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Unveiling the Impact of AI Utilization, Tools, and Training on Work Efficiency: A Mediation Analysis of Task Typologies

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Abstract - **Artificial Intelligence (AI) continues to be a transformative force in workplaces, not only reshaping traditional workflows but also enhancing operational efficiency. The frequency of AI usage, the complexity of AI tools, and the amount of employee training on these tools play a significant role in work effectiveness outcomes. However, its ramifications on work efficiency are not straightforward; rather, it is mediated by the nature of tasks performed, such as routine, analytical, or creative. The aim of this study is to probe how routine, analytical and creative task types mediates the application of AI usage, utilization of AI tools, and training in improving work efficiency. This is also intended to provide operational insights for both practitioners and researchers for policy formulation. For the purpose of this study, employs a quantitative cross sectional research design where a total of 233 responses were gathered. Data was collected from the Malaysian workforce residing in Klang Valley aged between 21 to 55 years, who are likely to use AI technology in their daily work routines. Data collection is carried out leveraging on a (5) five-point Likert scale, through a structured online questionnaire, developed using instrument adapted from prior studies. The GLM Mediation Model suggest a significant positive relationship between AI Usage significantly influences Routine Task ($\beta = 0.31674$, $p < 0.001$**), Analytical Task ($\beta = 0.18861$, $p = 0.023$*), and Creative Task ($\beta = 0.23839$, $p = 0.005$**), while AI Training demonstrates even stronger positive effects on Routine Task ($\beta = 0.43833$, $p < 0.001$**), Analytical Task ($\beta = 0.45248$, $p < 0.001$**), and Creative Task ($\beta = 0.35741$, $p < 0.001$). Additionally, the technology usage scores show a significant difference across technology adoption levels (all $p < 0.001$**), with the Advanced group consistently reporting higher mean compared to the Low and Moderate groups. In conclusion, a stronger organizational emphasis on AI utilization and training is expected to enhance task performance, leading to improved work efficiency. Thereby allowing businesses to make more effective data-driven decisions, and in building a more capable and versatile workforce.**

Keywords: **Artificial Intelligence Adoption, Digital Competency Development, Employee Performance Efficiency, Task Complexity and Typology, Mediating Effects**

I. INTRODUCTION

Amid the advancing business landscape, technology assimilation plays a crucial role to organization's success and sustainability. Artificial Intelligence (AI) application tools have transformed the way work groups operate by reducing the time spend on repetitive tasks by up to 40 percent (Song et al., 2026; Reuters, 2024). This technological augmentation indirectly influences work efficiency and serves as a principal factor in enhancing overall job performance. Phillips-Wren, (2012) emphasized that the use of right technology and tools can (i) streamline work, (ii) reduce delays, (iii) improve communication, and (iv) enhance productivity Ram Sing et al., (2025). Beyond these functional developments, technology adoption also shapes several organizational dimensions, including leadership and managerial effectiveness, workload and job design, work environment effectiveness, employee well-being and stress, communication and collaboration, motivation, engagement, job satisfaction, skills and training development, work–life balance, and organizational culture. Collectively, these considerations influence workplace productivity and the efficient utilization of organizational resources. These recurring themes have been consistently explored in contemporary academic and empirical research (Yao, 2024). Besides, in the context of technology adoption many studies are directed at system usage and usefulness using Technology Acceptance Model (TAM) as the key predictor of performance Liu & Li, (2025) and less studies on Task-Technology Fit (TTF). Goodhue & Thompson, (1995) argued that technology alone does not improve performance, yet it must fit the task being performed (i.e., task typologies). Goodhue & Thompson, (1995) survey of over 600 respondents (multiple organizations) showed that employees perform better when systems support their task requirements. The mere use of simple systems does not necessarily result in improved productivity unless it is accompanied by a comprehensive understanding and the effective utilization of

AI aligned with task typologies, which together contribute to enhanced work performance.

There are several recent studies on the function of AI at the workplace because organizations are rapidly integrating AI technologies. These studies seek to identify the critical linkage between AI adoption based on TAM and work efficiency within organizational context (Ndukaji, 2025). However, despite growing body of research crucial gaps remains. Most studies focus primarily on relations between technological capabilities of AI (usage, tools & training) and overall productivity outcomes. Researchers often give little understanding to how AI usage, tools & training interact to stimulate work efficiency shaped by different types of tasks (e.g., routine, analytical, and creative). This is due to the type of task performed by employees drives their attitudes and behaviour. Other existing gaps emerging from the adoption where researchers often examine AI integration at organizational level as a whole, rather than investigating how individual employees effectively utilize AI within specific job contexts. Although AI can increase thruput by automating repetitive tasks, however unwarranted dependence on AI may reduce employees' confidence in making analytical and creative problem-solving decisions. There is still insufficient empirical evidence explaining how AI usage, tools and training translate into improved work performance through appropriate task alignment.

Existing research only highlights the benefits of AI automation but lacks sufficient focus on task types and its potential drawbacks, such as employees' cognitive disengagement and skill degradation when involved. Moreover, the challenges associated with integration of AI in complex work environments remain poorly understood (Depoo et al., 2025). Hence, this raises concerns about AI's long-term impact on workforce adaptability, especially when task complexity increases. According to Brynjolfsson et al., (2023), if the technologies in place do not adequately enhance cognition, AI alone may not be sufficient to fully address tasks that require critical thinking or innovation.

The complexity of AI tools presents a substantial barrier to their adoption and efficient utilization, and this is particularly prone for employees with limited technical expertise. However, the relationship between tool complexity and its effects on task types and work efficiency is not well established, particularly given that tool usage is typically supported by training. Aldoseri et al., (2023) revealed that in most organizations, employees using AI-driven data analysis tools repeatedly struggles with unnecessary complexities, such as custom algorithm creation and multidimensional data interpretation. Most often navigating intricate interfaces and mastering advanced functionalities require substantial time and cognitive effort, which often can overwhelm users and increase cognitive load (Ndukaji, 2025). This not only contributes to heightened mental strain but also delays task completion and reduces overall productivity. As a result, rather than streamlining workflows, AI tools may inadvertently complicate processes, limiting their intended efficiency gains.

Suboptimal or insufficient training involving AI tools significantly hinders employees' ability to adapt and effectively integrate AI technologies in their roles. Many employees lack foundational knowledge of AI concepts struggle to understand the capabilities, limitations, and ideal use of AI. Muehlemann, (2025) highlighted that employees, due to a lack of understanding, fail to interpret AI-generated insights strategically for marketing analytics, leading to suboptimal utilization and failure to achieve desired outcomes. Besides, researchers pointed out that the current training models which are customized to adopt a "one-size-fits-all" approach, focusing on basic functionality rather than addressing the specific needs of different job roles, such as analytical or creative work has led to unsuccessful AI integration. This in turn, employees are ill-equipped to tailor AI capabilities to their specific tasks, thereby impeding both individual efficiency and broader organisational efficiency. The effect of AI on work efficiency diverges significantly across different task types of routine, analytical, and creative and each presenting unique challenge.

