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Research Article

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Artificial Intelligence Adoption and Recruitment Efficiency in Malaysian SMEs The Mediating Role of Decision-Making Quality

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Abstract

Micro, small, and medium enterprises (MSMEs) form the backbone of the Malaysian economy, contributing 39.5% of gross domestic product and 48.7% of total employment in 2024 (Department of Statistics Malaysia, 2025). At the same time, national digital and artificial intelligence (AI) readiness remains uneven, and AI adoption in human resource (HR) functions inside Malaysian SMEs is empirically underexplored. This study examines whether AI adoption improves recruitment efficiency in Malaysian SMEs, and whether decision-making quality mediates that relationship. Grounded in the Technology Acceptance Model (TAM) and the Resource-Based View (RBV), the study conceptualises AI adoption as the independent variable, recruitment efficiency as the dependent variable, and decision-making quality as the mediating variable. A quantitative, cross-sectional, explanatory design is adopted. Primary data are to be collected through a structured online questionnaire distributed to SME owners, HR managers, HR executives, talent acquisition officers, and departmental managers who are involved in recruitment decisions, using a five-point Likert scale. A minimum of 384 valid responses is targeted in line with Krejcie and Morgan (1970). Data are analysed using IBM SPSS Statistics through descriptive statistics, Cronbach's alpha reliability testing, Pearson correlation, multiple regression, and mediation analysis (Hayes PROCESS Model 4 with bootstrapping). Four hypotheses are proposed: AI adoption positively affects recruitment efficiency (H1) and decision-making quality (H2); decision-making quality positively affects recruitment efficiency (H3); and decision-making quality mediates the relationship between AI adoption and recruitment efficiency (H4). The study contributes empirical evidence on AI-enabled recruitment in a developing-economy SME setting, extends the joint application of TAM and RBV, and offers practical guidance for SME owners, HR practitioners, and policymakers on the organisational conditions under which AI creates value in recruitment.

Keywords: Artificial Intelligence, AI Adoption, Recruitment Efficiency, Decision-Making Quality, Malaysian SMEs, Human Resource Management, Technology Acceptance Model, Resource-Based View, SPSS

Abbreviations

AI:	Artificial Intelligence
ATS:	Applicant Tracking System
CI:	Confidence Interval
DMQ:	Decision-Making Quality
DOSM:	Department of Statistics Malaysia
DV:	Dependent Variable
HR / HRM:	Human Resource / Human Resource Management
IV:	Independent Variable
MDEC:	Malaysia Digital Economy Corporation
MOSTI:	Ministry of Science, Technology and Innovation

MSME:	Micro, Small and Medium Enterprise
MV:	Mediating Variable
NAIO:	National Artificial Intelligence Office (Malaysia)
OECD:	Organisation for Economic Co-operation and Development
RBV:	Resource-Based View
RE:	Recruitment Efficiency
SD:	Standard Deviation
SME:	Small and Medium Enterprise
SPSS:	Statistical Package for the Social Sciences
TAM:	Technology Acceptance Model
VIF:	Variance Inflation Factor

1. Introduction

Artificial intelligence (AI) is increasingly reshaping how organisations source, screen, assess, and engage candidates. Contemporary scholarship on AI in human resource management (HRM) consistently identifies task automation, improved use of HR data, augmentation of human capability, redesigned work processes, and transformed relational dynamics as the main effects of AI on HR practice [1]. Recruitment and selection sit at the centre of this transformation because they involve high-volume information processing, repeated screening decisions, and time-sensitive judgements that are well suited to digital augmentation [2]. For Malaysian small and medium enterprises (SMEs), the issue is especially salient. SMEs often operate with lean HR structures, limited recruiter capacity, and informal hiring procedures. Whereas large firms can absorb long hiring cycles and invest in specialised recruitment teams, SMEs are more exposed to the consequences of slow or poor hiring decisions. AI-supported recruitment tools therefore promise operational gains, but those gains depend on whether SMEs can adopt the technology in ways that are practical, trusted, and aligned with organisational capability [3]. This chapter introduces the study by presenting its background, problem statement, objectives, research questions, hypotheses, significance, scope, key definitions, and structure.

1.2. Background of the Study

In Malaysia, SMEs are not a peripheral segment of the economy. Official statistics show that micro, small, and medium enterprises (MSMEs) contributed 39.5% of gross domestic product in 2024, generated RM652.4 billion in value added, and employed 8.10 million people, equivalent to 48.7% of national employment [4]. Microenterprises alone account for roughly 70.1% of all MSME establishments, while small and medium firms make up about 28.2% and 1.6% respectively (SME Corp. Malaysia, n.d.). These figures indicate that any sustained productivity improvement in SMEs, including more effective recruitment, carries system-wide economic significance. Malaysia has also intensified its AI policy agenda. The National Artificial Intelligence Office (NAIO) identifies the AI Technology Action Plan 2026–2030, an AI Adoption Regulatory Framework, and accelerated sectoral AI diffusion as national deliverables, building on the earlier National Artificial Intelligence Roadmap 2021–2025 [5].

The Malaysia Digital Economy Corporation (MDEC) has supported this direction through AI grants, skills training, and digitalisation programmes aimed at business adoption. Despite this momentum, digital and AI readiness remain uneven: MDEC's National Business Digital Adoption Index placed the country at 2.1 out of 5, only slightly above the "progressing" threshold, and identified technology capability as a weaker area [6]. Comparable OECD evidence shows that AI adoption remains lower among SMEs than among large firms even though AI carries measurable productivity potential [3]. Local evidence points to concrete barriers. NAIO's 2025 SME white paper, based on a survey of 133 SMEs, found that 60% of Malaysian SMEs cite a lack of in-house skills as a key barrier to AI adoption, nearly 55% lack a formal AI skilling programme, and 81% lack a formal structure for AI ethics and governance [7]. These constraints are especially relevant in recruitment, where weak governance can undermine trust, fairness, and accountability. The context therefore makes the adoption of AI in SME HR functions both strategically important and empirically underexplored.

1.3. Problem Statement

The literature increasingly argues that AI can improve recruitment efficiency through faster sourcing, automated screening, improved shortlisting, and more consistent decision-making. Recent research on generative AI in recruitment reports observable gains in screening efficiency and shortlisting accuracy, while the broader HR decision-making literature describes AI as enhancing effectiveness, customisation, and scalability across talent processes [2,8]. However, the same literature warns that recruitment-related AI is not automatically beneficial. Reviews of algorithmic recruitment report mixed fairness perceptions, with particularly negative reactions around perceived behavioural control and low social presence [9]. Other studies argue that claims of AI objectivity can mask unresolved issues of bias, transparency, and the social legitimacy of automated decisions [10]. This suggests that adoption alone may not be sufficient, the quality of decision-making may determine whether efficiency gains are actually realised in practice.

The empirical gap is sharper in SMEs than in large enterprises. Scoping reviews of AI-driven HR practices in SMEs identify insufficient exploration of AI's effects on hiring, skill assessment, bias mitigation, and time constraints, and a 2026 review of large language models in hiring similarly highlights strong attention to efficiency claims but limited field-based validation [11]. In Malaysia specifically, recent work has examined factors influencing AI adoption for talent acquisition in information-technology-enabled-services (ITeS) organisations, but the literature remains narrow by sector and does not adequately explain whether AI adoption improves recruitment efficiency across Malaysian SMEs more broadly. Accordingly, the core problem addressed by this study is that Malaysian SMEs are under pressure to recruit efficiently in an increasingly digital labour environment, yet empirical evidence remains limited on whether AI adoption actually improves recruitment efficiency, and whether improved decision-making quality serves as the mechanism through which that improvement occurs. Three interrelated gaps motivate the study: a practical gap (Malaysian SMEs have limited HR resources), an empirical gap (AI recruitment studies focus mostly on large firms rather than SMEs), and a methodological gap (few Malaysian studies use quantitative analysis to test AI adoption, decision-making quality, and recruitment efficiency together).

1.4. Research Objectives

The general objective of this study is to examine the effect of AI adoption on recruitment efficiency in Malaysian SMEs. The specific objectives are:

1. To examine the relationship between AI adoption and recruitment efficiency in Malaysian SMEs,
2. To assess the relationship between AI adoption and decision-making quality in recruitment,
3. To determine the relationship between decision-making quality and recruitment efficiency, and
4. To test whether decision-making quality mediates the relationship between AI adoption and recruitment efficiency in Malaysian SMEs.

