

HUMAN–AI COLLABORATION AND ADAPTIVE PERFORMANCE: THE MEDIATING ROLE OF AI SELF-EFFICACY AMONG INDONESIAN STARTUP EMPLOYEES

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Abstract

The growing integration of artificial intelligence into workplace activities has transformed how employees obtain information, generate ideas, solve problems, and make decisions. Nevertheless, access to artificial intelligence does not automatically improve employees' capacity to respond effectively to changes in tasks, technologies, and organizational conditions. This study examines the influence of human–AI collaboration on adaptive performance and investigates the mediating role of AI self-efficacy among Indonesian startup employees. Social Cognitive Theory is employed to explain how successful interaction with artificial intelligence can provide mastery experiences that strengthen employees' confidence in using, evaluating, and integrating artificial intelligence into their work. A quantitative explanatory design was applied using a synthetic dataset of 180 cases constructed to represent startup employees who regularly use artificial intelligence at work. The measurement model was evaluated using reliability, convergent validity, and discriminant validity criteria. The structural relationships were examined using standardized regression-based mediation analysis with 5,000 bootstrap resamples. The simulation results indicate that human–AI collaboration has a positive effect on adaptive performance ($\beta = 0.210$, $t = 3.031$, $p = 0.003$) and AI self-efficacy ($\beta = 0.548$, $t = 8.738$, $p < 0.001$). AI self-efficacy also positively affects adaptive performance ($\beta = 0.499$, $t = 7.224$, $p < 0.001$). The indirect effect of human–AI collaboration on adaptive performance through AI self-efficacy is significant ($\beta = 0.274$, $t = 6.267$, $p < 0.001$, 95% CI [0.189, 0.363]), indicating partial mediation. The model explains 30.0% of the variance in AI self-efficacy and 40.8% of the variance in adaptive performance. These findings suggest that organizations should not focus exclusively on providing AI technologies but should also develop employees' confidence and capability to use AI responsibly and effectively.

Keywords: Human–AI Collaboration, AI Self-Efficacy, Adaptive Performance, Startup Employees, Artificial Intelligence; Social Cognitive Theory

INTRODUCTION

Artificial intelligence has increasingly become embedded in organizational activities. It is no longer used exclusively to automate routine work but also to support data analysis, idea generation, forecasting, problem solving, and decision-making. This development has created a new form of work arrangement in which employees and AI systems contribute different but potentially complementary capabilities. Employees provide contextual understanding, creativity, ethical judgment, and social awareness, while AI systems provide computational speed, pattern recognition, information processing, and analytical consistency. Therefore, the organizational value of AI is not determined only by technological sophistication but also by employees' ability to interact with, evaluate, correct, and integrate AI-generated outputs into their work processes.

Human–AI collaboration differs from passive AI use. Passive use merely indicates that employees have access to or occasionally operate an AI-enabled application. Human–AI collaboration, in contrast, involves an active and reciprocal work process in which employees divide tasks with AI systems, use AI recommendations as decision inputs, assess the accuracy of AI-generated outputs, correct inappropriate recommendations, and retain responsibility for final decisions. Existing research suggests that employee–AI collaboration can influence proactive behavior and other work outcomes through changes in psychological and job-related resources.

This issue is particularly relevant to startup organizations. Startups frequently operate in environments characterized by rapid technological development, shifting customer demands, limited resources, flexible job boundaries, and continuous changes in organizational priorities. Employees may be required to perform multiple roles, learn new digital tools, adjust to changing performance targets, and solve unfamiliar problems without established procedures. Under such conditions, organizations need employees who are not only capable of performing routine tasks but are also able to adapt their behavior and competencies when workplace demands change.

The capacity to respond effectively to changing job requirements is generally referred to as adaptive performance. Adaptive performance includes the ability to manage uncertain work situations, learn new tasks and technologies, solve problems creatively, and adjust work behavior when organizational or environmental conditions change. Pulakos et al. (2000) developed a comprehensive taxonomy of adaptive performance that distinguishes adaptability from routine task performance. The original taxonomy includes handling emergencies, managing work stress, solving problems creatively, dealing with uncertainty, learning new tasks and technologies, and demonstrating interpersonal, cultural, and physical adaptability.

AI systems may support adaptive performance by helping employees obtain information quickly, identify patterns, compare alternatives, and generate potential solutions. However, AI use may also introduce cognitive and psychological demands. Employees may experience technological learning anxiety, uncertainty about AI-generated outputs, fear of replacement, overdependence on automated recommendations, or reduced confidence in their own capabilities. Research on human–AI collaboration task complexity suggests that complex collaboration can increase technology-learning anxiety, while AI self-efficacy may operate as a personal resource that reduces negative employee responses.

