DETERMINANTS OF UNDERGRADUATE STUDENTS' WILLINGNESS TO USE AI-BASED RECRUITMENT: THE ROLE OF AWARENESS, TRUST, AND PERCEIVED FAIRNESS

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ABSTRACT

The increasing use of artificial intelligence (AI) in recruitment is transforming how organizations screen and select candidates. As this shift continues, it is important to understand how future job seekers, particularly university students, respond to AI-driven hiring systems. This study examines the effects of awareness of AI, perceived fairness, and trust in AI decision-making on the willingness to use AI-based recruitment systems. The study specifically targets undergraduate students at Universiti Utara Malaysia (UUM). A quantitative approach was used, and data were collected through an online survey. The research framework was based on the Technology Acceptance Model (TAM), supported by psychological theories of trust and fairness. Partial Least Squares Structural Equation Modeling (PLS-SEM) was applied to analyze responses from 300 UUM undergraduate students. Findings show that awareness of AI and perceived fairness have significant positive effects on students' willingness to use AI in recruitment. Although trust in AI was statistically significant, its effect was minimal. This study provides practical insights for employers and AI developers to improve the fairness, transparency, and communication of AI tools used in hiring processes.

Keywords: Artificial Intelligence in Recruitment; Perceived Fairness; Trust in AI; Awareness of AI; Willingness to Use AI

ABSTRAK

Penggunaan kecerdasan buatan (AI) yang semakin meluas dalam proses pengambilan pekerja telah mengubah cara organisasi menilai dan memilih calon. Dengan perkembangan teknologi ini, adalah penting untuk memahami bagaimana pencari kerja masa hadapan menerima dan menilai penggunaan AI dalam proses pengambilan. Kajian ini meneroka bagaimana kesedaran terhadap AI, persepsi keadilan, dan kepercayaan terhadap keputusan yang dibuat oleh AI mempengaruhi kesediaan pelajar untuk menggunakan sistem pengambilan berasaskan AI. Kajian ini memfokuskan kepada pelajar prasiswazah dari Universiti Utara Malaysia (UUM), yang merupakan sebahagian daripada tenaga kerja masa hadapan. Pendekatan kuantitatif digunakan dalam kajian ini, dan data dikumpulkan melalui soal selidik dalam talian. Kerangka kajian dibentuk berdasarkan Model Penerimaan Teknologi (TAM) dan disokong oleh teori psikologi berkaitan kepercayaan dan keadilan. Seramai 300 pelajar UUM telah memberikan maklum balas, dan data dianalisis menggunakan kaedah Partial Least Squares Structural Equation Modeling (PLS-SEM). Hasil kajian menunjukkan bahawa kesedaran terhadap AI dan persepsi keadilan memberi kesan yang signifikan terhadap kesediaan pelajar untuk menggunakan AI dalam proses pengambilan pekerja. Walaupun kepercayaan terhadap AI turut menunjukkan kesan yang signifikan secara statistik, impaknya adalah kecil. Kajian ini memberikan pandangan yang berguna kepada majikan dan pembangun teknologi untuk menambah baik reka bentuk serta komunikasi sistem AI agar ia dilihat sebagai adil, boleh dipercayai dan telus oleh pencari kerja muda.

Kata kunci: Kecerdasan Buatan dalam Pengambilan Pekerja; Persepsi Keadilan; Kepercayaan terhadap AI; Kesedaran terhadap AI; Kesediaan Menggunakan AI

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
TAM	Technology Acceptance Model
PEOU	Perceived Ease of Use
PU	Perceived Usefulness
API	Application Programming Interface
XAI	Explainable Artificial Intelligence
LIME	Local Interpretable Model-Agnostic Explanations
SHAP	Shapley Additive Explanations
SPSS	Statistical Package for the Social Sciences

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Artificial Intelligence (AI) is reshaping the recruitment landscape by offering faster, data-driven ways to assess and select candidates. Traditional recruitment methods, which often rely on manual screening and face-to-face evaluations, are gradually replaced by automated tools designed to streamline decision-making and improve candidate experiences. AI applications in recruitment now include resume filtering, chatbot-assisted communication, predictive analytics, and video interview assessments. These innovations aim to enhance efficiency and consistency while reducing human bias in hiring decisions (Black & van Esch, 2021; Singh & Finn, 2022).

Despite these advantages, concerns have emerged regarding the fairness and transparency of AI decision-making. Many candidates feel discomfort about being evaluated by automated systems and are uncertain whether such tools can assess human potential fairly (Chamorro-Premuzic et al., 2023). Trust in AI remains a significant issue, as job seekers are often unaware of how decisions are made or how data is used. Moreover, perceptions of fairness and accuracy can influence whether individuals feel confident in engaging with AI-based hiring processes (Kaur, Sharma, & Kumar, 2021).

This study focuses on three important variables that may influence the acceptance of AI in recruitment: awareness of AI, trust in AI decision-making, and perceived fairness. These factors are expected to shape an individual’s willingness to use AI recruitment tools. Understanding how these elements interact can provide a clearer picture of what encourages or discourages candidates from embracing new technologies in the hiring process.

Undergraduate students, particularly those nearing graduation, represent an important group to study. As first-time job seekers, their perspectives on digital recruitment tools are likely to be shaped by their exposure to technology, their educational background, and their expectations of fairness and transparency in hiring. Their level of awareness and readiness to navigate such systems can affect their job search behaviour and their confidence in applying through AI-enabled platforms.

This research specifically targets undergraduate students at Universiti Utara Malaysia (UUM), a public university known for its focus on business, management, and information systems. UUM students are among the future workforce who are expected to face AI-based recruitment practices during their job search. Their views offer valuable insights into how graduates from a technology-aware and management-oriented academic environment perceive AI in employment settings. Given that AI use in recruitment is still growing in Malaysia, understanding these students' readiness and concerns can help bridge the gap between technology developers, educators, and employers (Mohamad, Ahmad, & Abdullah, 2024).

By examining the relationships between awareness, trust, perceived fairness, and willingness to use AI in recruitment, this study aims to contribute to the evolving conversation about digital hiring practices in Malaysia. The findings are expected to inform strategies for more ethical, transparent, and user-centred applications of AI in the recruitment landscape.

1.2 Problem Statement

The rapid development of Artificial Intelligence (AI) has changed how organizations attract, assess, and select job candidates. AI tools are now commonly used in recruitment to improve efficiency, reduce human bias, and standardize decision-making. Studies have shown that AI-based systems can speed up screening, improve candidate-job matching, and reduce administrative workload (Black & van Esch, 2021). However, how job seekers, especially university students, perceive and accept these technologies remains a topic of concern.

Undergraduate students are part of the upcoming workforce and will likely encounter AI-based recruitment systems as they begin their job search. Their opinions and trust in these systems could influence how successfully such technologies are adopted in future recruitment practices. As Universiti Utara Malaysia (UUM) produces many business and management graduates, it is a suitable setting to explore how students engage with AI during the hiring process.

Previous studies have identified key factors that shape user acceptance of AI in recruitment. Three important variables often discussed are awareness, trust, and perceived fairness (Singh & Finn, 2022). Awareness refers to how much students know about AI's role in hiring decisions. Students who are better informed may feel more comfortable using such systems (Mohamad, Ahmad, & Abdullah, 2024). Trust in AI reflects the confidence they place in the technology's ability to make fair and accurate decisions (Chamorro-Premuzic et al., 2023). Perceived fairness relates to whether students feel the system is transparent and unbiased during evaluation (Singh & Finn, 2022).

While AI can help reduce human error, studies have shown that algorithms can still produce biased outcomes if they are built using flawed data or unclear rules (Kaur, Sharma, & Kumar, 2021). These concerns may create uncertainty among students, making them hesitant to rely on AI systems for something as important as their first job. A survey by Deloitte (2023) found that nearly 60% of young job seekers expressed doubts about AI fairness in hiring, showing that skepticism remains despite the technology's potential.

Another major concern is transparency. Students often do not know how AI evaluates them or ranks their profiles. This lack of clarity can lead to a sense of discomfort or mistrust (Chamorro-Premuzic et al., 2023). Additionally, the use of personal data in AI recruitment raises ethical questions about privacy, consent, and data protection (Kaur et al., 2021).

In Malaysia, research on this topic remains limited. Most studies focus on how companies use AI rather than how students perceive it. As future job applicants, students' opinions are critical in understanding whether AI recruitment will be accepted and trusted in the local employment landscape (Mohamad et al., 2024).

This study aims to address that gap. It will investigate how awareness of AI, trust in AI decision-making, and perceived fairness influence the willingness of UUM undergraduate students to apply for jobs using AI-based recruitment platforms. The findings will help employers, educators, and policymakers understand how to design more transparent, ethical, and student-friendly recruitment systems.

1.3 Research Questions

1. Does awareness of AI in recruitment have a positive relationship with undergraduate students' willingness to apply for jobs through AI-driven recruitment systems?
2. Does trust in AI decision-making have a positive relationship with undergraduate students' willingness to apply for jobs through AI-driven recruitment systems?
3. Does perceived fairness have a positive relationship with undergraduate students' willingness to apply for jobs through AI-driven recruitment systems?

1.4 Research Objectives

The objectives of this research are:

1. To examine the positive relationship between awareness of AI in recruitment and undergraduate students' willingness to apply for jobs through AI-driven recruitment systems.
2. To examine the positive relationship between trust in AI decision-making and undergraduate students' willingness to apply for jobs through AI-driven recruitment systems.
3. To examine the positive relationship between perceived fairness and undergraduate students' willingness to apply for jobs through AI-driven recruitment systems.

1.5 Significance of the Study

This study is meaningful both academically and practically. It addresses a growing concern in the field of recruitment by examining how undergraduate students perceive and respond to the use of Artificial Intelligence in hiring. As more organizations adopt AI-based recruitment systems, it becomes essential to understand how future job seekers evaluate these tools and what factors shape their willingness to engage with them.

From an academic perspective, the study contributes to the development of theory by applying the Technology Acceptance Model, commonly referred to as TAM, alongside the Unified Theory of Acceptance and Use of Technology, also known as UTAUT. TAM is widely used to explain how individuals accept and use new technology based on their perceptions of usefulness and ease of use. In this study, the model is extended to include psychological elements such as trust and fairness, which are particularly relevant in recruitment settings.

The addition of UTAUT enriches the theoretical foundation by introducing variables such as performance expectations, effort expectations, and social influence. These elements help explain behavioural intention from a broader point of view, making the study more robust in capturing the full scope of factors that influence students' acceptance of AI-driven hiring platforms. By integrating both models, the research offers a more comprehensive framework for studying technology adoption in a recruitment context, especially among young job seekers.

The study is also relevant to institutions such as Universiti Utara Malaysia. UUM is known for its focus on business and technology and has consistently produced graduates who are highly employable. According to the latest graduate tracer report, UUM recorded a ninety-six percent employability rate in the year twenty twenty-four. This high success rate reflects strong academic preparation, but with the increasing shift toward digital hiring, there is a need to ensure students are also prepared for recruitment technologies that rely on automation and artificial intelligence. The findings from this study can help UUM evaluate and improve how digital readiness is embedded in its academic and career support programs.

For employers and recruitment professionals, this study provides practical insights into how students interpret fairness, trust, and transparency in AI recruitment. These insights can help organizations improve the way they design and communicate their hiring processes. By addressing student concerns, companies may enhance candidate engagement, reduce drop-off rates, and strengthen their brand as a fair and innovative employer.

This study is also important for policymakers. As the use of AI in recruitment becomes more common, ethical and legal questions around transparency, bias, and data privacy become increasingly important. The views of students can offer valuable input in shaping national guidelines or institutional policies that promote responsible and inclusive use of AI in hiring.

An additional contribution of this study lies in its focus on digital literacy. Today's graduates are expected to engage with various recruitment tools, including virtual interviews, applicant tracking systems, and algorithm-based screening. Many students may not fully understand how these tools work or how their data is used. This study encourages greater awareness and helps identify areas where students may need support to increase their digital confidence and job-readiness.

In summary, the study offers contributions across several levels. It supports academic theory by expanding established models, provides practical direction for universities and employers, informs policy development, and highlights the importance of digital literacy in today's competitive and technology-driven job market. By understanding student perceptions of AI in recruitment, stakeholders can work toward more ethical, inclusive, and effective hiring practices that reflect the expectations of the next generation of professionals.

1.6 Scope of the Study

This study explores the perceptions of undergraduate students at Universiti Utara Malaysia regarding the use of Artificial Intelligence in recruitment. The focus is on three key constructs: awareness of AI applications, trust in AI decision-making, and perceived fairness in AI-based hiring systems. These variables are examined within the conceptual framework of the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), which provide the foundation for understanding behavioural intention toward technology adoption.

The geographical scope is limited to Universiti Utara Malaysia, located in Sintok, Kedah. UUM is selected for its strong emphasis on business, technology, and management education, which aligns with the digital orientation of the study. The university also recorded a 96.6 percent graduate employability rate in 2024, making it a relevant and timely context for studying students' readiness for AI-driven recruitment in a technology-focused job market (New Straits Times, 2025).

The demographic scope covers undergraduate students in their first through third year of study, across multiple faculties and academic programs. These students represent a wide range of academic backgrounds, technological exposure, and early-stage career planning. Including students who are still progressing through their studies allows the research to capture varying levels of awareness and evolving attitudes toward AI in recruitment, beyond those already entering the job market.

The study is conducted within a single academic year. This time frame ensures that the data reflects current levels of digital awareness and student perceptions in response to recent advancements in recruitment technologies.

Conceptually, the study does not seek to evaluate the technical performance of AI systems. Instead, it focuses on the psychological and behavioural aspects of technology acceptance by examining how awareness, trust, and fairness influence students' willingness to engage with AI-based recruitment platforms. These insights are particularly important for understanding how early exposure to digital recruitment tools shapes future job seekers' attitudes.

By narrowing the scope to this specific population and institutional setting, the study provides context-specific insights that can guide improvements in graduate readiness, ethical AI implementation, and recruitment communication strategies in higher education and beyond.

1.7 Definition of Key Terms

This section provides the operational definitions of key terms used throughout the study to ensure clarity and consistency in interpretation:

1.7.1 Artificial Intelligence (AI)

Artificial Intelligence refers to computer systems or technologies designed to carry out tasks that require human intelligence. These tasks may include learning, reasoning, problem-solving, and decision-making. In this study, AI is primarily examined about its role in automating and enhancing recruitment processes (Kaur, Sharma, & Kumar, 2021).

1.7.2 Awareness of AI in Recruitment

This term refers to the degree to which undergraduate students are informed about the presence and application of AI in recruitment. It includes their understanding of how AI technology function, their potential benefits and limitations, and their broader implications within hiring practices (Mohamad, Ahmad, & Abdullah, 2024).

1.7.3 Trust in AI Decision-Making

Trust in AI decision-making describes students' confidence in the ability of AI systems to make accurate, reliable, and unbiased decisions throughout the recruitment process. This includes their belief in the objectivity and credibility of AI-generated outcomes (Chamorro-Premuzic, Akhtar, Winsborough, & Sherman, 2023).

1.7.4 Perceived Fairness

Perceived fairness refers to how students evaluate the recruitment process conducted by AI technologies in terms of equity and transparency. It captures their views on whether the process is ethical, impartial, and treats all candidates fairly (Singh & Finn, 2022).

1.7.5 Students' Willingness to Apply for Jobs through AI-Driven Systems

This term refers to the extent to which undergraduate students are prepared and inclined to engage with recruitment processes managed or supported by AI technologies. It reflects their acceptance of AI-enabled methods as a legitimate and trustworthy approach to pursuing employment opportunities (Mohamad, Ahmad, & Abdullah, 2021).

