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The Intention to Adopt Artificial Intelligence for Software Testing by Organisations in Klang Valley to Achieve Sustainable Business Performance

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ABSTRACT

This study investigates factors influencing the intention to adopt Artificial Intelligence (AI) for software testing among organisations in Klang Valley, Malaysia. As software grows more complex, traditional testing struggles to keep up, increasing interest in AI. Despite its benefits like better defect detection and faster releases, adoption remains limited. Using the Technology-Organisation-Environment (TOE) framework, this study examines the effects of technological, organisational, and environmental readiness. A survey of 219 software testers was analyzed using Structural Equation Modelling (SEM) via SmartPLS. Results show that organisational and environmental readiness strongly influences AI adoption, while technological readiness has a moderate effect. The findings provide useful insights for improving software testing and supporting sustainable business performance.

INTRODUCTION

Software testing represents a critical phase within the Software Development Life Cycle (SDLC), serving as a fundamental mechanism to ensure software quality, reliability, and compliance with user requirements (Kusum et al., 2024). It plays a vital role in identifying and resolving defects at the early stages of development, thereby mitigating potential time delays and financial losses (Shetty, 2020). The significance of software testing extends across all phases of the SDLC, from initial development to post-deployment maintenance, underscoring its continuous and integral contribution to software assurance (Gupta & Gayathri, 2022).

In recent years, the integration of Artificial Intelligence (AI) and Machine Learning (ML) has introduced transformative opportunities within the field of software testing, offering substantial advancements in efficiency, accuracy, and test coverage (Kulkarni, 2024). These technologies support the automation of repetitive and time-consuming tasks, reduce the dependency on manual intervention, and enhance both test execution and defect detection capabilities (Pandhare, 2025). While issues such as data quality and algorithmic bias remain, the adoption of AI in testing environments presents promising outcomes, including accelerated software release cycles and improved quality standards (Kulkarni, 2024; Pandhare, 2025).

Despite the evident potential of AI, particularly in areas such as test case generation and automated code analysis, its practical application within real-world software testing environments remains relatively limited (Karhu et al., 2025). Although the integration of AI into test automation has yielded encouraging results such as enhanced test coverage and predictive insights, persistent challenges related to data dependency, technical complexity, and implementation barriers continue to hinder widespread adoption (Nama, 2024).

RESEARCH PROBLEM AND OBJECTIVES

As software systems grow increasingly complex, manually testing every potential test condition becomes increasingly challenging (Islam et al., 2023). Despite the growing recognition of the benefits associated with Artificial Intelligence (AI) in this domain, its adoption within software testing practices remains limited. While many organisations express an intention to adopt AI-based tools, the actual implementation is often obstructed by significant technological, organisational, and environmental barriers (Masod & Zakaria, 2024).

This study aims to examine the technological, organisational, and environmental factors that influence the intention to adopt AI for software testing among organisations in Klang Valley, utilising the Technology–Organisation–Environment (TOE) framework. The objectives of the research are:

1. To assess the influence of technological factors on the intention to adopt AI for software testing
2. To assess the influence of organisational readiness and support on the intention to adopt AI for testing purposes
3. To assess the influence of environmental factors on the intention to adopt AI tools for software testing

RESEARCH BACKGROUND

Software testing has evolved from traditional methodologies to AI-driven approaches, transforming quality assurance practices. Understanding the comparative effectiveness of conventional versus AI-powered testing is crucial for organisations optimizing their strategies. This shift represents a paradigmatic change in ensuring software quality and automating testing processes.

Traditional Software Testing Methods

Traditional software testing approaches follow systematic linear methodologies with formal processes and defined boundaries (Sinha & Das, 2021; Islam & Ferworn, 2020). While providing predictable processes, modern approaches like model-based testing achieve superior coverage and faster execution (Akpinar et al., 2020). Traditional methods continue in environments requiring rigorous documentation despite agile methodology growth (Najihi et al., 2022).