AI is most excellently can be used in automating routine tasks, which are repetitive and predictable, thereby facilitating greater efficiency and reducing manual effort. Nonetheless, when the tasks require human intervention, critical thinking, nuanced judgment, and decision-making, it poses potential risks because AI hinders employees' ability to develop analytical skills. Besides, creative tasks requiring originality and innovation, and the use of AI tools may unintentionally impede creativity if applied in a rigid or prescriptive manner. One issue observed in the marketing field concerning creativity is that AI marketing tools, when generating content, may limit the unique ideas of creative professionals by offering generic suggestions, thereby hindering originality (Wöhler & Reinhardt, 2021). Furthermore, if an organization relies too heavily on AI for routine tasks such as data administration and report generation, employees may become increasingly unskilled and overly dependent on AI, making them unable to complete the same tasks independently in situations where AI is unavailable or fails. Besides, human judgment is inevitable to make sense of the data generated by AI because AI lacks contextual awareness and most often can generate results that are biased or ethically questionable. Studies also indicate that AI lacks human emotions, empathy and social awareness (Song et al., 2026). Amid the growing significance of AI in the workplace, research has yet to fully explore on task types and their impact on work efficiency.

Additionally, a significant concern among employees aged 21 to 55 regarding AI adoption is the potential risk of job displacement, particularly as routine tasks are increasingly automated by AI technologies. According to Ernst & Young (2024), 75% of U.S. employees are concerned that AI might render certain jobs obsolete, with 65% expressing concern about their roles being replaced. Besides, this category finds it very difficult to adapt, leading to a decrease of confidence and productivity. Study found that 31% of employers identified a lack of employees with AI skills as a significant barrier to AI (Staton, 2024). This demonstrates that AI competencies are not always aligned with the specific requirements of a task, leading to decreased work efficiency. Therefore, AI systems require customization to complement rather than replace humans in applying analytical and creative capabilities. Drawing upon the identified gaps in the existing literature, the following research objectives were formulated to guide this study: (1) to determine the relationship between AI usage, AI tools adoption, and employee training needs and the mediating variable of task typologies (routine, analytical, and creative tasks); (2) to examine the relationship between task typologies (routine, analytical, and creative tasks) and work efficiency; (3) to investigate the mediating role of task types (routine, analytical, and creative tasks) in explaining how AI usage, AI tools adoption, and employee training needs influence work efficiency; and (4) to assess whether significant differences exist in the level of technology adoption with respect to AI usage, AI tools, employee training needs, task types ((routine, analytical, and creative tasks), and work efficiency. Understanding these relationships will not only help organizations design targeted AI integration strategies but also training lineups on how to respond to the specific demands of actual tasks, with the hope to provide actionable insights for both practitioners and researchers. This study systematically explores the following segments: literature review, methodology, data analysis, discussion of findings, and contributions.

II. Literature Review

When unveiling the impact of AI utilization, Liu & Li, (2025) argued that it remains a subject of ongoing debate, with researchers suggesting that it is not inherently beneficial nor detrimental intrinsically. Its effect on employee engagement depends on how it changes job structure. TTF is often used as mediator because technology alone does not guarantee performance (Kurniawati et al., 2021). A study on 214 government employees (East Java), showed that When technology fits employee tasks, job satisfaction increases significantly. One of the limitations of this study is that TTF was treated as a unidimensional construct without distinguishing between different types of task characteristics. Accordingly, Gurtov et al., (2022) propose a three-level classification of workplace tasks based on AI applicability, which can be aligned with routine (fully automatable), analytical (hybrid human–AI collaboration), and creative (human-centric) task categories. The classification provides organizations with a structured framework to determine where AI integration would yield maximum returns. While efficiency improvements are predominantly observed in fully automatable tasks, human-centric tasks tend to benefit more from AI-enabled augmentation rather than full automation. Hence, organizations must ensure AI systems augment rather than substitute meaningful task characteristics to maintain employee engagement. Conversely to make these technologies successful, proper training and change management strategies are necessary to make the best use of these. A study by Muehlemann (2025) shows that AI adoption leads to changes in training intensity and skill focus. Furthermore, skill polarization effect suggest that AI may widen skill gaps where high-skilled workers receive more training and routine-task workers may receive less investment. Muehlemann study focuses solely on training quantity while omitting training quality, which limits its accuracy in assessing improvements in work efficiency.

As suggested in many studies, organizations in AI-enabled environments that adopt flexible work arrangements report a 25–30 percent increase in efficiency (Huang et al., 2020; Huang & Rust, 2021; Liang et al., 2024). This modern work arrangements includes AI-integrated hybrid work models that let employees work remotely as well as in office depending on what they think is best for their projects and working style. The success of such compositions may vary across different task, routine, analytical, and creative as AI supports and augments these diverse task typologies. For example, in call centers, for routine tasks, AI chatbots and automated voice response (IVR) systems handle inquiries independently to answer frequently asked questions or to check order status. Remote agents supervise or intervene only when necessary, increasing efficiency and reducing handling time. In addition, AI models to deliver optimal results, time management and prioritization strategy is still a backbone of work efficiency. In recent years, structured frameworks, like agile approach, have been more effectively implemented, resulting in 30 percent higher project completion rates (Chinta, 2021). This agile implementation supports effective AI usage by allowing organizations to iteratively adapt AI tools to different task typologies.

As discussed earlier, most studies use Technology Acceptance Model (TAM) as a central theory in measuring adoption of technology. Based on this theory, Hemmer et al. (2024) noted that higher importance placed on perceived usefulness (PU) for routine and analytical tasks compared to creative tasks. Besides, the frequency of AI use is perceived by its usefulness (PU) that leads to increased productivity (Zahoor et al., 2024). In adopting AI to promote work efficiency, the perceived ease of use (PEOU) is also an important factor to consider. This refers to how intuitively AI tools simplify their application in the workplace, making it easier for employees to embed AI within their tasks without extensive technical expertise. Studies has shown that integrating AI into a work model exhibited a positive direct relationship between AI use and work efficiency, particularly in improving work prioritization, task completion and job satisfaction (Ahmad, 2023; Hemmer et al., 2025). Therefore, to enhance work efficiency, the following constructs derived from the Technology Acceptance Model (TAM) are considered crucial for integrating different task typologies.

AI Usage where Gartner, (2023) estimates that at least 80 percent of companies have transitioned their business processes to AI applications automating from customer service to optimizing supply chains. Today, both virtual assistants and recommendation algorithms are commonly employed, adjusting to user preferences to optimize the experience of the user (Baird & Maruping, 2021). A study conducted in the financial sector in Malaysia showed that the frequent use of AI resulted in a 20% increase in work performance, especially in tasks related to data processing and analysis (Tambe et al., 2019).