Consequently, the relationship between human–AI collaboration and adaptive performance may not be automatic. Providing employees with AI tools does not necessarily

mean that they can use those tools effectively when confronting new or uncertain work situations. Employees also need to believe that they are capable of understanding AI functions, producing appropriate instructions, evaluating AI-generated outputs, correcting errors, and applying AI responsibly to workplace problems. This technology-specific belief is conceptualized as AI self-efficacy.

AI self-efficacy refers to an individual's belief in their ability to use and interact effectively with AI-based technologies. Wang and Chuang (2024) developed and validated an AI self-efficacy scale consisting of four dimensions: assistance, anthropomorphic interaction, comfort with AI, and technological skills. Their work emphasizes that AI self-efficacy is broader than technical knowledge because it also incorporates confidence, comfort, interaction capability, and the ability to use AI as a task-supporting resource.

Social Cognitive Theory provides a relevant theoretical foundation for explaining the development of AI self-efficacy. Bandura (1977, 1997) proposed that self-efficacy is shaped by mastery experiences, vicarious learning, verbal persuasion, and physiological or emotional conditions. Successful experiences are generally regarded as the most influential source of self-efficacy. When employees successfully complete tasks with AI assistance, these experiences may strengthen their belief that they can use AI effectively in future tasks. In contrast, repeated failures, inaccurate AI outputs, inadequate organizational support, or a lack of employee control may weaken AI self-efficacy.

Previous studies have linked AI self-efficacy to AI adoption, use intensity, learning behavior, and employees' responses to technological change. Mah and Groß (2024), for example, found that AI self-efficacy was associated with patterns of AI use and professional development needs. However, limited research has examined AI self-efficacy as an explanatory mechanism linking human–AI collaboration with adaptive performance.

Several research gaps can therefore be identified. First, from a theoretical perspective, human–AI collaboration research has concentrated primarily on efficiency, proactive behavior, work engagement, organizational citizenship behavior, and general performance outcomes. The psychological mechanism through which collaboration with AI improves employees' ability to respond to workplace change has received comparatively limited attention.

Second, empirical findings concerning the consequences of workplace AI are not uniformly positive. AI can provide valuable informational and cognitive resources, but it may also create cognitive overload, technological anxiety, reduced task ownership, and uncertainty regarding employees' future roles. The effects of AI may therefore depend on the personal resources employees possess.

Third, a contextual gap exists because much of the existing literature has been developed in large corporations, educational institutions, hospitality organizations, or technologically advanced countries. Research specifically examining startup employees in Indonesia remains limited. The Indonesian startup environment provides a relevant setting because employees often work under high uncertainty, rapid technological change, and flexible role arrangements.

Fourth, a methodological gap exists because previous studies frequently position self-efficacy as an antecedent or moderator. Fewer studies examine whether AI self-efficacy transmits the influence of human–AI collaboration to adaptive performance.

Accordingly, this study examines the effect of human–AI collaboration on adaptive performance and evaluates AI self-efficacy as a mediating mechanism among Indonesian

startup employees. The study contributes to the literature by extending Social Cognitive Theory into the context of collaborative human–AI work and by explaining how employees’ experience of working with AI may be converted into adaptive workplace behavior.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Social Cognitive Theory

Social Cognitive Theory explains human behavior through reciprocal interactions among personal factors, behavioral patterns, and environmental conditions. Individuals are not passive recipients of environmental influences. They interpret their experiences, regulate their behavior, and influence their surroundings through their decisions and actions.

Self-efficacy is one of the central concepts within Social Cognitive Theory. It refers to an individual’s belief that they are capable of organizing and executing the actions necessary to achieve a particular outcome. Self-efficacy is task- and context-specific. An employee may have high general confidence but remain uncertain about using AI to analyze complex data, generate professional recommendations, or evaluate algorithmic outputs.

Self-efficacy influences the activities people choose, the effort they invest, their persistence when facing obstacles, and their emotional reactions to difficult tasks. Individuals with high self-efficacy are more likely to interpret demanding assignments as opportunities for learning and mastery. Conversely, those with low self-efficacy may avoid difficult tasks, reduce effort, or interpret technological change as a threat.

Bandura (1977) identified mastery experience as the strongest source of efficacy beliefs. Successful task completion strengthens the belief that similar tasks can be handled in the future. Human–AI collaboration may provide such mastery experiences when employees successfully use AI to solve problems, obtain relevant information, improve outputs, or complete unfamiliar assignments. Bandura’s foundational work on self-efficacy and his later elaboration of Social Cognitive Theory provide the theoretical basis for this proposed mechanism.

