

AI Adoption and Employee Performance: Evidence from Malaysia's Manufacturing Sector in Krubong, Malacca

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Abstract

This study examines the relationship between artificial intelligence (AI) adoption and employee performance in Malaysia's manufacturing sector, focusing on executive-level employees in Krubong, Malacca. While AI integration is increasingly recognized as a driver of organisational efficiency, empirical evidence on its direct impact on employee performance in regional manufacturing contexts remains limited. To address this gap, a quantitative approach was employed, utilising a structured questionnaire to collect data from 103 executives and senior managers. The survey assessed key dimensions of AI adoption, including perceived usefulness, ease of use, trust, and risk, alongside measurable performance outcomes. Statistical analysis, conducted using Spearman's rank correlation, revealed significant positive relationships between AI adoption and employee performance, with correlation coefficients ranging from moderate to strong ($\rho = 0.576$ to 0.762). Notably, perceived enjoyment ($\rho = 0.762$) and interaction needs ($\rho = 0.758$) exhibited the strongest associations, highlighting the role of user experience in enhancing productivity. Additionally, perceived risk demonstrated a meaningful correlation ($\rho = 0.713$), suggesting that employee concerns must be managed to optimize AI integration. The findings underscore the importance of addressing both functional and psychological factors in AI implementation strategies. These results contribute to the broader discourse on technology adoption by providing localized insights from Malaysia's manufacturing industry, emphasizing the need for tailored approaches to maximize workforce performance. The study concludes that while AI adoption significantly enhances productivity, its success depends on balancing technological capabilities with employee perceptions and organizational support. Future research could expand these findings by exploring longitudinal effects across diverse industrial settings.

1. Introduction

Employee performance as one of the most influential factors on organizational productivity can be defined as the level to which an employee completes her tasks and meets the objectives and goals assigned to him (Almulaiki, 2023). Reviews basically happen every one year or every three months or even more, depending on the organization's policy; the primary goals of the performance reviews are to focus on where the employee can do better and where the employee has done well; this usually aims at increasing productivity, increasing profitability and increasing the level of satisfaction in the workforce. Promotive factors affecting performance

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include; Working conditions offered by the organization, employee privileges and technological aids on the workplace. AI has emerged as one of the trending organizational adoption topics for a couple of years now this research is centred on how adoption of AI influences employee performance, in-order to establish the impact it has on performance management as well as the organizational performance (Cardy & Leonard, 2014). Modern economy has left organizations in a position in which they must seek ways in which they can enable their employees to work harder and better to get results (Diliantari & Dewi, 2019). Apart from talent acquisition, management, and investment, performance management assists in the improvement of individual performance and progression within a company. Measuring and monitoring employees' work accomplishment in terms of productivity, duties, tasks, and behaviour is fundamental to business operations and sustainability. Performance monitoring is helpful in diagnosing current changes and always planning for better growth in the future which will be good for the organization and the shareholders because this improves morale and productivity from the employees (Jeske & Santuzzi, 2015).

Nevertheless, the surveyed companies encounter numerous obstacles when it comes to employee performance management, and one of the biggest problems is that they lack of training (Mehale *et al.*, 2021). Lack of on-the-job training affects skills acquisition and promotions demoting organizational competencies and productivity. These gaps will call for more training or upskilling interventions to ensure employees' competencies are relevant to the required skill sets. If the employees of an organisation are not trained properly then they may not perform up to the expectations and this will result in customer dissatisfaction and the overall goals and objectives of an organisation may also be affected (Elnaga & Imran, 2019). The other another major challenge is that of the evaluation of employee performance bias (Grabner *et al.*, 2020). Although bias and prejudice are not necessarily considered to be detrimental during performance appraisals, these factors may easily distort the evaluative process and decrease its efficiency. Employees may also get high ratings due to nepotism or Employer bias such as gender bias, race bias or age bias where some employees are limited to promotion or other opportunities within the company. That is why such biases not only influence the morale of an employee and his readiness to work efficiently, but also have a negative impact on the general organizational effectiveness (Grabner *et al.*, 2020). To address this, managers require coaching on how the bias works to minimize it and set clear guidelines for assessment, in addition to creating a non-discriminatory working environment.

AI is the ultimate solution to these challenges that may be facing the organizations. This means that a human resource professional can assign specific content to an individual employee depending on that employee's learning needs in order to achieve the highest amount of results. Also, AI has the potential to minimize bias in performance appraisal by eliminating paid actors and using set criteria and figures for analysis. Through the use of AI, companies can avoid subjectivity, bias, and unfairness in doing performance appraisals, as well as increase organizational productivity since the overall goal is to improve employee performance. It indicates that the current theoretical frameworks of performance management focused on human resources and traditional technologies, and at the same time, the existing literature lacks a systematic way to determine how incorporation of recently emerged AI technologies will help in boosting employee performance. While the present study employs TAM for the assessment of the perceptiveness of usefulness and ease-of-use, the theoretical framework falls short of providing granularity in the use of AI, and its impact, specifically in the case of employing AI for decision making and subsequent impact on performance of the employees (Sharma *et al.*, 2022). Moreover, the current theories of performance management have least explanation about the roles through which AI supports to minimise the bias in the performance appraisal or; new ethicalities that is come up with using the help of the existing AI which demands an extended theoretical frame (Seyyed-Kalantari *et al.*, 2021). In addition, the interaction of human with these systems in terms of performance enhancement by the AI or camouflaging of human effort and interaction between human and AI systems requires additional theoretical construction of this concept at the human factors perspective with regards to productivity, motivation and stress levels. Moreover, among the existing theories, there is no adequate empirical studies for the local context, let alone other challenges and opportunities that define the use of AI in Malacca's manufacturing industry, implying the need for culture or broadening of the best-fit theories. Therefore, this study aims to identify the level of AI adoption and its impact on employee performance among manufacturing companies in Krubong, Melaka.

