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Adoption of Artificial Intelligent Driven Smart Inspection System at H Automotive Manufacturing Industry in Selangor

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Abstract

This study aims to assess the adoption of AI-driven smart inspection systems at H automotive manufacturing industry in Selangor. Furthermore, this research will also focus on those factors that influence the decision-making process regarding the integration of these AI technologies. As Malaysia moving towards to Industry 4.0, AI-driven inspection system has the potential to help the manufacturing company to improve the quality control, reduce defect rates, and improve the operational efficiency in automotive manufacturing. However, Malaysian company still faces several challenges, which including high implementation costs, of AI-driven smart inspection systems, organizational readiness, and lack of experienced workers. Based on the Unified Theory of Acceptance and Use of Technology (UTAUT) framework, this research investigates the key variables such as effort expectancy, performance expectancy, social influence, facilitating conditions, organizational readiness, cost, and how these variables affect the adoption of AI-driven inspection systems. Data will be collected by distributing questionnaires to professionals at H automotive manufacturing company located in Selangor, which includes quality control managers, production engineers, and technology officers. This study will use quantitative research technique to investigate the relationships between the independent factors, the dependent variable and the adoption of AI-driven smart inspection devices. The findings of this study will contribute knowledge on AI adoption in the Malaysian automotive sector, providing important information for manufacturers, policymakers, and industry leaders. Moreover, by identifying challenges to AI adoption, this research aims to support Malaysia in advancing its automotive manufacturing industry toward full integration with Industry 4.0 technologies.

Keywords: Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Organizational Readiness

Introduction

The automotive industry is an important part of economy in Malaysia. However, adoption of AI in automobile manufacturing is still in early stages in Malaysia (Ahmad et al., 2022). The use of AI inspection systems can assist in improving production efficiency, reduce human error and bolster quality. Besides, the previous research found that the knowledge of artificial intelligence (AI) can influence individual behavior towards the AI applications (Tin, 2024). Such technologies are being introduced rapidly to the automotive manufacturing industry in Malaysia for those manufacturers that play to global quality to enhance their company competitiveness. AI & ML in Malaysia Car Manufacturing Industry The early-2010s witnessed the trend of AI technology being used in Malaysia car manufacturing industry. To this end, the National Policy on Industry 4.0 (Industry4WRD) launched in 2018 made considerable headway to facilitate the adoption of AI in respective sectors, such as automotive manufacturing (Ministry of International Trade and Industry [MITI], 2018). The rationale for this policy is to augment productivity and creativity with the wider adoption of technology, which AI is a key driver of this transformation.

This study's focus is on the investigation of the adoption of AI-based smart inspection systems, which serves as the dependent variable (DV), in the Malaysian automotive manufacturing sector. According to studies, AI based approaches can improve inspection precision, minimize costs, and maximize overall production efficiency significantly (Dwivedi et al., 2019). To date, there has been little evidence of studies investigating the acceptance of AI use within the Malaysian automotive industry, despite the emergence of interest towards AI adoption worldwide. Investigation on AI adoption in general is mostly focusing on high-level issues such as supply chain management or manufacturing automation (see Chen et al., 2022), resulting in a limited understanding on applications of AI-powered smart inspection systems. This makes a significant gap in understanding what specific aspects affect these technologies in their usage in the inspection process.

The use of AI-driven smart inspection devices in Malaysia's automobile manufacturing industry has the possibility to increase productivity, improve quality control, and reduce costs of production. Despite these advantages, the actual implementation of these technologies is still limited, due to the factors such as high costs, organizational readiness, and technical knowledge. Therefore, additional studies are needed to explore how these areas impact the adoption process—organizational readiness, cost, and government regulations among others. The study addresses this gap by aiming to facilitate research that enhances knowledge on the challenges as well as opportunity for implementing the system in the automotive industry specifically from the point of view of the Industry 4.0 aspirations in Malaysia.