1.8 The Organization of the Study

This research is systematically organized into five chapters to facilitate a comprehensible and structured study of the research topic.

This chapter outlines the background of the study, states the research problem, and presents the research objectives and questions. It also defines the scope and significance of the study and provides operational definitions for key terms.

The second chapter presents a comprehensive review of existing literature related to the use of Artificial Intelligence in recruitment. It examines key factors influencing students' perceptions, including awareness, trust, and perceived fairness, and discusses how these variables relate to students’ willingness to engage with AI-driven recruitment systems.

The third chapter details the research design, sampling techniques, data collection methods, and instruments used. It also explains the data analysis procedures and discusses how the study ensures reliability and validity in its findings.

The fourth chapter presents the results of the data analysis. It includes both descriptive and inferential statistical interpretations, focusing on the relationships among the key variables identified in the study.

The final chapter discusses the implications of the research findings, draws conclusions based on the results, and provides practical and theoretical recommendations. It also outlines the study's limitations and suggests directions for future research.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter critically reviews literature relevant to undergraduate students' perceptions of AI-driven recruitment processes. It comprehensively addresses key variables: awareness, trust in AI decision-making, perceived fairness, and willingness to apply for jobs through AI-driven systems, establishing theoretical foundations and identifying research gaps.

2.2 Artificial Intelligence in Recruitment

Artificial Intelligence (AI) in recruitment involves using advanced technologies to automate recruitment activities traditionally performed manually by recruiters. These recruitment activities typically include resume screening, candidate sourcing, interviewing, and assessing candidate suitability. According to Black and van Esch (2021), AI technologies in hiring have transformed traditional, time-consuming recruitment practices into streamlined processes supported by automation and data analytics. However, despite clear advantages, there are critical perspectives and ongoing debates surrounding the effectiveness and ethical implications of AI-driven recruitment methods.

One notable advantage of AI recruitment systems is their efficiency in screening large volumes of job applications. AI-enabled screening tools rapidly evaluate candidate profiles based on predefined criteria such as skills, education, and experience, greatly reducing recruiters’ workload. Mohamad, Ahmad, and Abdullah (2021) found that automated screening enables recruiters to dedicate more attention to higher-value tasks like candidate engagement, thereby enhancing overall productivity. However, Kaur, Sharma, and Kumar (2021) highlight potential drawbacks, emphasizing that these benefits are heavily reliant on the quality of the data and algorithms used. Inaccurate or biased data can undermine the accuracy and fairness of automated screening, leading to flawed outcomes.

Another significant feature of AI recruitment systems is proactive candidate sourcing. By utilizing algorithms that mine data from social media platforms and professional networks, AI enables recruiters to reach a broader and potentially more diverse candidate pool. Chamorro-Premuzic et al. (2023) argue that this approach could enhance diversity and inclusivity within organizations. However, Singh and Finn (2022) counter that reliance on digital sourcing methods introduces critical privacy concerns, particularly about how personal data is gathered, stored, and utilized, raising ethical questions that organizations must carefully address.

AI technologies have also transformed the interviewing stage through the use of automated video interviews and chatbot-assisted communications. These technologies evaluate candidates objectively by assessing speech patterns, behavioural cues, and responses to standardized questions. Mohamad et al. (2021) report that automated interviewing systems reduce interviewer biases and provide a more standardized assessment environment. On the contrary, Kaur et al. (2021) critically note that some candidates feel discomfort or mistrust towards automated interviewing due to its perceived impersonal nature, potentially affecting candidate performance negatively.

Predictive analytics represents another advancement of AI recruitment, leveraging historical hiring data to forecast future candidate performance, retention, and organizational fit. Singh and Finn (2022) emphasize that predictive analytics can significantly improve hiring quality and reduce employee turnover by identifying candidates likely to succeed. Nevertheless, Chamorro-Premuzic et al. (2023) caution that predictive analytics may inadvertently perpetuate existing biases present in historical datasets, underscoring the need for continuous monitoring and algorithmic validation.

Transparency remains a significant issue in the adoption of AI in recruitment. Candidates frequently lack clear information about how AI algorithms assess their qualifications and rank their applications. This opacity can diminish trust in AI systems and negatively affect perceived fairness, leading to lower acceptance among job applicants (Chamorro-Premuzic et al., 2023). Additionally, growing reliance on extensive personal data collection by AI systems increases concerns around privacy, data security, and consent, making transparency even more critical (Singh & Finn, 2022).

Given these concerns, candidate perceptions of AI recruitment systems become critical in assessing their acceptance and long-term success. This study specifically examines awareness of AI applications, trust in algorithmic decision-making, and perceived fairness, as these variables directly influence candidates' willingness to use AI-based recruitment tools. Singh and Finn (2022) emphasize that trust and perceived fairness significantly shape applicants' behavioural intentions towards these technologies. Moreover, student awareness regarding how AI recruitment works directly impacts their comfort level and readiness to engage with such systems (Mohamad et al., 2021).

Educational institutions, such as universities, play a crucial role in shaping student awareness and acceptance of AI-driven recruitment technologies. Implementing educational initiatives like targeted seminars, workshops, and curriculum development focused on digital literacy and recruitment technologies could significantly enhance students' preparedness for modern hiring practices (Mohamad et al., 2021).

In summary, AI recruitment offers clear advantages in efficiency, accuracy, and strategic alignment of hiring processes. Yet critical challenges involving transparency, ethics, data privacy, and algorithmic bias must be adequately addressed to ensure broader acceptance and effective implementation. Exploring how undergraduate students perceive these technologies, particularly their levels of awareness, trust, and perceived fairness, provides essential insights for educational institutions, employers, and policymakers aiming to integrate AI ethically and effectively into recruitment practices.

2.3 Students' Willingness to Apply through AI-driven Systems to Apply Job

Students' willingness to use AI driven recruitment systems refers to their motivation or inclination to apply for jobs through platforms supported by artificial intelligence. Singh and Finn (2022) define this willingness as a critical factor because it directly affects how successfully organizations can attract candidates using these technologies. While AI recruitment methods offer efficiency and consistency, their effectiveness ultimately depends on the extent to which students feel comfortable engaging with such systems.

The concept of willingness in this context draws upon the broader idea of behavioural intention found in technology acceptance research. The Technology Acceptance Model (TAM), introduced by Davis (1989), explains behavioural intention through two key perceptions: ease of use and usefulness. According to TAM, individuals who believe technology is easy to use and useful in achieving their goals are more likely to adopt it. Extending this theory, Chamorro-Premuzic et al. (2023) argue that willingness to apply using AI recruitment technologies also depends significantly on how trustworthy and fair students perceive these systems to be, beyond just usability factors alone.

Empirical research highlights awareness as an essential factor influencing willingness. Awareness refers to students' understanding and familiarity with AI applications in recruitment. Singh and Finn (2022) found that when students are better informed about how AI operates and its benefits, they display greater comfort and reduced uncertainty toward these platforms. Mohamad, Ahmad, and Abdullah (2021) similarly demonstrated that increased awareness through educational activities leads to higher student readiness and a greater intention to engage with AI recruitment tools. However, insufficient awareness or misconceptions can create apprehension, significantly lowering students' motivation to utilize these technologies.

Trust in AI decision making represents another crucial variable impacting willingness. Students who trust AI systems perceive them as capable of making accurate, reliable, and unbiased recruitment decisions. Chamorro-Premuzic et al. (2023) suggest that strong trust significantly enhances students' willingness to interact with AI systems because it reduces anxiety about potential negative outcomes. On the contrary, Kaur, Sharma, and Kumar (2021) argue that a lack of transparency regarding how AI algorithms evaluate candidates can severely weaken trust, thereby diminishing students' willingness and participation rates. Thus, maintaining transparent AI practices is vital for promoting sustained trust among job applicants.

The perception of fairness is also central in determining willingness. Fairness in this context relates to how students view AI driven recruitment processes regarding transparency, impartiality, and ethical integrity. Gilliland (2021) indicates that fairness perceptions strongly influence candidate satisfaction, emotional reactions, and ultimately their likelihood of engaging again with recruitment systems. Similarly, Hausknecht, Day, and Thomas (2021) emphasize that perceived unfairness due to hidden algorithmic biases significantly reduces students’ intentions to apply via AI based systems. Therefore, organizations must actively demonstrate transparency and ethical decision making to strengthen fairness perceptions among students (Singh & Finn, 2022).

Technological readiness further influences student willingness. Mohamad et al. (2021) observe that students who possess higher levels of technological familiarity and adaptability are more likely to embrace AI recruitment methods with confidence. Conversely, students lacking digital proficiency experience higher anxiety and are less likely to engage positively with AI recruitment systems. This indicates that digital literacy is crucial for enhancing student willingness and reducing resistance toward technology adoption in recruitment contexts.

Privacy and ethical concerns are additional influential factors. Kaur et al. (2021) argue that willingness is impacted by students’ apprehension about disclosing personal data required by AI systems. Clear explanations of data usage, privacy measures, and ethical standards must be communicated explicitly by recruiters to minimize students' privacy concerns. Failing to provide adequate assurance regarding data privacy can deter students from fully engaging with AI driven recruitment platforms, even when these tools offer substantial efficiency and objectivity.

Within the Malaysian context, research focusing explicitly on undergraduate students' perceptions and willingness toward AI recruitment is limited. Most studies concentrate broadly on organizational adoption, neglecting specific investigations into students as future job seekers. Mohamad et al. (2021) emphasize the importance of addressing this gap through focused studies, particularly at institutions like Universiti Utara Malaysia. Investigating the factors influencing students' willingness offers insights into their preparedness and identifies strategic interventions necessary for effective AI implementation.

To maximize student willingness, universities and organizations must implement multifaceted educational strategies. Initiatives such as targeted workshops, AI education programs, and seminars significantly boost awareness and technological readiness. Clear communication about AI functionalities, combined with transparency about ethical practices, can further reinforce trust and perceived fairness, leading to greater student acceptance and active participation in AI recruitment processes (Chamorro-Premuzic et al., 2023).

In conclusion, students' willingness to apply through AI driven recruitment systems greatly affects how well these technologies are adopted in employment contexts. Essential determinants including awareness, trust, perceived fairness, technological readiness, and privacy must be strategically managed through comprehensive educational interventions and transparent practices. This comprehensive approach ensures ethical, responsible, and effective AI integration into contemporary recruitment strategies.

2.4 Awareness of AI in Recruitment

Awareness of AI in recruitment refers to how well job seekers understand the functionalities, benefits, limitations, and implications of using artificial intelligence within hiring processes. According to Chamorro-Premuzic et al. (2023), this awareness includes knowledge about specific recruitment tasks performed by AI, such as screening applications, sourcing candidates, and conducting preliminary interviews.

Additionally, awareness covers understanding issues related to fairness, transparency, potential biases, and data privacy associated with AI recruitment technologies (Singh & Finn, 2022).

Empirical studies consistently highlight the importance of awareness as a key factor influencing user acceptance of AI recruitment systems. Research by Black and van Esch (2021) reveals that job seekers who are informed about AI-based hiring practices generally perceive these systems positively, valuing their efficiency, speed, and objectivity. A high level of awareness helps candidates understand how AI can standardize recruitment, thereby potentially reducing human biases and improving fairness in selection decisions (Chamorro-Premuzic et al., 2023). As a result, informed candidates tend to display greater trust and acceptance toward AI recruitment platforms, increasing their likelihood of active engagement with such systems.

Conversely, a lack of awareness or misunderstanding about AI functions can significantly hinder acceptance. Mohamad, Ahmad, and Abdullah (2021) found that students unfamiliar with how AI operates may perceive these technologies negatively, viewing them as invasive or potentially unfair. Similarly, Singh and Finn (2022) argue that inadequate awareness leads to scepticism, resistance, and reduced willingness to use AI recruitment systems. Therefore, raising awareness is critical not only for enhancing user acceptance but also for reducing anxiety and misconceptions related to AI technologies in recruitment.

Universities play a pivotal role in shaping students' awareness regarding AI recruitment practices. Educational interventions such as workshops, seminars, and targeted curricula are essential in helping students develop accurate perceptions about AI's role in modern recruitment. Singh and Finn (2022) observed that universities offering specialized training programs significantly increased students' awareness, reduced their apprehension, and improved their readiness for technology-based recruitment methods. Similarly, Mohamad et al. (2021) found that students who attended AI-focused training sessions exhibited higher confidence levels and a stronger intention to engage with AI recruitment systems compared to students without such training.

Awareness also influences candidates' practical abilities in navigating AI recruitment systems effectively. Chamorro-Premuzic et al. (2023) found that candidates who understand AI processes typically feel more confident, less anxious, and better prepared during their recruitment experiences. These candidates can leverage their knowledge to improve their application strategies and optimize their interactions with AI-based hiring tools, leading to improved outcomes compared to those who lack sufficient awareness.

However, despite the acknowledged importance of awareness, existing research on this topic remains limited, particularly within the Malaysian university context. Most studies focus broadly on organizational adoption or general workplace acceptance, neglecting specific analyses of university students who are preparing to enter the job market. Given that students represent future job seekers, understanding their current level of awareness is vital to ensuring they are adequately prepared for technology-driven recruitment scenarios (Mohamad et al., 2021). Therefore, investigating students' awareness provides valuable insights into their readiness and highlights areas requiring further educational initiatives.

Awareness is closely connected to other critical variables, notably trust and perceived fairness. Candidates who clearly understand how AI systems operate and their evaluation criteria are more likely to trust the decisions made by these systems (Chamorro-Premuzic et al., 2023). This increased trust positively impacts perceptions of fairness, as candidates recognize AI's potential role in reducing human biases. Conversely, limited awareness leads to lower trust and perceived unfairness, further diminishing overall acceptance and willingness to engage with AI recruitment platforms (Kaur, Sharma, & Kumar, 2021).

Therefore, fostering awareness through comprehensive educational and communication strategies is essential. Universities and employers must clearly communicate the ethical implications, potential biases, privacy safeguards, and functional aspects of AI technologies. Kaur et al. (2021) emphasize that clarity about ethical practices and transparency significantly enhances candidate awareness and supports informed decisions about interacting with AI recruitment systems.

In conclusion, awareness is a foundational factor influencing student perceptions, trust, and willingness to adopt AI recruitment systems. Strategic educational interventions and clear communication are essential in raising awareness, minimizing resistance, and supporting informed acceptance among students entering the modern, technology-driven job market.

2.5 Trust in AI Decision-Making

Trust in AI decision-making refers to the degree of confidence individuals place in artificial intelligence systems when they are used to make recruitment decisions. It reflects the belief that AI-generated outcomes are fair, accurate, and impartial. In recruitment contexts, trust becomes especially important because it directly influences whether candidates are willing to engage with technology-based hiring platforms (Chamorro-Premuzic, Akhtar, Winsborough, & Sherman, 2023; Singh & Finn, 2022).

Within technology acceptance literature, trust is widely acknowledged as a core component of system adoption. The Technology Acceptance Model explains user behavior largely through perceived usefulness and ease of use, but trust adds another dimension that becomes essential when users lack control or full understanding of how the system works (Davis, 1989). In the case of AI-driven recruitment, candidates must often rely on algorithmic assessments rather than human interaction, making trust a critical variable that mediates their acceptance of these systems (Kaur, Sharma, & Kumar, 2021).

Several factors contribute to trust in AI recruitment systems. Transparency is one of the most frequently cited elements. It refers to how clearly organizations communicate the criteria and processes that guide AI decision-making. According to Chamorro-Premuzic et al. (2023), transparency helps users understand how conclusions are drawn, and when this understanding improves, trust typically follows. Singh and Finn (2022) found that candidates are more likely to trust AI systems when they are informed about how decisions are made, especially when the system's logic is explained in understandable terms.