2. Literature Review

2.1 Employee Performance

Insufficient training and performance evaluation bias might hurt employee productivity and morale (Mehale *et al.*, 2021). First, lack of training is a major employee performance issue (Mehale *et al.*, 2021). If employees are not given enough training and development, they may not have the skills to do their jobs well. This competence gap can lead to a lack of confidence in one's capacity to perform tasks, which can reduce efficiency, increase errors, and increase uncertainty. Without continuing learning and skill-building, employees may struggle to

meet changing job needs and industry norms. Their performance suffers, and the corporation cannot use their potential for progress. Effective training programmes give employees the skills and knowledge they need to succeed in their jobs and help the company succeed (Zemburuka & Dangarembizi, 2020). Second, performance evaluation bias is another major issue affecting employee performance (Grabner *et al.*, 2020). Performance reviews can be biased due to performance reviewers' beliefs, biases, or stereotypes. Performance reviews cannot accurately assess an employee's skills and contributions if they are not fair and impartial. This could lower staff morale and motivation and damage faith in the appraisal process. Employees who feel their performance is unfairly appraised may become disengaged and less devoted. This is because they know their efforts may not be appreciated. To avoid evaluation bias, firms must implement standardised, transparent, and objective performance rating procedures. These systems should also evaluate employees fairly and uniformly (Grabner *et al.*, 2020).

Performance measurement is an important factor in management and organizational performance with performance being the most important metric employed. Under this, the development entails the assessment of the performance, efficiency, and effectiveness of the employees regarding their achievement of the goals and objectives of the organization. Such approaches usually include but not limited to the goal setting in terms of specific, measurable targets, appraisal of the performance in terms of achievement of the set goals or milestones and peer and/or supervisor feedback. Specific goals and objectives are measured and reported using quantitative data from the organisation by means of Key performance indicators (KPIs) and metrics on the other hand, qualitative assessments take into account elements such as teaming, innovativeness, and leadership (Franco-Santos *et al.*, 2012). Feedback mechanisms and a means of professional development are also components of measurement that make sure that the employed personnel are matching objectives periodically. In conclusion, it can be said that not only does a well-developed performance measurement system help to describe the top and weak performing employees and business areas, but also it serves as the basis for creating distinct and strong motivational and accountability, as well as learning and improvement culture within the given organization.

There is no specific method or technique which can be utilized to capture the measure of performance of the employees and therefore it requires a combination of both qualitative and quantitative techniques. Key performance indicators (KPIs) allow for the development of tangible objectives and targets to work towards, while frequent performance appraisals are formal evaluations of an employee (Franco-Santos *et al.*, 2012). Adding the use of 360-degree feedback provide information from different perspectives by employing feedbacks from peers, subordinates, supervisors and using self-assessment, which can be effective as far as the employee is improving. OKRs establish the connection between the personal goals and the objectives of a larger organization (Nazari-Ghanbarloo, 2020). Performance indicators are concerned with how much and how well individuals accomplish their assignments and feedback from clients gives an outside appraisal of the contribution made by the employee. Monitoring patterns of behaviour at work can determine interpersonal and teaming skills while checking records of participation in professional development activities demonstrates a faculty's desire for professional growth. When these various methods are combined then any organization can be confident that the methods used for the appraisal of the performances of their employees are fair and comprehensive, while also promoting performance improvement in areas which align with the strategic direction of the organization.

2.2 AI Adoption

AI adoption is integrating AI technologies into an organization's operations to boost efficiency, productivity, and success (Braganza *et al.*, 2020). This integration includes the use of computer systems that can solve problems, recognise patterns, and make decisions (Dwivedi *et al.*, 2021). In the early 1950s, British mathematician Alan Turing pioneered artificial intelligence. Since then, the field has advanced. Turing's Turing Test and machine intelligence concept established artificial intelligence as a field. Systems that can process large amounts of data and automate many tasks were developed (Pillai & Sivathanu, 2020). AI implementation has many drawbacks despite its benefits. Production and management processes must be drastically altered to accommodate the implementation's complexity. Ethical considerations and biases in artificial intelligence systems must be addressed alongside data privacy and security rules (Strohm *et al.*, 2020). Automation may also lead to employment losses, necessitating retraining and education programmes. Despite this, AI is crucial to digital transformation. It revolutionises industries by enabling flexible production, customisation, and human resource performance. Organisations may use AI to boost performance, creativity, and business success if they manage these challenges. AI applications throughout Malacca's industries have a robust economic impact yet researchers have failed to produce thorough studies about these applications in the area. Exclusive characteristics within the Malacca business environment make it important to conduct unique research because universal studies from different locations cannot provide exact relevancy. The local adoption patterns and obstacles regarding Artificial Intelligence in Malacca have not been thoroughly examined by available research although industry plays an integral role in the region's economic activities.