AI Tools are AI driven platforms are used to boost personalization, efficiency and engagement. Companies such as Citigroup have installed AI systems-based tools to help employees through their internal policies and procedures, making workflows more productive and supporting new learning (Bautzer, 2024). Based on research done by Akinnagbe, (2024) successful integration of AI tools requires a delicate mix of technological capabilities and human sufficiency. Data collected from 200 employees showed that adopting the right tools enabled them to reduce work processing time and achieve an 18% decrease in errors. A survey of 120 hospital administrators concluded that while advanced AI tools offer greater capabilities, they can sometimes overwhelm users due to their lack of experience in handling advanced technical knowledge (Maassen et al., 2021).

AI-driven training systems stem from structured performance appraisal frameworks that emphasize continuous feedback, process-based assessment, and practical skill development, as pointed out by Hao et al., (2025). Hence, it is essential to examine the impact of identifying employees' training needs in relation to AI usage and its role in increasing their productivity. A study conducted by Zhao et al., (2025), on 200 employees demonstrated that staff trained on AI were able to complete their task 20 percent faster that individuals who were not AI savvy. Besides, workers AI trained were able to achieve greater operational efficiency Ahmad, (2023) and improve speed of task performance (Tariq et al., 2021).

Task types here are categorized to routine, analytical and creative exhibiting different AI implications and characteristics (Zahoor et al., 2024). Routine task includes data entry, scheduling, email management, invoice processing, scheduling meetings, inventory management, payroll processing, etc. It is repetitive, structured and predictable in nature. Whereas analytical task requires problem solving, critical thinking, and data interpretation skills. To perform this task, predictive analytics in AI can often be used to generate quick insights and accelerate decision-making. However, human judgment is required to interpret the outcomes (Song et al., 2026). Csaszar et al., (2024) found that using predictive AI tools enables improved decision-making functions by processing vast amounts of data, detecting patterns, and producing actionable insights for accurate outcomes. Creative tasks require new, creative and original ideas or solutions. According to Wöhler & Reinhardt, (2021), AI demonstrates creativity based on the specific ideas input by the user into the system.

III. Research Methodology

A cross-sectional research design employing a quantitative approach is used to explore the relationships between various artificial intelligence (AI) variables and work efficiency, particularly with task types serving as mediating factors. The research seeks to capture the attitudes of employees in Malaysia aged between 21 and 55 years, on AI usage at their workplace. The reason for selecting this age category of employees is because they often blend adaptability to new technologies with the informed judgment developed through experience (Schmidt, 2020). The target population for this research is 17.12 million working adults spread among all states in Malaysia (The Editor, 2024). However, due to practical constraints such as time, cost and accessibility, the data is only collected from Klang Valley region which represents the country's primary economic hub, with high concentration of employees' approximation 4.1 million (NST, 2026, April 2). Krejci and Morgan table (Krejci, 1970) used to calculate sample size and the projected sample size for this research is 384 participants.

Sampling Technique

The random sampling technique employed to select respondents from Klang Valley (New Straits Times, 2026). This sampling technique is deemed appropriate as it ensures that every individual has equal chance of being selected thus minimizing selection bias and increasing representativeness. This limitation is acknowledged, as it may affect the generalizability of the findings to a broader population. For future studies it is recommended to consider a more extensive sampling approach to enhance external validity (Bryman, 2016).

Data Collection Procedures

Primary data collected using 5-point Likert scale questionnaire distributed using google form. This instrument was developed using an adapted approach validated by Kassa & Worku, (2025). JAMOVI mediation analysis (GLM) is used to examine the proposed hypotheses. This method allows for a comprehensive measurement of the relationships between variables, particularly in identifying direct and indirect effects based on the mediating factors.

Hypothesized Model

Based on the literature review and the theoretical grounds of technology acceptance model by Davis, (1989), the hypothesized model presented in fig. 1 was developed to illustrate the proposed associations among the study variables. The task types introduced as mediating is because according to Hackman & Oldham, (1976), different task types influence the outcome of the work. Their study indicates that autonomy, complexity, and skill requirements will affect the task type differently and likely to produce different work efficiency outcomes.

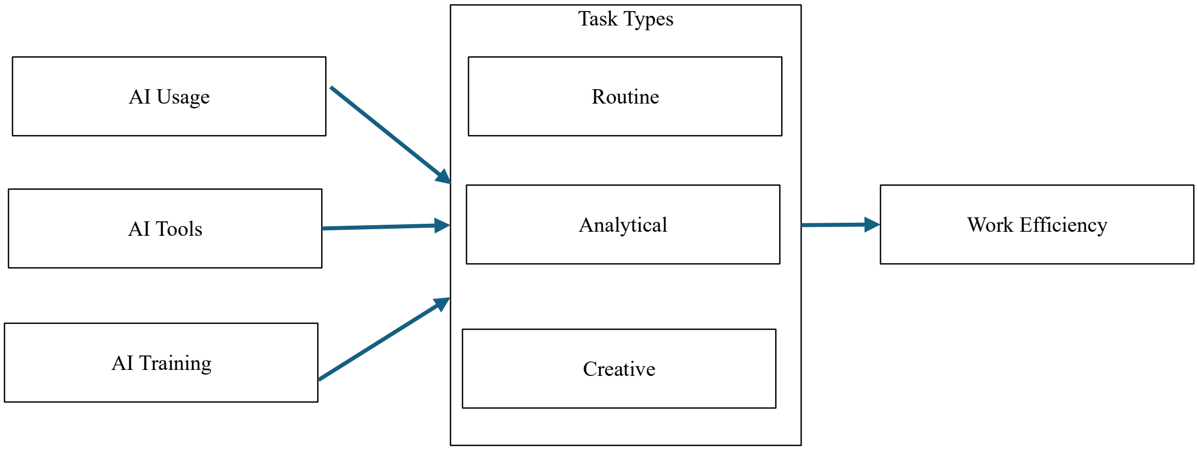

Fig. 1 Hypothesized Model for AI Integration to Promote Work Efficiency

Hypothesis Development

Building on the mediation framework proposed by Kenny, (1986), the following hypotheses were developed to address the research objectives. Kenny, (1986) suggested that mediation analysis requires testing a series of relationships among the independent variable, mediator, and dependent variable.

H1: There is a significant relationship between AI Usage and Routine Task

H2: There is a significant relationship between AI Usage and Analytical Task

H3: There is a significant relationship between AI Usage and Creative Task

H4: There is a significant relationship between AI Tools and Routine Task

H5: There is a significant relationship between AI Tools and Analytical Task

H6: There is a significant relationship between AI Tools and Creative Task

H7: There is a significant relationship between AI Training and Routine Task

H8: There is a significant relationship between AI Training and Analytical Task

H9: There is a significant relationship between AI Training and Creative Task

H10: There is a significant relationship between Routine Task and Work Efficiency

H11: There is a significant relationship between Analytical Task and Work Efficiency

H12: There is a significant relationship between Creative Task and Work Efficiency

H13: Routine task type mediates the relationship between AI Training and Work Efficiency

H14: Routine task type mediates the relationship between AI Tools and Work Efficiency

H15: Routine task type mediates the relationship between AI Usage and Work Efficiency

H16: Creative task type mediates the relationship between AI Training and Work Efficiency

H17: Creative task type mediates the relationship between AI Tools and Work Efficiency