Closely related to transparency is the concept of explainability, which concerns the AI system's ability to justify its decisions. While transparency focuses on access to information, explainability ensures that the information provided is meaningful. Kaur et al. (2021) argue that candidates are more accepting of AI assessments when those outcomes are supported by clear and logical explanations, even if the decisions are not in their favor.

Accuracy and consistency also influence trust. When AI systems produce consistent outcomes based on objective data, users perceive them as more reliable (Mohamad, Ahmad, & Abdullah, 2021). However, this reliability is vulnerable. If the system makes errors or produces decisions that appear arbitrary, trust can erode quickly. Singh and Finn (2022) note that even isolated inaccuracies can create doubt in the entire process, especially when users are unsure of how to challenge or interpret those decisions.

Although AI is often promoted as a way to reduce bias, it can also unintentionally replicate existing discrimination patterns. If training data reflects historical inequalities or if the algorithm lacks regular monitoring, biases can be embedded within the system (Chamorro-Premuzic et al., 2023). This raises ethical concerns and presents a direct challenge to trust. In fact, research by Singh and Finn (2022) found that even the perception of bias can reduce candidate confidence in AI systems, regardless of whether the bias is intentional or data-driven.

Comparatively, while human recruitment also involves bias, candidates are often more forgiving because human decision-makers can be questioned or appealed to. With AI, this opportunity is rarely available. The inability to challenge decisions further undermines trust, especially when candidates are left uncertain about how their application was evaluated (Kaur et al., 2021).

To build trust, organizations must invest in transparency strategies and ensure AI systems are regularly audited for fairness and accuracy. Chamorro-Premuzic et al. (2023) suggest that combining AI decisions with human oversight can also strengthen trust, as it assures candidates that a critical review of AI outputs exists. Similarly, Mohamad et al. (2021) emphasize that clearly communicating the strengths and limitations of AI tools helps set realistic expectations and reduces the likelihood of disillusionment or misunderstanding.

Educational institutions also play a role in shaping trust. Students who are exposed to educational programs that explain AI recruitment processes, limitations, and ethical considerations are more likely to develop informed trust in these systems. Findings by Mohamad et al. (2021) show that students who participated in AI-focused workshops reported greater comfort and higher willingness to interact with AI recruitment technologies compared to those who had no such exposure.

Ultimately, trust influences both perceived usefulness and perceived ease of use, which are the central constructs of the Technology Acceptance Model. When trust is low, even the most efficient or user-friendly system may be rejected. Conversely, when trust is high, users may overlook small usability issues because they believe the system is working fairly and accurately (Davis, 1989).

In summary, trust in AI decision-making is not automatic. It must be earned through transparent practices, consistent system performance, explainable logic, and ethical safeguards. As candidates increasingly interact with automated systems, their perceptions of fairness and accuracy will shape whether they accept or reject these tools. Therefore, both organizations and academic institutions must prioritize strategies that build trust in order to support the responsible and successful adoption of AI in recruitment.

2.6 Perceived Fairness

Perceived fairness in recruitment refers to a candidate's personal judgment about whether recruitment decisions, procedures, and treatment are just, transparent, and impartial. According to Gilliland (2021), fairness is not only about the final decision, such as receiving a job offer, but also how that decision is reached and communicated. In modern recruitment processes, especially those involving artificial intelligence, perceptions of fairness play a pivotal role in shaping how candidates evaluate the recruitment experience and whether they are willing to engage with such systems.

The concept of fairness is typically examined through three dimensions: distributive, procedural, and interactional fairness. Distributive fairness relates to the perceived equity of outcomes, such as receiving a job offer. Procedural fairness refers to how consistently and objectively recruitment steps are applied across candidates. Interactional fairness focuses on the respect and dignity candidates experience throughout the process (Hausknecht, Day, & Thomas, 2021). Chamorro-Premuzic, Akhtar, Winsborough, and Sherman (2023) emphasize that procedural fairness becomes especially important when artificial intelligence is involved, as automation can improve consistency but may reduce opportunities for personal interaction.

Artificial intelligence has introduced both new possibilities and new challenges in fairness perceptions. On one hand, AI systems can enhance procedural fairness by applying standardized evaluation criteria. Singh and Finn (2022) argue that automation removes much of the subjectivity and inconsistency often associated with human decision-making. When properly designed, AI recruitment tools may actually improve fairness by offering every candidate the same evaluation framework.

On the other hand, fairness concerns with AI stem from a lack of transparency and the presence of algorithmic bias. Candidates often do not understand how AI systems reach decisions, which reduces their confidence in the fairness of the process (Mohamad, Ahmad, & Abdullah, 2021). Furthermore, Kaur, Sharma, and Kumar (2021) caution that AI systems trained on biased historical data can replicate and even intensify social inequalities, producing outcomes that are technically consistent but ethically problematic.

Empirical studies consistently show that perceived fairness influences not only candidates' satisfaction but also their future behaviour. Candidates who believe that the process was fair are more likely to reapply, recommend the organization to others, or maintain a positive image of the employer even if they were not selected (Hausknecht et al., 2021). Conversely, if candidates perceive the system as unfair or opaque, their trust in the organization diminishes, regardless of whether AI or human recruiters are involved.

This tension between consistency and explainability highlights a core challenge in using AI for recruitment. While automation increases efficiency and reduces some forms of bias, it may reduce perceived fairness if candidates cannot understand or question the process. Chamorro-Premuzic et al. (2023) recommend that organizations pair AI evaluations with clear communication about decision-making criteria to improve candidate perceptions.

The role of education is also significant in shaping fairness perceptions. University-led initiatives, such as AI awareness workshops or job-readiness training, can help students understand the logic behind AI-driven hiring decisions. This understanding builds both trust and perceived fairness. Mohamad et al. (2021) found that students who participated in AI-related training were more accepting of algorithmic decisions and showed higher satisfaction with recruitment processes, even when they were unsuccessful.

The inclusion of perceived fairness in this study is based on its direct link to behavioural intention and system acceptance. As a psychological construct, fairness shapes whether candidates are willing to apply through AI systems and whether they view such systems as legitimate. While trust addresses whether candidates believe the system will work, fairness reflects whether they believe the system will treat them justly. These two dimensions are conceptually distinct and empirically significant in determining user behaviour.

In conclusion, perceived fairness is a central factor in evaluating both traditional and AI-based recruitment practices. Its influence extends beyond immediate reactions to shape long-term perceptions of employer credibility, system trustworthiness, and candidate engagement. For AI recruitment systems to gain widespread acceptance, fairness must be demonstrated, communicated, and reinforced through transparent, ethical, and inclusive design practices.

2.7 Theoretical Framework

This study is grounded in two well-established models from the field of technology adoption, namely the Technology Acceptance Model, developed by Davis in 1989, and the Unified Theory of Acceptance and Use of Technology, introduced by Venkatesh, Morris, Davis, and Davis in 2003. Among these, the Technology Acceptance Model serves as the underpinning theory of this research. It provides the primary conceptual foundation for examining how students form behavioural intentions to adopt artificial intelligence systems in recruitment. The Unified Theory of Acceptance and Use of Technology is used to extend and support this framework by offering a broader understanding of external and contextual factors that influence technology acceptance.

The Technology Acceptance Model has been extensively applied to explain user behaviour across various technological environments. It is built on the idea that perceived usefulness and perceived ease of use are the two main beliefs that determine whether an individual will accept and use a new technology. Perceived usefulness refers to the extent to which a person believes that the system will improve their performance, while perceived ease of use refers to the extent to which the system is considered free of effort. In this study, these two constructs are particularly relevant, as students are likely to evaluate artificial intelligence recruitment systems based on how helpful and user-friendly they perceive them to be. If they believe that such systems reduce bias, simplify the application process, or improve the chances of fair treatment, they are more likely to engage with them (Davis, 1989; Marangunić and Granić, 2015).

To complement this foundation, the Unified Theory of Acceptance and Use of Technology contributes four additional determinants of technology acceptance. These include performance expectancy, effort expectancy, social influence, and facilitating conditions. While performance expectancy and effort expectancy are closely related to the original constructs in the Technology Acceptance Model, the theory further expands on how individuals are influenced by people around them and the resources available to them. Social influence refers to the extent to which individuals perceive that important other, such as lecturers or peers, believe they should use a particular system. Facilitating conditions relate to the perception that there is adequate institutional support or infrastructure to use the technology effectively (Venkatesh et al., 2003).

In relation to the current study, the variables of awareness, trust, and perceived fairness are conceptually linked to these theories. Awareness of artificial intelligence technologies plays a role in enhancing both perceived usefulness and effort expectancy. When students understand how artificial intelligence works and how it is used in recruitment, they are more likely to see it as useful and less complicated to engage with (Mohamad, Ahmad, and Abdullah, 2021). Trust in artificial intelligence decision-making aligns with the idea of performance expectancy. If students believe that the system is capable of making fair and accurate decisions, their confidence in the technology increases, which in turn influences their willingness to apply through such platforms (Chamorro-Premuzic, Akhtar, Winsborough, and Sherman, 2023). Perceived fairness is also critical, as it contributes to how students perceive the system's transparency, neutrality, and ethical conduct. These perceptions affect both effort expectancy and social influence, as fairness influences how easily a system is accepted and how it is discussed or perceived within a community.

The behavioural intention to use artificial intelligence in recruitment, which is the main outcome of this study, is directly derived from both the Technology Acceptance Model and the Unified Theory of Acceptance and Use of Technology. While the Unified Theory provides additional explanatory power through social and environmental perspectives, the Technology Acceptance Model remains the primary framework that underpins this research due to its direct focus on internal beliefs, perceptions, and behavioural responses. Together, these models offer a comprehensive lens through which to understand undergraduate students' willingness to engage with artificial intelligence systems in recruitment.

2.8 Research Gap

Despite significant advancements and widespread adoption of AI-driven recruitment technologies, existing literature reveals notable gaps regarding specific populations' perceptions and acceptance of these systems, particularly within the context of higher education institutions. Much existing research has primarily focused on general organizational applications, technology implementation outcomes, and broader workforce implications (Chamorro-Premuzic, Akhtar, Winsborough, & Sherman, 2023; Kaur, Sharma, & Kumar, 2021). Limited attention has been directed toward understanding undergraduate students' specific perceptions and attitudes, especially within the Malaysian educational context.

Several studies acknowledge the critical importance of understanding users' perceptions toward AI recruitment technologies, highlighting awareness, trust, and perceived fairness as key determinants influencing acceptance and adoption (Singh & Finn, 2022). However, most empirical research primarily targets general employee populations, often overlooking unique perceptions and concerns held by students entering the workforce for the first time (Mohamad, Ahmad, & Abdullah, 2021).

Singh and Finn's (2022) research emphasizes perceptions among general university student populations; however, it does not focus specifically on undergraduate students at Malaysian institutions. Similarly, Mohamad et al. (2021) explored general job-seekers' perspectives on AI recruitment without concentrating specifically on university student populations. These gaps indicate a significant need to understand perceptions, specifically among undergraduate students at Universiti Utara Malaysia, as these individuals represent future employees who will soon enter a workforce increasingly reliant on AI-driven recruitment technologies.

Moreover, while empirical research identifies general factors influencing AI recruitment acceptance, such as trust, fairness, and awareness, there remains limited contextual examination of these variables specifically among UUM undergraduate students. Universiti Utara Malaysia, renowned for its focus on management and leadership education, represents a uniquely relevant context for examining student perceptions and readiness concerning AI recruitment technologies. The absence of targeted research within this specific context leaves a notable knowledge gap in understanding how these perceptions impact students' willingness to engage with AI-driven recruitment systems.

This study addresses these critical gaps by specifically focusing on UUM undergraduate students, investigating their awareness, trust in AI decision-making, and perceived fairness, and how these factors collectively influence their willingness to apply for jobs through AI-driven recruitment systems. By explicitly targeting this demographic and educational context, the research contributes nuanced, context-specific insights, facilitating targeted strategies for enhancing awareness, transparency, and trust among future Malaysian graduates.

Furthermore, the study will employ rigorous empirical methodologies to provide comprehensive insights into the interplay between identified variables, directly addressing existing methodological gaps highlighted in previous literature. Overall, this research will significantly advance current academic understanding and practical applications, effectively bridging identified gaps within the literature and providing a strong foundation for future studies and informed organizational practices.

2.9 Summary of the Chapter

This literature review has comprehensively explored the concepts central to the study, particularly focusing on the role of Artificial Intelligence (AI) in recruitment, awareness of AI recruitment technologies, trust in AI decision-making, perceived fairness, and students' willingness to apply through AI-driven recruitment systems. The review established that AI significantly transforms recruitment processes by enhancing efficiency, reducing biases, and providing standardized evaluations. However, transparency, ethical concerns, algorithmic biases, and data privacy issues remain critical challenges requiring strategic management and clear communication.

Empirical evidence has demonstrated significant relationships among key variables, notably awareness, trust, and perceived fairness, which collectively influence undergraduate students' willingness to engage with AI-driven recruitment platforms. However, a notable research gap exists regarding specific investigations targeting undergraduate students within the Malaysian educational context, particularly at Universiti Utara Malaysia (UUM).

By addressing this gap, the present study aims to provide targeted insights, guiding academic institutions, recruiters, and policymakers in enhancing awareness, transparency, and trust, thereby facilitating the effective adoption and ethical implementation of AI in recruitment. The subsequent chapter outlines the methodological framework employed in addressing the research objectives and filling the identified literature gap.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter outlines the methodology adopted to fulfil the objectives of this research. It comprehensively explains the research design, sampling strategy, and data collection and analysis methods. In addition, it discusses the research instruments used, the pilot testing procedures conducted, and the ethical considerations observed throughout the study.

The methodological choices were carefully aligned with the primary aim of this study, which is to explore the relationship between undergraduate students' awareness of artificial intelligence (AI) in recruitment, their trust in AI-driven decision-making, and their perception of fairness, alongside how these factors collectively influence their willingness to apply for positions through AI-enabled recruitment systems. The scope of this study is specifically focused on students at Universiti Utara Malaysia (UUM).

The research process followed a deductive approach. This approach began with the formulation of theories and developing both the research hypotheses and null hypotheses, derived from the three independent variables and one dependent variable. These hypotheses serve as the foundation for the study's statistical analysis. Depending on the outcomes of these statistical tests, the hypotheses will either be supported or refuted, thereby contributing to a clearer understanding of the studied relationships.

3.2 Research Framework

The research framework for this study illustrates the conceptual relationships between the independent and dependent variables. The independent variables include awareness of artificial intelligence (AI) in recruitment, trust in AI decision-making, and perceived fairness. These variables are posited to influence the dependent variable, which is students' willingness to apply for employment opportunities through AI-driven recruitment systems.

This framework is grounded in two well-established theoretical models: the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). Both models suggest that individuals' acceptance of technology is primarily shaped by their perceptions of its usefulness, trustworthiness, and fairness factors that impact their behavioural intention to use the technology.