2.3 Technology Acceptance Model (TAM)

Davis established the Technology Acceptance Model in 1989 as a research framework that current academics continue to frequently utilize. According to Venkatesh & Davis (2020) the Technology Acceptance Model serves as a predictor for information systems technology adoption by users. Davis (1985) identified two key factors influencing an individual's willingness to adopt new technology: The two key drivers behind individuals adopting these systems are their perception of technological simplicity and the assessment of value they obtain from them. Research conducted by Hasni *et al.* (2021) reveals two central factors: "perceived ease of use" describes system user-friendly design while "perceived usefulness" represents job enhancement capabilities. Perceptual assessments regarding how easy a technology is to use alongside how beneficial its use can be formed the basis of technology adoption intentions that have direct impact on system usage. The theoretical model of the TAM presented in Fig. 1.

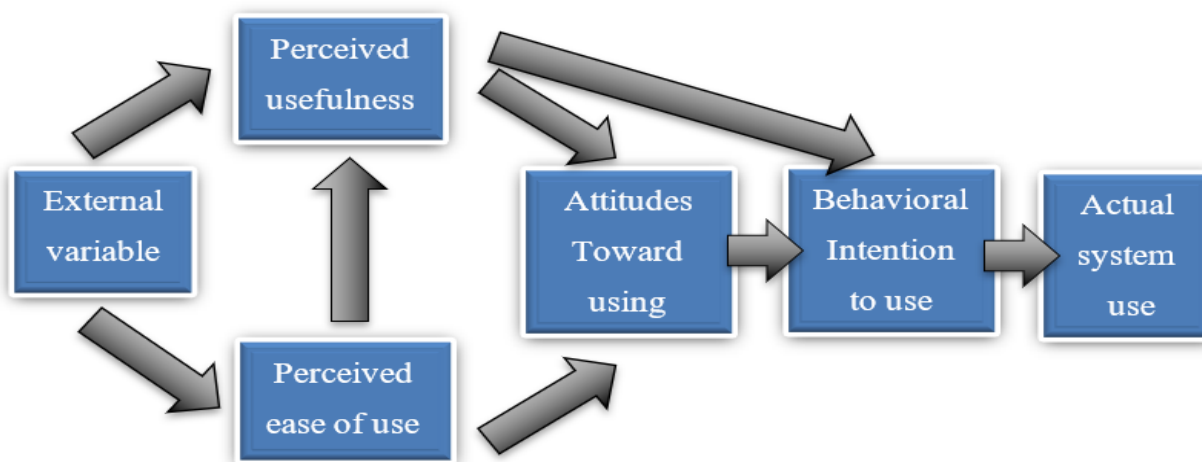


Fig. 1 TAM framework

2.4 Hypothesis Development and Conceptual Framework

2.4.1 Perceived Usefulness

The phrase "perceived usefulness" refers to how much an individual thinks a system or technology. A person's perception of usefulness describes their belief about how system or technological tools will improve their work performance. TAM uses this fundamental concept as its base to explain information systems research-based predictions about user behaviour and acceptance. According to Yuan *et al.* (2021) users develop "perceived usefulness" through their assessment that a technological system can enhance job performance alongside increased productivity at work. Workers show higher acceptance rates for new technologies when they see how it improves operational effectiveness and data organization capabilities and communication systems. The successful implementation of new processes enables organizations to reach higher productivity standards together with increased data precision while reducing task durations. A user's perception of technological unhelpfulness usually stops them from adopting the technology (Venkatesh & Davis, 2020). Research shows reported usefulness stands as a fundamental element which guides how people adopt new technologies ranging from the Internet to IoT to AI to robotics to CME. Davis (2020) explained that perceived usefulness stands as the primary factor which determines technology adoption.

H1: There is a significant relationship between perceived usefulness of AI adoption to employee performance.

2.4.2 Perceived Ease of Use

The Technology Acceptance Model (TAM) emphasises perceived ease of use, the belief that a system or technology would be easy to use. In 1989, Fred Davis defined perceived ease of use as "the degree to which a person believes that using a particular system would be free of effort". It shows how people view a system's ease of use and simplicity, which affects whether they adopt and use the technology. In addition to the lack of effort, (Venkatesh & Davis, 2020) expanded the notion to include the reduction of physical and mental strain associated with technology use. They defined perceived ease of use as "the extent to which a person believes that using a particular system will be free of physical and mental effort" (Venkatesh & Davis, 2020). Both definitions emphasise how important it is for technology to be simple and easy to use for new systems to be accepted and

adopted in various settings. Employee performance is highly affected by perceived ease of use since it affects how they employ new technologies at work. Easy-to-use systems are more likely to be adopted and integrated into everyday routines, increasing productivity and efficiency. This positive image allows employees to focus on higher-order activities and decision-making by lowering job time, effort, and learning curve. A user-friendly system may be utilised more often and effectively, improving work performance. According to Venkatesh & Davis (2020), user-friendly technology reduces annoyance and cognitive overload, which boosts productivity and workplace happiness. Ease of use promotes technological workflow integration, which can boost worker satisfaction, process speed, and organisational performance. Companies looking to boost staff productivity should prioritise building and implementing user-friendly and intuitive technology (Chatterjee *et al.*, 2020).