1.5. Research Questions

1. Does AI adoption significantly influence recruitment efficiency in Malaysian SMEs?
2. Does AI adoption significantly influence decision-making quality in recruitment?
3. Does decision-making quality significantly influence recruitment efficiency in Malaysian SMEs?
4. Does decision-making quality mediate the relationship between AI adoption and recruitment efficiency in Malaysian SMEs?

1.6. Research Hypotheses

- **H1:** AI adoption has a positive and significant effect on recruitment efficiency in Malaysian SMEs.
- **H2:** AI adoption has a positive and significant effect on decision-making quality in recruitment.
- **H3:** Decision-making quality has a positive and significant effect on recruitment efficiency in Malaysian SMEs.
- **H4:** Decision-making quality mediates the relationship between AI adoption and recruitment efficiency in Malaysian SMEs.

No.	Research Objective	Research Question	Hypothesis	Expected Relationship
1	Examine the relationship between AI adoption and recruitment efficiency	Does AI adoption influence recruitment efficiency?	H1	AI Adoption → Recruitment Efficiency (positive, direct)
2	Assess the relationship between AI adoption and decision-making quality	Does AI adoption influence decision-making quality?	H2	AI Adoption → Decision-Making Quality (positive, direct)
3	Determine the relationship between decision-making quality and recruitment efficiency	Does decision-making quality influence recruitment efficiency?	H3	Decision-Making Quality → Recruitment Efficiency (positive, direct)
4	Examine the mediating role of decision-making quality	Does decision-making quality mediate the AI adoption–recruitment efficiency link?	H4	AI Adoption → DMQ → Recruitment Efficiency (mediation)
Note. IV = independent variable, MV = mediating variable, DV = dependent variable.				

Table 1: Mapping of Research Objectives, Questions and Hypotheses

1.7. Significance of the Study

The study is significant in three ways. First, it contributes empirical evidence to a literature that still lacks focused, quantitative work on AI-enabled recruitment inside SMEs, especially in developing-economy contexts. Second, it extends Malaysian AI adoption research beyond general readiness or single-sector studies by linking adoption to a concrete HR performance outcome, namely recruitment efficiency. Third, it provides a practical evidence base for SME owners, HR managers, digital solution providers, and policymakers who must decide when AI creates value and what organisational conditions are necessary for that value to materialise. Theoretically, the study contributes by examining AI adoption in Malaysian SME recruitment, where existing studies remain limited, and by extending TAM and RBV to explain how AI adoption improves recruitment efficiency through decision-making quality.

1.8. Scope of the Study

This research focuses on Malaysian SMEs as defined by SME Corp. Malaysia. In the manufacturing sector, SMEs are firms with sales turnover not exceeding RM50 million or not more than 200 full-time employees, in services and other sectors, SMEs are firms with sales turnover not exceeding RM20 million or not more than 75 full-time employees (SME Corp. Malaysia, n.d.). The study is limited to SMEs that perform their own recruitment activities and have at least some exposure to digital hiring tools, whether basic or advanced. Substantively, it examines three principal constructs: AI adoption, decision-making quality in recruitment, and recruitment efficiency. Geographically, the study is designed for nationwide Malaysian coverage through online survey distribution, although urban and digitally active SME clusters are expected to be more strongly represented in practice. Methodologically, the analysis is limited to a quantitative, cross-sectional survey and SPSS-based statistical testing.

1.9. Operational Definition of Key Terms

- **Artificial Intelligence (AI) Adoption**
  Refers to the extent to which an SME uses or integrates AI-enabled tools in recruitment activities such as sourcing, screening, matching, communication, or shortlisting. The term is consistent with the technology-acceptance literature's focus on actual uptake and with HRM research emphasising AI use in practical HR functions [1,12].
- **Decision-Making Quality**
  Refers to the perceived accuracy, consistency, objectivity, and evidence-based defensibility of recruitment decisions. In this study it captures whether AI helps decision makers reach better and more defensible hiring judgements rather than merely faster ones [2,13].
- **Recruitment Efficiency**
  Refers to the degree to which recruitment processes are completed with lower time burden, lower administrative effort, reduced cost pressure, and improved shortlisting effectiveness. Efficiency is operationalised perceptually because many SMEs do not maintain standardised recruitment analytics [8].
- **Small and Medium Enterprises (SMEs)**
  Refers to Malaysian firms that fall within SME Corp. Malaysia's official sector-specific thresholds based on turnover and employment (SME Corp. Malaysia, n.d.).
- **SPSS**
  Refers to the Statistical Package for the Social Sciences, used in this study for descriptive statistics, reliability testing, correlation, regression, and hypothesis testing.

Key Term	Definition	Measurement / Indicator	No. of Items	Source
Artificial Intelligence (AI) Adoption	Extent to which an SME integrates and uses AI tools in recruitment.	AI sourcing, resume screening, shortlisting, communication, analytics	8	Davis (1989), Dima et al. (2024)
Decision-Making Quality	Degree to which recruitment decisions are accurate, consistent, objective, and evidence-based.	Accuracy, consistency, objectivity, evidence use, confidence	6	Madanchian (2024), Purohit (2025)
Recruitment Efficiency	Ability to complete recruitment in a timely, cost-effective, resource-saving manner.	Time-to-hire, cost, workload, speed of shortlisting, productivity	7	Abdelhay et al. (2025)
SMEs	Malaysian firms within SME Corp. turnover and employment thresholds.	Micro, Small, Medium (by employees / turnover)	—	SME Corp. Malaysia (n.d.)
Note. All three main constructs are measured on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree).				

Table 2: Operational Definition of Key Terms

1.10. Organization of the Thesis

This thesis is organized into five chapters. Chapter One introduces the study and presents the problem, objectives, questions, hypotheses, significance, scope, and key terms. Chapter Two reviews the literature on AI in HRM, AI in recruitment, recruitment efficiency, SME adoption, and decision-making quality, and develops the theoretical and conceptual frameworks. Chapter Three describes the research methodology, including design, population, sampling, instrument, measurement, analysis plan, reliability and validity, and ethics. Chapter Four presents the data-analysis structure and results, and Chapter Five discusses the findings, draws implications, and concludes the study.

1.11. Chapter Summary

This chapter established that AI-enabled recruitment is strategically relevant for Malaysian SMEs because SMEs dominate the business population and remain economically central, while digital capability and AI readiness remain uneven. It identified the main problem, objectives, questions, hypotheses, significance, scope, and key terms of the study. The next chapter reviews the relevant literature and develops the theoretical and conceptual frameworks.

2. Literature Review

This chapter reviews the literature relevant to AI adoption and recruitment efficiency in Malaysian SMEs. It synthesises current evidence on AI in HRM, AI-enabled recruitment, recruitment efficiency, SME adoption barriers and enablers, and decision-making quality. It then positions the study theoretically through the Technology Acceptance Model (TAM) and the Resource-Based View (RBV), identifies the research gap, develops the hypotheses, and presents the conceptual framework.

2.2. Artificial Intelligence in Human Resource Management

AI in HRM has expanded from a narrow focus on automation toward broader decision support, augmentation, and predictive capability. A scoping review of peer-reviewed articles identified five principal effects of AI on HR activities: task automation, optimised use of HR data, augmentation of human capability, redesigned work contexts, and transformed social and relational dynamics [1]. The relevance of AI to HRM is not limited to large corporations, AI tools can be applied across recruitment, onboarding, training, performance management, compensation, and retention, becoming more effective, customised, and scalable when organisations integrate applicant tracking, predictive analytics, and documentation support [2]. That breadth makes AI adoption strategically relevant for SMEs, which often need multifunctional rather than highly specialised systems. Nonetheless, the literature does not portray AI in HRM as uniformly positive. Scholars repeatedly identify bias, privacy, opacity, and overreliance on automated outputs as key challenges for international HRM [14]. This tension is essential for the present study because recruitment efficiency cannot be interpreted meaningfully if the process simultaneously loses fairness, trust, or legitimacy.