AI Software Testing Method

AI transforms software testing through machine learning and natural language processing, automating test generation, defect prediction, and execution (Singh & Al-Azzam, 2023; Trudova et al., 2020). These approaches enhance coverage, reduce manual effort, and excel in continuous integration pipelines (Kulkarni, 2024). Implementation faces challenges including data quality requirements and algorithmic complexity (Hayat et al., 2024).

Assessing Software Testing Using AI

AI-powered testing automates test generation and analysis while improving efficiency and accuracy (Ramadan et al., 2024; Gomathy & Meyrina, 2025). Current research emphasises hybrid approaches combining AI capabilities with human expertise for contextual interpretation (Deliu, 2024; Farber, 2025). This integration addresses challenges related to data quality and algorithmic bias (Kulkarni, 2024).

THEORETICAL FRAMEWORK

This study's framework is based on the Technology–Organisation–Environment (TOE) framework, which has been modified to align with the research objectives concerning the intention to adopt AI for software testing. The framework encompasses three main dimensions: technological readiness, organisational readiness, and environmental readiness.

Technological readiness refers to the extent to which an organisation possesses the necessary infrastructure and technological capabilities to adopt new innovations (Maroufkhani et al., 2019). Key factors include cost considerations, system complexity, compatibility with existing systems, relative advantage, and technology infrastructure capabilities.

Organisational readiness encompasses the internal capabilities, structures, and resources that determine an organisation's ability to adopt, integrate, and benefit from technological innovations (Maroufkhani et al., 2019). This includes sustainable human capital, organisational support systems, organisational competency, overall organisational readiness, and operational complexity management.

Environmental readiness considers external influences such as government support, competitive pressure, industry trends, and the legal and regulatory environment that influence an organisation's motivation to adopt new technologies, including AI (Maroufkhani et al., 2019).

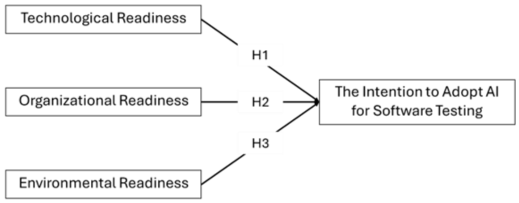

*Figure 1: SEQ Figure * ARABIC 1: Theoretical framework*

Figure 1 is the theoretical framework of the study that examines AI adoption for software testing through three interconnected readiness dimensions. Firstly, technological readiness encompasses infrastructure capabilities and employee attitudes toward technology, where factors like cost, complexity, compatibility, and perceived benefits shape adoption decisions, leading researchers to hypothesise that technological readiness significantly impacts the intention to adopt AI for software testing (H1). Next is the organisational readiness which addresses internal capabilities including human capital, management support, and organisational competency, with evidence showing that larger organisations with stronger internal resources demonstrate greater adoption potential, supporting the hypothesis that organisational readiness positively influences AI adoption intentions (H2). Finally, environmental readiness considers external influences such as government support, competitive pressures, and regulatory frameworks that create adoption incentives, particularly for smaller enterprises, forming the basis for the hypothesis that environmental readiness positively affects AI adoption intentions (H3). Together, these three readiness dimensions work synergistically to influence organisational decisions about AI implementation, ultimately driving sustainable business performance through enhanced productivity, operational efficiency, and strategic decision-making capabilities.

METHODOLOGY

This study employs a quantitative survey research methodology to investigate the intention to adopt artificial intelligence for software testing by organisations in Klang Valley. The research uses purposive sampling to target software testers from various organisations within the Klang Valley region, regardless of organisational size or industry, if they have departments or personnel responsible for software testing activities. Using a conservative population estimate of 500 individuals based on online job postings and professional networking platforms, the study determined a minimum sample size of 218 responses through the Raosoft Sample Size Calculator at a 95% confidence level with a 5% margin of error. Data collection was conducted through online questionnaires distributed to the target population, measuring responses using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The questionnaire covers technological factors (cost, complexity, compatibility, relative advantage, technology infrastructure), organisational factors (sustainable human capital, organisational support, organisational competency, organisational readiness, operational complexity), environmental factors (government support, market and customer factors, competitive pressure, industry trends, legal and regulatory environment), and the AI adoption intention, with items adapted from validated instruments in previous research. Structural Equation Modelling (SEM) was selected over other analytical methods due to its capability to simultaneously examine multiple relationships between latent constructs and handle measurement error, making it particularly suitable for testing the complex relationships proposed in the TOE framework. Data analysis will be performed using SPSS version 22, employing descriptive statistics, common method variance testing, and SEM to examine the relationships between variables and test the proposed hypotheses.