H2: There is a significant relationship between the perceived ease of use of AI adoption to employee performance.

2.4.3 Perceived Need for Interaction with Technology

Perceived necessity for contact with technology is the extent to which an individual believes using a certain technology is essential to their personal or professional goals. This perception evaluates the value of using technology to improve productivity, work performance, and results. It involves acknowledging that technology helps people work, solve problems, and be more efficient. This perceived need can be influenced by task difficulty, technology capabilities, the individual's familiarity with technological tools, and the organisational or environmental setting that emphasises technological integration. To encourage technology adoption and use among employees, organisations must understand the perceived need for engagement with technology. This highlights the motivational factors that lead people to incorporate technology into their everyday routines and workflows. Employee performance is closely tied to their beliefs of their need for technological interaction, which affects how often they use these technologies to improve work efficiency. When employees want to use technology, they're more likely to optimise their work and perform better. According to the Unified Theory of Acceptance and Use of Technology (UTAUT), performance expectancy, the belief that using technology will improve job performance is a key factor in technology adoption and use (Venkatesh & Davis, 2020). Research also shows that workers who believe technology engagement is important are more likely to learn how to utilise these tools efficiently, which boosts output and job satisfaction (Lu *et al.*, 2020). This shows how important it is for organisations to promote technology engagement to boost worker productivity.

H3: There is a significant relationship between the perceived need for interaction with technology of AI adoption to employee performance.

2.4.4 Perceived Enjoyment

The phrase "perceived enjoyment," taken from Davis *et al.* (1992), refers to how much a system's use is enjoyed without regard to performance. As users gain more hands-on experience with the target system, their view of its ease of use will shift from generic computer playfulness to system-specific delight (Zhu *et al.*, 2022). Software developers are aiming to make Windows-based user interfaces enjoyable, "cute," and social (think Office 97's "animated assistant icons"). These design features are supposed to be fun while making a system easier to use. As expertise increases, system use may become ordinary, less adventurous, and less difficult. Dissatisfaction may make utilising the system appear more tedious (Venkatesh & Davis, 2020). Since technology enjoyment affects user engagement, motivation, and job satisfaction, it greatly impacts employee performance. When technology is attractive, employees are more likely to use it, increasing production and efficiency (Yang & Lee, 2018). According to studies, users' attitudes towards technology are positively impacted by perceived enjoyment, which may affect job satisfaction and performance (Venkatesh & Davis, 2020). Enjoying technology can also increase intrinsic motivation, which can lead to more effort and persistence. Technology enthusiasts may experiment with its features and capabilities, improving skill growth and expertise. In general, boosting technology love improves employee performance and workplace happiness.

H4: There is a significant relationship between the perceived enjoyment with technology of AI adoption to employee performance.

2.4.5 Perceived Trust

The phrase "Trust," means believing the technology will work efficiently and with integrity (Asan *et al.*, 2020). Technology trust is an individual's conviction in it (Yuen *et al.*, 2020). Vigilant customers actively assess information reliability before buying new products and services (Asan *et al.*, 2020). Confidence in artificial intelligence (AI) systems affects adoption and employee effectiveness. When they trust AI systems to do their

tasks reliably, accurately, and morally, employees are more likely to adopt it. Research shows that trust in AI increases staff acceptance and use (Bawack & Desveaud, 2022). By automating monotonous tasks, improving decision-making, and providing timely insights, dependable AI systems can boost worker performance (Sebastian *et al.*, 2022). Confident AI users are more likely to follow its advise and use its results, improving output, efficiency, and work satisfaction. Trustworthy AI reduces resistance to technological change and makes organisation adoption easier, easing job displacement and control concerns. Overall, creating trust in AI technologies is crucial to realising their potential to increase worker performance and organisational outcomes.

H5: There is a significant relationship between the perceived trust in technology of AI adoption to employee performance.

2.4.6 Perceived Risk

The sense of threat associated to AI integration affects company employee productivity. High perceived risk, such as job loss, autonomy loss, or ethical issues, may hinder employee involvement with AI technology (Chen *et al.*, 2022). Workers who consider AI as hazardous may avoid utilising it, missing out on productivity and innovation. Increased tension or worry caused by unpredictability may also impair worker concentration, drive, and job satisfaction. AI adoption can improve worker performance if perceived risk is managed appropriately (Esmailzadeh, 2020). Addressing employee concerns and providing sufficient AI technology training, support, and communication can lower perceived risks and encourage experimentation and creativity (Hong & Cho, 2023). By fostering trust, openness, and cooperation, these firms allow employees to explore AI's potential benefits. It boosts performance and organisational efficacy. The relationship between employee performance, AI adoption, and perceived risk is complex. Even though high perceived risk might hamper employee engagement with AI technologies, effective risk management can improve performance. AI technology can help organisations improve performance and competitiveness in the digital era by addressing concerns, providing support, and building trust.