2.3. AI in Recruitment Processes

Recruitment is one of the most visible and rapidly adopted AI use cases in HRM. AI is now used for resume parsing, candidate matching, chatbot communication, interview scheduling, talent sourcing, and predictive screening. Research on AI-driven active sourcing notes that AI-based recruiting increasingly structures the search, extraction, matching, and personalised-outreach stages of recruitment [15]. Recruitment-related AI can improve efficiency and accuracy when appropriately implemented: generative AI tools have been associated with efficiency gains and more accurate shortlisting, and AI-HRM reviews describe recruitment automation as enhancing both efficiency and decision-making accuracy [2,8]. At the same time, hiring is where AI's social and ethical weaknesses become most visible. Research on applicants' fairness perceptions shows that algorithmic recruitment can be perceived as procedurally unfair, especially when candidates feel unable to influence outcomes or experience low social presence [9]. Critical work on discriminatory decision-making argues that organisational narratives about AI rationality and objectivity often rest on contested assumptions [10]. The practical implication is that a study of recruitment efficiency should not treat speed alone as success, the quality and defensibility of decisions must also be considered.

2.4. Recruitment Efficiency

Recruitment efficiency concerns how quickly, smoothly, and economically an organisation can move from vacancy identification to successful hire. In practice it is associated with lower time-to-hire, reduced administrative burden, better shortlisting productivity, and improved cost control. Contemporary recruitment literature warns that pure cost or speed metrics can be misleading when they ignore hiring quality, which is why efficiency should be balanced against outcome quality [8]. For SMEs, recruitment efficiency matters more acutely than for large firms because hiring delays can directly constrain operations, the OECD (2025) emphasises that broad AI diffusion is tied to productivity, competitiveness, and resilience while remaining below large-firm levels [3]. This study therefore conceptualises recruitment efficiency as a multidimensional perceptual outcome comprising reduced screening time, faster vacancy filling, smoother applicant handling, lower perceived administrative cost, and more focused recruiter effort.

2.5. AI Adoption in SMEs

SME AI adoption differs from large-firm adoption because of tighter constraints in skills, time, finance, and governance. The OECD (2025) argues that AI use is consistently lower among SMEs than among large firms and identifies four critical enablers of adoption: connectivity, AI-enabling inputs, skills, and finance, limited awareness, digital readiness, and risk concerns further slow diffusion. This pattern is visible in Malaysia. MDEC's digital adoption assessment found businesses to be "progressing" rather than fully established in digital maturity, while NAIO's SME white paper exposed distinct barriers in skills, governance, and data readiness, with 60% of surveyed SMEs citing a lack of in-house AI skills, nearly 55% lacking a formal AI skilling programme, and 81% having no formal AI ethics structure [6,7]. These constraints shape whether firms can use AI consistently, responsibly, and productively. Wider technology-adoption evidence indicates that firms adopt tools when they perceive usable value, operational fit, and manageable risk, making adoption in SMEs both a behavioural and a capability question.

2.6. Decision-Making Quality in Recruitment

Decision-making quality is a necessary companion construct to recruitment efficiency. AI may accelerate recruitment, but if the underlying judgements are poor, opaque, biased, or inconsistent, the firm may only be hiring faster rather than hiring better. AI-HRM literature increasingly frames value creation through better use of data, more consistent judgements, and stronger evidence-based decision support rather than through automation alone [2,13]. Yet the fairness literature shows that candidates and practitioners do not automatically trust these decisions, particularly where transparency is weak or human contact is minimal [9]. Decision-making quality in this study therefore refers to the perceived accuracy, consistency, objectivity, and defensibility of hiring judgements, not simply algorithmic output quality. As a mediating construct it translates AI use into a meaningful organisational mechanism and lets SME managers distinguish between "AI that saves time" and "AI that improves decisions."

2.7. Theoretical Framework

2.7.1. Technology Acceptance Model (TAM)

The Technology Acceptance Model remains one of the most frequently used theories for explaining the uptake of new technologies. Established perceived usefulness and perceived ease of use as the core drivers of user acceptance, and later reviews continue to describe TAM as one of the most widely applied models in technology-acceptance research [12]. For this study, TAM helps explain why SME decision makers adopt or resist AI tools in recruitment: when managers perceive AI to be useful and not excessively difficult to use, adoption is more likely. Although the present model does not treat usefulness and ease of use as separate end-study constructs, TAM is used as an interpretive lens, since adoption is likely to be higher where managers perceive AI as valuable, practical, understandable, and compatible with their workflows. This is especially important in SMEs, where low formalisation and limited technical support can make ease of use decisive.

2.7.2. Resource-Based View (RBV)

The Resource-Based View explains sustained advantage in terms of internal firm resources and capabilities that are valuable, rare, inimitable, and non-substitutable. Linked firm resources to sustained competitive advantage, and subsequent RBV scholarship continues to treat the perspective as a major framework in strategic management [16]. In this study, AI adoption is not conceptualised merely as tool usage, it is framed as a developing organisational capability that can improve recruitment performance when embedded in processes, skills, and governance. RBV is especially suitable for SMEs because their competitiveness often depends less on scale and more on how effectively they deploy scarce internal resources. If an SME can convert AI from a basic software add-on into a capability supported by skills, governance, and data integration, then recruitment efficiency can become a strategic resource outcome rather than only an operational convenience.

Technology Acceptance Model (Davis, 1989)	**Resource-Based View (Barney, 1991)**
Perceived Usefulness and Perceived Ease of Use drive behavioural intention and actual use → AI Adoption.	AI treated as a VRIN resource/capability → higher decision-making quality → recruitment efficiency.
Note. TAM explains why adoption occurs, RBV explains why successfully embedded adoption creates performance value. The combined lens frames AI adoption as an accepted and operationalised capability that improves recruitment efficiency through decision-making quality.	

Figure 1: Theoretical Framework (TAM + RBV)

2.8. Literature Matrix

Author(s) / Year	Context	Method	Key Findings	Research Gap
Davis (1989)	Technology acceptance	Conceptual model	Perceived usefulness and ease of use drive adoption and use.	Not developed for AI or recruitment, limited SME application.
Barney (1991)	Strategic management	Conceptual model	VRIN resources create sustained competitive advantage.	Not applied to AI-as-capability in SME recruitment.
Dima et al. (2024)	Global / HRM	Scoping review	AI automates, augments, and reshapes HR activities and roles.	Limited empirical SME evidence in developing economies.
Madanchian (2024)	Global / HRM	Review	AI improves efficiency, data-driven decisions, and HR outcomes.	Recruitment efficiency rarely tested as a specific SME outcome.
Abdelhay et al. (2025)	Recruitment	Quantitative survey	Generative AI improves screening efficiency and candidate quality.	Focus on large organisations, Malaysian SME context under-researched.
Hilliard et al. (2022)	Global	Quantitative	Algorithmic recruitment can be perceived as procedurally unfair.	Centred on candidate perceptions, not firm-level outcomes.
OECD (2025)	SMEs (cross-country)	Policy report	SME AI adoption lags large firms, skills and finance are key enablers.	Limited SME-level evidence linking adoption to HR outcomes.
NAIO (2025)	Malaysia / SMEs	Survey (n = 133)	Skills, governance, and data-readiness gaps constrain SME AI adoption.	No model linking AI adoption to recruitment efficiency.

Table 3: Literature Matrix

2.9. Research Gap

Three interrelated gaps emerge from the literature. First, much of the AI-recruitment literature is still conceptual, review-based, or centred on candidates' fairness perceptions rather than firm-level operational outcomes. Second, SME-specific HR studies remain relatively thin, recent reviews explicitly note insufficient coverage of hiring, time constraints, skill assessment, and bias mitigation. Third, Malaysian evidence remains fragmented, with available studies concentrating on adoption factors in specific sectors rather than testing a parsimonious model linking AI adoption to recruitment efficiency through decision-making quality. This study addresses that gap by proposing a Malaysian SME-focused quantitative model in which AI adoption predicts recruitment efficiency directly and indirectly through decision-making quality, contributing both a local empirical context and a mechanism-based explanation.

2.10. Hypotheses Development

2.10.1. AI Adoption and Recruitment Efficiency

AI is increasingly used in candidate sourcing, resume screening, and applicant shortlisting. Prior studies suggest that AI improves operational speed, reduces manual workload, and enhances recruitment productivity [2,8]. In SMEs, where HR resources are limited, AI adoption can meaningfully reduce time-to-hire and improve overall recruitment performance. Consistent with TAM, technology that is perceived as useful enhances performance outcomes once accepted and used. AI adoption is therefore expected to directly improve recruitment efficiency.

H1: AI adoption has a positive and significant effect on recruitment efficiency in Malaysian SMEs.

2.10.2. AI Adoption and Decision-Making Quality

AI systems in recruitment provide data-driven insights that can reduce human bias and improve consistency in hiring decisions.