Literature Review

Underpinning Theories

The study is theoretically formulated on Venkatesh et al. Unified Theory of Acceptance and Use of Technology (2003). The framework helps to understand how people adopt innovative technology. Additionally, this model focuses on four major factors that affect the user in terms of adopting and utilizing such a technology: performance expectancy, effort expectancy, social influence, and facilitating conditions. This model is not a new concept; it has been applied across a range of sectors, from manufacturing, healthcare, and education to the adoption of AI technologies in the automobile industry.

Performance expectance refers to the opinion of individuals that the use of new technology would increase his/her job performance; like how an individual would elect to use a new software programme, if they were of the belief that it would increase productivity. Contrary is effort expectancy which describe about the easiness of the technology itself; for example, the user will more be prefer to have an easy use apps than the hard and complicated apps. In addition, social impact is the pressure from other individuals' opinions on the decision for using a certain technology. Finally, facilitating conditions are the environmental factors that promote the use of technology use, including preparedness of necessary technical support.

Adoption of AI Drivers Smart Inspection System (DV)

The adoption of smart inspection technologies driven by AI is the dependent variable for this research. The adoption gives an overview of how the company used these technologies in the routine tasks in the company, such as quality control and defects detection. In addition, the other elements such as utilization, successful assimilation and the impact of operational efficiency are all metrics of the adoption process. Adoption is the most frequent result when analysing new technology, according to Venkatesh et al. (2003) in the Unified Theory of Acceptance and Use of Technology (UTAUT).

Despite this, the automotive manufacturing industry in Malaysia is still in the early stage of adoption of AI where only a handful of firms have introduced these systems within their operations (Roszelan & Shahrom, 2025). Cost sensitivity, the company's culture, and technology complexity perception affect the rate of new technology adoption. Previous studies confirmed that clear data on ROI (returning on investments), productivity and accuracy associated with the implementation and use of AI technologies will make companies more willing to invest in AI technologies.

The ZDM concept has increased in popularity in reason years due to the fourth industrial revolution and the promise of smart manufacturing (Powell et al., 2022; Caiazzo et al., 2022). According to this approach "quality has a performance standard of Zero Defects, not acceptable quality levels" and "quality is achieved by prevention, not appraisal"(Crosby, 1979).

AI sees the whole system required for intelligent behavior (Russel, 2020). Sensors detect the environment, intelligence methods evaluate data and make conclusions automatically, and actuators carry out the decisions. Machine learning (ML) may provide intelligence to a system by learning from examples and understanding how it acts. ML is a data-driven strategy for inspecting products using traditional methodology devices or cameras (Papageorgiou et al., 2021). Data and ML algorithms are critical for making reliable judgments, and different AI strategies may be applied based on the job (Kang et al., 2020). Many literature evaluations have identified AI and its subfield, machine learning (ML), as major enabling technologies for ZDM.

According to Russell (2020), AI perceives the entire system needed for intelligent activity. Actuators execute the decisions, intelligence procedures analyse data and draw conclusions automatically, and sensors sense the surroundings. The information from examples and comprehending how a system behaves, machine learning (ML) has the potential to give it intelligence. ML is a data-driven approach to product inspection that makes use of cameras or classic methodological devices (Papageorgiou et al., 2021). Making accurate decisions requires data and machine learning algorithms, and depending on the work, several AI techniques may be used (Kang et al., 2020). AI and its subfield, machine learning (ML), have been identified as key enabling technologies for ZDM in numerous literature reviews.

AI has revolutionized the manufacturing sector with its capacity to analyze large amounts of data and make decisions in real time (Robert, 2023). Artificial intelligence (AI) not only can helped company to increase productivity and quality control (Robert, 2023). It also can use data from inventory management and production lines to provide recommendations and improve the manufacturing process.

Moreover, AI-powered robots with sensors and AI algorithms can execute complicated tasks. Collaborative robots (cobots) operate alongside human workers can improve productivity, provide safer working conditions, and enable jobs that need accuracy and strength (Henry, 2024).