H6: There is a significant relationship between the perceived risk in technology of AI adoption to employee performance.

2.4.7 Conceptual Framework

Fig. 2 shows how independent and dependent variables relate. The independent variable determining AI adoption's impact on employee performance is its perceived usefulness, ease of use, need for technology interaction, enjoyment, trust, and risk. The sole dependent variable is employee performance when the Krubong, Malacca industry adopts AI.

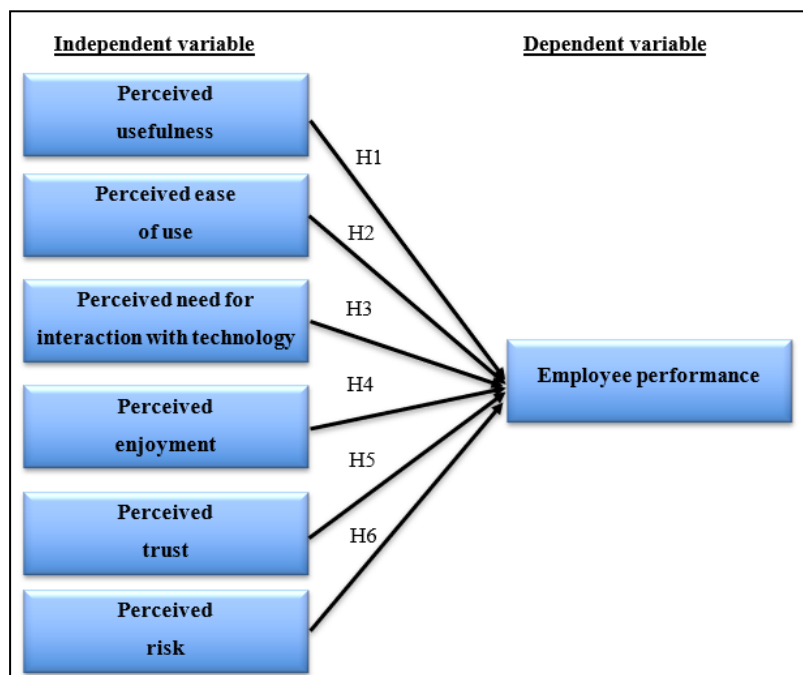


Fig. 2 Conceptual framework

3. Research Methodology

3.1 Research Design

A quantitative approach was adopted to examine the relationship between AI adoption and employee performance among manufacturing employees in Krubong, Malacca. A survey questionnaire served as the primary data collection tool, targeting executives and senior management personnel in Krubong's manufacturing sector to efficiently gather quantitative data. This method enabled rapid data collection and analysis from the target demographic, aiding in the identification of key variables and the formulation of hypotheses and research questions. The study aimed to capture focused insights from executive-level employees in Krubong, Malacca, to achieve its research objectives.

3.2 Population and Sampling

The research population refers to a broad group of individuals relevant to a study's theoretical framework. By focusing exclusively on supervisory and higher-level managers, this study ensures that data is collected from decision-makers with firsthand experience in AI adoption and its effects within the manufacturing sector. These individuals are best positioned to provide detailed insights into the operational and technical implications of AI integration, as they possess a clear understanding of its impact on productivity. Bujang & Baharum (2017) emphasize that proper research design requires sample size estimation to ensure population representation. Accordingly, this study selects a sample from the specified demographic—manufacturing employees in Krubong, Malacca, estimated at 1,300 individuals. To determine the required sample size, G*Power was employed, a statistical tool that provides graphical analysis, effect size calculations, and support for both distribution-based and design-based input methods (GPower 3.1 Manual, 2020). Additionally, it includes calculators for various central and noncentral probability distributions. Based on the GPower analysis (refer Fig. 3, a minimum of 103 respondents was deemed necessary. Thus, this study engaged at least 103 participants holding supervisory or higher-level roles to leverage their expertise and insights. A purposive sampling technique was applied, also known as judgmental sampling, where participants are selected based on their relevance to the study's objectives. Researchers deliberately targeted supervisors and senior managers, as they are most likely to provide critical insights aligned with the research goals. This method ensures that respondents possess industry expertise and sufficient experience to offer credible, meaningful responses to the survey questions. Given their deep understanding of AI's organizational impact, these participants are instrumental in generating high-quality data on AI adoption and employee performance.