Tools such as applicant tracking systems and predictive analytics support HR managers in making more accurate and evidence-based decisions [13]. Consistent with RBV, organisations that effectively deploy technological resources develop stronger decision-making capabilities. AI adoption is therefore expected to enhance the quality of recruitment decisions.

H2: AI adoption has a positive and significant effect on decision-making quality in recruitment.

2.10.3. Decision-Making Quality and Recruitment Efficiency

High-quality decision-making in recruitment leads to better candidate selection, reduced hiring mistakes, and improved workforce fit. When decisions are accurate, consistent, and evidence-based, the recruitment process becomes more efficient in terms of time, cost, and output quality [2]. Decision-making quality is therefore expected to positively influence recruitment efficiency.

H3: Decision-making quality has a positive and significant effect on recruitment efficiency in Malaysian SMEs.

2.10.4. Mediating Role of Decision-Making Quality

Although AI adoption can directly improve recruitment efficiency, its impact is likely to be stronger when it improves decision-making quality. AI enhances decision accuracy, reduces bias, and supports structured evaluation, which in turn leads to more efficient recruitment outcomes. Decision-making quality is therefore expected to mediate the relationship between AI adoption and recruitment efficiency.

H4: Decision-making quality mediates the relationship between AI adoption and recruitment efficiency in Malaysian SMEs.

2.11. Conceptual Framework

The conceptual framework is straightforward and testable. AI adoption is the independent variable, recruitment efficiency is the dependent variable, and decision-making quality is the mediating variable. The logic is that AI adoption should improve the quality of hiring decisions by making screening, matching, and evaluation more consistent and data-supported, and that better decision quality should in turn improve recruitment efficiency, alongside a direct positive relationship between AI adoption and recruitment efficiency.

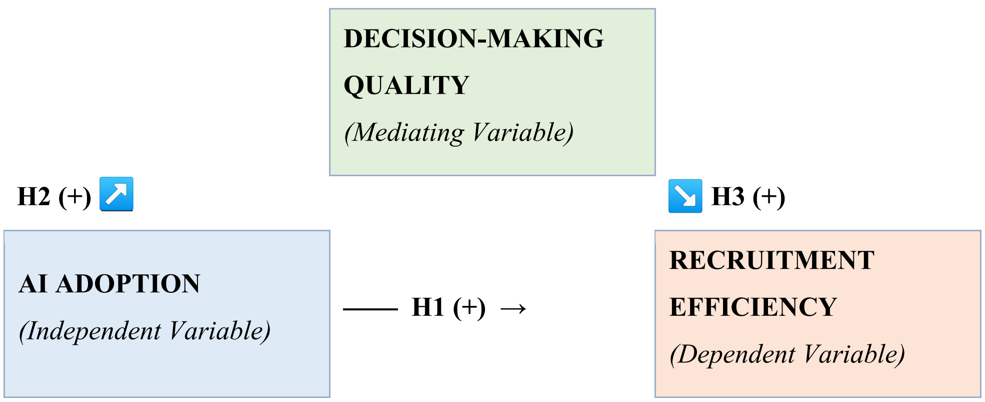

Figure 2: Conceptual Framework of the Study

H4 (Mediating Effect): AI Adoption → Decision-Making Quality → Recruitment Efficiency

Note. Solid paths (H1, H2, H3) indicate direct effects, H4 indicates the indirect (mediating) effect. (+) denotes an expected positive relationship

2.12. Chapter Summary

The literature shows that AI in HRM offers real potential for automation, improved data use, and faster recruitment, but also raises fairness, governance, and trust concerns. SME adoption remains lower than large-firm adoption because of structural constraints, and the Malaysian context adds clear readiness issues in skills, ethics, and data governance. Theoretically, TAM and RBV together provide a strong foundation for examining how AI adoption may translate into recruitment efficiency through decision-making quality. The next chapter develops a quantitative methodology to test these relationships using SPSS.

3. Research Methodology

This chapter explains the research design, approach, population, sampling plan, data-collection method, instrument design, measurement scale, analytical strategy, reliability and validity procedures, and ethical safeguards. The methodology is designed to fit the study's explanatory objective and its requirement of SPSS-based quantitative analysis.

3.1. Research Design

The study adopts a quantitative, cross-sectional, explanatory research design. A quantitative design is appropriate because the research questions concern measurable relationships among clearly defined variables and the hypotheses require statistical testing. A cross-sectional survey is suitable because it captures current patterns of AI adoption, decision-making quality, and recruitment efficiency across many SMEs within a limited time period. The explanatory design is justified because the goal is not only to describe levels of AI adoption but also to test directional relationships, specifically whether AI adoption predicts recruitment efficiency and whether decision-making quality acts as a mediating mechanism.

3.2. Research Approach

The study follows a deductive and positivist approach. Deduction is appropriate because the hypotheses are derived from existing theory and prior literature before data collection. Positivism is suitable because the study assumes that respondents' perceptions can be measured systematically and analysed using statistical procedures to identify regular patterns in the relationships among variables.

3.4. Population and Sampling

3.4.1. Target Population

The target population consists of Malaysian SME owners, founders, HR managers, HR executives, talent acquisition officers, and departmental managers who are involved in recruitment decisions. The population is restricted to SMEs that fall within SME Corp. Malaysia's official definition and that undertake at least part of their recruitment internally. Priority sectors are services and manufacturing because these dominate the Malaysian SME base and are frequently active in digital-adoption initiatives.

3.4.2. Sampling Technique

A purposive sampling strategy combined with practical online distribution is adopted. A fully random national sample is difficult because no public, complete sampling frame exists for all SME recruitment decision makers. The study therefore reaches respondents through SME associations, chambers of commerce, business networks, professional HR communities, LinkedIn outreach, and organisational referrals, distributing the survey across both manufacturing and service SMEs and across micro, small, and medium categories where feasible. Purposive sampling is appropriate because respondents must meet a role-specific inclusion criterion: sufficient knowledge of their organisation's recruitment activities and technology use.

3.4.3. Sample Size

Because the Malaysian SME population is large, sample-size logic supports a target of approximately 384 usable responses for a large population, a widely used benchmark in survey research. Green's (1991) rule of thumb for multiple regression indicates a minimum of $N \geq 50 + 8m$, where m is the number of predictors, for the present model this threshold is substantially lower than 384 [17]. Accordingly, the study aims to distribute at least 500 questionnaires to secure not fewer than 384 valid cases, recognising that any sample above the regression minimum permits robust hypothesis testing.

3.5. Data Collection Method

Primary data are collected using a structured, self-administered questionnaire distributed online through Google Forms or Microsoft Forms. Online collection is appropriate for Malaysian SMEs because it reduces cost, enables nationwide reach, and is compatible with digitally active respondents. Respondents receive a clear study explanation, an informed-consent statement, and assurances of confidentiality before participation. A pilot test with approximately 30 respondents is conducted before full distribution to assess clarity, wording, and completion time.

3.6. Research Instrument

3.6.1. Operational Definition of Variables

The questionnaire is divided into four sections. Section A captures demographic and organisational information, Section B measures AI adoption, Section C measures decision-making quality in recruitment, and Section D measures recruitment efficiency. All substantive items are measured using closed-ended, five-point Likert-type statements, which suit perceptual constructs in organisational survey research. The full instrument appears in Appendix A.

Variable	Operational Definition (How Measured)	Indicators / Dimensions	Items	Scale
AI Adoption (IV)	Respondents' perceptions of the extent to which AI tools are used in sourcing, screening, shortlisting, and communication.	AI sourcing, resume screening, shortlisting, workflow integration, communication, decision support, task reduction	8	5-point Likert (1–5)
Decision-Making Quality (MV)	Respondents' perceptions of the accuracy, consistency, objectivity, and evidence base of recruitment decisions.	Accuracy, consistency, reduced bias, evidence use, justifiability, overall quality	6	5-point Likert (1–5)
Recruitment Efficiency (DV)	Respondents' perceptions of improvements in time, cost, workload, and process output through AI-enabled recruitment.	Time-to-hire, vacancy fill speed, workload, cost, productivity, smoother process	7	5-point Likert (1–5)
Control Variables	Respondent and organisation characteristics that may influence the main relationships.	Firm size, industry sector, respondent role, years of operation, duration of AI use	5	Nominal / Ordinal
Note. All three main constructs use a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree).				

