 was supported. Generative AI Use retained a positive and statistically significant direct relationship with Workplace Creativity after Learning Agility was included in the structural model.

Table 8 shows that the indirect relationship between GAIU and Workplace Creativity through Learning Agility was statistically significant. The bias-corrected 95% confidence interval ranged from 0.179 to 0.509, and the p-value was 0.002. Because the confidence interval did not include zero, *H4* was supported. This result provides bootstrap-based evidence of a statistically significant indirect association between Generative AI Use and Workplace Creativity through Learning Agility. Given the cross-sectional design, the finding represents a pattern consistent with mediation rather than evidence of a definitive causal mechanism.

The findings are consistent with complementary partial mediation because both the direct relationship between GAIU and Workplace Creativity and the indirect relationship through Learning Agility were positive and statistically significant. Generative AI Use was therefore statistically related to Workplace Creativity through two pathways: a direct relationship with creative work behavior and an indirect association through Learning Agility. This interpretation describes the pattern observed in the structural model without establishing temporal or causal ordering among the constructs.

Substantively, the findings suggest that Generative AI Use may be associated with employees' access to cognitive resources for idea exploration and problem solving. Learning agility represents an additional statistical pathway linking Generative AI Use with Workplace Creativity, as employees reporting greater Learning Agility may also be more inclined to reflect on, adapt, and transfer AI-supported knowledge across work situations. Because the study uses cross-sectional data, these findings should be interpreted as direct and indirect statistical associations rather than as evidence that Generative AI Use or Learning Agility causally produces Workplace Creativity.

# 4. DISCUSSION

The positive and statistically significant association between Generative AI Use and Learning Agility indicates that employees who reported more intensive use of generative AI for workplace learning also tended to report stronger adaptive learning capabilities. This finding is particularly relevant in electronic retail, where employees regularly encounter product updates, technical comparisons, changing customer preferences, and situational service demands. Generative AI tools may provide accessible explanations, alternative responses, and product-related scenarios that employees can use as learning resources during their daily work. The observed relationship is consistent with Rigolizzo and Zhu (2020), who emphasized the importance of reflection and awareness in workplace learning.

The finding is also consistent with the view that Learning Agility involves repeated engagement with experience, feedback, and adjustment. Employees who use generative AI more extensively may have greater opportunities to compare alternative explanations, question their initial understanding, and consider different responses to workplace problems. Such activities correspond with the adaptive and experimental characteristics of Learning Agility described by DeRue et al. (2012) and Wolor et al. (2025). In electronic retail, this association is particularly meaningful because employees often need to transfer knowledge acquired from one customer interaction to another. The result also aligns with Bobrowicz and Thibaut (2023), who highlighted the importance of flexible problem solving when individuals encounter changing or unfamiliar situations.


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From the perspective of Social Cognitive Theory, the association between Generative AI Use and Learning Agility can be interpreted as a relationship between employees' engagement with a technology-enabled learning environment and their personal adaptive capacity. Generative AI tools provide environmental resources in the form of explanations, examples, feedback, and possible solutions, whereas the measured usage construct reflects how actively employees engage with these resources. Employees reporting broader and deeper use also reported stronger tendencies to seek feedback, reflect on experience, and develop systematically. However, the cross-sectional design does not establish whether Generative AI Use precedes the development of Learning Agility, whether learning-agile employees are more likely to use AI intensively, or whether both processes occur reciprocally.

The positive and statistically significant direct association between Generative AI Use and Workplace Creativity indicates that employees who reported more intensive use of generative AI for workplace learning also tended to report higher levels of creative work behavior, even after Learning Agility was included in the model. In electronic retail, generative AI tools may expand employees' access to product information, alternative explanations, customer-response scenarios, and possible solutions to service problems. These resources may be associated with employees' ability to generate useful ideas, adapt product recommendations, and consider different ways of responding to customer needs.