In the present study, human–AI collaboration is treated as an environmental and behavioral experience that may strengthen AI self-efficacy. AI self-efficacy is then expected to influence the way employees approach technological changes, unfamiliar assignments, and uncertain work situations.

Human–AI Collaboration

Human–AI collaboration refers to a work process in which employees and AI systems make complementary contributions toward completing tasks or achieving organizational objectives. Collaboration does not imply the elimination of human involvement. Employees remain responsible for defining objectives, interpreting context, evaluating outputs, considering ethical consequences, and making final decisions.

In practice, human–AI collaboration may include asking AI systems to analyze data, generate alternative solutions, summarize information, identify patterns, or provide recommendations. Employees subsequently compare AI outputs with their professional knowledge, identify errors, revise outputs, and integrate relevant recommendations into their work.

Effective collaboration requires an appropriate division of labor. AI is generally suited to activities involving computational speed, repetitive information processing, and large-scale pattern detection. Human employees remain essential for contextual interpretation, empathy, creativity, moral judgment, and accountability. When these capabilities are combined effectively, employees may devote more attention to learning, decision-making, and adaptive problem solving.

Sun et al. (2025) found that employee–AI collaboration could promote proactive behavior through changes in work-related resources. Bai and Zhang (2025) similarly examined how collaboration with AI could affect organizational citizenship behavior through employees' impression-management concerns. These studies demonstrate that human–AI collaboration may influence employee outcomes through both task-related and psychological mechanisms.

AI Self-Efficacy

AI self-efficacy is defined as an individual's confidence in their ability to understand, use, evaluate, and interact effectively with AI-based technologies. It differs from computer self-efficacy because AI systems possess characteristics such as autonomy, recommendation generation, natural-language interaction, and unpredictable or probabilistic outputs.

Wang and Chuang (2024) identified four dimensions of AI self-efficacy. The assistance dimension concerns an individual's belief that they can use AI to support task completion. Anthropomorphic interaction concerns confidence in communicating with AI systems that use human-like interfaces. Comfort with AI reflects the degree to which an individual feels calm and secure when using AI. Technological skills refer to confidence in understanding and operating AI-related features.

In workplace settings, AI self-efficacy may be reflected in employees' confidence that they can select an appropriate AI tool, construct useful prompts, evaluate output accuracy, recognize technological limitations, correct inadequate responses, and learn unfamiliar AI applications.

AI self-efficacy is not determined exclusively by technical ability. It may develop through repeated use, organizational support, observational learning, feedback, and successful task experiences. Mah and Groß (2024) found meaningful associations between AI self-efficacy and AI-use patterns, although their study was conducted in a higher-education setting. This supports the broader proposition that efficacy beliefs are related to the extent to which individuals are willing and able to engage with AI.

Adaptive Performance

Adaptive performance refers to behaviors through which employees adjust to changes in work systems, technologies, procedures, tasks, or environmental conditions. It is conceptually distinct from task performance. Task performance concerns the effective completion of established job duties, whereas adaptive performance concerns the capacity to respond when established routines are no longer sufficient.

Pulakos et al. (2000) identified eight dimensions of adaptive performance: handling emergencies, managing work stress, solving problems creatively, dealing with uncertain work situations, learning new tasks and technologies, demonstrating interpersonal adaptability, demonstrating cultural adaptability, and demonstrating physically oriented adaptability.

For startup employees, the most relevant dimensions are likely to include dealing with uncertainty, learning new technologies and procedures, solving unfamiliar problems creatively,

and adjusting behavior when work requirements change. These dimensions reflect the dynamic nature of startup employment, where employees frequently confront ambiguous responsibilities and rapidly changing technological systems.

Pulakos et al. (2002) further demonstrated that adaptability-related individual differences, including efficacy beliefs, can contribute to the prediction of adaptive performance. This supports the argument that AI-specific efficacy beliefs may influence adaptive behavior in AI-enabled workplaces.

Human–AI Collaboration and Adaptive Performance

Human–AI collaboration may improve adaptive performance by helping employees access relevant information, identify patterns, evaluate alternatives, and produce potential solutions. These capabilities become particularly valuable when employees face changes in procedures, technology, or customer expectations.

AI may also reduce the time required for repetitive administrative work and information searching. The resulting cognitive and temporal resources can then be redirected toward learning, creative problem solving, and adjustment to emerging work requirements. However, such benefits depend on employees maintaining critical oversight and using AI-generated outputs appropriately.