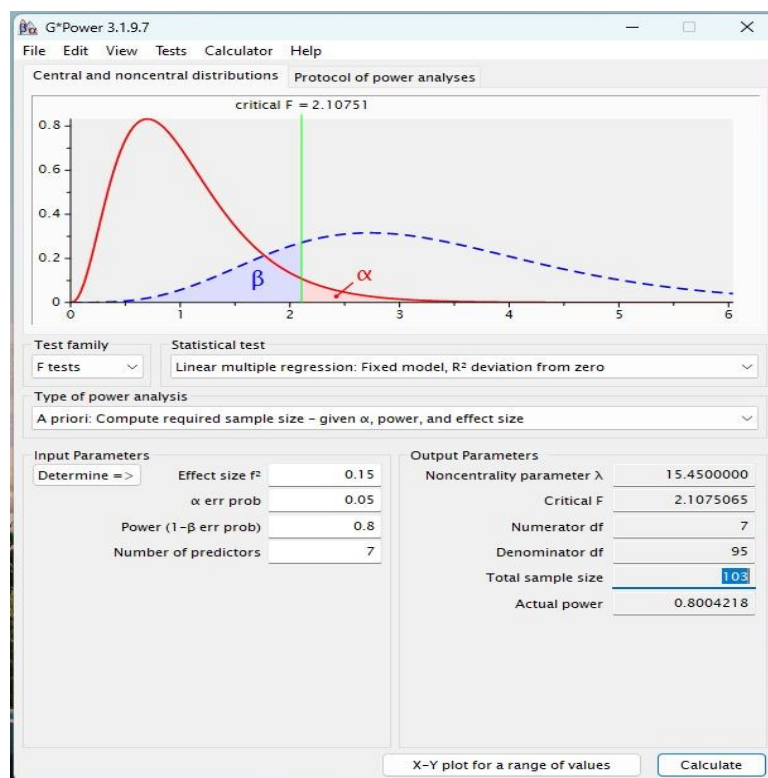


Fig. 3 Sample size calculation using G*Power

3.3 Research Instrument

This study employed a quantitative research approach using a structured questionnaire survey as the primary data collection instrument, comprising four sections: (A) respondent demographics, (B) AI adoption factors, and (C) employee performance metrics. Distributed digitally via Google Forms to executives and senior management in Krubong, Malacca's manufacturing sector, the survey utilized a five-point Likert scale (1=Strongly Disagree to 5=Strongly Agree) to systematically measure responses, providing a reliable method for quantifying attitudes and perceptions regarding AI implementation in the workplace.

3.4 Data Analysis

Pilot studies serve as preliminary investigations that assist in planning and refining larger research projects, with primary objectives including feasibility assessment, participant recruitment, consent procedures, and intervention evaluation (Arain *et al.*, 2010). These small-scale studies enable researchers to test methodologies before full implementation, where a properly conducted pilot can inform sample size determination by identifying unknown variables and exploring their relationships (Viechtbauer *et al.*, 2015). For this pilot study, the survey questionnaire was administered to 30 participants, as this sample size represents an appropriate benchmark for initial scale development or preliminary surveys. Following data collection, Cronbach's alpha was employed to measure the internal consistency reliability of the instrument. Following data collection from all respondents, the analysis phase commenced using SPSS software. The researcher manually input the collected data into SPSS for processing, measurement, and computation of complex quantitative information, enabling efficient analysis of findings. During this analytical process, data screening and cleaning procedures were implemented to identify and address any erroneous or missing entries, thereby ensuring the accuracy of subsequent analyses. Table 1 presents the specific analytical methods employed to examine the data and address the research questions in alignment with the study's objectives.

Table 1 Analysis based on each of research question and research objective

Research question	Research objective	Analysis
What is the level of AI adoption and employee performance?	To identify the level of AI adoption and employee performance	Descriptive Analysis
What is the relationship between AI adoption and employee performance?	To identify the relationship between AI adoption and employee performance	Correlation Analysis
What is the impact of the AI adoption on the performance management	To determine the impact of the AI adoption on the employee performance	Comparison Analysis

4. Results and Discussion

4.1 Responses Rate and Data Cleaning

The required sample size of 103 respondents was determined through GPower calculations, and all contacted participants completed the survey, yielding 103 valid responses. A thorough data cleansing process was implemented to verify accuracy, which included detecting and correcting errors, resolving inconsistencies, and eliminating duplicate or incomplete entries. This rigorous quality control process enhanced data integrity and consistency, ensuring the reliability of findings for organizational decision-making in line with the Data Asset Management Framework (Stedman, 2022). The final dataset contains no missing values and fully meets all research requirements, providing a robust foundation for analysis.

4.2 Demographic Information

This study collected data from 103 employees with artificial intelligence (AI) implementation experience across manufacturing companies in Krubong, Malacca. The sample comprised 54 female respondents (52.4%) and 49 male respondents (47.6%), with a mean age of 33 years. Age distribution analysis revealed the largest cohort (30-39 years) represented 33.0% of participants, followed by 40-49 years old (25.2%), 20-29 years olds (18.4%), and 50-59 years old (10.7%). Minor age groups included respondents below 19 years (3.0%) and above 60 years (1.9%). All participants (100%) reported active AI usage in their daily work responsibilities, with detailed demographic breakdowns presented in Table 2.

Table 2 Reliability analysis

Demographic	Category	Frequency	Percentage (%)
Gender	Male	49	47.6
	Female	54	52.4
Age	< 20 years old	9	8.7
	20 – 29 years old	19	18.4
	30 – 39 years old	34	33.0
	40 – 49 years old	26	25.2
	50 – 59 years old	11	10.7
	> 59 years	4	3.0
Education level	SPM and below	8	7.8
	Diploma	21	20.4
	Bachelor Degree	59	57.3
	Master Degree	11	10.7
	Other	4	3.9
Working experience	Less than 1 year	7	6.8
	1 – 2 years	25	24.3
	3 – 4 years	55	53.4
	5 – 6 years	12	11.7
	More than 6 years	4	3.9

4.3 Reliability Analysis

The reliability analysis for the main study demonstrated strong internal consistency, with all Cronbach's alpha values exceeding the 0.70 threshold, confirming instrument reliability. The independent variables showed alpha coefficients ranging from 0.763 to 0.911, indicating good to excellent reliability levels. For the employee performance construct, the alpha value of 0.852 reflected very good reliability, as detailed in Table 3. These results collectively validate the measurement scales used throughout the study.