H18: Creative task type mediates the relationship between AI Usage and Work Efficiency

H19: Analytical task type mediates the relationship between AI Training and Work Efficiency

H20: Analytical task type mediates the relationship between AI Tools and Work Efficiency

H21: Analytical task type mediates the relationship between AI Usage and Work Efficiency

IV. Result Analysis

Demographic Profiling

The total number of respondents for this research is (N) = 233 which is 61%, considered adequate for most survey research (Babbi, 2016; EY, 2024). The tabulation for the demographic profile as shown in table I. Gender displays 53.7 percent and is male and 6.4 percent female. Age groups divided into 4 categories consist of 21- 30 (19.7 percent), 31 – 40 (37.8 percent), 41 -50 (30.5 percent) and 51 and above (11.6 percent). The largest proportion of respondents holds a bachelor's degree (48.9 percent), while the lowest proportion comes from the Doctorate/PhD level (17.6 percent) Master's degree holders constitute 33.5% of the respondents. The professional experience of the respondents is predominantly from the technology sector (38.4 percent), followed by supply chain (20.7 percent), while the lowest representation is from the healthcare sector (11.6 percent).

TABLE I DEMOGRAPHIC PROFILE (N=233)

Category	Subcategory	Frequency (n)	Percentage (%)
Gender	Male	125	53.7
	Female	108	46.4
Age Group	21–30	46	19.7
	31 – 40	88	37.8
	41 – 50	71	30.5
	51 – 55	27	11.6
Educational Background	Bachelor's Degree	114	48.9
	Master's Degree	78	33.5
	Doctorate/PhD	41	17.6
Professional Field	Technology	89	38.4
	Supply Chain	48	20.7
	Healthcare	27	11.6
	Education	45	19.4
	Others	55	23.9
Technology Usage Level	High	94	40.3
	Moderate	86	36.9
	Low	53	22.7

The reliability plot generated using Jamovi in fig. 2 illustrates the consistency of respondents' scores across the study constructs. The relatively clustered and parallel response patterns across AI usage, AI tools, AI training, task types, and work efficiency indicate stable measurement trends among respondents. The absence of highly irregular response patterns suggests acceptable internal consistency of the scales, supporting the reliability of the measurement instruments used in this study.

Reliability Analysis

The Intraclass Correlation Coefficient (ICC) results in table II specify that the reliability of single measurements is relatively low, as shown by the low values of ICC1 (−0.0156) and ICC2 (0.0889). This implies weak agreement among individual measurements. Nevertheless, the two-way fixed model for single measures (ICC3 = 0.3184) indicates satisfactory consistency when the raters or measurement conditions are treated as fixed. For average measurements, reliability improves significantly. While ICC1k (−0.1207) still indicates poor reliability under the one-way random model, the two-way random average agreement (ICC2k = 0.4059) shows moderate reliability. The two-way fixed average consistency (ICC3k = 0.7658) demonstrates good reliability, indicating strong consistency when the measurements are averaged. Overall, the findings suggest that the measurement model provides stronger and more reliable results when aggregated scores are used rather than individual measurements. Fig. 2 shows the graphical representation for the measurement item. The x axis consists, AIU, AIT, AITRA, RT, A, C, WE which represents the composite score of the construct. Y-axis represents the observed values (scores) for each construct, values ranging approximately from 2 to 25 summated from Likert-scale scores.

Measurement Values for Reliability Analysis

Coefficient of Variation (%)	:	20.26
Standard Error of Measurement (SEM)	:	2.3132
Standard Error of the Estimate (SEE)	:	6.2008
Standard Error of Prediction (SEP)	:	12.6176

TABLE II INTRACLASS CORRELATION COEFFICIENTS

Model	Measures	Type	ICC	Lower C.I.	Upper C.I.
one-way random	Agreement	ICC1	-0.0156	-0.0354	0.00829
two-way random	Agreement	ICC2	0.0889	0.0322	0.15574
two-way fixed	Consistency	ICC3	0.3184	0.2739	0.36743
one-way random	Avg. Agreement	ICC1k	-0.1207	-0.3146	0.05526
two-way random	Avg. Agreement	ICC2k	0.4059	0.1887	0.56356
two-way fixed	Avg. Consistency	ICC3k	0.7658	0.7253	0.80261

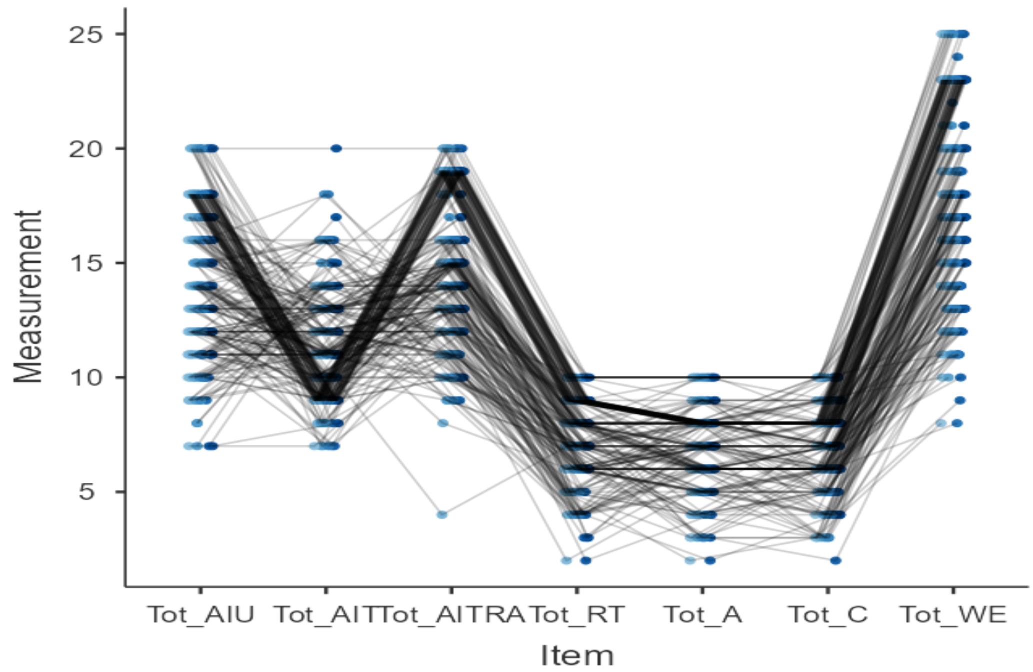

Fig. 2 Plot Reliability Data

GLM Mediation Analysis

Fig. 3 shows the statistical diagram derived from the GLM Mediation Analysis represents the conceptual framework of the study. The dashed arrows between these three variables indicate that they are interrelated, collectively representing the organization's AI capability environment.