This finding is consistent with Jia et al. (2024), who demonstrated that artificial intelligence can augment employee creativity when workers actively integrate AI-generated information into their tasks. It also aligns with Lee and Chung (2024), who found that interaction with generative AI can be associated with creative performance by expanding the range of ideas considered during problem solving. The present result suggests that Generative AI Use is relevant not only as a source of information but also as a resource that employees may draw upon when developing alternative approaches to work-related situations.

Nevertheless, the significant association should not be interpreted as evidence that generative AI automatically produces creative behavior. AI-generated content still requires human evaluation, contextual judgment, and adjustment before it can be applied in customer-facing work. In electronic retail, an explanation that appears technically correct may not necessarily suit a customer's level of understanding, budget, or immediate needs. The findings are therefore consistent with Vredenburg et al. (2024), who emphasized the importance of employee improvisation and contextual adaptation in creating value during service encounters. Generative AI Use may provide greater access to creative resources, but the usefulness of those resources remains associated with how employees interpret and apply them in specific work situations.

The positive and statistically significant association between Learning Agility and Workplace Creativity indicates that employees who reported stronger tendencies to learn from experience, seek feedback, and adapt systematically also tended to report higher levels of creative behavior. This relationship is particularly relevant in electronic retail because creativity often appears through practical service behaviors, such as explaining technical features more clearly, adjusting recommendations to customer preferences, or proposing alternative solutions when standard approaches are ineffective.

Learning-agile employees may be more willing to question existing routines, consider feedback, and revise their approaches when workplace conditions change. These tendencies correspond with the cognitive flexibility and adaptive learning processes associated with creative and innovative work behavior (Bouland-van Dam et al., 2022; Jo & Hong, 2022). The result also supports the argument that experimentation and reflection are closely related to the development of useful workplace ideas. Bojinov and Gupta (2022) emphasized that experimentation allows individuals to compare alternatives and learn from outcomes, while Mathafena and Grobler (2020) linked proactive experimentation with workplace improvement.

The relationship should nevertheless be interpreted as an observed statistical association rather than as evidence that learning agility directly produces creativity. It is also plausible that employees who frequently engage in creative work become more reflective, feedback oriented, and adaptive over time. Besides, organizational conditions such as job autonomy, supervisory support, workload, and climate for creativity may be associated with both constructs. The current findings therefore support the theoretical relevance of Learning Agility to Workplace Creativity while leaving the temporal and reciprocal nature of this relationship open for future investigation.

The mediation analysis provides an important theoretical insight into how Generative AI Use for workplace learning is associated with Workplace Creativity. The results showed that both the direct relationship between Generative AI Use and Workplace Creativity and the indirect relationship through Learning Agility were positive and statistically significant. This pattern is consistent with complementary partial mediation, indicating that Generative AI Use is related to Workplace Creativity through more than one pathway. Employees may benefit directly from access to alternative ideas, explanations, and problem-solving perspectives, while Learning Agility provides an additional pathway through which AI-supported information is evaluated, adapted, and transferred into useful work practices. This interpretation is consistent with Benbya et al. (2024), who argued that generative AI can expand the cognitive resources available for knowledge and creative work, and with Jia et al. (2024), who showed that AI can augment employee creativity when workers actively integrate AI-generated input into their tasks.

The significant direct relationship suggests that Generative AI Use may be associated with creativity even after employees' Learning Agility is considered. AI tools can support idea generation, provide alternative product explanations, and help employees explore different responses to customer needs. Previous findings similarly indicate that generative AI can support creative performance by increasing access to ideas and reducing the cognitive effort required during early stages of problem solving (Lee & Chung, 2024). However, the significant indirect relationship shows that access to AI-generated information alone does not fully explain Workplace Creativity. Employees also need the capacity to reflect on feedback, question initial responses, experiment with alternatives, and apply learning across different situations. This interpretation is consistent with Ouyang (2025) and Tomisu et al. (2025), who emphasized the importance of self-regulated learning and metacognitive processes in AI-supported learning environments. Ahn (2024) also found that the value of AI-supported learning extends beyond information access when learners can apply acquired knowledge to relevant tasks.