RESULTS

A comprehensive data analysis results in the study investigating the intention to adopt AI for software testing by organisations in Klang Valley. The analysis was conducted using SmartPLS 4.0 on 219 responses with a 100% response rate, revealing that most respondents were below 30 years old with almost equal gender distribution across various seniority levels and organisational sizes. The measurement model assessment demonstrated satisfactory psychometric properties, with all constructs achieving composite reliability values above 0.7, adequate indicator reliability with most item loadings exceeding acceptable thresholds, and established discriminant validity through HTMT, Fornell-Larcker criterion, and cross-loading tests, though some constructs showed moderate convergent validity with AVE values slightly below the recommended threshold.

Demographic Profile

The demographic analysis revealed that the majority of respondents (57.5%) were below 30 years old, with 23.3% aged between 31-40 years. Gender distribution was almost equal with 49.8% male and 50.2% female respondents. The sample included various seniority levels from intern software testers (23.7%) to senior software testers (18.7%), with good representation across different organisational sizes.

Population and Sampling

The population for this study includes software testers from various organisations located in the Klang Valley. Using the Raosoft Sample Size Calculator with a conservative population estimate of 500 individuals, at a 95 percent confidence level with a 5 percent margin of error and 50 percent response distribution, a minimum of 218 responses was required. The study successfully collected 219 complete responses, achieving a 100% response rate. Table 1 below shows the demographic information collected using survey methods.

Table 1: The demographic information

Variable	Frequency (n)	Percentage (%)
Age		
20 – 30 years old	126	57.5
31 – 40 years old	51	23.2
41 – 50 years old	35	16.0
51 years old and above	7	3.2
Organisation Size		
Small and Medium Enterprises	62	28.3
Large Enterprises	109	49.8
Startups	48	21.9

Measurement Model Assessment

The measurement model demonstrated satisfactory reliability and validity. Internal consistency reliability was confirmed with composite reliability (CR) values ranging from 0.721 to 0.791, all exceeding the recommended threshold of 0.7, as shown in Table 2.

Table 2: CR and AVE value

Construct	Composite Reliability (CR)	Average Variance Extracted (AVE)
Environmental Factors	0.791	0.655
Organisational Factor	0.765	0.522
Technological Factor	0.724	0.470
Intention to Adopt AI	0.721	0.342

Indicator reliability achieved acceptable loadings for most items, with values ranging from 0.543 to 0.841. Most items achieved the recommended threshold of 0.7, demonstrating satisfactory indicator reliability for the measurement model.

It should be noted that some constructs, particularly the Intention to Adopt AI (AVE = 0.342) and Technological Factor (AVE = 0.470), fall below the commonly accepted AVE threshold of 0.5, indicating moderate convergent validity. However, these constructs were retained due to their theoretical importance and adequate composite reliability scores. Discriminant validity was established through HTMT analysis, Fornell-Larcker criterion, and cross-loading examination, confirming that the measurement model is valid and reliable. Table 3 presents the HTMT analysis results, showing that all values are below the recommended threshold of 0.85, confirming discriminant validity.