Table 3 Reliability analysis

Variables	No. of items	Cronbach's alpha	Interpretation
Perceived usefulness (PU)	5	0.813	Very Good
Perceived ease of use (PEU)	5	0.787	Good
Perceived need for interaction with technology (PNIT)	5	0.763	Good
Perceived enjoyment (PE)	5	0.829	Very Good
Perceived trust (PT)	5	0.906	Excellent
Perceived risk (PR)	5	0.911	Excellent
Employee performance (EP)	5	0.852	Very Good

4.4 Normality Test

The selection between the Kolmogorov-Smirnov and Shapiro-Wilk tests depends on sample size considerations, with the Kolmogorov-Smirnov test being employed for our dataset of 103 valid responses. As presented in Table 4, the analysis revealed statistically significant p-values ($p = 0.00$) for all independent and dependent variables, providing clear evidence of non-normally distributed data. This finding necessitated the use of non-parametric statistical methods for subsequent analyses to ensure appropriate handling of the data distribution characteristics.

Table 4 Normality analysis

	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Perceived usefulness (PU)	.168	103	.001	.875	103	.001
Perceived ease of use (PEU)	.163	103	.001	.864	103	.001
Perceived need for interaction with technology (PNIT)	.161	103	.001	.855	103	.001
Perceived enjoyment (PE)	.150	103	.001	.877	103	.001
Perceived trust (PT)	.187	103	.001	.862	103	.001
Perceived risk (PR)	.177	103	.001	.873	103	.001
Employee performance (EP)	.164	103	.001	.884	103	.001

4.5 Descriptive Analysis

The descriptive analysis reveals consistently positive perceptions across all measured constructs related to AI adoption and employee performance (Table 5). All variables demonstrated mean scores above 4.0 on what is presumably a 5-point scale, indicating strong agreement among respondents. Particularly noteworthy are the exceptionally high ratings for perceived trust (M = 4.33, SD = 0.886) and perceived ease of use (M = 4.32, SD = 0.912), suggesting that employees view AI systems as both reliable and user-friendly. The narrow range of standard deviations (0.886-0.979) across these positive constructs indicates remarkable consistency in responses, with perceived usefulness showing slightly more variation (SD = 0.979) than other factors. These findings collectively paint a picture of an organizational environment where AI systems are generally well-received and trusted by employees.

A closer examination of the results shows particularly strong performance across experiential and interaction-related factors. Perceived enjoyment (M = 4.32, SD = 0.897) and perceived need for interaction with technology (M = 4.30, SD = 0.907) both scored in the "very high" range, indicating that employees not only find AI systems functional but also engaging to use. The high mean score for employee performance (M = 4.30, SD = 0.891) suggests that these positive perceptions translate into measurable workplace outcomes. Interestingly, perceived risk, while still in the "high" range (M = 4.17, SD = 0.945), represents the lowest mean score among the measured constructs, potentially indicating a slight but meaningful area of concern that warrants further investigation despite the overall positive outlook.

The pattern of results suggests a strong correlation between positive AI perceptions and enhanced employee performance, with all constructs falling within a remarkably tight range of mean scores (4.17-4.33). The consistency across these measurements implies that the various dimensions of AI adoption - including practical utility, user experience, and emotional response - are similarly developed within this organizational context. The minimal variation in standard deviations (all below 1.0) across constructs further reinforces the reliability of these findings. These results provide empirical support for the notion that comprehensive positive perceptions of AI systems, encompassing both functional and affective dimensions, coincide with strong employee performance outcomes in this industrial setting. The findings offer valuable insights for organizations implementing AI solutions, highlighting the importance of addressing multiple perception domains to maximize technology adoption and workforce performance.

Table 5 Descriptive statistics

Variable	N	Mean (M)	Std. deviation (SD)	Interpretation
Perceived usefulness (PU)	103	4.28	0.979	Very high
Perceived ease of use (PEU)	103	4.32	0.912	Very high
Perceived need for interaction with technology (PNIT)	103	4.30	0.907	Very high
Perceived enjoyment (PE)	103	4.32	0.897	Very high
Perceived trust (PT)	103	4.33	0.886	Very high
Perceived risk (PR)	103	4.17	0.945	High
Employee performance (EP)	103	4.30	0.891	Very high

4.6 Correlation Analysis

Correlation analysis serves as a quantitative method to examine the nature and strength of relationships between variables. In this study, the Spearman's rank correlation test was employed due to the non-normal distribution of the data, which precluded the use of parametric tests. This non-parametric method assesses the monotonic relationship between variables by evaluating their rank orders. As shown in Table 6, the analysis revealed a strong positive correlation ($\rho = 0.636$, $p < 0.001$) between perceived usefulness of AI adoption and employee performance, leading to the acceptance of H1. These findings demonstrate that as perceptions of AI's usefulness increase, so does its positive impact on employee performance.