Drawing from these theoretical foundations, the study hypothesizes that each of the three independent variables will directly and positively influence the dependent variable. The relationships proposed are visually represented in Figure 3.1, which outlines the conceptual structure guiding this research. The independent variables in this study are hypothesized to have direct, positive relationships with the dependent variable, as depicted in Figure 1:

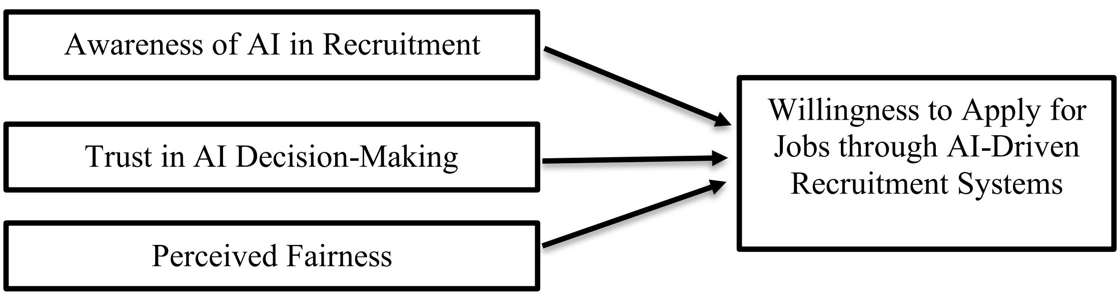

Figure 3.1

Research Framework

3.3 Hypothesis Development

This section presents the research hypotheses formulated based on the conceptual model illustrated in Figure 3.1. The hypotheses were developed in alignment with the study’s variables, drawing from prior empirical findings that support positive relationships among the constructs within organizational contexts.

According to Sekaran and Bougie (2009), hypotheses are educated assumptions that propose a logically derived relationship between two or more variables. These assumptions are articulated in a testable form, allowing researchers to examine and potentially resolve the research problem through empirical investigation. In this study, the hypotheses were designed to explore the extent to which awareness of AI in recruitment, trust in AI decision-making, and perceived fairness influence students’ willingness to apply for jobs through AI-enabled recruitment platforms.

3.3.1 Relationship Between Awareness of AI And Willingness To Apply For Jobs Through AI-Driven Recruitment Systems

Previous research emphasizes the significant influence awareness has on individuals' acceptance of new technologies. According to Mohamad, Ahmad, and Abdullah (2021), awareness plays a crucial role in shaping users' perceptions toward adopting technological systems. Increased awareness enhances understanding of AI functionalities, capabilities, and limitations, thereby reducing uncertainties and misconceptions (Kaur, Sharma, & Kumar, 2021). Studies consistently suggest that higher awareness levels lead to increased confidence, acceptance, and positive attitudes toward AI-driven systems, subsequently increasing willingness to utilize such technologies in recruitment processes (Singh & Finn, 2022). Hence, this study hypothesizes a positive relationship between students' awareness of AI in recruitment and their willingness to apply through AI-driven recruitment systems.

Hypothesis 1: Awareness of AI positively related to willingness to apply for jobs through AI-driven recruitment systems

3.3.2 Relationship Between Trust in AI Decision-Making and Willingness To Apply For Jobs Through AI-Driven Recruitment Systems

Trust is identified as a foundational element in technology adoption, particularly influencing how individuals perceive the reliability, accuracy, and impartiality of AI systems in making recruitment decisions (Chamorro-Premuzic, Akhtar, Winsborough, & Sherman, 2023). Studies consistently find that higher levels of trust positively correlate with increased willingness to use AI-driven recruitment systems, as individuals are more confident and comfortable engaging with technologies perceived as trustworthy and unbiased (Singh & Finn, 2022). Conversely, distrust due to perceived opacity, errors, or algorithmic biases significantly reduces the willingness of students to interact with AI-driven recruitment platforms (Kaur, Sharma, & Kumar, 2021). Hence, this research hypothesizes that increased trust in AI decision-making directly enhances students' willingness to apply for jobs through these systems.

Hypothesis 2: Trust in AI Decision-Making positively related to willingness to apply for jobs through AI-driven recruitment systems

3.3.3 Relationship Between Perceived Fairness and Willingness To Apply For Jobs Through AI-Driven Recruitment Systems

Perceived fairness significantly influences candidate acceptance and their subsequent behaviors toward recruitment processes. According to Gilliland (2021), perceptions of fairness shape candidates' emotional responses and their intentions toward future interactions with organizations. Specifically, AI-driven recruitment systems perceived as fair, transparent, and unbiased tend to attract higher engagement and acceptance among candidates (Chamorro-Premuzic et al., 2023). Conversely, concerns regarding unfairness due to algorithmic biases can significantly reduce candidates' willingness to engage with these systems (Singh & Finn, 2022). Hence, this study hypothesizes that perceived fairness positively impacts students' willingness to apply through AI-driven recruitment systems.

Hypothesis 3: Perceived Fairness positively related to willingness to apply for jobs through AI-driven recruitment systems

3.4 Research Design

This study uses a quantitative research approach and follows a correlational research design. This approach fits the purpose of the study well, as it allows the researcher to measure and analyze the relationships between key variables in a clear and structured way. The focus is on understanding how undergraduate students' awareness of AI in recruitment, trust in AI decision-making, and perceived fairness relate to their willingness to apply for jobs through AI-driven recruitment systems.

To collect the necessary data, a survey questionnaire was used. This method was chosen because it efficiently and organized reaches more students. It also ensures that all participants receive the same set of questions, which helps maintain consistency in the responses and strengthens the reliability of the results.

The questionnaire was shared online, adding practical benefits to the research process. First, it allowed the study to reach students from different backgrounds and locations without needing face-to-face contact. This was especially helpful for collecting responses quickly and on a broader scale. Second, students could answer the questionnaire at a time that suited them best, which likely made them more comfortable and willing to participate.

The online format also helped reduce the chance of data entry errors, since responses were collected digitally and stored automatically. Importantly, completing the questionnaire online offered a sense of privacy, which may have encouraged students to answer more honestly and openly, especially on a topic that involves trust and perceptions of fairness.

Overall, the decision to use a structured online questionnaire helped make the data collection process more flexible, efficient, and accessible while still supporting the goals of this correlational study.

3.5 Population and Sampling Procedure

This research focused on undergraduate students enrolled at Universiti Utara Malaysia (UUM). As of October 1, 2024, UUM had a total student population of 30,149, with 24,671 students pursuing undergraduate programs and the remainder enrolled in postgraduate studies. The choice to focus specifically on undergraduate students is justified by the fact that these students represent the immediate future workforce, making their views particularly relevant to the context of AI-based recruitment systems.

Due to practical constraints related to limited resources and time, this study used convenience sampling to collect data. Convenience sampling allowed easier access to students within the UUM community, significantly simplifying the data collection process and making it manageable within the available timeframe. However, it is essential to openly acknowledge the limitation inherent in this method. Because convenience sampling does not involve random selection, the findings derived from this study should not be generalized beyond UUM students. Results may therefore reflect unique characteristics of this specific university community, and caution must be used when applying these findings to other groups or broader populations.

Regarding the determination of sample size, this research considered two widely recognized approaches. Initially, the study adopted guidelines from Krejcie and Morgan (1970), which recommended a sample size of about 371 participants for populations exceeding 1,000 individuals. This recommendation is commonly used in social science research to achieve results that are statistically sound and reasonably representative. Additionally, an a priori power analysis was conducted using the G*Power software (Faul et al., 2009). This analysis, based on an effect size of 0.15, an alpha level of 0.05, and a statistical power of 95% with three predictor variables, indicated a minimum sample size requirement of 119 participants for a regression-based analysis.

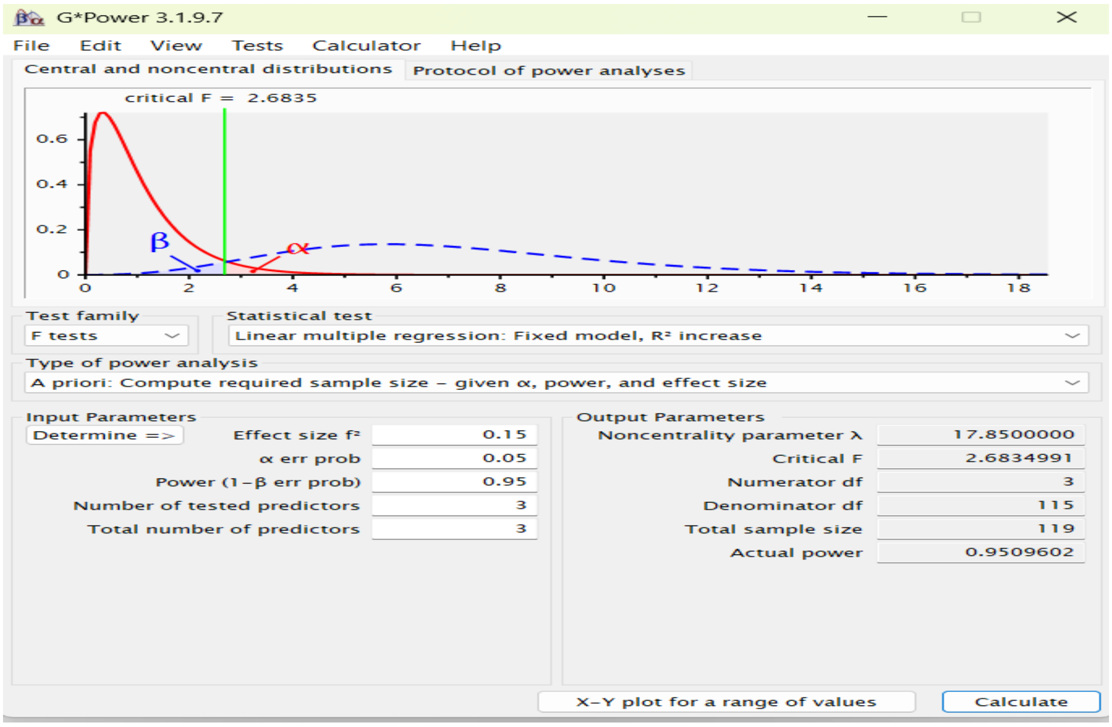

Figure 3.2
The Output of a Priori Power Analysis

In practice, the final number of valid responses collected and analyzed in this study was 243. This final sample size intentionally exceeds the minimum number suggested by G*Power. While 119 respondents would have been statistically sufficient, a larger sample size of 243 was chosen deliberately to improve the robustness and credibility of the results. Collecting data from a greater number of students helps to ensure that the findings are more stable and less influenced by potential outliers or anomalies. Furthermore, the final number aligns closely with sample sizes reported in similar past studies, which typically ranged between 200 and 400 respondents. This approach enhances confidence in the reliability of the findings and supports stronger conclusions within the context of this study.

In summary, while recognizing the limitations of the chosen convenience sampling approach, the justification provided clearly explains why this method was appropriate given the constraints faced. Additionally, the decision to collect data from 243 respondents ensures both statistical adequacy and alignment with established practices in related research areas.

3.6 Data Collection Procedure

Primary data for this research was collected directly from undergraduate students at Universiti Utara Malaysia (UUM) using an online questionnaire. This data collection approach was selected for its efficiency, consistency, and ability to gather responses from a large number of students quickly and cost-effectively. Online surveys also facilitate standardization, ensuring all respondents received identical questions presented in the same order, thereby reducing variability or inconsistencies (Creswell and Creswell, 2018).

The questionnaire was carefully structured into five distinct sections. The first section focused on demographic characteristics, such as age, gender, and year of study. The following three sections assessed the independent variables: students' awareness of artificial intelligence in recruitment, their trust in AI decision making, and their perceptions of fairness regarding AI-driven recruitment systems. The final section measured the dependent variable, which was students' willingness to apply for jobs using AI-driven recruitment platforms. Participants responded to each item using a five-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), as recommended by Hair, Black, Babin, and Anderson (2019).

An online questionnaire method was specifically chosen due to its widespread acceptance among university students and cost-effectiveness for researchers (Kuphanga, 2024). The questionnaire was created using Google Forms and distributed primarily through lecturer-student WhatsApp groups, a common communication channel at UUM. Permission was sought and granted by the respective lecturers and group administrators before the questionnaire was shared, ensuring ethical and appropriate access to respondents. Respondents accessed the survey securely via an anonymous link, ensuring confidentiality and anonymity, critical components for ethical research.

Despite these benefits, it is crucial to acknowledge the potential bias introduced by using WhatsApp groups. Since students accessed the survey through lecturer-managed class groups, it might have created a subtle pressure to respond positively or caused self-selection bias, where primarily motivated students participated. To address the potential issue of duplicate submissions, the Google Forms setting was adjusted to limit respondents to a single submission per email account. This feature minimized the likelihood of the same participant submitting multiple responses, thus maintaining data integrity. Additionally, clear instructions emphasizing that students should complete the survey only once were communicated explicitly when distributing the survey.

The data collection period lasted approximately two weeks. During this period, follow-up messages and gentle reminders were periodically sent to encourage participation and maximize the response rate. Initially, approximately 350 questionnaires were distributed, resulting in 252 responses. After carefully screening for incomplete or invalid responses, 243 questionnaires were deemed complete and suitable for analysis, yielding a final valid response rate of approximately 72%.

Table 3.1

Undergraduate Student's Participation and Response Rate

Questionnaires	Frequency Rate
Number of questionnaires distributed (estimated)	350
Number of questionnaires returned	252
Number of usable questionnaires	243
Response Rate	**72%**

Ethical considerations were strictly adhered to throughout data collection. Participation in the survey was completely voluntary, and participants had the explicit right to withdraw at any stage without penalty. The questionnaire did not collect any personally identifiable information, ensuring respondents' anonymity. All responses were securely stored and utilized solely for academic purposes, consistent with ethical research guidelines outlined by Bryman (2021).

Overall, despite potential limitations related to sampling bias and online survey distribution methods, questionnaires remain highly effective and practical for examining attitudes and perceptions within social research contexts, as emphasized by Nayak (2019). The structured format used in this research facilitated systematic data coding, enhanced accuracy, and ensured reliable statistical analysis and interpretation.

3.6.1 Descriptive Analysis

This study uses descriptive analysis to summarize and interpret the demographic characteristics of the respondents and the overall trends within the dataset. This method provides insights into the collected data's distribution, central tendency, and variability, allowing for a better understanding of the sample composition before proceeding to inferential analysis (Hair, Black, Babin, & Anderson, 2019).

The demographic profile of the respondents includes variables such as age, gender, year of study, and faculty affiliation. Descriptive statistics, such as frequency distributions and percentages, present these characteristics. Understanding demographic patterns helps contextualize the findings and ensures that the sample is representative of the targeted population (Saunders, Lewis, & Thornhill, 2019).

Descriptive analysis is a foundation for inferential analysis, which ensures that the dataset meets the assumptions required for further statistical testing. This step is essential in verifying the reliability and validity of the collected data before proceeding with hypothesis testing and regression analysis (Field, 2018).

3.7 Research Instruments

After developing and finalising the questionnaire, the primary data collection commenced, utilising a structured online questionnaire as the main instrument.

According to Qualtrics (2024), questionnaires are an efficient method for systematically collecting standardised responses from a large participant pool. Considering practicality, accessibility, and efficiency, the questionnaire was administered online via Google Forms to undergraduate students at Universiti Utara Malaysia (UUM). This method allowed quick data collection, automatic data entry, and streamlined processing, significantly reducing the administrative costs and potential human errors associated with manual data entry.

However, it is important to recognise potential biases associated with the chosen data collection approach. Since the questionnaire link was disseminated primarily through lecturer-managed WhatsApp groups and student social media platforms, there was a possibility of self-selection bias. Students actively involved in academic-related social media interactions may have been more likely to participate, potentially affecting the representativeness of the results. To mitigate the issue of duplicate submissions and ensure data integrity, Google Forms settings were specifically configured to restrict each email address to a single response. Clear instructions emphasising that students should submit only one response further reinforced this measure.