Previous research showing a relationship between employee–AI collaboration and proactive behavior suggests that AI collaboration may support self-initiated and change-oriented workplace behavior. Sun et al. (2025) demonstrated that collaboration with AI could enhance proactive behavior through changes in employees’ resources. Adaptive performance may represent another outcome of these enhanced informational and cognitive resources.

Accordingly, the following hypothesis is proposed:

H1: Human–AI collaboration has a positive effect on adaptive performance.

Human–AI Collaboration and AI Self-Efficacy

According to Social Cognitive Theory, successful experiences strengthen self-efficacy. When employees successfully use AI to complete tasks, improve analyses, or generate useful solutions, they obtain evidence that they can operate the technology effectively.

Repeated collaboration may also help employees understand how AI systems respond to instructions, identify their limitations, and develop appropriate strategies for evaluating outputs. This accumulated experience can reduce uncertainty and strengthen perceived control.

However, poorly designed collaboration may have the opposite effect. If employees merely receive automated outputs without understanding or evaluating them, they may not develop a sense of mastery. Excessive AI control may even reduce employees’ perceptions of task ownership and independent capability.

Assuming that human–AI collaboration is designed as augmentation rather than complete substitution, the following hypothesis is formulated:

H2: Human–AI collaboration has a positive effect on AI self-efficacy.

AI Self-Efficacy and Adaptive Performance

Employees with high AI self-efficacy are expected to be more willing to explore new AI functions, learn unfamiliar applications, and use AI to solve nonroutine problems. They are

also likely to persist when AI-generated outputs are inaccurate or when the technology is difficult to operate.

AI self-efficacy may increase employees' perceived control over technological change. When organizations introduce new AI tools or revise work procedures, employees with strong efficacy beliefs are more likely to view the change as manageable and learnable rather than threatening.

The adaptive-performance literature indicates that efficacy beliefs are relevant predictors of adaptability. Pulakos et al. (2002) found that dimension-specific efficacy measures contributed to the prediction of adaptive performance. Extending this argument to AI-enabled work suggests that confidence in using AI should improve employees' capacity to respond to changing work demands.

The following hypothesis is therefore proposed:

H3: AI self-efficacy has a positive effect on adaptive performance.

The Mediating Role of AI Self-Efficacy

Human–AI collaboration may directly provide informational and analytical resources. However, collaboration may also change how employees evaluate their own capabilities.

When collaboration produces successful work experiences, employees become more confident that they can apply AI in different situations. This confidence may increase their willingness to learn, experiment with new strategies, and persist when confronted with technological or task-related difficulties.

Thus, human–AI collaboration is expected to improve adaptive performance partly because it strengthens AI self-efficacy. This mediating mechanism is consistent with Social Cognitive Theory because environmental experiences influence behavior through changes in personal efficacy beliefs.

The following hypothesis is proposed:

H4: AI self-efficacy mediates the positive relationship between human–AI collaboration and adaptive performance.

The conceptual model is presented below:

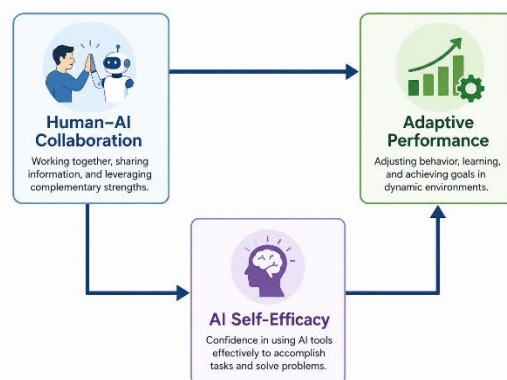


Figure. 1 The conceptual model

METHODOLOGY

Research Design

This study adopts a quantitative explanatory design to evaluate the direct and indirect relationships among human–AI collaboration, AI self-efficacy, and adaptive performance.

For manuscript-development and analytical-demonstration purposes, a synthetic dataset containing 180 cases was generated. The dataset was designed to represent Indonesian startup employees who use AI regularly in their work. The design follows a cross-sectional survey structure, although no actual respondents participated in this version of the study.

A future field study should use an online questionnaire and preferably adopt a time-lagged design. Human–AI collaboration could be measured at Time 1, AI self-efficacy at Time 2, and adaptive performance at Time 3. Temporal separation would help reduce common method bias and provide stronger support for the proposed causal sequence.