Further analysis indicated moderate to strong positive correlations for additional constructs. Perceived ease of use showed a moderate correlation with employee performance ($\rho = 0.576$, $p < 0.001$), supporting H2. The need for interaction with technology demonstrated a particularly strong association ($\rho = 0.758$, $p = 0.001$), suggesting that employees' comfort with AI interfaces significantly influences performance outcomes. Similarly, perceived enjoyment exhibited a robust correlation ($\rho = 0.762$, $p = 0.001$), confirming H4. These consistent patterns across multiple dimensions of AI adoption highlight the multifaceted nature of technology acceptance in the workplace and its performance implications. The examination of perceived risk revealed a strong negative correlation ($\rho = 0.713$, $p = 0.001$) with employee performance, leading to the acceptance of H6. This finding suggests that concerns about AI technology significantly influence its effectiveness in enhancing work performance. The consistently significant results ($p < 0.05$) across all hypotheses underscore the comprehensive impact of various AI adoption factors on employee performance metrics. These correlations collectively provide

empirical evidence for the importance of considering multiple psychological and practical dimensions when implementing AI solutions in organizational settings.

Table 6 Spearman's rho correlation coefficient

			EP	Interpretation
Spearman's rho	PE	Correlation Coefficient	0.636	Accepted
		Sig. (2-tailed)	0.001	
	PEU	Correlation Coefficient	0.576	Accepted
		Sig. (2-tailed)	0.001	
	PNIT	Correlation Coefficient	0.758	Accepted
		Sig. (2-tailed)	0.001	
	PE	Correlation Coefficient	0.762	Accepted
		Sig. (2-tailed)	0.001	
	PT	Correlation Coefficient	0.667	Accepted
		Sig. (2-tailed)	0.001	
	PR	Correlation Coefficient	0.713	Accepted
		Sig. (2-tailed)	0.001	

The Spearman's rho analysis reveals statistically significant positive correlations (all $p < 0.001$) between employee performance (EP) and all examined AI adoption factors, with coefficients ranging from moderate to strong ($\rho = 0.576$ - 0.762). Perceived enjoyment (PE) and perceived need for interaction with technology (PNIT) demonstrated the strongest associations ($\rho = 0.762$ and 0.758 respectively), suggesting that affective experiences and interface usability are particularly critical drivers of performance outcomes. While slightly weaker, the remaining correlations still indicate substantial relationships, with perceived ease of use (PEU) showing the lowest yet still moderate correlation ($\rho = 0.576$). Notably, perceived risk (PR) maintained a strong positive correlation ($\rho = 0.713$), challenging conventional assumptions about risk perceptions in technology adoption. The uniformly significant results (all $p = 0.001$) provide robust evidence that multiple dimensions of AI perception collectively influence employee performance, with affective components (enjoyment) appearing slightly more influential than utilitarian factors (usefulness). These findings underscore the multidimensional nature of successful AI implementation in organizational settings, where both practical and emotional factors significantly impact workforce outcomes.

5. Conclusion

This study examined the relationship between artificial intelligence (AI) adoption and employee performance in the manufacturing sector of Krubong, Malacca. The research aimed to identify the level of AI adoption and explore key factors influencing this relationship. Findings revealed consistently high perceptions of AI across multiple dimensions, including usefulness, ease of use, trust, and enjoyment, with mean scores exceeding 4.0 on a 5-point scale. These positive perceptions were strongly correlated with enhanced employee performance, suggesting that AI adoption significantly contributes to workplace efficiency. The correlation analysis demonstrated robust relationships between AI adoption factors and performance outcomes. Perceived enjoyment ($\rho = 0.762$) and the need for interaction with technology ($\rho = 0.758$) exhibited the strongest associations, highlighting the importance of user experience and engagement in AI implementation. Notably, perceived risk also showed a significant correlation ($\rho = 0.713$), indicating that addressing employee concerns about AI is critical for maximizing its benefits. These findings underscore the multidimensional nature of AI adoption, where both functional and affective factors play pivotal roles in driving performance improvements. This research contributes to the existing literature by providing empirical evidence on AI adoption in a regional manufacturing context, an area previously underexplored. The results suggest that organizations should prioritize user-friendly AI systems, foster trust, and mitigate perceived risks to enhance employee performance. However, the study is limited by its focus on a specific geographic and industrial setting, which may affect generalizability. Future research could expand to diverse sectors and longitudinal designs to assess long-term impacts. Ultimately, this study highlights the transformative potential of AI in optimizing workforce productivity while emphasizing the need for balanced implementation strategies.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: **study conception and design:** Yim Chee Hoe, Mohamad Ali Selimin; **data collection:** Yim Chee Hoe; **analysis and interpretation of results:** Yim Chee Hoe, Mohamad Ali Selimin; **draft manuscript preparation:** Yim Chee Hoe, Mohamad Ali Selimin. All authors reviewed the results and approved the final version of the manuscript.

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