The use of AI in manufacturing, for example, through automation and predictive maintenance, comes with costs for sensors, robotic machinery, AI software, and staff development. Depending on how automated the system is, the initial costs could be anything from a few hundred thousand to several million dollars. However, automation in manufacturing processes driven by AI may increase productivity while lowering labor costs. AI might, for instance, increase factory productivity by 20–30%, saving up to $500,000 annually per site (Adam, 2024). Increased profitability and a competitive edge could arise from savings that significantly exceed the initial expenditure over a five-year period (Adam, 2024).

Drivers of AI Implementation
AI implementation is influenced by effort expectancy, performance expectancy, social influence, facilitating conditions, organizational readiness, and cost. These variables, developed from the UTAUT model (Venkatesh et al., 2003), are critical for understanding the factors that influence the adoption of AI technology.

Performance Expectancy: Is perceived value of using AI-driven inspection systems to improve operational efficiency and product quality. It’s found that organizations are more willing to implement AI technology when they foresee good results such as improved quality control and reduced production downtime.

Effort Expectancy: This variable indicates how at ease it is for users to use technology. The simpler and more user-friendly system is more likely to help achieve recognition. Because of this complexity, companies in the context of Malaysian automobile production cited the complexity of AI systems as a barrier to adoption, and as a result, companies were more reticent to adopt these technologies.

Social Influence: Strong Push from Industry leaders, and Stakeholders. Previous studies mentioned that social effects play a large role in the adoption and diffusion of technologies in the automotive industry as well, especially since opponents implemented AI technologies.

Facilitating Conditions: This construction relates to the availability of resources, infrastructure, and organizational support for implementing AI-driven systems. Things such as providing basic human and technological infrastructure might facilitate the adoption of AI-based solutions in some other companies and countries.

Organizational Readiness: How prepared an organization is to integrate new technology is critical. In Malaysia, a lack of technology infrastructure and skilled personnel are the main obstacles that limit an organizational readiness. Companies must have the necessary environment, training, and leadership commitment to successfully implement AI- driven technologies.

Conceptual Framework
The conceptual framework of thus study is developed based on the discussion in section above. This conceptual framework provides a broad understanding of factors that significantly affecting the adoption of AI driven smart inspection system in the Malaysian automotive manufacturing industry.