Table 3: HTMT Analysis Results

Construct	Environmental Factors	Organisational Factor	Technological Factor	Intention to Adopt AI
Environmental Factors	-	-	-	-
Organisational Factor	0.730	-	-	-
Technological Factor	0.797	0.848	-	-
Intention to Adopt AI	0.817	0.746	0.739	-

Structural Model Results

The structural model analysis revealed that the three independent variables (Environmental Factors, Organisational Factor, and Technological Factor) explain 28.7% of the variance in the intention to adopt AI, indicating moderate explanatory power. This R^2 value suggests that the TOE framework explains approximately 29% of the variation in AI adoption intentions, which represents a moderate level of predictive power for behavioural intention models in technology adoption research.

Table 4 below shows path coefficient analysis. Path coefficient analysis showed significant relationships for all hypothesised paths.

Table 4: Path coefficient analysis

Hypothesis	Path Coefficient (β)	t-statistics	p-value	Result
H1: Technological → Intention	0.212	2.929	0.003	Supported
H2: Organisational → Intention	0.321	4.656	0.000	Supported
H3: Environmental → Intention	0.153	2.085	0.037	Supported

The results demonstrate that organisational factors have the strongest influence on AI adoption intention (β=0.321), followed by technological factors (β=0.212) and environmental factors (β=0.153). These findings directly address the research objectives:

1. Technological factors significantly influence AI adoption intention, supporting the importance of technical readiness.
2. Organisational readiness emerges as the most critical factor, highlighting the importance of internal capabilities and support.
3. Environmental factors, while having the smallest effect, still significantly shape adoption intentions, confirming the relevance of external pressures and support systems.

DISCUSSION

Impact of Technological Factors

The study confirmed that technological readiness significantly influences the intention to adopt AI for software testing (β=0.212, p=0.003). This finding aligns with previous research emphasising the importance of technological considerations in innovation adoption decisions (Maroufkhani et al., 2019). Organisations with better technological infrastructure, lower perceived complexity, higher compatibility with existing systems, and greater recognition of relative advantages are more likely to intend to adopt AI for software testing. The moderate effect size suggests that while technological readiness is important, it is not the primary driver of adoption intention, indicating that organisations may be willing to overcome technological challenges when other factors are favourable.

Influence of Organisational Readiness

Organisational readiness emerged as the most significant factor influencing AI adoption Organisational readiness emerged as the most significant factor influencing AI adoption intention (β=0.321, p<0.001). This finding is consistent with literature highlighting the critical role of organisational factors in technology adoption. The strong positive relationship indicates that organisations with skilled personnel, strong management support, clear strategic vision, adequate resources, and streamlined processes are significantly more likely to adopt AI for software testing. This finding underlines the importance of internal preparation and changes management in successful technology adoption initiatives.

Environmental Factors Impact

Environmental readiness demonstrated a positive and significant relationship with AI adoption intention (β=0.153, p=0.037). While the effect size is the smallest among the three factors, the significant relationship indicates that external environmental factors play a meaningful role in shaping organisational intentions toward AI adoption. Organisations operating in supportive regulatory environments and facing competitive pressure are more likely to consider AI adoption. The relatively smaller effect suggests that while external factors influence adoption intentions, internal organisational factors are more critical in driving adoption decisions.

CONCLUSION

This research has provided valuable insights into the factors influencing organisational intention to adopt Artificial Intelligence for software testing among organisations in Klang Valley, Malaysia. The study successfully validated all three proposed hypotheses, demonstrating that technological readiness, organisational readiness, and environmental readiness all significantly influence AI adoption intentions.

The findings revealed that organisational factors exert the strongest influence on adoption intentions, suggesting that successful AI implementation requires comprehensive organisational preparation rather than just technical readiness. This includes investment in human capital development, building strong support systems, encouraging cultural change, and developing internal competencies.

From a practical perspective, organisations planning to adopt AI should prioritize organisational readiness development, strengthen technological infrastructure, and consider environmental factors in their strategic planning. The research provides evidence-based guidance for technology providers, decision-makers, and policymakers aiming to enhance software testing efficiency and support sustainable business performance in the digital era.

Future research should consider longitudinal studies to track the evolution from adoption intention to actual implementation behaviour, and mixed methods approaches to provide deeper contextual understanding of AI adoption processes in software testing environments.

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