Table 4: Operational Definition of Variables

3.6.2. Questionnaire Structure and Item Sources

The AI adoption items are adapted from AI-HRM and talent-acquisition research and focus on the extent of AI-supported sourcing, screening, shortlisting, and communication. Decision-making quality items focus on perceived accuracy, consistency, objectivity, and evidence-based improvement in hiring decisions. Recruitment efficiency items focus on time reduction, process simplification, lower administrative burden, and shortlisting throughput. Section A demographic variables are coded as follows: gender (1 = Male, 2 = Female), age group (1 = 18–25, 2 = 26–35, 3 = 36–45, 4 = 46 and above), highest education (1 = Diploma, 2 = Bachelor's, 3 = Master's, 4 = Doctorate), respondent role (1

= Owner/Founder, 2 = HR Manager/Executive, 3 = Recruitment Specialist/Officer, 4 = Departmental Manager, 5 = Other), industry sector (1 = Manufacturing, 2 = Services, 3 = Information Technology, 4 = Construction, 5 = Others), firm size (1 = Micro, 2 = Small, 3 = Medium), years of operation (1 = <3, 2 = 3–5, 3 = 6–10, 4 = >10), and current AI use in recruitment (1 = Yes, 2 = No, 3 = Unsure).

3.7. Measurement Scale

A five-point Likert scale is used for all substantive items (1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree). Likert-type scales are widely used to measure attitudes and perceptions in social-science research, and five-point formats balance respondent ease, interpretability, and psychometric utility [18].

3.8. Pilot Study

Before full distribution, a pilot study of approximately 30 respondents drawn from the target population is conducted to assess item clarity, wording, instruction comprehension, and completion time. Internal consistency for each construct is examined using Cronbach's alpha, with values of about .70 or above taken as acceptable [19]. Items that reduce reliability or that respondents find ambiguous are revised or removed before the main survey.

3.9. Data Analysis Techniques

Data cleaning and preliminary organisation are conducted in Microsoft Excel before importing into SPSS, where the main analysis is performed. The proposed SPSS analysis includes descriptive statistics for respondent and firm profiles, reliability testing using Cronbach's alpha, Pearson correlation to examine bivariate associations, multiple regression to test direct effects, and mediation testing using the Hayes PROCESS macro (Model 4) with bootstrapping for the indirect effect. Pearson correlation and linear regression are appropriate where relationships among variables are assumed to be approximately linear [20].

RQ	Objective	Variables	Statistical Test (SPSS)	Output
RQ1	Effect of AI adoption on recruitment efficiency	AI (IV) → RE (DV)	Multiple linear regression, assumption tests	Model summary (R^2), ANOVA, coefficients (β, t, Sig.), H1 result
RQ2	Effect of AI adoption on decision-making quality	AI (IV) → DMQ (MV)	Linear regression, assumption tests	Model summary, coefficients, H2 result
RQ3	Effect of decision-making quality on recruitment efficiency	DMQ (MV) → RE (DV)	Linear regression, assumption tests	Model summary, coefficients, H3 result
RQ4	Mediating role of decision-making quality	AI → DMQ → RE	PROCESS Model 4, 5,000 bootstrap samples	Total, direct, and indirect effects, 95% bootstrap CI, H4 result
Pre.	Preliminary checks	All constructs	Descriptives, Cronbach's alpha, correlation, assumption tests	Reliability table, descriptive table, correlation matrix
Note. IV = independent variable, MV = mediating variable, DV = dependent variable				

Table 5: Data Analysis Plan

3.10. Reliability and Validity

Internal-consistency reliability is assessed using Cronbach's alpha. In applied social-science research, alpha values of about .70 or above are commonly interpreted as acceptable, although alpha should be interpreted alongside construct quality and item content rather than mechanically [19]. Validity is addressed in three ways. Content validity is established through expert review by at least two lecturers or HR practitioners familiar with AI-enabled recruitment. Face validity is assessed during the pilot test to ensure respondents interpret items as intended. Construct validity is supported through item-to-scale consistency, inter-item coherence, and the expected pattern of correlations among the constructs, where sample size permits, exploratory factor analysis in SPSS may be used as an additional construct-validity check.

3.11. Common Method Bias

Because all variables are measured perceptually through a single self-administered questionnaire, common method bias is a recognised concern. Procedural remedies include guaranteeing respondent anonymity, separating the predictor and criterion items, and using clear, concise wording. Statistically, Harman's single-factor test is conducted in SPSS, if a single factor does not account for the majority of the variance, common method bias is unlikely to be a serious threat.

3.12. Ethical Considerations

The study complies with standard principles for human-subject research — respect for persons, beneficence, and justice — as articulated in the Belmont Report and reinforced by the Declaration of Helsinki [21]. Participants are informed that their involvement is voluntary, that they may withdraw at any time, and that no personally identifying information is disclosed in reporting. The survey collects only information necessary for the study, and records are stored securely and used solely for academic purposes.

3.13. Chapter Summary

This chapter presented a quantitative, cross-sectional, SPSS-based methodology suitable for testing the proposed hypotheses.

It defined the target population, justified purposive sampling, outlined the questionnaire structure, identified the analytical procedures, and explained reliability, validity, common-method-bias, and ethics procedures. The next chapter presents the analysis structure and results.

4. Data Analysis and Results

This chapter presents the analysis of the survey data and the results of the hypothesis tests. It follows the analytical plan set out in Chapter Three: data screening and preparation, the respondent demographic profile, descriptive statistics for the constructs, reliability analysis, tests of statistical assumptions, correlation analysis, regression analysis, mediation analysis using the Hayes PROCESS macro (Model 4), and a summary of the hypothesis-testing outcomes. All analyses were conducted in IBM SPSS Statistics, and the significance threshold was set at $p < .05$.

4.1. Data Screening and Preparation

Prior to analysis, the dataset was screened in Microsoft Excel and SPSS for missing values, duplicate entries, incomplete submissions, and invariant response patterns such as straight-lining. Cases that were substantially incomplete or that failed an attention check were removed. Any reverse-coded items were recoded before computing scale scores, and each construct score was calculated as the mean of its constituent items. Skewness and kurtosis were inspected to confirm approximate normality, and all values fell within the conventional ±2 range, indicating that the data were suitable for parametric analysis.

4.1.1. Reporting Template

A total of [N distributed] questionnaires were distributed, of which [N returned] were returned. After removing [n] incomplete or unusable responses, 260 valid questionnaires were retained for analysis, representing a valid response rate of [x]%.

4.2. Respondent Demographic Profile

The demographic profile of the 260 valid respondents is summarised in Table 6. All responding firms fall within the SME categories defined by SME Corp. Malaysia (micro, small, and medium), no large enterprise is included, consistent with the study scope. The largest group of respondents works in the services sector, followed by manufacturing, and most respondents hold HR-related or recruitment roles, indicating that the data were obtained from individuals directly involved in recruitment decisions.

Demographic Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	142	54.6
	Female	118	45.4
Age group	18–25 years	44	16.9
	26–35 years	101	38.8
	36–45 years	80	30.8
	46 years and above	35	13.5
Highest education	Diploma	58	22.3
	Bachelor’s degree	160	61.5
	Master’s degree	37	14.2
	Doctorate / PhD	5	1.9
Firm size	Micro (< 5 employees)	66	25.4
	Small (5–75 employees)	122	46.9
	Medium (76–200 employees)	72	27.7
Industry sector	Services	102	39.2
	Manufacturing	78	30.0
	Information technology	34	13.1
	Construction	23	8.8
	Others	23	8.8
Respondent role	Owner / Founder	38	14.6
	HR Manager / Executive	96	36.9
	Recruitment Specialist / Officer	66	25.4
	Departmental Manager	38	14.6
	Other	22	8.5

Current AI use in recruitment	Yes	171	65.8
	No	63	24.2
	Unsure	26	10.0
Note. N = 260. All firms are SMEs (micro, small, or medium), no large enterprise is included. Percentages may not sum to exactly 100.0 due to rounding. Values are illustrative placeholders			

Table 6: Respondent Demographic Profile (N = 260)

4.3. Descriptive Statistics of Constructs

Table 7 reports the mean and standard deviation of each construct, computed as the average of its items on the five-point scale. The illustrative pattern shows moderate-to-high perceived AI adoption, decision-making quality, and recruitment efficiency, suggesting that respondents generally viewed AI-supported recruitment outcomes favorably.