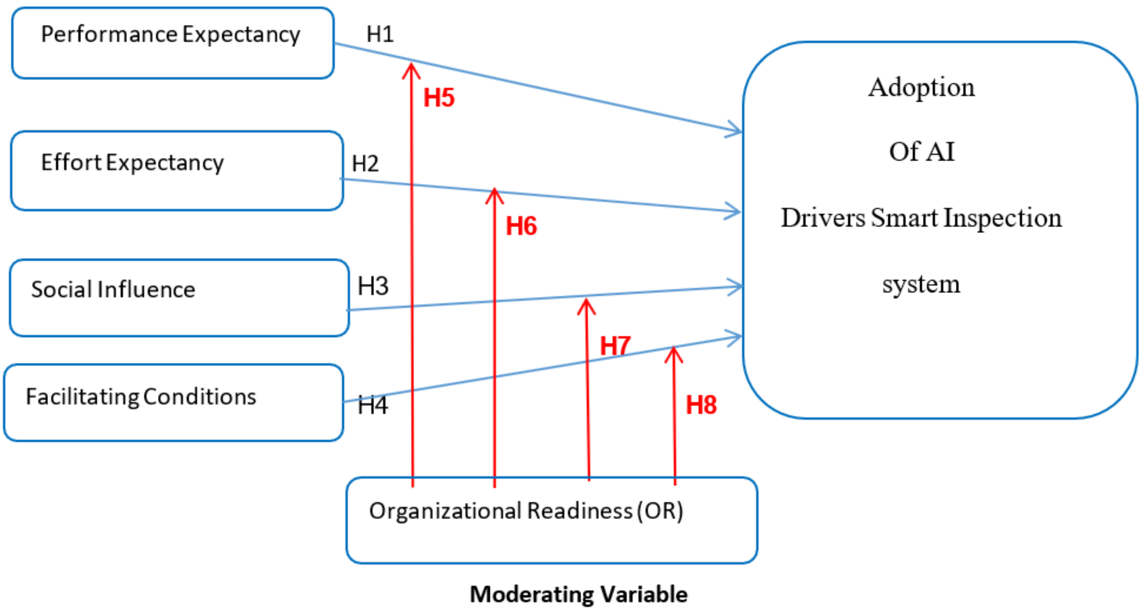

Figure 1: The conceptual framework

Method
This study will employ a systematic, scientific approach to ensure that the research findings are reliable, valid, and generalization. Data is gathered using a structured questionnaire consisting of closed-ended Likert scale measurements on performance expectancy, effort expectancy, social influence and facilitating conditions. The target population for this study is professionals in the H automotive manufacturing industry sector at Selangor, Malaysia who oversee decision-making, and operational execution. The sample size is applies using the online Raosoft sample size calculator, which is a tool for calculating a proper sample size necessary for a research project. It calculates the needed sample size with statistical methods according to the population size. To ensure a representative sampling of different sub-groups this study employs a stratified random sampling technique where sub-groups include engineers, managers, and technicians among others within the H automotive industry. To

facilitate distribution and data collection, the survey will be done online through a platform such as Google Forms. The data collected on the Likert scale will be analyzed by Smart PLS (Partial Least Squares). Examination of the relationships between variables will be conducted to evaluate both the measurement model and structural model with the software. Reliability analysis is one of the major aspects of research that ensures the stability and consistency of the Measurement instruments used in a study. Assessing the validity of each construct is an important step in evaluating the measurement model because you want to make sure the constructs accurately represent the theoretical concepts they are intended to capture.

Discussion and Future Research

The study looked at the respondents, collected demographic statistics, and analyzed the relationships between the variables and the hypotheses. An impressive 81.75% response rate was obtained from the distribution of 400 questionnaires, 327 of which were entirely completed. Strong internal consistency was shown by reliability analysis, with Cronbach's Alpha coefficients ranging from totally consistent to quite appropriate. Table 1 indicates good Cronbach's Alpha alignment for AI adoption in automotive manufacturing.

Table 1
Construct Reliability and Validity Analysis for AI adoption in Automotive Manufacturing

The study Variables	No. of Items	Cronbach's Alpha
Performance Expectancy (PE)	4	0.923
Effort Expectancy (EE)	4	0.93
Social Influence (SI)	4	0.937
Facilitating Conditions (FC)	4	0.935
Organizational Readiness (OR)	5	0.944
Overall Intention to adopt AI-Driven Smart Inspection Systems (OI)	5	0.938

The data analysis incorporated an examination of the demographic profile of the individuals who participated in the study. A breakdown of the 327 respondents by demographics was performed. Of those who participated, 56% identified as male while 44% identified as female, reflecting a slight imbalance typical in the automotive manufacturing sector but also signalling growing gender diversity. The largest age group among the respondents was 45 to 54 years old at 27% of the total, followed closely by 25 to 34 years old at 25% and 35 to 44 years old at 24%. Most holders of advanced degrees participated at 35% with master's degrees, followed by those with bachelor's degrees at 32%, indicating a high level of educational attainment in this field. Engineers made up the largest portion of respondents at 128, followed by quality control specialists at 99, technicians at 55, and managers at 45. The group with the most experience ranged from 6 to 10 years at 116 respondents, representing a wide spectrum of experience across the industry. The largest companies, those with over 500 employees, accounted for 78 respondents, while medium-sized firms between 100-499 employees totaled 167 and small companies with fewer than 100 employees totaled 82.