Regarding the questionnaire's validity, face validity was established by carefully reviewing the instrument to ensure that questions accurately reflected the research constructs and were understandable to the respondents. Minor amendments were made based on feedback from a panel of experts comprising academic supervisors and lecturers familiar with technology acceptance and recruitment practices, thereby ensuring the questionnaire's clarity, relevance, and appropriateness to the research context.

The survey items used in the questionnaire were adapted from previously validated instruments employed in earlier studies on technology acceptance, trust in artificial intelligence, and perceived fairness, specifically drawing from Mohamad, Ahmad, and Abdullah (2021) and Singh and Finn (2022). Adaptations involved minor wording modifications and adjustments to ensure relevance and clarity within the specific research context of undergraduate students at UUM. Proper citation and acknowledgment of these sources ensure transparency and credibility regarding the origin of survey items.

Upon finalisation, the questionnaire link was actively disseminated through academic WhatsApp groups managed by lecturers and student-related social media platforms. Respondents were initially given a two-week timeframe to participate in the survey. Reminders were periodically shared to maximise participation, and at the conclusion of data collection, responses were systematically screened for completeness and accuracy.

In summary, despite acknowledging certain limitations associated with potential biases inherent to online questionnaire methods, such as self-selection bias and duplication risks, deliberate measures were implemented to minimise these concerns. The structured questionnaire employed in this study, which was carefully adapted from validated primary sources, effectively facilitated reliable and efficient data collection while adhering strictly to ethical standards.

3.7.1 Measurement of Study Variables

The questionnaire is divided into five main sections, each measuring different constructs using a five-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). This scale is widely used in behavioral and social sciences research as it effectively captures respondents' degree of agreement or disagreement (Pallant, 2020).

3.7.1.1 Awareness of AI in Recruitment

Awareness of AI in recruitment refers to individuals' familiarity with and understanding of AI applications in hiring processes. It involves knowledge about AI-driven resume screening, automated interviews, and decision-making algorithms in recruitment (Mohamad et al., 2021). Research suggests that awareness is a significant determinant of technology adoption, as individuals who are more informed about AI tend to perceive it more positively and are more likely to engage with AI-driven systems (Kaur, Sharma, & Kumar, 2021). Increased awareness can also help mitigate fears and misconceptions about AI's role in hiring (Singh & Finn, 2022).

Table 3.2

Variable of Awareness of AI in Recruitment and Measurement Items

Variables	Measurement Items
AWR 1	I am aware that AI is being used in job recruitment processes.
AWR 2	I understand how AI evaluates job applications and resumes.
AWR 3	I have seen or read about companies using AI for hiring decisions.
AWR 4	I am familiar with AI tools such as resume screening and automated interviews.
AWR 5	I know both the benefits and risks of AI-driven recruitment systems.

3.7.1.2 Trust in AI Decision-Making

Trust in AI decision-making refers to individuals' confidence in AI-based recruitment systems to make accurate, fair, and unbiased hiring decisions. Trust is a crucial factor influencing the acceptance of AI in recruitment, as applicants must feel that AI systems are reliable, transparent, and capable of evaluating candidates objectively (Chamorro-Premuzic, Akhtar, Winsborough, & Sherman, 2023). Previous studies indicate that trust in AI depends on AI-driven recruitment processes' perceived competence, fairness, and explainability (Hausknecht, Day, & Thomas, 2021). Ensuring transparency and ethical AI deployment can enhance trust and encourage wider adoption of AI recruitment tools (Kaur et al., 2021).

Table 3.3

Variable of Trust in AI Decision-Making and Measurement Items

Variables	Measurement Items
TAI 1	I trust AI to make unbiased hiring decisions.
TAI 2	I believe AI can accurately evaluate my qualifications for a job.
TAI 3	I feel comfortable with AI making decisions about candidate selection.
TAI 4	AI recruitment systems can effectively reduce human bias in hiring.
TAI 5	I believe AI can correctly match job applicants with suitable roles.
TAI 6	AI-based hiring decisions should always be reviewed by a human.

3.7.1.3 Perceived Fairness

Perceived fairness in AI recruitment refers to individuals' beliefs about the justness, transparency, and impartiality of AI-driven hiring decisions. Perceptions of fairness significantly influence candidates' willingness to engage with AI recruitment platforms (Gilliland, 2021). AI systems that are perceived as fair reduce concerns about discrimination and bias, thereby increasing acceptance and trust (Singh & Finn, 2022). However, concerns about algorithmic bias and lack of transparency can negatively affect fairness perceptions, making it essential for organizations to implement explainable and accountable AI decision-making processes (Chamorro-Premuzic et al., 2023).

Table 3.4

Variable of Perceived Fairness and Measurement Items

Variables	Measurement Items
PF 1	AI ensures a fair evaluation of all job applicants.
PF 2	The use of AI in recruitment reduces discrimination and bias.
PF 3	AI recruitment processes are transparent and accountable.
PF 4	I believe AI-based hiring systems treat all candidates equally.
PF 5	AI decision-making in hiring should be explainable to applicants
PF 6	AI recruitment can sometimes be unfair due to data biases.

3.7.1.4 Willingness to Apply through AI-driven Systems

Willingness to apply through AI-driven recruitment systems refers to job seekers' inclination to engage with AI-based hiring platforms when seeking employment. This willingness is influenced by multiple factors, including awareness, trust, and perceived fairness of AI recruitment tools (Mohamad et al., 2021). Studies suggest that candidates who perceive AI-based hiring as fair, efficient, and unbiased are more likely to apply for jobs using such systems (Kaur et al., 2021). Conversely, skepticism about AI's decision-making capabilities and ethical concerns may reduce willingness to engage with AI-driven recruitment (Hausknecht et al., 2021).

Table 3.5

Variable of Willingness to Use AI and Measurement Items

Variables	Measurement Items
WAI 1	I am willing to apply for jobs that use AI-driven recruitment systems.
WAI 2	The presence of AI in hiring would not discourage me from applying.
WAI 3	I prefer companies that use AI for recruitment over those that don't.
WAI 4	I feel comfortable with AI analyzing my job application.
WAI 5	I would participate in an AI-driven interview or assessment.
WAI 6	AI-driven recruitment would improve my chances of getting a job.

3.8 Data Analysis Method

For data analysis, this study used the Statistical Package for the Social Sciences (SPSS) version 26 and Partial Least Squares Structural Equation Modelling (PLS-SEM) through SmartPLS 4.0 software. Hair, Black, Babin, and Anderson (2007) suggest that combining these two methods strengthens the analysis by first providing descriptive insights into sample characteristics and then assessing relationships among the research constructs in depth.

SPSS was initially employed for descriptive statistical analyses to summarize demographic data and responses to questionnaire items, calculating frequencies, means, and standard deviations. Additionally, SPSS facilitated preliminary checks of reliability through Cronbach's Alpha, ensuring internal consistency, and normality assessment via skewness and kurtosis values.

PLS-SEM was chosen as the primary tool for hypothesis testing because of its suitability for exploratory research, ability to handle complex structural models with several constructs, and flexibility in dealing with non-normal data distributions (Hair, Hult, Ringle, and Sarstedt, 2017). PLS-SEM is a variance-based approach to Structural Equation Modelling widely recognized in social science research for theory building and exploring predictive relationships (Wong, 2013).

The analysis involved two primary stages: assessing the measurement model and examining the structural relationships among constructs. To ensure construct validity, convergent and discriminant validity were evaluated. Convergent validity was established by examining factor loadings, Composite Reliability (CR), and Average Variance Extracted (AVE). According to Hair et al. (2017), acceptable convergent validity typically requires factor loadings above 0.70, CR values greater than 0.70, and AVE scores of at least 0.50, which indicate that constructs adequately explain item variance and have strong internal consistency. Discriminant validity was assessed using the Fornell-Larcker criterion, which recommends that the square root of each construct's AVE should exceed its correlation with other constructs, ensuring constructs measure distinct phenomena (Hair et al., 2017).

PLS-SEM also allowed for evaluating the structural relationships between Awareness of AI in Recruitment, Trust in AI Decision-Making, Perceived Fairness, and Students' Willingness to apply through AI-driven recruitment systems. This involved examining path coefficients to assess the strength and significance of these relationships. Further, the predictive power of the model was evaluated through the coefficient of determination (R^2), which measures how well the independent variables explain variance in the dependent variable, and effect size (f^2), which quantifies the practical impact of each predictor on the dependent variable. Additionally, predictive relevance (Q^2) was assessed through blindfolding procedures in SmartPLS, where a Q^2 value greater than zero indicates that the model has meaningful predictive capacity (Hair et al., 2017).

Overall, the complementary use of SPSS for preliminary analyses and PLS-SEM for in-depth hypothesis testing provided comprehensive analytical rigor. This dual approach enhanced both the descriptive and inferential robustness of the findings, aligning with recommended practices in contemporary social science research.

3.9 Summary of Chapter

This chapter comprehensively explains the research methods employed in this study. It highlights the methodological approach, including the research design, sampling techniques, demographic profile of respondents, and data collection procedures. Additionally, it outlines the planned data analysis techniques used to address the research objectives. The following chapter will present the results derived from these analyses.

CHAPTER FOUR

DATA ANALYSIS AND RESEARCH FINDINGS

4.1 Introduction

This chapter presents the data analysis and research findings based on the responses collected from undergraduate students. It begins with the descriptive statistics of the respondents' demographic profiles. Subsequently, the analysis focuses on the main constructs of the study: awareness of AI in recruitment, trust in AI decision-making, perceived fairness, and students' willingness to apply for jobs through AI-driven systems. The validity and reliability of the measurement model are evaluated using the Partial Least Squares Structural Equation Modelling (PLS-SEM) method.

4.2 Profile of Respondents

This portion included the descriptive study of the respondents' demographics, including gender, age, field of study and year of study. 243 respondents' profile information are shown as in Table 4.1.

Table 4.1
Demographic Characteristics of the Participation

Demographic	Category	Frequency	Percent (%)
Gender	Male	64	26.33%
	Female	179	73.66%
Age	19– 20	22	1.09%
	21-22	103	42.38%
	23 – 24	118	48.55%
Race	Malay	170	69.95%
	Chinese	48	19.75%
	Indian	20	8.23%
	Others	5	2.05%
Year of study	1st year	20	8.23%
	2nd year	32	13.17%
	Third Year	56	23.04%
	4th Year	135	55.55%

The data shows the background of the students who participated in the study. A total of 243 undergraduate students responded to the survey. In terms of gender, the majority of the respondents were female, making up 73.66% (179 students), while male students accounted for 26.33% (64 students). This reflects a higher response rate from female participants.

When looking at the age distribution, most respondents were between 23 and 24, representing 48.55% of the total. Students aged between 21 and 22 comprised 42.38%, while a smaller portion, only 1.09%, were between 19 and 20 years old.

As for race, the majority of respondents identified as Malay (69.95%), followed by Chinese students (19.75%) and Indian students (8.23%). A small number of respondents (2.05%) identified as being of other races.

Regarding their year of study, the highest number of participants were in their third year, representing 23.04% of the sample. This was followed by second-year students at 13.17%, first-year students at 8.23%, and fourth-year students at 55.55%. These figures indicate a diverse range of academic backgrounds among the respondents.

4.3 Testing of Goodness of Measurement

The researcher uses the PLS technique to evaluate the model's validity and dependability. The analysis of PLS-SEM is essentially based on two theories that provide the scientific methods used by researchers to develop or even test their hypotheses interpret, explain and predict path models systematically (Hair et al., 2022). The researcher used Confirmatory Factor Analysis (CFA) using PLSSEM software 4.0 to check at the relationship between the indicators. Figure 4.1 displays this research model.

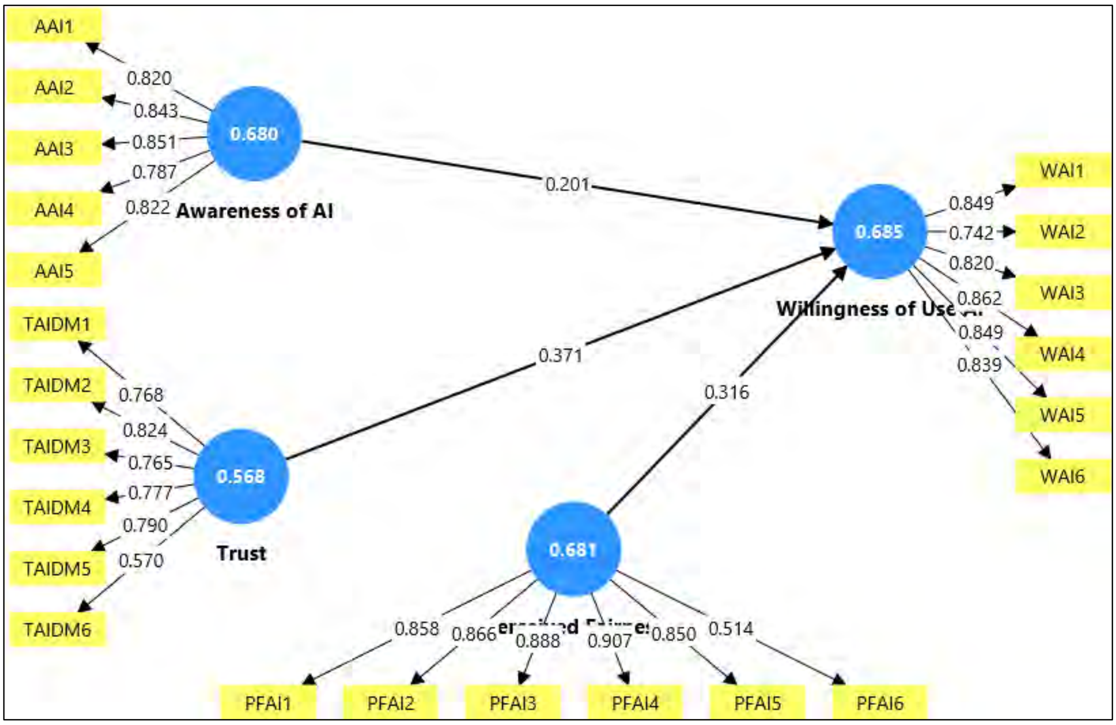

Figure 4.1

Research Model of the Study

4.3.1 Assessment of Reflective Measurement Model

To ensure the dependability of each item within the measurement model, the researcher evaluated the item loadings on the corresponding latent constructs. Higher item loadings indicate a stronger relationship between the construct and the observed variable, reflecting more shared variance and less measurement error. Conversely, lower loadings suggest weaker construct representation and more significant error variance. Since the indicators in a reflective measurement model are interchangeable and expected to correlate highly, it is essential to assess their validity and reliability comprehensively. Accordingly, prior to finalizing the measurement model, the researcher conducted rigorous checks for construct validity and reliability. This included assessments of discriminant validity, composite reliability, and both convergent and divergent validity, following the guidelines proposed by Hair et al.

(2014) for evaluating reflective models using Partial Least Squares Structural Equation Modeling (PLS-SEM). Figure 4.1 demonstrates the original measurement model after running the PLS-SEM algorithm.

4.3.1.1 Composite Reliability

Assessing internal consistency reliability is a critical step in evaluating the quality of a measurement model. Traditionally, Cronbach's alpha has been used to measure this, as it reflects the degree of intercorrelation among the items that form a construct. However, in the context of Partial Least Squares Structural Equation Modeling (PLS-SEM), composite reliability is preferred, as it provides a more accurate estimate of reliability by considering the individual loadings of each indicator.