Population and Sample

The intended population consists of employees working in Indonesian startup or digitally oriented companies who use AI-based applications as part of their job activities.

The proposed respondent criteria are as follows:

1. currently employed by a startup or digital company;
2. employed by the organization for at least six months;
3. using an AI-enabled application or system at work;
4. possessing at least three months of work-related AI experience;
5. using AI at least once or twice per week; and
6. being directly involved in tasks completed with AI assistance.

Purposive sampling is recommended because not all startup employees possess relevant AI-work experience. Snowball sampling may be used as an additional strategy through startup communities, professional networks, incubators, and digital-industry associations. The original methodological draft recommends a target of approximately 150–200 valid respondents.

The dataset contains 180 cases, which falls within the proposed sampling range.

Measurement

All indicators were represented using a seven-point Likert scale ranging from 1, “strongly disagree,” to 7, “strongly agree.”

Human–AI Collaboration

Human–AI collaboration was represented by five indicators covering complementary contributions, the use of AI outputs in decision-making, output verification, task allocation according to AI capabilities, and the integration of AI recommendations with professional judgment.

Representative items included:

1. The AI system and I make complementary contributions to completing my work.
2. I use AI-generated outputs as inputs when making work-related decisions.

3. I examine and revise AI-generated outputs before using them.
4. The AI system supports the parts of my work that are suited to its capabilities.
5. I integrate AI recommendations with my professional knowledge and judgment.

AI Self-Efficacy

AI self-efficacy was represented by six indicators adapted conceptually from the scale developed by Wang and Chuang (2024). Their original scale contains 22 items across four dimensions.

Representative items included:

1. I am confident that I can use AI to support my work.
2. I can learn new AI functions required for my job.
3. I can provide appropriate instructions or prompts to an AI system.
4. I can evaluate whether an AI-generated output is reliable.
5. I can revise an AI-generated output when it is inappropriate.
6. I remain comfortable when using AI for complex tasks.

Adaptive Performance

Adaptive performance was represented by six indicators based on the adaptive-performance taxonomy developed by Pulakos et al. (2000).

Representative items included:

1. I can adjust my work methods when job requirements change.
2. I can work effectively in uncertain situations.
3. I quickly learn new technologies or work procedures.
4. I develop creative solutions to unfamiliar problems.
5. I can change my priorities when working conditions change.
6. I can remain effective when the available information is incomplete.

Instrument Adaptation for a Future Field Study

In a future empirical study, English-language instruments should be translated into Indonesian through translation and back-translation procedures. The translated items should be reviewed by experts in human resource management, organizational behavior, AI-enabled work, and language.

A pilot study involving approximately 30–50 employees with characteristics similar to those of the intended sample should be conducted. The pilot study should evaluate item clarity, contextual relevance, completion time, and preliminary reliability.

Data-Analysis Procedure

The analysis followed measurement-model and structural-model criteria commonly used in PLS-SEM studies. The measurement model was evaluated using indicator loadings, Cronbach's alpha, composite reliability, average variance extracted, and the heterotrait–monotrait ratio.

The structural relationships were estimated using standardized regression-based path analysis. Mediation was evaluated using 5,000 bootstrap resamples. The indirect effect was considered significant when its 95% confidence interval did not include zero.

PLS-SEM guidance emphasizes the separate assessment of measurement quality, structural relationships, explanatory power, effect sizes, predictive relevance, and indirect effects. The methodological sources identified in the uploaded document also recommend bootstrapping for estimating direct, indirect, and total effects.

RESULTS AND DISCUSSION

Results

Respondent Profile

The dataset consisted of 180 cases. Of these, 100 cases, or 55.6%, were categorized as male, and 80 cases, or 44.4%, were categorized as female.

Most respondents were between 25 and 34 years old, representing 101 cases or 56.1% of the sample. A total of 56 cases, or 31.1%, were younger than 25 years, while 23 cases, or 12.8%, were 35 years old or older.

Regarding education, 136 cases, or 75.6%, held a bachelor's degree. Twenty-four cases, or 13.3%, held a postgraduate degree, while 20 cases, or 11.1%, held a diploma.

Most cases had worked for the represented organization for one to three years. This category included 96 cases, or 53.3% of the sample. Fifty-four cases, or 30.0%, had between six and twelve months of tenure, while 30 cases, or 16.7%, had more than three years of tenure.