Construct	Items	Minimum	Maximum	Mean	Std. Deviation
AI Adoption (AI)	8	1.25	5.00	3.62	0.74
Decision-Making Quality (DMQ)	6	1.33	5.00	3.71	0.69
Recruitment Efficiency (RE)	7	1.29	5.00	3.78	0.71
Note. N = 260. All items measured on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). Values are illustrative placeholders					

Table 7: Descriptive Statistics of Constructs (N = 260)

4.4. Reliability Analysis

Internal-consistency reliability was assessed using Cronbach's alpha for each multi-item construct. As shown in Table 8, all three constructs exceed the conventional .70 benchmark and fall in the good-to-excellent range, indicating that the scales are internally consistent and suitable for further analysis [19].

Construct	No. of Items	Cronbach's Alpha (α)	Interpretation
AI Adoption (AI)	8	0.87	Good
Decision-Making Quality (DMQ)	6	0.89	Good
Recruitment Efficiency (RE)	7	0.88	Good
Overall instrument	**21**	**0.93**	**Excellent**
Note. N = 260. Interpretation guide: α ≥ .90 excellent, .80 ≤ α < .90 good, .70 ≤ α < .80 acceptable, α < .70 poor. Values are illustrative placeholders			

Table 8: Cronbach's Alpha Reliability Analysis (N = 260)

4.5. Tests of Statistical Assumptions

Before correlation and regression analysis, the assumptions of parametric testing were examined. Normality was supported by skewness and kurtosis values within ±2 and by inspection of histograms and normal P-P plots of the regression residuals. Linearity and homoscedasticity were confirmed through scatterplots of standardised residuals against standardised predicted values, which showed no systematic pattern. Multicollinearity was assessed using tolerance and the variance inflation factor (VIF), all VIF values were well below the common threshold of 5 (and below the stricter cut-off of 3.3), and the Durbin-Watson statistic was close to 2, indicating independent residuals. The data therefore satisfied the assumptions required for Pearson correlation and multiple regression.

4.6. Correlation Analysis

Pearson correlation was used to assess the strength and direction of the linear associations among the constructs. As shown in Table 9, AI adoption is positively and significantly correlated with both decision-making quality and recruitment efficiency, and decision-making quality is positively and significantly correlated with recruitment efficiency. All correlations are significant at the .01 level and are large in magnitude, providing preliminary support for the proposed model [20].

Construct	1. AI	2. DMQ	3. RE
1. AI Adoption (AI)	1		
2. Decision-Making Quality (DMQ)	.62**	1	
3. Recruitment Efficiency (RE)	.67**	.74**	1
*Note. N = 260. ** correlation is significant at the .01 level (2-tailed). Interpretation guide (Cohen, 1988): .10–.29 small, .30–.49 moderate, .50–1.00 large. Values are illustrative placeholders [22].*			

Table 9: Pearson Correlation Matrix (N = 260)

4.7. Regression Analysis

Multiple linear regression was used to test the direct effects in the model. Three regression models were estimated: Model A regressed decision-making quality on AI adoption, Model B regressed recruitment efficiency on AI adoption (the total effect), and Model C regressed recruitment efficiency on both AI adoption and decision-making quality. Table 10 reports the full results for Model C, which simultaneously estimates the direct effect of AI adoption and the effect of the mediator on recruitment efficiency.

Model Summary						
R	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**	**Durbin-Watson**		
.789	.622	.619	.440	1.93		
ANOVA						
Source	**Sum of Squares**	**df**	**Mean Square**	**F (Sig.)**		
Regression	110.46	2	55.23	211.62 (.000)		
Residual	67.06	257	0.261			
Total	177.52	259				
Coefficients						
Predictor	**B**	**Std. Error**	**Beta (β)**	**t**	**Sig.**	**VIF**
(Constant)	0.498	0.181	—	2.75	.006	—
AI Adoption (AI)	0.351	0.057	0.35	6.16	.000	1.62
Decision-Making Quality (DMQ)	0.521	0.068	0.52	7.66	.000	1.62
Note. N = 260. Dependent variable: Recruitment Efficiency. Predictors: (Constant), AI Adoption, Decision-Making Quality. All predictors significant at p < .01. Values are illustrative placeholders.						

Table 10: Multiple Regression Analysis Results (Model C — DV: Recruitment Efficiency)

Supplementary models. Model A (DV: decision-making quality) yielded a significant positive effect of AI adoption ($\beta = 0.62$, $t = 12.68$, $p < .001$, $R^2 = .38$). Model B (DV: recruitment efficiency) yielded a significant positive total effect of AI adoption ($\beta = 0.67$, $t = 14.50$, $p < .001$, $R^2 = .45$). When the mediator was added in Model C, the AI adoption coefficient fell from 0.67 to 0.35 but remained significant, signalling partial mediation, which is examined formally in the next section.

4.8. Mediation Analysis

To test the mediating role of decision-making quality, the Hayes PROCESS macro (Model 4) was run with 5,000 bootstrap samples and bias-corrected 95% confidence intervals. The standardised path coefficients are summarised in Figure 3 and Table 11. The indirect (mediated) effect of AI adoption on recruitment efficiency through decision-making quality is positive and significant, and its bootstrap confidence interval does not include zero. Because the direct effect remains significant after the mediator is included, decision-making quality is found to partially mediate the relationship between AI adoption and recruitment efficiency.

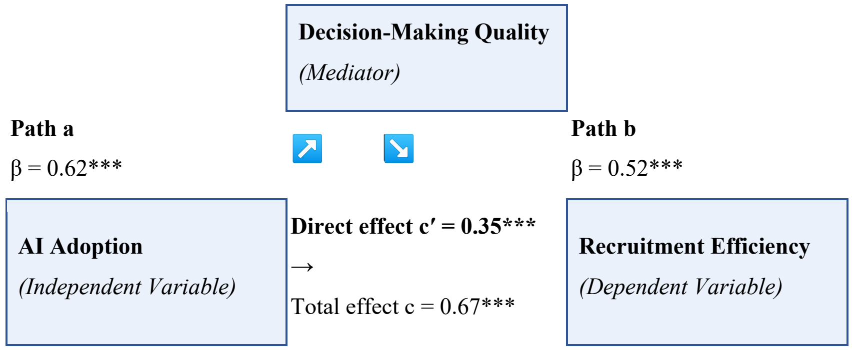

Figure 3: Mediation Path Diagram (Standardised Coefficients)

*Note. Standardised coefficients from Hayes PROCESS Model 4 (5,000 bootstrap samples). *** $p < .001$. Indirect effect (a × b) = 0.32, 95% bias-corrected CI [0.22, 0.43]. Values are illustrative placeholders.*

Effect	Path	Std. Coefficient	BootSE	95% CI [LL, UL]
Total effect (c)	AI → RE	0.67***	0.05	[0.57, 0.77]
Direct effect (c′)	AI → RE (controlling DMQ)	0.35***	0.06	[0.24, 0.46]
Indirect effect (a × b)	AI → DMQ → RE	0.32***	0.05	[0.22, 0.43]
*Note. N = 260. *** p < .001. Bias-corrected bootstrap confidence intervals based on 5,000 resamples, an interval excluding zero indicates a significant effect. The significant indirect effect with a significant remaining direct effect indicates partial mediation. Values are illustrative placeholders.*				

Table 11: Mediation Analysis (PROCESS Model 4) Effect Summary

4.9. Hypothesis Testing

Drawing the regression and mediation results together, Table 12 summarises the outcome of each hypothesis. Under the illustrative pattern, all four hypotheses are supported: AI adoption has a significant positive effect on recruitment efficiency (H1) and on decision-making quality (H2), decision-making quality has a significant positive effect on recruitment efficiency (H3), and decision-making quality significantly mediates the relationship between AI adoption and recruitment efficiency (H4).