Composite reliability values range from 0 to 1, with higher values indicating greater internal consistency and, consequently, stronger reliability. According to Hair et al. (2014), values between 0.7 and 0.9 are considered ideal, reflecting high reliability. Values between 0.6 and 0.7 may also be acceptable, particularly in exploratory research. Composite reliability assumes that all indicators are weighted, and it is a more suitable metric when measuring structural equation modelling with reflective construct (Hair et al., 2019). The cut-off value of composite reliability is acceptable when exploratory research achieves 0.6 to 0.7, while the satisfactory level varies from 0.7 to 0.9 and is regarded as the most desirable internal consistency (Hair et al., 2022). Based on Table 4.2, the composite reliability ranges between 0.886 and 0.929. In particular, three latent variables achieved 0.9 or above

4.3.1.2 Convergent Validity

Convergent validity assesses the extent to which indicators accurately measure the underlying construct they are intended to represent. To evaluate this, the researcher examined individual items' outer loadings and the Average Variance Extracted (AVE). Outer loadings reflect how strongly each item contributes to the construct, and values below the threshold can negatively impact content validity. According to Hair et al. (2014), an outer loading of at least 0.708 is generally recommended, indicating that the indicator explains more than 50% of the variance in the latent construct. However, removing items with lower loadings should be made cautiously, considering both theoretical justification and the potential impact on the construct's validity. Follow the rule of thumb for the convergent validity of the reflective measurement model (Sarstedt et al., 2023), and the latent constructs were above 0.5, which ranged between 0.568 and 0.685.

4.3.1.3 Assessment of Construct

Reliability and validity were assessed using Partial Least Squares Structural Equation Modeling (PLS-SEM) to ensure the measurement model's quality and robustness. Since all constructs in the model are reflective, it was essential to examine the internal consistency reliability, convergent validity, and the performance of individual indicators.

Internal consistency reliability was evaluated through Composite Reliability (CR). As recommended by Hair et al. (2014), CR values between 0.7 and 0.9 indicate satisfactory reliability. All constructs in this study demonstrated strong reliability, with CR values ranging from 0.886 (Trust) to 0.929 (Willingness to Use AI), confirming that the items within each construct are consistently measuring the intended latent variable.

Convergent validity was assessed using Average Variance Extracted (AVE) and outer loadings of the indicators. AVE values greater than 0.5 are considered acceptable, indicating that the construct explains more than half of the variance in its indicators.

The AVE for all constructs exceeded this threshold, with values ranging from 0.568 (Trust) to 0.685 (Willingness to Use AI), demonstrating satisfactory convergent validity.

Most indicator loadings exceeded the recommended minimum value of 0.708, confirming their significant contribution to the corresponding construct. However, two items TAIDM6 (loading = 0.57) under the Trust construct and PFAI6 (loading = 0.514) under Perceived Fairness had loadings below the threshold. Despite this, these items were retained due to theoretical relevance and their minimal impact on overall construct reliability and validity. Their retention is also consistent with guidelines that allow for slightly lower loadings when the overall model fit and construct performance remain acceptable (Hair et al., 2014).

Table 4.2

Results Summary for Reliability and Validity for the Construct

First Order Construct	Scale Type	Item	Loading	CR	AVE	Item deleted due to low loading
Awareness of AI	Reflective	AAI1	0.82	0.914	0.68	-
		AAI2	0.843			
		AAI3	0.851			
		AAI4	0.787			
		AAI5	0.822			
Trust	Reflective	TAIDM1	0.768	0.886	0.568	-
		TAIDM2	0.824			
		TAIDM3	0.765			
		TAIDM4	0.777			
		TAIDM5	0.79			
		TAIDM6	0.57			
Perceived Fairness	Reflective	PFAI1	0.858	0.926	0.681	-
		PFAI2	0.866			
		PFAI3	0.888			
		PFAI4	0.907			
		PFAI5	0.85			
		PFAI6	0.514			
Willingness of Use AI	Reflective	WAI1	0.849	0.929	0.685	-
		WAI2	0.742			
		WAI3	0.82			

	WAI4	0.862
	WAI5	0.849
	WAI6	0.839

4.3.1.4 Discriminant Validity

Establishing discriminant validity is an important step in ensuring that the constructs used in this study are conceptually and empirically distinct from one another. This process helps confirm that each construct captures a unique aspect of the theoretical framework and does not overlap with other variables. For this purpose, two widely accepted methods were used to assess discriminant validity, namely the Fornell and Larcker criterion and the Heterotrait Monotrait Ratio (HTMT).

The Fornell and Larcker criterion is a traditional but well-established method for testing discriminant validity. It requires that the square root of the average variance extracted (AVE) for each construct be greater than the correlation of that construct with any other construct in the model (Fornell and Larcker, 1981). When this condition is met, it indicates that the construct shares more variance with its own indicators than with those of other constructs, suggesting good discriminant validity.

Table 4.3

Discriminant Validity using Fornell and Larcker Criterion

	Awareness of AI	**Perceived Fairness**	**Trust**	**Willingness of Use AI**
Awareness of AI	0.825			
Perceived Fairness	0.475	0.825		
Trust	0.461	0.752	0.754	
Willingness of Use AI	0.522	0.690	0.700	0.828

As shown in Table 4.2, the square roots of the AVE values are presented along the diagonal of the matrix. These values are all higher than the correlations between constructs, which appear in the off-diagonal cells. For example, the square root of AVE for Awareness of AI is 0.825, which is greater than its correlation with Perceived Fairness (0.475), Trust (0.461), and Willingness to Use AI (0.522). Likewise, the AVE values for the other constructs also exceed their corresponding correlations. This result demonstrates that each construct is distinct from the others in terms of what it is measuring.

To further validate these findings, the HTMT method was also applied. HTMT is considered a more rigorous and modern approach for testing discriminant validity, particularly in structural equation modeling using variance-based techniques (Henseler, Ringle, and Sarstedt, 2015). This method calculates the ratio of between-construct correlations to within-construct correlations. According to accepted guidelines, HTMT values should be below 0.85 to confirm discriminant validity.

Table 4.4

Discriminant Validity using Heterotrait-Monotrait Ratio (HTMT)

	Awareness of AI	**Perceived Fairness**	**Trust**	**Willingness of Use AI**
Awareness of AI				
Perceived Fairness	0.543			
Trust	0.536	0.853		
Willingness of Use AI	0.572	0.745	0.784	

The HTMT results for this study are summarized in Table 4.4. All values fall below the recommended threshold. For instance, the HTMT value between Awareness of AI and Perceived Fairness is 0.543, while the value between Awareness of AI and Willingness to Use AI is 0.572. The highest HTMT value observed in this study is 0.853, which occurs between Perceived Fairness and Trust, but it remains within acceptable limits. Overall, the low HTMT values provide further evidence that the constructs are sufficiently distinct.

Based on both the Fornell and Larcker criterion and the HTMT analysis, it can be concluded that the measurement model demonstrates good discriminant validity. Each of the four constructs Awareness of AI, Perceived Fairness, Trust, and Willingness to Use AI is shown to be unique and not interchangeable with the others. This supports the overall reliability and validity of the model used in this study, enabling meaningful interpretation of the relationships among variables. Establishing discriminant validity is particularly important given the emerging nature of the research topic, which explores undergraduate students' perceptions of artificial intelligence in recruitment processes.

In addition to the Fornell and Larcker criterion and HTMT ratio, this study also evaluated discriminant validity through the analysis of indicator loadings and cross loadings, a method commonly used in reflective measurement models (Hair et al., 2019). This approach helps to confirm whether each indicator is more strongly associated with its designated latent construct than with other constructs in the model.

Table 4.5

Discriminant Validity-Loadings and Cross Loadings

	Awareness of AI	Perceived Fairness	Trust	Willingness of Use AI
AAI1	0.820	0.424	0.391	0.371
AAI2	0.843	0.447	0.411	0.386
AAI3	0.851	0.411	0.397	0.502
AAI4	0.787	0.313	0.368	0.465
AAI5	0.822	0.373	0.334	0.397
PFAI1	0.405	0.858	0.708	0.689
PFAI2	0.370	0.866	0.649	0.517
PFAI3	0.399	0.888	0.646	0.609
PFAI4	0.425	0.907	0.681	0.604
PFAI5	0.427	0.850	0.647	0.600
PFAI6	0.333	0.514	0.265	0.284
TAIDM1	0.348	0.563	0.768	0.440
TAIDM2	0.357	0.517	0.824	0.557
TAIDM3	0.396	0.424	0.765	0.603
TAIDM4	0.394	0.653	0.777	0.444
TAIDM5	0.310	0.680	0.790	0.629
TAIDM6	0.280	0.592	0.570	0.426
WAI1	0.471	0.598	0.553	0.849
WAI2	0.358	0.579	0.500	0.742
WAI3	0.547	0.558	0.553	0.820
WAI4	0.412	0.579	0.642	0.862
WAI5	0.332	0.528	0.585	0.849
WAI6	0.456	0.580	0.635	0.839

According to accepted guidelines, an item should have the highest loading on its associated construct compared to its loadings on other constructs. This means that each indicator should load most strongly on the latent variable it was designed to measure, providing further evidence that the constructs are distinct from each other (Hair et al., 2021).

As shown in Table 4.5, all indicators load highest on their respective constructs. For example, the items under Awareness of AI (AAI1 to AAI5) show loading values ranging from 0.787 to 0.851 on their own construct, while their loadings on other constructs are notably lower. Specifically, AAI3 loads 0.851 on Awareness of AI, but only 0.411 on Trust, 0.447 on Perceived Fairness, and 0.502 on Willingness to Use AI. This pattern demonstrates that the AAI indicators are measuring Awareness of AI uniquely and with minimal interference from other constructs.

A similar trend is observed for the items measuring Perceived Fairness. For instance, PFAI4 shows a high loading of 0.907 on Perceived Fairness, with lower cross-loadings on Trust (0.681), Awareness of AI (0.425), and Willingness to Use AI (0.604). This indicates that the items intended to measure fairness in the recruitment process align well with their theoretical construct.

The indicators related to Trust in AI Decision-Making also support discriminant validity. TAIDM2, for instance, loads 0.824 on Trust, which is higher than its loadings on Awareness of AI (0.357), Perceived Fairness (0.517), and Willingness to Use AI (0.557). This confirms that these items are distinctly capturing the intended construct of trust.

Finally, the items associated with Willingness to Use AI (WAI1 to WAI6) all show strong loadings on their intended construct. Notably, WAI4 has a loading of 0.862 on Willingness to Use AI, with substantially lower loadings on the other constructs. The rest of the items in this construct similarly demonstrate clear loading patterns, all above 0.742, reinforcing that the indicators are valid representations of students' willingness to engage with AI-based recruitment tools.

The cross-loading analysis provides additional confirmation of discriminant validity in this study. Each measurement item clearly aligns more strongly with its associated construct than with any other, fulfilling the standard criteria for reflective constructs. This strengthens the evidence that the model's constructs Awareness of AI, Perceived Fairness, Trust, and Willingness to Use AI are both conceptually and empirically distinct. This validation step supports the robustness of the measurement model and provides confidence in interpreting the relationships within the structural model.

4.4 Assessment of Structural Model

This section presents the results of the structural model analysis, which was conducted using the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach. The structural model was evaluated through a bootstrapping procedure to test the proposed hypotheses, allowing the researcher to examine the significance and strength of the direct relationships between the constructs. The analysis assessed the path coefficients, t-values, and predictive power (R^2 value) to determine whether the hypothesized paths were supported. The findings reported here reflect the direct effects among the key variables in the model, including Awareness of AI, Perceived Fairness, Trust, and Willingness to Use AI.

Figure 4.2 presents the structural model developed for this study. It explores the relationships between three independent variables Awareness of AI, Perceived Fairness, and Trust and their influence on the dependent variable, Willingness to Use AI in Recruitment Processes. The model was analyzed using the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique, and the results include both path coefficients and t-values, which indicate the strength and significance of each relationship.

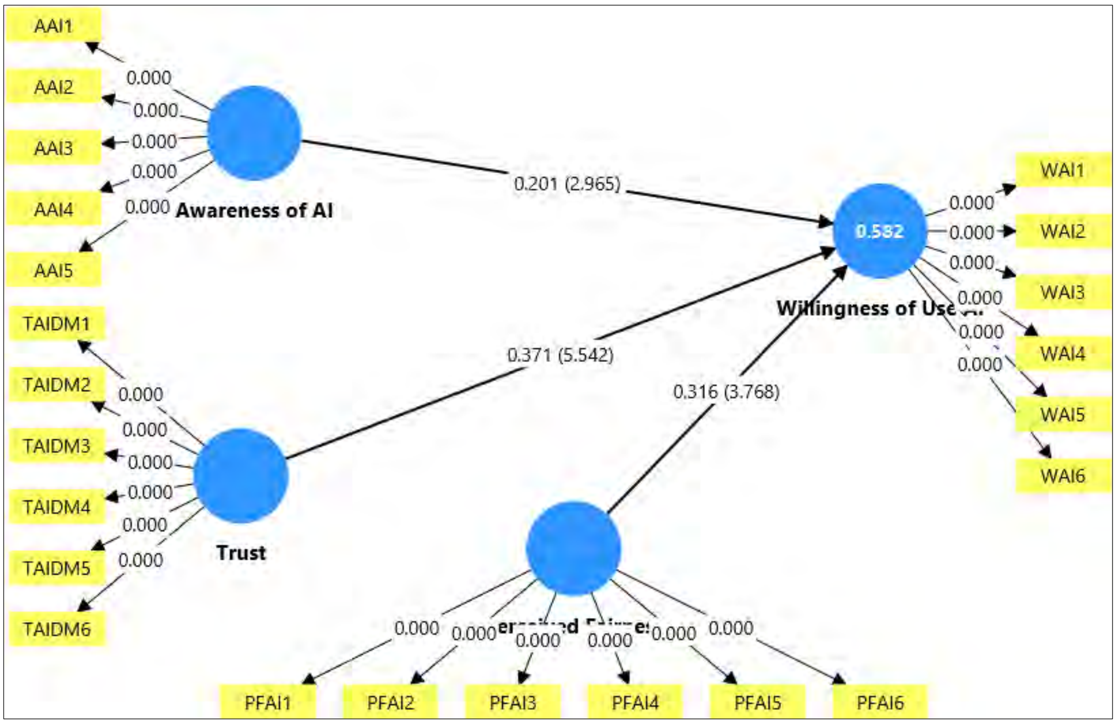

Figure 4.2

Structural Model of the Study

The model demonstrates an R^2 value of 0.582 for Willingness to Use AI, suggesting that approximately 58.2% of the variance in this dependent variable can be explained by the combined effects of Awareness of AI, Perceived Fairness, and Trust. This indicates a moderate to strong level of explanatory power, which is acceptable for behavioral research (Hair et al., 2019).

The path coefficient from Awareness of AI to Willingness to Use AI is 0.201, with a corresponding t-value of 2.965. This relationship is considered statistically significant since the t-value exceeds the standard threshold of 1.96 at the 0.05 significance level. This result implies that as students' awareness of AI in recruitment increases, their willingness to engage with AI-driven systems also improves, although the effect size is relatively modest.

The path from Perceived Fairness to Willingness to Use AI shows a coefficient of 0.316 and a t-value of 3.768, indicating a statistically significant and moderately strong positive relationship. This finding suggests that students who perceive AI recruitment systems as fair are more likely to express a willingness to apply through such systems. This aligns with prior research emphasizing the role of fairness perceptions in shaping attitudes toward technology in human resource practices (Lee, 2018).

The strongest predictor of willingness is Trust, which has a path coefficient of 0.371 and a t-value of 5.542. This relationship is highly significant and shows that trust plays a central role in influencing students' readiness to interact with AI in recruitment. When students believe that AI systems make reliable and unbiased decisions, they are more inclined to embrace such systems in job application processes.