The findings therefore suggest that Learning Agility is not the only pathway linking Generative AI Use with Workplace Creativity, but it represents an important adaptive learning pathway. Employees with stronger Learning Agility may be better able to assess the accuracy and relevance of AI-generated recommendations, modify them to suit particular customer situations, and learn from the outcomes of their application. This is especially relevant in electronic retail, where employees must translate technical product information into clear explanations and respond flexibly to diverse customer preferences. The findings are also consistent with Bouland-van Dam et al. (2022), who conceptualized Learning Agility as a multidimensional adaptive capacity involving growth orientation, feedback seeking, and systematic development.

From the perspective of Social Cognitive Theory, generative AI tools can be understood as part of the digital learning environment, while Generative AI Use reflects employees' active engagement with that environment. Learning agility represents a personal adaptive capacity associated with how employees interpret, evaluate, and apply AI-supported information, whereas workplace creativity reflects a work-related behavioral outcome associated with these environmental and personal factors. The results therefore extend the application of Social Cognitive Theory to AI-supported workplace learning by showing that Generative AI Use is statistically associated with creative behavior both directly and indirectly through Learning Agility. Nevertheless, because the study used cross-sectional data, these relationships should be interpreted as associations consistent with complementary partial mediation rather than as evidence of causal or temporally ordered processes.


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## CONCLUSION, LIMITATIONS AND IMPLICATION

This study examined the relationships among Generative AI Use for Workplace Learning, Learning Agility, and Workplace Creativity among electronic retail employees in Indonesia. The findings showed that Generative AI Use was positively associated with Learning Agility And Workplace Creativity. Learning Agility was positively associated with Workplace Creativity. Bootstrap analysis indicated a significant indirect relationship between Generative AI Use and Workplace Creativity through Learning Agility. Because both the direct and indirect relationships were significant, the findings support complementary partial mediation. Thus, Generative AI Use was related to Workplace Creativity both directly and through employees' adaptive learning capacity.

Theoretically, this study applies Social Cognitive Theory to generative AI-supported workplace learning by distinguishing between AI-enabled environmental resources and employees' use of those resources. Generative AI tools provide information, feedback, and alternative problem-solving approaches within the digital work environment, while the measured usage construct reflects employees' behavioral engagement with these resources. Learning Agility represents a personal adaptive capacity associated with how AI-supported information is evaluated and transferred across work situations, and Workplace Creativity represents a related behavioral outcome. The findings therefore demonstrate the relevance of SCT for explaining the relationships among technology-enabled learning resources, adaptive learning capacity, and creative work behavior. However, the study examines only a directional segment of the broader SCT framework and does not test reciprocal causation among environmental, personal, and behavioral factors.

Practically, electronic retail managers should not treat generative AI only as an instant-answer or productivity tool. Employees should be encouraged to use it for idea exploration, product comparison, scenario development, and customer-service problem solving. Organizations should also strengthen Learning Agility through feedback seeking, reflective questioning, experimentation, verification of AI-generated content, and learning transfer.

Several limitations should be acknowledged. All variables were measured through self-reports collected at one point in time, creating common method bias risk. Although Harman's single-factor test suggested that no single factor dominated the variance, this risk cannot be fully excluded. Besides, GFI and AGFI remained below conventional thresholds, and the Indonesian sector-specific sample limits generalizability. Future research should use longitudinal, time-lagged, or experimental designs, include supervisor or co-workers' ratings, examine contextual moderators, and test the model across industries, countries, and organizational levels.

## DECLARATIONS

The authors declare that there are no conflicts of interest.

## INFORMED CONSENT DECLARATION

Participation was voluntary and based on informed consent obtained electronically prior to the anonymous online survey. No personally identifiable information was collected, and data were analyzed only in aggregate form.

## AUTHOR CONTRIBUTIONS

Conceptualization: William Widjaja, Devi Rahnjen Wijayadne.
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# APPENDIX A

Source: Authors' work (2026).