The measurement model was evaluated by analyzing individual sub-factors and assessing scale reliability through convergent and discriminant validity tests. Performance Expectancy showed strong internal consistency and reliability, with a Cronbach's Alpha of 0.923, Composite Reliability (CR) of 0.945, and Average Variance Extracted (AVE) of 0.840. Effort Expectancy reflected excellent reliability and convergent validity, with a Cronbach's Alpha of

0.930, CR of 0.950, and AVE of 0.827. Social Influence had high reliability, with a Cronbach's Alpha of 0.937, CR of 0.955, and AVE of 0.840. Facilitating Condition construct had a Cronbach's Alpha of 0.935, CR of 0.953, and AVE of 0.837. Organizational Readiness constructed the highest reliability measures, with a Cronbach's Alpha of 0.944, CR of 0.957, and AVE of 0.818. The intention to adopt AI construct achieved a Cronbach's Alpha of 0.938, CR of 0.953, and AVE of 0.803. Figure 2 illustrates the final path model resulting from the research.

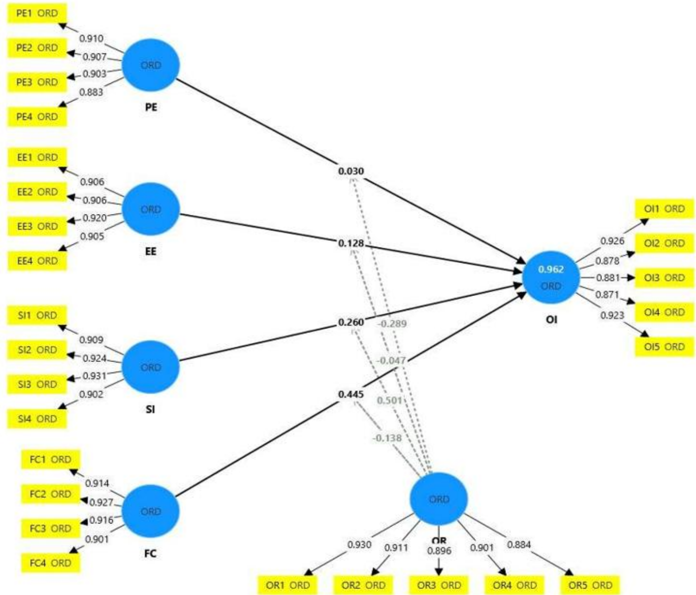

Figure 2: Final path model

Conclusion

The study explored factors influencing the adoption of AI-based smart inspection systems using the UTAUT framework. Facilitating Conditions (FC) and Social Influence (SI) emerged as critical predictors of adoption intention, while Organizational Readiness (OR) served as a significant moderator. FC had the strongest direct effect on Overall Intention (OI), emphasizing infrastructure, training, and technical support as key drivers. SI also significantly influenced OI through management and peer endorsement. OR amplified the effects of FC and SI on OI, highlighting its importance in organizational preparedness. Unlike previous studies that prioritized Performance Expectancy (PE) and Effort Expectancy (EE), these factors were found to have no direct impact on adoption intention in this industrial context. The findings contribute to literature by emphasizing OR's moderating role and contextualizing technology adoption models for specialized industries.

Finally, we encourage future research to further extend the geography and industries under exploration to improve generalizability. Longitudinal studies are needed to measure changes in adoption intentions as enabling conditions and challenges are encountered during implementation phases. Mixed methods approache that combine quantitative data with qualitative insights can enrich understanding of organizational dynamics and resistance to AI adoption. Moreover, factors at the system level, including government policies, economic conditions, and international technology transfer, should be incorporated in future analyses, as they offer a broader framework for understanding AI deployment across environments.

This research project contributes to existing knowledge systems. It offers an empirical evaluation of the many influences on AI-driven smart inspection systems adoption among Malaysia's automotive manufacturing industry. The analysis of the data confirms that effort expectancy, performance expectancy, social influence and facilitating condition both apply to the Malaysian context as well. It is also necessary to include organisational readiness and cost diversion from homeland security departments for cushioning risks. This study has practical implications for both manufacturers and policy makers, as well as those who provide the necessary technology. These insights can assist Malaysia in the smooth transition of integrating AI technology, therefore allowing it to move closer to Industry 4.0.

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