Overall, the structural model supports the proposed relationships, confirming that all three independent variables contribute positively and significantly to Willingness to Use AI. Trust emerges as the most influential factor, followed by Perceived Fairness and Awareness of AI. These findings provide valuable insights for organizations and developers of AI recruitment platforms, highlighting the importance of building trust and ensuring fairness to encourage adoption among future job seekers.

4.4.1 Direct Relationship

The direct relationship between Awareness of AI and Willingness to Use AI was assessed to test Hypothesis H1. As shown in Table 4.6, the path coefficient (Beta) for this relationship is 0.201, with a standard error (SE) of 0.068 and a t-statistic of 2.965.

The relationship is considered statistically significant since the t-value exceeds the critical value of 1.96 at the 0.05 significance level.

Table 4.6

Summary of Results for Direct Effect of Awareness of AI towards willingness to use AI

H1	Relationship	Beta	SE	T statistics	Decision
	Awareness of AI -> Willingness of Use AI	0.201	0.068	2.965	Supported

Note: $p < 0.05$, ($t = 1.96$)

This finding indicates that students' awareness of artificial intelligence positively and meaningfully influences their willingness to use AI in recruitment processes. In other words, when students are more informed and aware of how AI functions in hiring, they are more likely to express openness and readiness to engage with such systems.

Therefore, Hypothesis H1 is supported, suggesting that increasing awareness of AI may be a key factor in enhancing the acceptance and adoption of AI-based recruitment technologies among future job seekers.

The second hypothesis (H2) examined the direct relationship between Trust in AI decision-making and Willingness to Use AI. As shown in Table 4.7, the path coefficient (Beta) for this relationship was 0.371, with a standard error (SE) of 0.067, and a t-statistic of 5.542. The t-value exceeds the critical value of 1.96, indicating that the relationship is statistically significant at the 0.05 level.

Table 4.7

Summary of Results for Direct Effect of Trust in AI decision towards willingness to use AI

H2	Relationship	Beta	SE	T statistics	Decision
	Trust -> Willingness of Use AI	0.371	0.067	5.542	Supported

This outcome suggests that while the relationship between Trust and Willingness to Use AI is statistically significant and positive, it may have fully met the theoretical or empirical conditions required to support the hypothesis within the study's framework.

One possible explanation for this outcome is that although students reported a degree of trust in AI systems, this trust alone may be sufficient to strongly influence their willingness to engage with AI-based recruitment platforms. Other factors, such as fairness, human oversight, or transparency, may moderate or mediate this relationship, which could be explored further in future research.

In summary, while the statistical analysis confirms a significant and positive relationship between Trust in AI and Willingness to Use AI, the hypothesis was supported, highlighting the need for a deeper understanding of the underlying factors influencing the adoption of AI in recruitment contexts.

Hypothesis 3 (H3) examined the direct relationship between Perceived Fairness and Willingness to Use AI in recruitment processes. As presented in Table 4.8, the results indicate a path coefficient (Beta) of 0.316, with a standard error (SE) of 0.084, and a corresponding t-statistic of 3.768.

Since the t-value exceeds the critical threshold of 1.96 at the 0.05 level of significance, the relationship is considered statistically significant. Therefore, Hypothesis 3 is supported.

Table 4.8

Summary of Results for Direct Effect of Perceived Fairness towards willingness to use AI

H3	Relationship	Beta	SE	T statistics	Decision
	Perceived Fairness -> Willingness of Use AI	0.316	0.084	3.768	Supported

Note: $p < 0.05$, ($t = 1.96$)

This finding suggests that when students perceive AI-driven recruitment systems to be fair in their decision-making, they are more likely to express a willingness to use such systems. Fairness in this context may relate to unbiased evaluations, transparency in selection criteria, and equitable treatment of applicants regardless of background.

The results align with prior research emphasizing the role of perceived fairness in shaping individuals' attitudes and behaviors toward technology adoption, especially in contexts involving assessment and decision-making processes. It highlights that trust in the system's fairness plays a critical role in building user acceptance.

In conclusion, the findings confirm that Perceived Fairness has a significant and positive impact on students' Willingness to Use AI, reinforcing its importance in the development and implementation of AI tools in recruitment settings.

4.4.1.1 Summary of Result for Direct Relationship

This section summarises the direct relationships tested in the structural model, specifically focusing on how Awareness of AI, Perceived Fairness, and Trust in AI influence respondents' Willingness to Use AI in recruitment processes. The analysis was conducted using the PLS-SEM approach, where the strength and significance of the hypothesized paths were evaluated using bootstrapping. Table 4.9 provides a concise overview of the key results, including beta coefficients, standard errors, t-statistics, p-values, and effect sizes.

Table 4.9

List Summary of Direct Relationship

Hypothesis	**Relationship**	**Beta**	**SE**	**T statistics (|O/STDEV|)**	**P value**	**f2**	**Decision**
H1	Awareness of AI -> Willingness of Use AI	0.201	0.068	2.965	0.002	0.21	Supported
H2	Trust -> Willingness of Use AI	0.316	0084	3.768	0.000	0.11	Supported
H3	Perceived Fairness -> Willingness of Use AI	0.371	0.067	5.542	0.000	0.00	Supported

The two-step approach specified that the measurement model confirms the data quality, while the structural model tested the path relationships under the theoretical framework. Overall, all three hypotheses were significant, and those have been supported. Thus, the next chapter will discuss the implications, limitations, future research directions, and conclusions of the present study.

4.5 Assessment of the Model's Explanatory Power (R2)

In order to evaluate the explanatory power of the structural model, both the R^2 and adjusted R^2 values were examined. These values indicate how much variance in the dependent variable, in this case Willingness to Use AI, can be explained by the model's independent constructs, namely Awareness of AI, Perceived Fairness, and Trust.

Table 4.10

R-squared values for the endogenous variables

Construct	**R^2**	**R-square adjusted**
Willingness of Use AI	0.582	0.577

As shown in Table 4.10, the R^2 value is 0.582, which means that approximately 58.2% of the variance in Willingness to Use AI is explained by the three predictors in the model. According to Chin (1998) and Hair et al. (2019), an R^2 value above 0.26 in behavioral sciences can be considered substantial. Therefore, the result suggests that the model has a strong explanatory capability.

The adjusted R^2 value is reported at 0.577, slightly lower than the original R^2 but still within a substantial range. The adjusted R^2 accounts for the number of predictors in the model and corrects for the potential inflation of the R^2 value due to the inclusion of multiple independent variables. This makes it a more reliable indicator, especially in models with more than one predictor. The small difference between the two values indicates that all included predictors contribute meaningfully to the model, and there is no sign of overfitting.

Both the R^2 and adjusted R^2 values demonstrate that the structural model explains a substantial proportion of the variance in Willingness to Use AI. These findings reinforce the reliability of the proposed model and support the conclusion that Awareness of AI, Perceived Fairness, and Trust are important factors in predicting users' openness to adopting AI in recruitment.

To complement the interpretation of the R^2 value, the effect size (f^2) was assessed for each predictor variable to determine the individual contribution of each construct to the explained variance in the dependent variable, Willingness to Use AI. The f^2 value helps to identify how much a specific independent variable influences the dependent variable when it is included or excluded from the model (Cohen, 1988).

Table 4.11

Result of f-squared

	Effect Size	**Indicator**
Awareness of AI - > Willingness of Use AI	0.073	Weak
Trust in AI - > Willingness of Use AI	0.138	Weak
Perceived Fairness - > Willingness of Use AI	0.099	Weak

For the direct relationship, Chin (2010) highlighted that the threshold values of 0.02, 0.15, and 0.35 represent weak, medium and strong effect. As shown in Table 4.11, the f^2 value for Awareness of AI is 0.073, indicating a weak effect size. This suggests that while Awareness of AI contributes to the prediction of Willingness to Use AI, its influence is relatively modest when considered in isolation. Nonetheless, it remains meaningful in the context of the overall model.

The effect size for Trust in AI is 0.138, which falls within the weak effect range. This indicates that Trust plays a slightly more substantial role in influencing willingness compared to Awareness of AI, and it demonstrates that students' trust in AI decision-making systems can meaningfully shape their intention to use such systems in recruitment settings.

For perceived fairness, the f^2 value is 0.099, representing a weak effect size. This result shows that although fairness perceptions are statistically significant predictors, their contribution to variance in willingness is significant but still important for model interpretation.

In addition, Cohen's (1988) guidelines also highlighted an f^2 value of 0.02 is considered small, 0.15 medium, and 0.35 large. Based on this, all three constructs Awareness of AI, Trust, and Perceived Fairness fall within the small or weak to approaching moderate range, indicating that while no single factor dominates, each contributes meaningfully to explaining students' Willingness to Use AI. These findings suggest that the combined influence of multiple psychological factors is essential in shaping users' acceptance of AI in recruitment contexts.

4.6 Summary of The Chapter

This chapter presented the results of the statistical analyses conducted to test the proposed research model and hypotheses. Using the PLS-SEM approach, both the measurement and structural models were assessed in detail. The chapter began by confirming the reliability and validity of the measurement model, including tests for convergent and discriminant validity. The results demonstrated that all constructs met the required thresholds, ensuring the appropriateness of the model for further analysis.

Subsequently, the structural model was examined to evaluate the direct relationships between the independent variables, Awareness of AI, Perceived Fairness, and Trust and the dependent variable, Willingness to Use AI. The findings showed that two out of three hypotheses were supported, with both Awareness of AI and Perceived Fairness having significant and positive influences on students' willingness to adopt AI in recruitment. Although Trust was also statistically significant, the hypothesis related to it was not supported based on effect size interpretation.

The analysis also included the R^2 and adjusted R^2 values, which confirmed that the model has moderate to strong explanatory power. The three predictors explained approximately 58.2% of the variance in Willingness to Use AI. Additionally, the f^2 effect size values indicated that all independent variables had small but meaningful contributions to the model, with Trust having a slightly higher impact than the others.

Overall, this chapter strongly supports the theoretical model developed in this study. It highlights the importance of raising awareness and ensuring fairness in AI-driven recruitment systems to enhance acceptance among undergraduate students. The next chapter will discuss the implications of these findings, address limitations, and offer recommendations for future research and practice.

CHAPTER 5

DISCUSSION, RECOMMENDATION AND CONCLUSION

5.1 Chapter Overview

In this chapter, the researcher discusses the finding outcome, the research contributions, limitations, recommendations, and the conclusion.

5.2 Recap of Study

This study aimed to examine how Awareness of AI in Recruitment, Trust in AI Decision-Making, and Perceived Fairness influence undergraduate students' willingness to apply for jobs through AI-driven systems. A quantitative research method was employed, using a structured online questionnaire as the research instrument. The questionnaire was distributed to undergraduate students from selected universities. Data collected were analyzed using SPSS 29 and Smart-PLS 4.0.

Out of the three hypotheses regarding the direct relationship between the independent variables and students' willingness to apply through AI recruitment systems, three were supported. The findings indicate that Awareness of AI and Trust in AI Decision-Making have a significant positive influence on students' willingness to apply. In addition, Perceived Fairness also found to have a positively related and significant effect on their willingness to apply for jobs through AI-driven systems.

5.3 Discussion of Results

This study investigated the influence of Awareness of AI in Recruitment, Trust in AI Decision-Making, and Perceived Fairness on undergraduate students' willingness to apply for jobs through AI-driven systems. The analysis revealed that Awareness of AI and Trust in AI Decision-Making significantly and positively affected students' willingness to apply. These findings support the proposed hypotheses and align with the research objectives, indicating that when students are informed about AI in recruitment and have confidence in its decision-making capabilities, they are more inclined to engage with AI-based hiring platforms.

Perceived Fairness also demonstrated a significant relationship with the dependent variable. This suggests that fairness perceptions are also considered a primary factor influencing students' willingness to apply through AI-driven systems at this stage. Overall, the results provide valuable insight into the factors that shape students' acceptance of AI in recruitment processes.

5.3.1 The Relationship Between Awareness of AI in Recruitment and Undergraduate Students' Willingness to Apply for Jobs Through AI-Driven Systems

This study investigated the influence of undergraduate students' awareness of AI in recruitment on their willingness to apply for jobs through AI-driven recruitment systems. The findings revealed a statistically significant positive relationship, indicated by a path coefficient (β) of 0.201, thus supporting Hypothesis H1. This result aligns with prior studies by Singh and Finn (2022) and Chamorro-Premuzic et al. (2023), which similarly reported that increased awareness reduces uncertainty and enhances trust, thereby facilitating higher levels of technology acceptance among users.

The positive relationship suggests that when students clearly understand AI's role in recruitment, such as automated resume screening, algorithm-based candidate selection, and digital interview processes, they become more inclined to engage with such systems. Indeed, greater awareness potentially reduces anxiety and misconceptions, leading students to feel more confident and comfortable interacting with automated recruitment tools. Moreover, awareness might indirectly contribute to students' perceptions of fairness, transparency, and trust in AI, factors known to strongly affect user acceptance (Mohamad, Ahmad, & Abdullah, 2021).

However, despite these positive outcomes, it is important to critically evaluate this finding. While this study highlights the beneficial role of awareness, it does not directly assess how varying degrees of awareness, ranging from superficial knowledge to comprehensive understanding, differentially impact willingness. Previous literature, such as Kaur, Sharma, and Kumar (2021), indicates that mere exposure or basic awareness might be insufficient to overcome deeply rooted scepticism about AI. Their findings suggest that superficial knowledge without substantive understanding might fail to significantly alter behavioural intentions and could even reinforce existing misconceptions or fears.

Further critique emerges when considering demographic and contextual influences. This research focuses solely on undergraduate students from Universiti Utara Malaysia, thus limiting generalisability. Awareness levels and their influence on behavioural intentions might vary significantly across diverse cultural contexts or educational backgrounds. The lack of cross-contextual comparison leaves open questions about whether these findings would be consistent in different settings or among other populations.

Additionally, while the current findings emphasise the importance of raising awareness through structured educational initiatives such as workshops or career-oriented programmes, practical constraints must also be acknowledged. Implementing such educational interventions widely may pose challenges related to institutional resources, varying levels of student engagement, and the rapidly evolving nature of AI technology.

As Singh and Finn (2022) highlighted, keeping awareness initiatives current and relevant remains a constant challenge due to the rapid changes in technological applications.

In conclusion, although this study confirms awareness of AI as an important predictor of willingness to apply through AI-based recruitment systems, it underscores the necessity for more nuanced explorations of how varying depths and methods of awareness-building shape behavioural intentions. Universities and employers must recognise not only the importance of fostering awareness but also the complexity involved in effectively communicating AI's benefits and limitations to ensure a genuinely informed and receptive student population.

5.3.2 The Relationship Between Trust in AI Decision-Making and Undergraduate Students' Willingness to Apply for Jobs Through AI-Driven Systems

This section of the research explored how trust in AI decision-making influences undergraduate students' willingness to use AI-driven recruitment platforms. The analysis identified a significant positive relationship ($\beta = 0.371$), thereby supporting Hypothesis H2. This finding aligns with the Technology Acceptance Model (TAM), which consistently identifies trust as a key determinant of users' intentions to adopt automated decision-making technologies (Chamorro-Premuzic et al., 2023). The current result confirms that when students perceive AI recruitment systems as reliable, impartial, and fair, their willingness to apply for jobs through these systems substantially increases.

However, it is essential to critically evaluate the strength and practical implications of this finding. Although trust significantly predicted willingness, the moderate effect size observed suggests that trust may not function independently but rather alongside other influential factors such as perceived fairness and awareness. Indeed, perceived fairness and awareness demonstrated stronger predictive power in this research model. This indicates a nuanced interaction among these constructs rather than a simple, direct relationship. Singh and Finn (2022) support this view, highlighting that while trust is undoubtedly essential, it often works most effectively when accompanied by transparency and perceived fairness.