Table 1. Respondent Characteristics

Characteristic	Category	Frequency	Percentage
Gender	Male	100	55.6%
	Female	80	44.4%
Age	Below 25 years	56	31.1%
	25–34 years	101	56.1%
	35 years or older	23	12.8%
Education	Diploma	20	11.1%
	Bachelor's degree	136	75.6%
	Postgraduate degree	24	13.3%
Organizational tenure	6–12 months	54	30.0%
	1–3 years	96	53.3%
	More than 3 years	30	16.7%

Regarding AI-use frequency, 93 cases, or 51.7%, represented daily AI users. Fifty-eight cases, or 32.2%, represented employees using AI three to five times per week, while 29 cases, or 16.1%, represented employees using AI once or twice per week.

Generative AI assistants were the most frequently represented technology category, accounting for 84 cases or 46.7%. Analytics or prediction AI accounted for 42 cases or 23.3%, automation systems or chatbots accounted for 28 cases or 15.6%, and coding or design AI accounted for 26 cases or 14.4%.

Descriptive Statistics

Human–AI collaboration had a mean score of 4.393 and a standard deviation of 1.310. AI self-efficacy had the highest mean score at 4.548, with a standard deviation of 1.345. Adaptive performance had a mean score of 4.462 and a standard deviation of 1.299.

Table 2. Descriptive Statistics

Construct	Mean	Standard Deviation	Minimum	Maximum
Human–AI collaboration	4.393	1.310	1.000	7.000
AI self-efficacy	4.548	1.345	1.000	7.000
Adaptive performance	4.462	1.299	1.000	7.000

All three means were above the midpoint of the seven-point scale. Within the data, this indicates relatively favorable levels of collaboration with AI, confidence in using AI, and adaptive work behavior.

Measurement-Model Assessment

The indicator loadings for human–AI collaboration ranged from 0.806 to 0.843. The loadings for AI self-efficacy ranged from 0.834 to 0.889, while those for adaptive performance ranged from 0.776 to 0.866. All loadings exceeded the conventional threshold of 0.70.

Table 3. Reliability and Convergent Validity

Construct	Cronbach's Alpha	Composite Reliability	AVE	Loading Range
Human–AI collaboration	0.886	0.917	0.687	0.806–0.843
AI self-efficacy	0.922	0.939	0.720	0.834–0.889
Adaptive performance	0.906	0.928	0.682	0.776–0.866

Cronbach's alpha and composite reliability exceeded 0.70 for all constructs, indicating adequate internal consistency. Average variance extracted exceeded 0.50 for every construct, supporting convergent validity.

Discriminant validity was assessed using the heterotrait–monotrait ratio. All HTMT values were below 0.85.

Table 4. Discriminant Validity

Construct Pair	HTMT
Human–AI collaboration and AI self-efficacy	0.605
Human–AI collaboration and adaptive performance	0.538
AI self-efficacy and adaptive performance	0.673

These results indicate that the three constructs were empirically distinguishable in the measurement model.

Structural-Model Assessment

Human–AI collaboration explained 30.0% of the variance in AI self-efficacy. Human–AI collaboration and AI self-efficacy jointly explained 40.8% of the variance in adaptive performance.

The predictive-relevance value for adaptive performance was 0.385, which was greater than zero. Within the model, this indicates meaningful predictive relevance.

The effect size of human–AI collaboration on adaptive performance was 0.052, representing a small effect. The effect size of AI self-efficacy on adaptive performance was 0.295, representing a moderate-to-large effect.

Table 5. Explanatory Power and Effect Sizes

Structural Indicator	Value
R ² for AI self-efficacy	0.300
R ² for adaptive performance	0.408
f ² for human–AI collaboration on adaptive performance	0.052
f ² for AI self-efficacy on adaptive performance	0.295
Q ² for adaptive performance	0.385

Hypothesis Testing

Table 6. Direct-Effect Results

Hypothesis	Relationship	β	t-statistic	P-value	Decision
H1	Human–AI collaboration → adaptive performance	0.210	3.031	0.003	Supported
H2	Human–AI collaboration → AI self-efficacy	0.548	8.738	<0.001	Supported
H3	AI self-efficacy → adaptive performance	0.499	7.224	<0.001	Supported

Human–AI collaboration had a positive and statistically significant effect on adaptive performance. The coefficient was 0.210, with a t-statistic of 3.031 and a p-value of 0.003. H1 was therefore supported.

Human–AI collaboration also had a positive and statistically significant effect on AI self-efficacy. The coefficient was 0.548, with a t-statistic of 8.738 and a p-value below 0.001. H2 was supported.

AI self-efficacy had a positive and statistically significant effect on adaptive performance. The coefficient was 0.499, with a t-statistic of 7.224 and a p-value below 0.001. H3 was therefore supported.