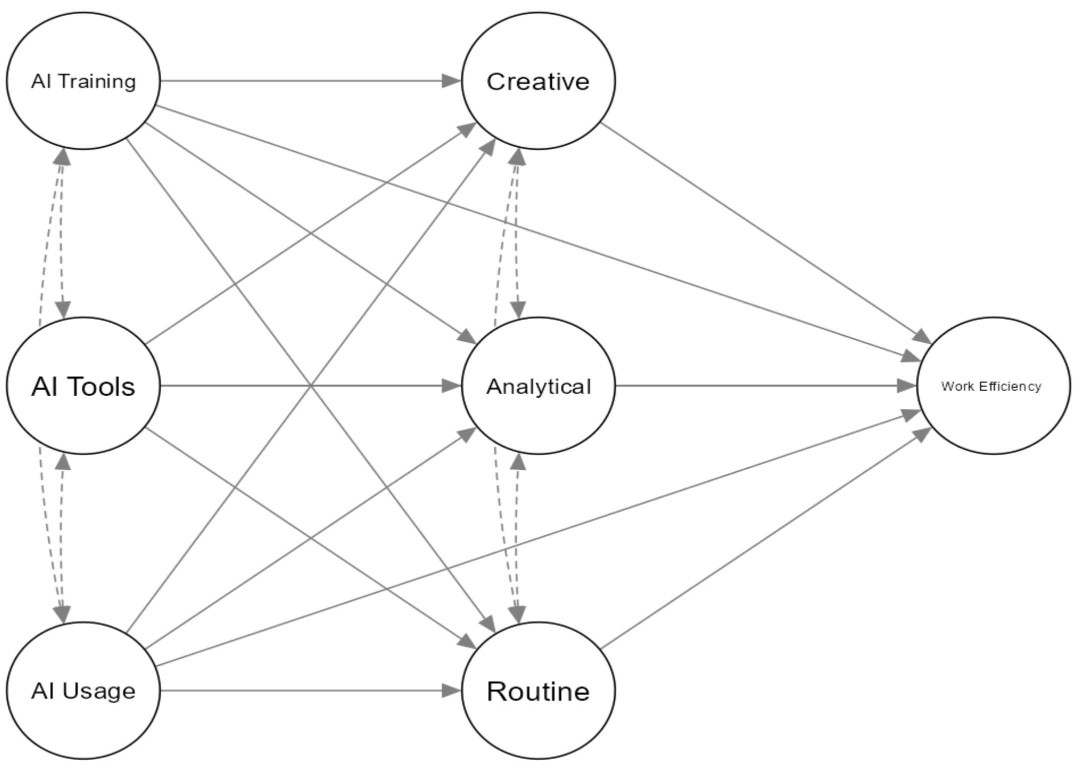

Fig. 3 Statistical Diagram

The hypothesis testing was conducted in Jamovi software V2.6.19. There are 21 hypotheses identified including 12 Component Analysis, 9 Mediation Analysis using GLM Mediation Analysis and Inferential analysis for Technology

Adoption hypothesis using *One-Way ANOVA (Welch's)*. The model fit value in table III shows the following that for Model 1, correlation coefficient (R = 0.781) indicates a strong positive relationship between these variables. The R^2 value of 0.611 suggests that 61.1% of the variance in Work Efficiency can be explained by AI Usage, AI Tools, and AI Training. Model 2, the R value of 0.691, shows a moderately strong positive relationship. The R^2 value of 0.477 indicates that 47.7% of the variance in Routine Tasks is explained by AI Usage, AI Tools, and AI Training. For Model 3, the R value of 0.576 indicates a moderate relationship. The R^2 value of 0.322 means that 32.2% of the variance in Analytical Tasks is explained by the AI-related variables. As for Model 4, value of 0.558 indicates a moderate positive relationship, while the R^2 value of 0.311 shows that 31.1% of the variance in Creative Tasks can be explained by AI-related factors. Finally for Model 5, The R value of 0.703 indicates a strong relationship, while the R^2 value of 0.494 shows that 49.4% of the variance in Work Efficiency is explained by these task types. While the technology-enabled resources (usage, tools and training), and task types (routine, analytical, and creative) support work efficiency, a substantial proportion of variability remains unexplored.

TABLE III MODEL FIT MEASURES

	Model	R	R^2
1	AI Usage, AI Tools, AI Training → Work Efficiency	0.781	0.611
2	AI Usage, AI Tools, AI Training → Routine	0.691	0.477
3.	AI Usage, AI Tools, AI Training → Analytics	0.576	0.322
4.	AI Usage, AI Tools, AI Training → Creative	0.558	0.311
5.	Routine, Analytics and Creative → Work Efficiency	0.703	0.494

TABLE IV COMPONENT PATH ANALYSIS

Hypothesis	Effect	Estimate	SE	β	z	p	Results
H1	AI Usage ⇒ Routine Task	0.17190	0.03943	0.31674	4.3600	<0.001**	Supported
H2	AI Usage ⇒ Analytical Task	0.09224	0.04050	0.18861	2.2776	0.023*	Supported
H3	AI Usage ⇒ Creative Task	0.12470	0.04408	0.23839	2.8292	0.005**	Supported
H4	AI Tools ⇒ Routine Task	0.01448	0.04046	0.01921	0.3579	0.720	Not Supported
H5	AI Tools ⇒ Analytical Task	0.04500	0.04156	0.06623	1.0826	0.279	Not Supported
H6	AI Tools ⇒ Creative Task	-0.00126	0.04524	-0.00173	-0.0278	0.978	Not Supported
H7	AI Training ⇒ Routine Task	0.23651	0.04107	0.43833	5.7580	<0.001**	Supported
H8	AI Training ⇒ Analytical Task	0.22000	0.04219	0.45248	5.2144	<0.001**	Supported
H9	AI Training ⇒ Creative Task	0.18587	0.04592	0.35741	4.0479	<0.001	Supported
H10	Routine Task ⇒ Work Efficiency	0.28608	0.13460	0.11935	2.1254	0.034*	Supported
H11	Analytical Task ⇒ Work Efficiency	0.08893	0.15795	0.03343	0.5630	0.573	Not Supported
H12	Creative Task ⇒ Work Efficiency	0.38764	0.14450	0.15588	2.6826	0.007**	Supported

Note: ** Denotes significant at 1% level

* Denotes significant at 5% level

Table IV represents the component analysis. The results demonstrate that AI training has highly significant effects on routine ($\beta = 0.43833$, $p < 0.001$**), followed by analytical ($\beta = 0.45248$, $p < 0.001$**), and creative tasks ($\beta = 0.35741$, $p < 0.001$**), suggesting that competence cultivation plays a more imperative role than mere usage. While AI Usage significantly augments routine task ($\beta = 0.31674$, $p < 0.001$**), analytical task analytical ($\beta = 0.18861$, $p = 0.023$*), and creative tasks ($\beta = 0.23839$, $p = 0.005$**). Besides, routine tasks have a compelling effect because AI functions as a cognitive and automation enabler that improves work efficiency. AI Tools show no significant effects across all task types ($p > 0.05$), implying that technology availability alone does not improve task performance, which is consistent with Technology Organization Environment (TOE) framework (Tornatzky & Fleischer, 1990) and human capital theory (Becker, 1964). Moreover, *routine tasks ($\beta = 0.11935$, $p = 0.034$)* and creative tasks ($\beta = 0.15588$, $p = 0.007$*) significantly enhance work efficiency because since routine task is structured, repetitive, process driven, and time sensitive, while creative task generates ideation, operational optimization and innovation-related activities are more directly linked to efficiency outcomes, aligning with arguments on skill-biased technological change (Autor, 2015). Whereas analytical tasks ($p = 0.573$) do not positively contribute to work efficiency. This is because "Analytical" improves decision quality rather than speed or productivity, which are the core components of efficiency.