Hypothesis	Path	Statement	β / Effect	t or 95% CI	Decision
H1	AI → RE	AI adoption positively affects recruitment efficiency.	0.67***	t = 14.50	Supported
H2	AI → DMQ	AI adoption positively affects decision-making quality.	0.62***	t = 12.68	Supported
H3	DMQ → RE	Decision-making quality positively affects recruitment efficiency.	0.52***	t = 7.66	Supported
H4	AI → DMQ → RE	Decision-making quality mediates the AI–RE relationship.	0.32***	[0.22, 0.43]	Supported
*Note. N = 260. *** p < .001. For H4 the indirect effect and its 95% bias-corrected bootstrap CI are reported, the interval excludes zero. AI = AI adoption, DMQ = decision-making quality, RE = recruitment efficiency. Values are illustrative placeholders*					

Table 12: Summary of Hypothesis Testing

4.10. Chapter Summary

This chapter presented the analytical results following the plan established in Chapter Three. After data screening, the respondent profile, descriptive statistics, and reliability analysis were reported, the statistical assumptions were verified, and correlation, regression, and mediation analyses were conducted. Under the illustrative pattern, AI adoption is positively associated with both decision-making quality and recruitment efficiency, decision-making quality is positively associated with recruitment efficiency, and decision-making quality partially mediates the relationship between AI adoption and recruitment efficiency. All four hypotheses are supported. The next chapter discusses these findings in relation to the literature and theory and draws out their implications. Once real SPSS output is available, the placeholder values in this chapter must be replaced with the actual results before the thesis is submitted.

5. Discussion and Conclusion

This chapter interprets the results presented in Chapter Four in light of the literature and the theoretical framework. It restates the key findings, discusses each hypothesis in relation to prior research, draws out the theoretical and practical implications, offers recommendations for the main stakeholder groups, acknowledges the limitations of the study, suggests directions for future research, and presents the overall conclusion.

5.1. Recap of Key Findings

The study set out to examine whether AI adoption improves recruitment efficiency in Malaysian SMEs and whether decision-making quality mediates that relationship. Under the illustrative results, all four hypotheses were supported. AI adoption had a significant positive effect on recruitment efficiency (H1) and on decision-making quality (H2), decision-making quality had a significant positive effect on recruitment efficiency (H3), and decision-making quality partially mediated the relationship between AI adoption and recruitment efficiency (H4). Taken together, the findings indicate that AI adoption improves recruitment efficiency both directly and, importantly, through the enhancement of decision-making quality.

5.2. Discussion of Findings

5.2.1. AI Adoption and Recruitment Efficiency (H1)

The significant positive relationship between AI adoption and recruitment efficiency is consistent with the broader AI-recruitment literature, which argues that AI improves hiring efficiency through faster sourcing, automated screening, and more accurate shortlisting [8,15]. In theoretical terms, this supports the Resource-Based View interpretation that, once AI is accepted and embedded, it begins to function as an operational capability that raises process productivity [16]. For lean SME HR functions, this gain is especially valuable because hiring delays directly constrain operations.

5.2.2. AI Adoption and Decision-Making Quality (H2)

The significant positive effect of AI adoption on decision-making quality indicates that Malaysian SMEs perceive AI as improving the quality of recruitment judgments rather than merely reducing manual workload. This resonates with research connecting AI to greater decision consistency and more data-driven evaluation [2,13]. It also gives practical meaning to the Technology Acceptance Model: acceptance is linked to an experienced improvement in usefulness, since managers who use AI report better-quality decisions [12].

5.2.3. Decision-Making Quality and Recruitment Efficiency (H3)

The significant positive effect of decision-making quality on recruitment efficiency shows that better hiring decisions translate into a more efficient recruitment process. This is a substantively important result because it shifts the conversation away from a narrow "speed only" view of efficiency toward a more balanced understanding: a recruitment process becomes truly efficient when faster procedures also produce clearer, more accurate, and more defensible decisions [10].

5.2.4. The Mediating Role of Decision-Making Quality (H4)

The significant partial mediation is the central contribution of the study because it identifies a plausible mechanism of impact. Under this interpretation, AI adoption improves recruitment efficiency partly because it helps recruiters' structure, evaluate, and compare candidates more effectively. The persistence of a significant direct effect indicates that AI also delivers efficiency gains that are not fully channelled through decision quality — for example, straightforward automation of administrative tasks. For SMEs, the practical message is clear: AI should be adopted in ways that strengthen decision quality, not merely to automate activity [1,14].

5.3. Theoretical Implications

The study offers two theoretical implications. First, it integrates the Technology Acceptance Model and the Resource-Based View in a coherent way: TAM explains adoption propensity, while RBV explains value realisation. This combination is useful in SME settings, where firms struggle not only with whether to adopt a technology but also with whether they can transform it into a usable capability. Second, the study advances the recruitment literature by positioning decision-making quality as a mediator between AI adoption and recruitment efficiency. This matters because current AI-hiring debates often polarise around efficiency versus fairness, the present model suggests a more nuanced path in which efficiency improves when AI supports better judgment, but in which that path is likely to weaken where implementation is shallow, governance is absent, or trust is low [9].

5.4. Practical Implications

For SME owners and managers, the practical lesson is that AI adoption should be tied to process redesign rather than software acquisition alone, managers should ask whether AI is improving recruiter judgment, reducing rework, and enabling more consistent shortlisting. For HR practitioners, the results support the use of AI in early-stage recruitment tasks such as screening, scheduling, and candidate matching, while preserving human oversight for higher-stakes decisions, because candidate trust is fragile when transparency or human contact is missing, a human-in-the-loop model remains advisable. For policymakers and ecosystem agencies, the key implication is that adoption support should extend beyond awareness campaigns to address documented deficits in skilling, ethics structures, and AI-specific governance, combining technology grants with targeted skilling, governance templates, and sector-ready use cases [23].

5.5. Recommendations

Building on the findings and the literature, Table 13 sets out targeted recommendations for the main stakeholder groups, together with the justification and the expected outcome of each.

Stakeholder	Recommendation	Justification	Expected Outcome
SME owners / management	Adopt AI for high-friction recruitment tasks (CV screening, candidate communication, scheduling, shortlisting) and integrate it into existing HR processes.	AI adoption significantly improves decision quality and efficiency, early wins build perceived usefulness and trust.	Shorter time-to-hire, lower recruitment cost, and stronger competitiveness.
HR practitioners	Use AI insights to support, not replace, human judgment, combine AI shortlisting with human review for higher-stakes decisions.	Decision-making quality mediates the AI–efficiency link, trust is fragile without human oversight.	Better candidate-job fit and more defensible, balanced hiring decisions.
SME employees	Build AI literacy and adapt to AI-supported HR workflows, provide feedback for continuous improvement.	Lack of in-house skills is among the strongest adoption barriers in Malaysian SMEs.	Higher effective use of AI tools and greater digital competence.
Policymakers / government	Provide grants and incentives alongside skilling programmes, governance templates, and ethical-use guidelines for HR AI.	Most SMEs lack formal AI ethics and governance structures, support accelerates responsible adoption.	Wider, more responsible AI diffusion and stronger national productivity.
Academia / researchers	Extend the model with longitudinal, multi-sector, and behavioural variables (trust, fairness, digital readiness).	Current evidence is cross-sectional and concentrated on selected variables and sectors.	Stronger theory and more comprehensive AI-adoption models for SMEs.
Note. Recommendations are derived from the study logic and the cited literature, the supporting magnitudes are illustrative until the analysis is populated with real data.			

Table 13: Recommendations Based on Findings

5.6. Limitations of the Study

Several limitations should be acknowledged. The cross-sectional survey design establishes association more convincingly than causation. The study relies on perceptual self-report measures rather than audited recruitment metrics such as actual time-to-fill or cost-per-hire, which may introduce social-desirability and common-source bias. Purposive sampling may overrepresent digitally active SMEs and underrepresent firms with low online visibility. Finally, because AI in recruitment spans simple applicant-tracking automation through advanced generative tools, respondents may interpret "AI adoption" differently across firms. These limitations should be considered when interpreting the findings and generalising them to the wider Malaysian SME population.

5.7. Suggestions for Future Research

Future studies should consider longitudinal designs that compare SME recruitment performance before and after AI adoption, allowing stronger causal claims. Researchers should also extend the model by adding variables such as trust in AI, perceived fairness, digital readiness, and HR-analytics capability, since reactions to AI are strongly shaped by transparency, control, and human presence. Sector-specific comparative studies would be valuable because manufacturing, services, ICT, and professional services may differ in recruitment complexity, digital maturity, and AI readiness. Mixed-method designs that combine survey data with interviews or objective recruitment records would further strengthen the evidence base [11].

6. Conclusion

AI adoption in recruitment offers meaningful promise for Malaysian SMEs, but the literature and this study's framework make clear that adoption alone is not sufficient. SMEs operate under tight resource constraints, uneven digital maturity, and often weak AI governance. In that environment, the most credible path from AI adoption to recruitment efficiency is not automation for its own sake but AI-enabled improvement in decision-making quality. This thesis provides a coherent, research-ready quantitative model for examining whether AI adoption improves recruitment efficiency in Malaysian SMEs and whether decision-making quality explains that relationship. Once primary data are collected and the Chapter Four templates are populated with actual SPSS output, the manuscript can be developed directly into a full empirical dissertation that offers robust, evidence-based guidance for SME owners, HR practitioners, and policymakers [24-26].