Mediation Analysis

The indirect effect of human–AI collaboration on adaptive performance through AI self-efficacy was 0.274. The effect was statistically significant, with a t-statistic of 6.267 and a p-value below 0.001.

Table 7. Mediation Result

Indirect Relationship	Indirect Effect	t-statistic	p-value	95% Confidence Interval	Decision
Human–AI collaboration → AI self-efficacy → adaptive performance	0.274	6.267	<0.001	[0.189, 0.363]	Supported

The bootstrap confidence interval did not contain zero, indicating a significant indirect effect. The direct effect of human–AI collaboration on adaptive performance remained significant after AI self-efficacy was included in the model.

The total effect of human–AI collaboration on adaptive performance was 0.483. The variance accounted for was 56.6%, indicating that more than half of the total effect was transmitted through AI self-efficacy. Because both the direct and indirect effects were significant and had the same positive direction, the result represents complementary partial mediation.

Discussion

Human–AI Collaboration and Adaptive Performance

The results support the proposition that human–AI collaboration positively affects adaptive performance. Employees who effectively divide tasks with AI, evaluate AI-generated outputs, and integrate technological recommendations with professional judgment are expected to be better prepared to respond to changing work requirements.

AI collaboration may improve adaptive performance by increasing access to relevant information and reducing the time required to identify alternatives. In uncertain situations, AI can support employees by summarizing large amounts of information, identifying possible patterns, and generating preliminary solutions. Employees can subsequently interpret and modify these outputs according to the organizational context.

This relationship is particularly relevant in startup organizations. Startup employees frequently encounter changing priorities, customer demands, technological platforms, and role

expectations. Effective collaboration with AI may allow them to respond more quickly while maintaining human responsibility for interpretation and final decisions.

The finding is consistent with Sun et al. (2025), who reported that employee–AI collaboration could promote proactive behavior. Although proactive behavior and adaptive performance are distinct, both require employees to move beyond rigid execution of routine tasks and respond constructively to changing conditions.

However, the direct effect of human–AI collaboration was smaller than the effect of AI self-efficacy. This suggests that technological collaboration alone may be insufficient. Its benefits appear to depend substantially on whether collaboration strengthens employees' confidence in their ability to use AI.

Human–AI Collaboration and AI Self-Efficacy

The simulation indicates that human–AI collaboration has a strong positive effect on AI self-efficacy. This relationship is consistent with Social Cognitive Theory, particularly the role of mastery experiences in developing efficacy beliefs.

When employees successfully use AI to solve a problem, produce an analysis, or improve the quality of their work, they obtain evidence that they are capable of managing the technology. Repeated successful interaction may also help them learn how to formulate prompts, recognize inaccurate responses, and determine when AI-generated outputs should be accepted, revised, or rejected.

The result supports the view that AI self-efficacy is not simply an inherent individual characteristic. Organizations can strengthen it through appropriate work design, training, feedback, peer learning, and opportunities for safe experimentation.

Bandura's self-efficacy framework emphasizes that successful experiences strengthen perceived capability, whereas repeated failure may weaken it. Accordingly, organizations should design human–AI collaboration in ways that preserve employee involvement, decision authority, and opportunities for learning.

AI Self-Efficacy and Adaptive Performance

AI self-efficacy had the strongest direct effect on adaptive performance in the model. Employees who believe they can use AI effectively are more likely to explore unfamiliar functions, learn new systems, persist when technological difficulties occur, and apply AI to nonroutine problems.

AI self-efficacy may also reduce perceptions of threat associated with technological change. Employees with strong efficacy beliefs are more likely to interpret a new AI system as a manageable learning challenge rather than as evidence that their current skills are becoming obsolete.

This finding is consistent with the broader adaptive-performance literature. Pulakos et al. (2002) showed that efficacy-related individual differences contribute to the prediction of adaptive performance. The present model extends this reasoning by showing how AI-specific efficacy may support adaptation in technology-intensive workplaces.

Nevertheless, organizations should distinguish realistic AI self-efficacy from overconfidence. Employees who feel highly confident but lack the ability to identify hallucinations, bias, or inaccurate outputs may misuse AI. Therefore, efficacy-building

interventions should be combined with AI literacy, critical thinking, domain knowledge, and ethical-awareness training.

The Mediating Role of AI Self-Efficacy

The findings show that AI self-efficacy partially mediates the relationship between human–AI collaboration and adaptive performance. Human–AI collaboration therefore appears to operate through both direct and psychological pathways.

The direct pathway reflects the informational and cognitive resources provided by AI. Employees can use AI to accelerate information processing, compare alternatives, and generate possible responses to unfamiliar conditions.