The mediation results in table V indicate that only AI Training produces significant indirect effects on work efficiency, specifically through Routine Task (β = 0.05232, p = 0.046*) and Creative Task (β = 0.05571, p = 0.025*), whereas all indirect paths involving AI Usage and AI Tools are statistically non-significant (p > 0.05).

TABLE V MEDIATING PATH ANALYSIS

Hypothesis	Effect	Estimate	SE	β	z	p	Results
H13	AI Training ⇒ Routine Task ⇒ Work Efficiency	0.06766	0.03393	0.05232	1.9939	0.046*	Supported
H14	AI Tools ⇒ Routine ⇒ Work Efficiency	0.00577	0.0113	0.00317	0.5110	0.609	Not Supported
H15	AI Usage ⇒ Routine ⇒ Work Efficiency	0.03956	0.0216	0.03048	1.8323	0.067	Not Supported
H16	AI Training ⇒ Creative Task ⇒ Work Efficiency	0.07205	0.03222	0.05571	2.2361	0.025*	Supported
H17	AI Tools ⇒ Creative Task ⇒ Work Efficiency	0.00161	0.0163	8.83e-4	0.0986	0.921	Not Supported
H18	AI Usage ⇒ Creative ⇒ Work Efficiency	0.04415	0.0230	0.03402	1.9188	0.055	Not Supported
H19	AI Training ⇒ Analytical ⇒ Work Efficiency	0.03342	0.0338	0.02559	0.9891	0.323	Not Supported
H20	AI Tools ⇒ Analytical ⇒ Work Efficiency	0.00773	0.0100	0.00425	0.7726	0.440	Not Supported
H21	AI Usage ⇒ Analytical ⇒ Work Efficiency	0.01605	0.0170	0.01237	0.9423	0.346	Not Supported

Note: *Denotes significant at 5% level

The reason for non-significant paths is because the usage and tools alone does not translate to productivity improvement unless supported by skills, training, and organizational alignment (Autor, 2015). This finding demonstrates the TOE framework by Tornatzky & Fleischer (1990), which underpins that technological infrastructure alone does not ensure work efficiency without organizational and human readiness. Based on human capital theory introduced by Becker (1964), he emphasizes investment in skills enhances productivity, thus training is an essential component to improve task performance.

Null Hypothesis: There are no significant differences in respect to Technology Adoption and factors, AI Usage, AI Tools, AI Training, Task Types and Work Efficiency.

Based on table VI results, this hypothesis is tested to prove if technology adoption for these individuals plays a significant role for the factors identified in AI integration. Based on the outcome of ANOVA results in table III, the findings demonstrate statistically significant differences across technology adoption levels (Low, Moderate, Advanced) for all variables (all p < 0.001**), indicating that technology adoption level is a strong differentiator of AI engagement, task performance, and work efficiency.

Technology Adoption

TABLE VI ONE-WAY ANOVA (WELCH'S) FOR SIGNIFICANT DIFFERENCES IN RESPECT TO TECHNOLOGY ADOPTION AND FACTORS; AI USAGE, AI TOOLS, AI TRAINING, TASK TYPES AND WORK EFFICIENCY

Factors	Technology Adoption			F Value	P Value
	Low	Moderate	Advance		
AI Usage	13.29 (2.78)	12.72 (2.99)	16.93 (2.67)	51.1	<0.001**
AI Tools	11.53 (2.32)	12.29 (2.67)	9.86 (1.79)	23.1	<0.001**
AI Training	13.32 (2.56)	13.40 (2.49)	17.29 (3.11)	48.2	<0.001**
Task Type: Routine	6.75 (1.70)	6.51 (1.77)	8.38 (1.44)	31.6	<0.001**
Task Type: Analytical	6.67 (1.79)	6.71 (1.58)	7.74 (1.25)	14.1	<0.001**
Task Type: Creative	6.73 (1.90)	6.44 (1.77)	7.65 (1.35)	11.5	<0.001**
Work Efficiency	15.91 (3.81)	16.67 (3.71)	21.32 (3.16)	60.2	<0.001**

Note: The value within bracket refers to SD.

** Denotes significant at 1% level

The following fig. 4 illustrates the outcome of this study. This study extends to the theoretical contributions made by Tornatzky & Fleischer, (1990) the Technology Organization Environment (TOE) framework and Becker (1964), the Human Capital Theory. These two theories illustrate on organizational readiness in embracing AI and the role of training in developing the human capital. However, it should note that the benefits of AI implementation are not equal across the board because some organizations gain more benefits from AI compared to others due to availability of technology-enabled resources.

Supported Relationship Only

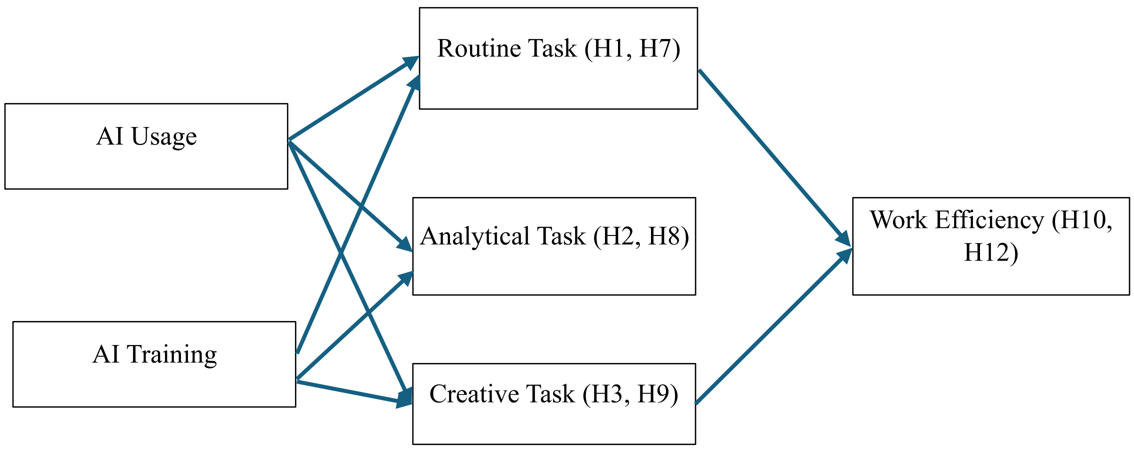

Fig. 4 AI Driven Task Performance and Work Efficiency

Supported Mediation Relationship

H13: AI Training → Routine Task → Work Efficiency

H14: AI Training → Creative Task → Work Efficiency

V. Discussion

This study found that the technology-enabled resources have the ability to optimize workplace productivity, however the outcome depends on its application. It has the greatest advantage with routine and creative tasks as this type of application allows employees to shift their focus on works that align closely with AI's core strengths (Ahmad, 2023; Ndukaji, (2025); Izzaty Roszelan & Shahrom, 2025). However, the findings did not favor analytical tasks because decision-making using AI still requires human intellectual contribution. As AI cannot have the appropriate contextual understanding and ethical considerations in making such decisions it is challenging to solely rely on AI suggestions. For the perspective of TAM, AI engagement across task types can interpreted within the framework of perceived usefulness (PEOU) and ease of use (PU). For PEOU and PU, Routine tasks enhance both by making AI integration highly desirable and functional for everyday operations. Creative tasks on the other hand, less structured, however demonstrated highly perceived usefulness (PU), for a distinct reason. Since AI enhances rather than constrains creative expression, it considered as a valuable collaborative partner. In contrast, analytical tasks tend to exhibit only moderate PU and lower compatibility with automation.