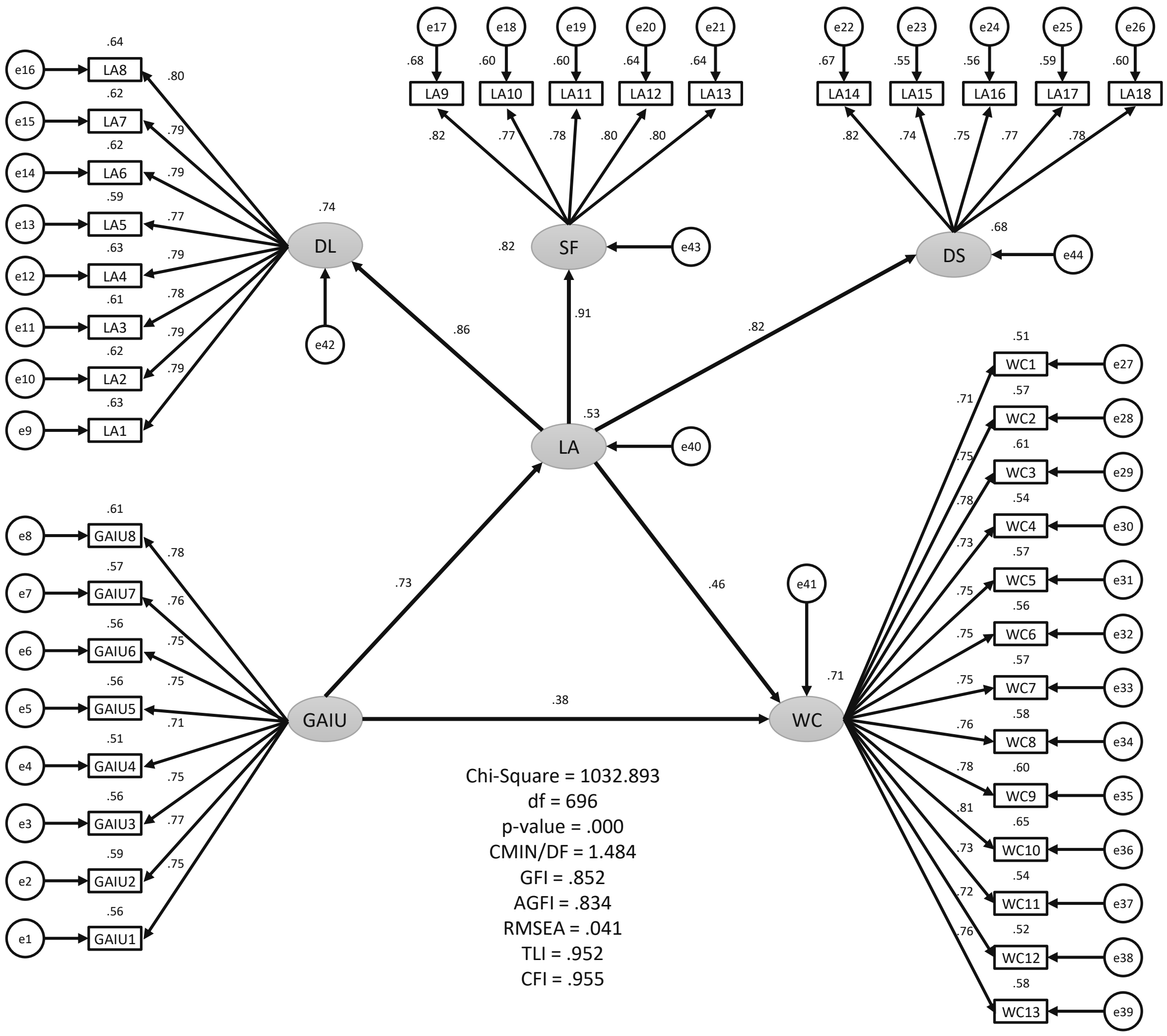


**Figure A1.** Full model


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