The indirect pathway reflects changes in employees' perceptions of their own capabilities. Successful collaboration strengthens AI self-efficacy, which subsequently increases persistence, learning motivation, willingness to experiment, and perceived control during technological or task-related change.

The variance-accounted-for value of 56.6% indicates that AI self-efficacy represents a substantial mechanism in the model. However, it is not the only mechanism. Human–AI collaboration may also influence adaptive performance through learning agility, work engagement, psychological empowerment, reduced workload, perceived control, or access to knowledge.

The mediation result extends Social Cognitive Theory by positioning collaborative AI experience as a source of mastery experience. It also responds to the gap identified in the original manuscript concerning the limited use of AI self-efficacy as a mediator between human–AI collaboration and employee outcomes.

Theoretical Implications

First, the study extends Social Cognitive Theory into the context of AI-enabled work. AI systems are not merely environmental technologies; experiences of interacting with them can change employees' beliefs about their own abilities.

Second, the study contributes to the human–AI collaboration literature by treating adaptive performance as an individual outcome. Prior research has more commonly examined proactive behavior, organizational citizenship behavior, engagement, or general performance.

Third, the study positions AI self-efficacy as a mediating mechanism. This perspective helps explain why employees exposed to similar AI technologies may demonstrate different adaptive responses. The critical difference may not lie only in access to technology but in the confidence developed through collaborative experience.

Fourth, the model contributes contextually by focusing on the Indonesian startup setting. Startup environments provide a relevant context for adaptive performance because employees frequently face changing tasks, technologies, and organizational priorities.

Managerial Implications

Startup organizations should avoid implementation strategies that merely provide employees with access to AI applications. Access should be combined with training and work experiences that increase employees' capability and confidence.

AI training should use authentic workplace assignments. Employees could be asked to formulate prompts, compare alternative outputs, identify hallucinations, check sources, detect

potential bias, and revise inaccurate responses. Such activities are more likely to create mastery experiences than training that focuses only on explaining software features.

Organizations should also provide psychologically safe opportunities for experimentation. Errors made during supervised AI learning should be treated as opportunities for feedback and improvement rather than immediate evidence of poor performance.

Managers need to define clear responsibility boundaries. AI may generate analyses or recommendations, but employees should remain responsible for verification, contextual interpretation, and final decisions. Maintaining human oversight may strengthen both accountability and employees' sense of task ownership.

Human resource departments should incorporate AI literacy and AI self-efficacy into learning and development, recruitment, performance management, and job redesign. However, AI self-efficacy should not be used as a substitute for demonstrated competence. Confidence and actual ability should be developed simultaneously.

CONCLUSION

This study examined the influence of human–AI collaboration on adaptive performance and evaluated AI self-efficacy as a mediating mechanism. Using a synthetic dataset of 180 cases, the simulation showed that human–AI collaboration positively affected both adaptive performance and AI self-efficacy. AI self-efficacy also had a positive effect on adaptive performance.

The indirect-effect analysis indicated that AI self-efficacy partially mediated the relationship between human–AI collaboration and adaptive performance. Human–AI collaboration may therefore support adaptive performance directly by providing informational and analytical resources and indirectly by strengthening employees' confidence in their ability to use AI.

The model explained 30.0% of the variance in AI self-efficacy and 40.8% of the variance in adaptive performance. AI self-efficacy provided a stronger contribution to adaptive performance than the direct effect of human–AI collaboration.

The theoretical implication is that successful AI implementation depends not only on technological characteristics but also on employees' efficacy beliefs. Human–AI collaboration becomes more valuable when employees believe they can understand, evaluate, correct, and responsibly apply AI-generated outputs.

The managerial implication is that startups should combine AI adoption with experiential training, learning support, appropriate job design, and human oversight. Providing AI tools without developing employee capability and confidence may limit their contribution to adaptive performance.

The principal limitation of this manuscript is that the results are based entirely on data. The findings cannot be generalized to Indonesian startup employees and should not be presented as actual empirical evidence. A field study using real respondents is required to determine whether the proposed relationships occur in organizational practice.

Future research should collect data from startup employees in different Indonesian regions and sectors. Time-lagged or longitudinal designs should be considered to strengthen causal

inference. Supervisor-rated adaptive performance and objective performance indicators could reduce reliance on self-reported measures. Future studies may also examine AI anxiety, trust in AI, AI literacy, learning orientation, leadership support, job complexity, work engagement, or psychological empowerment as additional mediators or moderators.

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