From the analytical viewpoint of this study, a key barrier in relation to AI integration was determined. The application of AI tools did not produce statistically significant outcomes. This may be ascribed to their likelihood to impose high cognitive load on employees, thereby exacerbating stress and attenuating productivity Aldoseri et al., (2023). In light of this, AI tools should be reduced in complexity and thoughtfully designed with a user-centered approach, accompanied by adequate and structured training to ensure effective adoption and utilization (Baird & Maruping, 2021; Hasan & Kumar, 2024). Training on the other hand reported as the strongest predictor, reinforcing previous claims that lack of training results in employees having limited practical knowledge and thus underutilizing AI tools. This shows that if AI not incorporated efficiently, improved productivity will not be achieved.

VI. Conclusion

In conclusion, this study shows that's work efficiency is governed by tasks transformation, however limited to routine and creative tasks because AI improves efficiency for structured or generative but not necessarily tasks that require deep human judgement. AI usage and AI Training are robust antecedents that influence the task types. While AI tools are found to be insignificant, suggesting access to technology alone does not improve work efficiency. Since analytical tasks require higher order thinking or cognitive processing or contextual judgement, AI cannot fully replicate this. Consequently, the results demonstrate that analytical tasks are not significantly linked to work efficiency. Mediation analysis shows that AI training extensively enhances work efficiency through its impact on routine and creative tasks. This study also contributes in two ways, theoretically, it adopts and extends the Technology Acceptance Model (TAM) by incorporating task type as a mediating variable within AI's impact and literature. In real world settings, the findings suggest prioritizing on training and AI use that augments employee's judgment and creative potential is vital, especially in domains were over-automation risks disengagement or skill degradation. In conclusion, this study is evident that AI integration can help reduce employees' work stress while enhancing productivity. At policy level, it offers a practical application under Sustainable Development Goals, particularly SDG 8 (Decent Work and Economic Growth) and SDG 3 (Good Health and Well-being). As for the limitation, since this study only captures data from Klang Valley, generalizability of the findings to other regions of Malaysia may not fully reflect the patterns linked to AI integration and work efficiency due to disparities in technology usage. Besides, the identified variables based on TAM alone may not fully account for the model success as there are other AI factors that influence work efficiency. Moreover, the use of JAMOVI may not capture complex relationships or latent constructs as effectively as advanced techniques such as Structural Equation Modeling (SEM). Therefore, for future studies could employ more comprehensive analytical methods to validate the relationships among variables.

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References

[1] Ahmad, A. (2023). Application of artificial intelligence in improving the efficiency of corporate information systems. *Journal Informatic, Education and Management (JIEM)*, *5*(2), 1-7. https://doi.org/10.61992/jiem.v5i2.55

[2] Akinnagbe, O. B. (2024). Human-AI collaboration: Enhancing productivity and decision-making. *International Journal of Education, Management, and Technology*, *2*(3), 387-417. https://doi.org/10.58578/ijemt.v2i3.4209

[3] Aldoseri, A., Al-Khalifa, K. N., & Hamouda, A. M. (2023). Re-thinking data strategy and integration for artificial intelligence: concepts, opportunities, and challenges. *Applied Sciences*, *13*(12), 7082. https://doi.org/10.3390/app13127082

[4] Baird, A., & Maruping, L. M. (2021). The next generation of research on IS use: A theoretical framework of delegation to and from agentic IS artifacts. *MIS quarterly*, *45*(1), 315-341. https://doi.org/10.25300/MISQ/2021/15882

[5] Bautzer, T. (2024, December 5). *Citigroup rolls out artificial intelligence tools for employees in eight countries.* Reuters. https://www.reuters.com/technology/artificial-intelligence/citigroup-rolls-out-artificial-intelligence-tools-employees-eight-countries-2024-12-04/

[6] Bryman, A. (2016). *Social research methods*. Oxford university press.

[7] Brynjolfsson, E., Li, D., & Raymond, L. R. (2023). Generative AI at work. national bureau of economic research. *Working Papers*, (31161).

[8] Chinta, S. (2021). The impact of AI-powered automation on agile project management: transforming traditional practices. *International Research Journal of Engineering and Technology (IRJET)*, *8*(10), 2025-2036. https://dx.doi.org/10.2139/ssrn.5034076

[9] Csaszar, F. A., Ketkar, H., & Kim, H. (2024). Artificial intelligence and strategic decision-making: Evidence from entrepreneurs and investors. *Strategy Science*, *9*(4), 322-345. https://doi.org/10.1287/stsc.2024.0190

[10] Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, *13*(3), 319-340. https://doi.org/10.2307/249008

[11] Depoo, L., Hajerová-Mullerová, L., Kronberger, Z., Říhová, G., Stříteský, M., Hořáková, M., ... & Kopecký, M. (2025). Bridging the AI Gap: How Organizational Literacy and Individual Competencies Drive Implementation Success Across Industries. *Journal of Applied Technical and Educational Sciences*, *15*(1), 400-400. https://doi.org/10.24368/jates400

[12] EY (Ernst & Young). (2024). *EY AI Pulse Survey: How AI is turning promise into payoff.* https://www.ey.com/en_us/insights/emerging-technologies/pulse-ai-survey

[13] Gartner, Inc. (2023, October 11). *Gartner says more than 80% of enterprises will have used generative AI APIs or deployed generative AI-enabled applications by 2026*. https://www.gartner.com/en/newsroom/press-releases/2023-10-11-gartner-says-more-than-80-percent-of-enterprises-will-have-used-generative-ai-apis-or-deployed-generative-ai-enabled-applications-by-2026

[14] Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS quarterly*, *19*(2), 213-236. https://doi.org/10.2307/249689

[15] Gurtov, V. A., Averyanov, A. O., Korzun, D. Z., & Smirnov, N. V. (2022). A system for classification of technologies in the field of artificial intelligence for personnel forecasting. *Economic and social changes: facts, trends, forecast*, *15*(3), 113-133. https://doi.org/10.15838/esc.2022.3.81.6