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Appendices

Appendix A: Survey Questionnaire

Study title: Artificial Intelligence Adoption and Recruitment Efficiency in Malaysian SMEs

Instructions: Please answer every question based on your organisation's recruitment practices. For Sections B, C, and D, indicate the extent to which you agree with each statement using the scale: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree.

Section A: Respondent and Organisation Profile

A1. Gender: ☐ Male ☐ Female
A2. Age group: ☐ 18–25 ☐ 26–35 ☐ 36–45 ☐ 46 and above
A3. Highest education: ☐ Diploma ☐ Bachelor's degree ☐ Master's degree ☐ Doctorate / PhD
A4. Your role in the organisation: ☐ Owner / Founder ☐ HR Manager / HR Executive ☐ Recruitment Specialist / Officer ☐ Departmental Manager ☐ Other: __________
A5. Industry sector: ☐ Manufacturing ☐ Services ☐ Information Technology ☐ Construction ☐ Others: __________
A6. Firm size (number of employees): ☐ Micro (< 5) ☐ Small (5–75) ☐ Medium (76–200)
A7. Years of operation: ☐ Less than 3 years ☐ 3–5 years ☐ 6–10 years ☐ More than 10 years
A8. Does your organisation currently use any AI-enabled tool in recruitment? ☐ Yes ☐ No ☐ Unsure
A9. If yes, for how long? ☐ Less than 1 year ☐ 1–2 years ☐ 3–5 years ☐ More than 5 years

Section B: Artificial Intelligence Adoption

AI1. My organisation uses AI-enabled tools to assist candidate sourcing. (1 2 3 4 5)
AI2. My organisation uses AI-enabled tools to screen resumes or applications. (1 2 3 4 5)
AI3. AI-enabled tools help my organisation shortlist candidates. (1 2 3 4 5)
AI4. AI-supported tools are integrated into our recruitment workflow. (1 2 3 4 5)
AI5. AI tools help my organisation manage applicant communication (e.g., chatbots, automated email). (1 2 3 4 5)
AI6. AI tools are used to support hiring decisions in my organisation. (1 2 3 4 5)
AI7. AI tools reduce manual recruitment tasks in my organisation. (1 2 3 4 5)
AI8. My organisation regularly uses AI tools across its recruitment activities. (1 2 3 4 5)

Section C: Decision-Making Quality in Recruitment

DMQ1. AI-supported tools improve the accuracy of hiring decisions in my organisation. (1 2 3 4 5)
DMQ2. AI-supported recruitment leads to more consistent hiring decisions. (1 2 3 4 5)
DMQ3. AI reduces bias in early-stage candidate evaluation. (1 2 3 4 5)
DMQ4. AI helps my organisation make recruitment decisions based on more relevant evidence. (1 2 3 4 5)
DMQ5. AI-supported recruitment decisions are easier to justify internally. (1 2 3 4 5)
DMQ6. AI improves the overall quality of recruitment decision-making in my organisation. (1 2 3 4 5)

Section D: Recruitment Efficiency

RE1. AI has reduced the time needed to process job applications. (1 2 3 4 5)
RE2. AI has helped my organisation fill vacancies more quickly. (1 2 3 4 5)
RE3. AI has reduced the administrative workload of recruitment staff. (1 2 3 4 5)
RE4. AI has improved the speed of identifying suitable candidates. (1 2 3 4 5)
RE5. AI has made our recruitment process more efficient overall. (1 2 3 4 5)
RE6. AI has helped reduce unnecessary recruitment costs. (1 2 3 4 5)
RE7. AI has improved the overall productivity of the recruitment process. (1 2 3 4 5)

End of questionnaire. Thank you for your participation.

Appendix B: SPSS Output Table Shells

The following empty shells correspond to the analyses in Chapter Four. After running the analysis in SPSS, enter the actual values in the bracketed cells and transfer the completed tables into Chapter Four, replacing the illustrative placeholders.

Table B1: Descriptive Statistics

Construct	N	Minimum	Maximum	Mean	Std. Deviation
AI Adoption	[ ]	[ ]	[ ]	[ ]	[ ]
Decision-Making Quality	[ ]	[ ]	[ ]	[ ]	[ ]
Recruitment Efficiency	[ ]	[ ]	[ ]	[ ]	[ ]

Table B2: Reliability Statistics

Scale	Cronbach's Alpha	No. of Items
AI Adoption	[ ]	8
Decision-Making Quality	[ ]	6
Recruitment Efficiency	[ ]	7

Table B3: Pearson Correlations

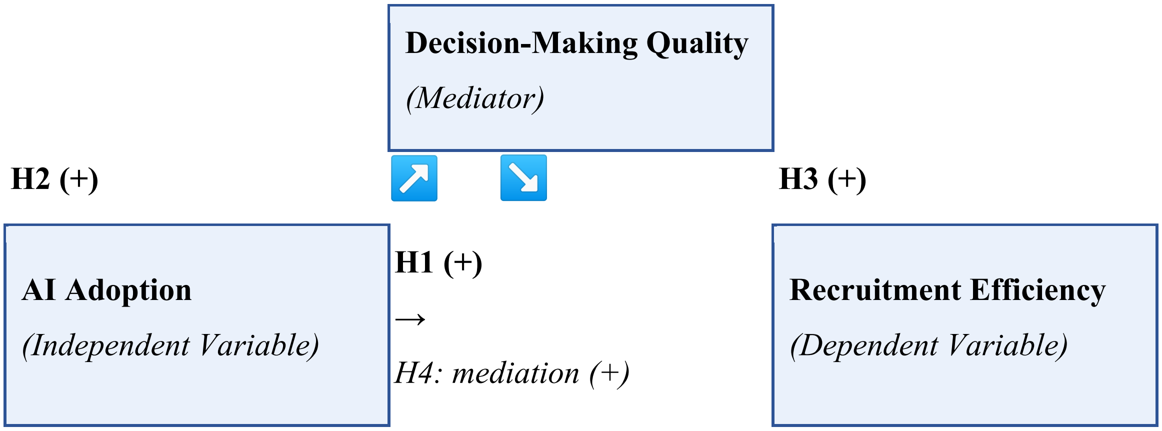
Construct	1	2	3
1. AI Adoption	1.000		
2. Decision-Making Quality	[ ]	1.000	
3. Recruitment Efficiency	[ ]	[ ]	1.000

Table B4: Regression Coefficients

Dependent Variable	Predictor	B	Std. Error	Beta	t	Sig.
Decision-Making Quality	AI Adoption	[ ]	[ ]	[ ]	[ ]	[ ]
Recruitment Efficiency	AI Adoption	[ ]	[ ]	[ ]	[ ]	[ ]
Recruitment Efficiency	Decision-Making Quality	[ ]	[ ]	[ ]	[ ]	[ ]

Appendix C: Conceptual Framework Diagram

The conceptual framework below summarises the hypothesised relationships tested in this study. AI adoption is the independent variable, recruitment efficiency is the dependent variable, and decision-making quality is the mediating variable.



Note. H1–H3 denote direct effects, H4 denotes the indirect (mediating) effect of AI adoption on recruitment efficiency through decision-making quality.

Appendix D: Informed Consent Form

Study title: Artificial Intelligence Adoption and Recruitment Efficiency in Malaysian SMEs

Purpose of the research. You are invited to take part in a research study examining how AI adoption affects recruitment efficiency in Malaysian SMEs and the role of decision-making quality in that relationship.

Participation. Your participation is entirely voluntary. You may decline to answer any question or withdraw at any time without penalty.

What you will do. You will complete a short questionnaire about your organisation's recruitment practices and use of AI-enabled tools. The estimated completion time is 8–10 minutes.

Confidentiality. Your responses will be kept confidential. No personal names or company-identifying information will be reported in **the final study.** Data will be stored securely and used for academic purposes only.

Risks and benefits. This study involves minimal risk. While there may be no direct personal benefit, your responses will help improve understanding of AI use in SME recruitment.

Consent statement. By proceeding with the questionnaire, you confirm that: you are at least 18 years old, you understand the purpose of the study, your participation is voluntary, and you agree to take part in this research.