[16] Hackman, J. R., & Oldham, G. R. (1976). Motivation through the design of work: Test of a theory. *Organizational behavior and human performance*, *16*(2), 250-279. https://doi.org/10.1016/0030-5073(76)90016-7

[17] Hao, H., JunRu, Z., & Salim, N. (2025). *Exploration And Implementation of Labor Education Evaluation System in Experimental and Practical Training Courses*. *Asian Journal of Social Science Research,* 6,1, pg. 48-58. https://doi.org/10.5281/zenodo.12703208

[18] Hasan, M. K. H., & Kumar, L. K. (2024). Determining Adequate sample size for social survey research: sample size for social survey research. *Journal of the Bangladesh Agricultural University*, *22*(2), 146-157. https://doi.org/10.3329/jbau.v22i2.74547

[19] Hemmer, P., Schemmer, M., Kühl, N., Vössing, M., & Satzger, G. (2025). Complementarity in human-AI collaboration: Concept, sources, and evidence. *European Journal of Information Systems*, *34*(6), 979-1002. https://arxiv.org/pdf/2404.00029

[20] Huang, F., Teo, T., & Zhou, M. (2020). Chinese students' intentions to use the Internet-based technology for learning. *Educational Technology Research and Development*, *68*(1), 575-591. https://doi.org/10.1007/s11423-019-09695-y

[21] Huang, M. H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. *Journal of the academy of marketing science*, *49*(1), 30-50. https://doi.org/10.1007/s11747-020-00749-9

[22] Izzaty Roszelan, A. I. R., & Shahrom, M. (2025). Readiness for artificial intelligence adoption in Malaysian manufacturing companies. *Journal of Information Technology Management*, *17*(1), 1-13. https://doi.org/10.22059/jitm.2025.99920

[23] Kassa, B. Y., & Worku, E. K. (2025). The impact of artificial intelligence on organizational performance: The mediating role of employee productivity. *Journal of open innovation: technology, market, and complexity*, *11*(1), 100474. https://doi.org/10.1016/j.joitmc.2025.100474

[24] Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of personality and social psychology*, *51*(6), 1173-1182. https://doi.org/10.1037/0022-3514.51.6.1173

[25] Kurniawati, D. T., Ikhram, W. A. D., & Yuana, P. (2021). The mediating role of task-technology fit (TTF) in the effect of knowledge sharing intention on job satisfaction and employee performance. *International Journal of Research in Business and Social Science*, *10*(6), 93-100. https://doi.org/10.20525/ijrbs.v10i6.1336

[26] Liang, J. T., Yang, C., & Myers, B. A. (2024, February). A large-scale survey on the usability of ai programming assistants: Successes and challenges. In Proceedings of the 46th IEEE/ACM international conference on software engineering (pp. 1-13). https://doi.org/10.1145/3597503.3608128

[27] Liu, X., & Li, Y. (2025). Examining the double-edged sword effect of AI usage on work engagement: The moderating role of core task characteristics substitution. *Behavioral Sciences*, *15*(2), 206. https://doi.org/10.3390/bs15020206

[28] Maassen, O., Fritsch, S., Palm, J., Deffge, S., Kunze, J., Marx, G., ... & Bickenbach, J. (2021). Future medical artificial intelligence application requirements and expectations of physicians in German university hospitals: web-based survey. *Journal of medical Internet research*, *23*(3), e26646. https://doi.org/10.2196/26646

[29] Muehlemann, S. (2025). Artificial intelligence adoption and workplace training. *Journal of Economic Behavior & Organization*, *238*, 107206.https://doi.org/10.1016/j.jebo.2025.107206

[30] Ndukaji, A. (2025). The Role of Artificial Intelligence in Business Decision-Making. https://dx.doi.org/10.2139/ssrn.6000194

[31] New Straits Times. (2026, April 2). *RimbaWatch: 50pct WFH in Klang Valley could save government RM169mil monthly.* https://www.nst.com.my/news/nation/2026/04/1409321/rimbawatch-50pct-wfh-klang-valley-could-save-government-rm169mil

[32] Phillips-Wren, G. (2012). AI tools in decision making support systems: a review. *International Journal on Artificial Intelligence Tools*, *21*(02), 1240005. https://doi.org/10.1142/S0218213012400052

[33] Ram Sing, R. D., Abdul Rahman, S. Y., Kumar, P., Arasu, R., Beigi, M. A., & Pramila, R. (2025). Harnessing AI for enhanced student learning and performance in higher education: A multinational collaboration. *International Journal of Information and System Security, 15*(2), 208–217. https://doi.org/10.51983/ijiss-2025.IJISS.15.2.28

[34] Reuters. (2024, December 4). Citigroup rolls out artificial intelligence tools for employees in eight countries. https://www.reuters.com/technology/artificial-intelligence/citigroup-rolls-out-artificial-intelligence-tools-employees-eight-countries-2024-12-04

[35] Schmidt, A. (2020, September). Interactive human centered artificial intelligence: A definition and research challenges. In *Proceedings of the 2020 International Conference on Advanced Visual Interfaces (AVI '20)* (pp. 1–4). Association for Computing Machinery. https://doi.org/10.1145/3399715.3400873

[36] Song, Y., Zeng, M., & Su, T. (2026). Opportunity or threat? A meta-analysis of the impact of human–AI collaboration systems on employee work effectiveness. *Advances in Psychological Science, 34*(3), 461–486. https://doi.org/10.3724/SP.J.1042.2026.0461

[37] Staton, B. (2024, November 7). *Employers look to AI tools to plug skills gap and retain staff*. Financial Times https://www.ft.com/content/9cf58a76-5245-4cdf-9449-239e90077eb5

[38] Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial intelligence in human resources management: Challenges and a path forward. *California management review*, *61*(4), 15-42. https://doi.org/10.1177/0008125619867910

[39] Tariq, M. U., Poulin, M., & Abonamah, A. A. (2021). Achieving operational excellence through artificial intelligence: Driving forces and barriers. *Frontiers in psychology*, *12*, 686624. https://doi.org/10.3389/fpsyg.2021.686624

[40] Wöhler, J., & Reinhardt, R. (2021). The users' perspective on how creativity techniques help in the idea generation process—A repertory grid study. *Creativity and Innovation Management*, *30*(1), 144-163. https://doi.org/10.1111/caim.12424

[41] Yao, Q. (2024). Concepts and reasoning: A conceptual review and analysis of logical issues in empirical Social Science Research. *Integrative Psychological and Behavioral Science*, *58*(2), 502-530. https://doi.org/10.1007/s12124-023-09792-x

[42] Zahoor, S., Chaudhry, I. S., Yang, S., & Ren, X. (2024). Artificial intelligence application and high-performance work systems in the manufacturing sector: a moderated-mediating model. *Artificial Intelligence Review*, *58*(1), 11. https://doi.org/10.1007/s10462-024-11013-9

[43] Zhao, H., Ye, L., Guo, M., & Deng, Y. (2025). Reflection or dependence: How AI awareness affects employees' in-role and extra-role performance? *Behavioral Sciences*, *15*(2), 128. https://doi.org/10.3390/bs15020128