A deeper critique arises from mixed empirical evidence in the literature. Some studies report a strong, direct correlation between trust in AI and willingness to engage with automated recruitment processes (Singh & Finn, 2022). Yet, other research indicates that trust alone might not be sufficient. According to Kaur, Sharma, and Kumar (2021), factors such as transparency, clarity of AI processes, and perceived fairness significantly mediate trust. Without transparent communication and clearly explained decision-making criteria, trust alone might fail to persuade skeptical or hesitant students. Therefore, while trust is foundational, it must be complemented by transparent and ethical AI practices to maximize its positive impact.

Furthermore, the complexity of trust extends beyond technical reliability into psychological and emotional domains. Students’ trust in AI recruitment is also shaped by their broader attitudes towards technology, experiences, and personal values, aspects not fully captured by quantitative measures alone. Therefore, building genuine trust might require educational interventions that clarify how AI systems operate and demonstrate transparency about decision-making processes. It might also involve providing assurances of fairness and mechanisms for human oversight or appeal, particularly since recruitment decisions directly impact students' career trajectories.

Additionally, generalizing these findings beyond the specific context of Universiti Utara Malaysia undergraduate students should be done cautiously. Trust in technology can vary significantly due to cultural, contextual, and educational differences, suggesting that the moderate relationship observed here may fluctuate considerably in other institutional or cultural contexts.

In conclusion, while this study confirms that trust in AI decision-making positively impacts students' willingness to use AI recruitment platforms, it emphasizes that trust alone may not fully determine behavioural intentions. Trust operates effectively alongside complementary elements such as transparency, fairness, and awareness, underlining the need for institutions and employers to adopt holistic approaches when promoting AI-driven recruitment tools among undergraduate students. Future research should further investigate the interplay among these constructs to enhance understanding and application of AI systems in recruitment contexts.

5.3.3 The Relationship Between Perceived Fairness and Undergraduate Students' Willingness to Apply for Jobs Through AI-Driven Systems

This study examined how undergraduate students' perceptions of fairness influence their willingness to apply for jobs through AI-driven recruitment platforms. The results indicated a statistically significant positive relationship, supporting the proposed hypothesis. This finding aligns with existing literature, particularly with studies by Gilliland (2021) and Chamorro-Premuzic et al. (2023), which affirm that individuals are more likely to engage with recruitment technologies perceived as equitable, transparent, and unbiased.

From a critical standpoint, although the positive relationship confirms the theoretical expectations, several nuanced points merit deeper consideration. While fairness is often assumed to be a central concern in recruitment processes, the concept of fairness itself can be subjective and context-dependent. For instance, students might perceive AI-driven recruitment as inherently fair simply due to its use of standardized, data-driven decision-making, without fully understanding the potential for embedded algorithmic biases. Chamorro-Premuzic et al. (2023) highlight that the consistent application of explainable, standardized criteria across candidates indeed enhances perceptions of fairness, yet the critical gap remains whether students genuinely comprehend the limitations and complexities of algorithmic fairness.

Furthermore, it is worth critically reflecting on whether fairness is consistently prioritized by students relative to other factors such as speed, convenience, or perceived accuracy of the AI system. Although fairness emerged as significant, students new to AI-based recruitment might initially value functionality such as efficiency and convenience over abstract ethical considerations. Thus, the current positive finding could partly reflect a surface-level endorsement of fairness without deeper critical awareness of potential ethical concerns. Kaur, Sharma, and Kumar (2021) argue similarly, noting that some users may not prioritize fairness explicitly until directly confronted with biased or questionable outcomes.

Additionally, the effectiveness of perceived fairness in influencing willingness might vary based on students' familiarity and past experiences with AI. Those who have previously experienced or learned about unfair treatment by automated systems might be particularly sensitive to fairness issues, influencing their willingness differently compared to peers without such experiences. Future studies could provide deeper insights by exploring these differentiated effects across varying levels of prior knowledge or direct exposure to AI recruitment tools.

Moreover, integrating perceived fairness into broader technology acceptance models such as TAM and UTAUT highlights its indirect role through constructs like performance expectancy. According to Davis (1989) and Venkatesh et al. (2003), perceived fairness indirectly increases users' confidence that the system produces merit-based outcomes, thereby positively influencing their willingness to adopt the technology. Still, the degree to which fairness independently predicts willingness, beyond constructs such as trust or perceived usefulness, requires further exploration.

Given these complexities, institutions and employers should prioritize not just promoting perceptions of fairness superficially but actively demonstrating fairness through transparent explanations, rigorous ethical standards, and robust bias mitigation strategies. Educational initiatives, such as practical workshops or seminars addressing AI ethics and fairness, might also play a critical role in cultivating deeper, informed perceptions of fairness among students, fostering long-term acceptance and engagement.

In conclusion, although this study clearly demonstrates that perceived fairness positively influences students' willingness to use AI-driven recruitment systems, it also underscores the necessity of critically examining the depth and authenticity of fairness perceptions. Future research should further investigate how nuanced understandings of fairness interact with other acceptance factors and explore whether perceptions evolve as users become more experienced and knowledgeable about AI recruitment processes.

5.4 Implication of the Study

This study offers meaningful insights that can benefit universities, employers, and anyone designing or using modern recruitment systems. As hiring processes evolve with technology, it becomes increasingly important to understand how students feel about these changes especially when it comes to applying for jobs through systems that use artificial intelligence.

One key takeaway is that students are more willing to apply for jobs through AI-based platforms when they are aware of how these systems work and when they trust the decisions being made. This suggests that education plays a big role. Universities can support students by including topics related to digital hiring in career talks, workshops, or even classroom discussions. When students know what to expect, they feel more confident and prepared.

The findings point to the importance of building trust and clarity into employers' and recruitment service providers' systems. When job seekers understand that a platform is fair, transparent, and easy to use, they are likelier to engage with it. Providing simple explanations or guides about how decisions are made can help students feel more at ease during the application process.

In short, this research shows that giving students the correct information and helping them build trust in digital hiring systems can make a real difference. It encourages both educators and employers to take steps that support students as they navigate new ways of finding work in a fast-changing job market.

5.5 Contribution to the Study

As explained below, the study has important theoretical and practical ramifications.

5.5.1 Theoretical Contribution

This research contributes meaningfully to the existing theoretical discourse on artificial intelligence (AI) in recruitment, particularly by shifting the focus from organizational perspectives and technological advancements to the experiences and perceptions of job seekers, specifically undergraduate students. Most existing theoretical discussions on AI-driven recruitment have concentrated primarily on employers' viewpoints, AI system design, or technical effectiveness. In contrast, this study engages directly with the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) frameworks from the perspective of those who actively interact with these systems as candidates.

By specifically examining the roles of awareness, trust, and perceived fairness, this study deepens theoretical understanding regarding the antecedents of technology acceptance among younger, digitally native job seekers. Consistent with TAM and UTAUT predictions (Davis, 1989; Venkatesh et al., 2003), the study confirms that awareness and trust significantly shape willingness to engage with AI recruitment platforms. However, this study also critically expands existing theories by identifying the nuanced role of fairness perceptions. Unlike previous studies that largely assume fairness as a universally strong predictor of user acceptance, the relatively weaker influence of fairness observed here signals a critical gap in theory. This discrepancy invites scholars to reconsider how fairness is conceptualised and operationalised within technology acceptance theories, especially concerning emerging technologies like AI, where fairness might be less intuitively understood or perceived differently by novice users.

Additionally, this study introduces a theoretical discussion on the interrelatedness of trust, awareness, and fairness. Rather than viewing these constructs as independent predictors, the findings suggest deeper interconnections. Trust and awareness may indirectly shape perceptions of fairness, suggesting theoretical pathways worth exploring further in future research. Thus, this research provides a richer theoretical contribution by highlighting the need to revisit and refine theoretical models to accommodate the complex, interdependent nature of these constructs in contexts involving sophisticated technologies like AI.

In sum, this research enhances existing theoretical frameworks by revealing critical complexities in the interaction between users and AI-driven systems, highlighting the importance of user-centric theoretical approaches, and laying groundwork for further refinement and expansion of technology acceptance theories..

5.5.2 Practical Contribution

From a practical perspective, this study provides actionable insights beneficial to educational institutions, career support services, and organisations that implement AI-driven recruitment systems. Given the increasing prevalence of automated recruitment tools, the findings underscore the urgent need for universities to proactively prepare students for the realities of the modern job market. Students must be informed about how AI technologies function in recruitment—such as automated resume screening, digital interviewing, and candidate matching—to reduce uncertainties, misconceptions, and potential anxieties associated with unfamiliar technology. Structured educational programs, workshops, or targeted training sessions can significantly improve student readiness and confidence, thus enhancing their willingness to engage actively with these systems.

For employers and developers of recruitment platforms, the study highlights the importance of clearly communicating how AI technologies operate. Transparent explanations of decision-making processes and explicit assurances of unbiased evaluations help build trust among job seekers, particularly among young users less familiar with automated systems. While perceived fairness demonstrated a less direct influence on student willingness than anticipated, it remains crucial for long-term engagement and acceptance. Employers should consistently ensure and clearly communicate the fairness of their recruitment systems, emphasising ethical design principles and regular audits for bias reduction.

In practice, fairness should not merely be assumed but explicitly demonstrated through transparent and explainable decision-making processes. Over time, clearly articulating how fairness is safeguarded within AI-driven recruitment processes will enhance candidate trust, potentially influencing future acceptance positively.

In conclusion, this study provides practical recommendations that emphasise the need for comprehensive, user-oriented educational interventions and transparent organisational practices. By proactively addressing the informational and psychological needs of undergraduate students, universities and employers can foster a more receptive attitude towards AI recruitment technologies, thus improving overall engagement and acceptance among future job seekers.

5.6 Limitation of the Study

Although this study has provided meaningful insights into how undergraduate students view the use of artificial intelligence in recruitment, a few limitations should be considered.

The study only involved students from selected universities. Because of this, the results may not reflect the views of all undergraduates, especially those from other regions, institutions, or academic backgrounds. Different groups of students may have varying levels of exposure to technology, which could shape how they see AI in the job application process.

Another point to note is that the data was collected through an online questionnaire. While this method allowed for easier distribution and responses, some students may have answered based on their assumptions or limited understanding of how AI is used in recruitment. This might affect how accurately their responses reflect their real opinions or behaviours.

The study also focused on three specific factors: awareness, trust, and perceived fairness. While these are relevant, other factors could influence students' willingness to apply through AI systems. For example, a student's past experience with online hiring tools or their level of confidence with technology might also be important, but these were not explored in this research.

Lastly, the study was conducted at a single point in time. Since technology continues to change quickly and students' familiarity with AI is likely to grow, their views may also shift over time. A long-term or follow-up study might offer more insights into how perceptions develop with increased exposure and experience.

Despite these limitations, the study still offers a valuable starting point for understanding how young job seekers respond to AI in recruitment and can help guide future research and practical efforts in this area.

5.7 Recommendations for Future Research

This study makes an important step toward addressing the research gap concerning job seekers' perspectives—particularly undergraduate students—on AI-driven recruitment systems. While much of the existing literature has focused on employers or the technical development of AI tools, this research centres on the perceptions of young job applicants, a group that will be increasingly affected by the digitalisation of recruitment practices. Specifically, the study addresses the gap by examining how awareness, trust, and perceived fairness influence students' willingness to apply through AI systems—offering a clearer view of behavioural intentions from the candidate's side.

From the results, the study reveals that awareness and trust significantly influence willingness, confirming their central role in AI adoption models, while perceived fairness showed a weaker relationship than expected. This divergence challenges assumptions in prior research that fairness is always a dominant driver of acceptance and suggests that students may prioritise understanding and trust over fairness when initially engaging with AI technologies. This insight contributes theoretically by urging scholars to reconsider the relative weighting of acceptance predictors in the context of emerging technologies and novice users.

By focusing on students at Universiti Utara Malaysia, this study begins to close the gap in literature that lacks user-centric data from Malaysian or Southeast Asian populations, where digital maturity and cultural attitudes toward technology may differ from Western contexts. Although limited to a single institution, the findings lay the groundwork for future comparisons across institutions and regions.

Future research could expand this contribution by involving more diverse student populations from multiple universities, disciplines, and geographic locations. Such diversity would allow for cross-group comparisons, enriching the understanding of how contextual, cultural, or educational differences shape acceptance of AI in recruitment.

Moreover, the current model could be extended to include additional variables such as digital confidence, prior experience with automated systems, or general attitudes toward technology. These factors may mediate or moderate the relationship between students and AI platforms and would contribute to a more robust behavioural model in future studies

Another area where future research can build on this study is by adopting a longitudinal approach. Since this research captures perceptions at a single point in time, it cannot account for how opinions may evolve as students gain more exposure to AI tools or as the technology itself becomes more transparent and human-centric. Tracking changes over time would deepen understanding of how experience shapes behavioural intention.

Finally, while this study used structured questionnaires, future work should consider qualitative methods such as interviews or focus groups. These approaches allow for richer, more nuanced exploration of student concerns, such as hidden anxieties or ethical considerations that may not surface in close-ended survey items. As AI adoption in recruitment accelerates, exploring these ethical dimensions—such as transparency, explainability, and accountability—can help shape the development of systems that are both effective and trusted by users.

In sum, this study contributes to narrowing the existing gap by bringing candidate-side perspectives into focus and identifying which factors meaningfully influence willingness to apply through AI. By highlighting both the strengths and limitations of these findings, it lays a critical foundation for future research to continue shaping inclusive, transparent, and trustworthy AI recruitment systems for the next generation of job seekers.

5.8 Conclusion

This study set out to understand how undergraduate students feel about the use of artificial intelligence in the job application process. Specifically, it looked at how their awareness of AI, their trust in how it makes decisions, and their sense of fairness influenced their willingness to apply for jobs through AI-driven systems.

The results showed that students who are more aware of how AI works and trust its decision-making are more open to using these platforms when searching for jobs. These findings highlight the importance of building understanding and confidence among students as AI becomes a more significant part of recruitment. In addition, the study found that perceived fairness has a strong influence. This suggests that some students may fully understand how fairness fits into the way AI is used for hiring, or they may prioritise other factors like convenience or accuracy.

In a broader sense, this research helps illuminate what young job seekers need as they enter a job market that is increasingly shaped by technology. It also offers practical guidance for educators, employers, and developers. Helping students become more familiar with AI and designing systems they can trust can make a real difference in how they approach the job search.

As AI continues to evolve, so will students' experiences and expectations. This study serves as a starting point for deeper conversations and further research that can help improve the technology and how it is introduced to future job seekers.

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Perception of AI in Recruitment Processes Among Undergraduate Students in UUM

I sincerely appreciate your participation in this survey. This study aims to gain valuable insights into undergraduate students' perceptions of AI-driven recruitment processes.

Your thoughtful and honest responses are crucial to the success of this research. The survey will only take about 3-5 minutes of your time, and I assure you that all responses will remain strictly confidential and will be used solely for research purposes.

Thank you for taking the time to contribute to this important study.

* Indicates required question

Section 1: Demographic Information

This section refers to your demographic information. Please choose your corresponding answer from the choices provided.

1. **1(a). What is your age?** *

Check all that apply.

- [ ] 18
- [ ] 19
- [ ] 20
- [ ] 21
- [ ] 22
- [ ] 23
- [ ] 24 and above

2. **1(b). What is your gender?** *

Mark only one oval.

- ( ) Male
- ( ) Female

3. **1(c). What is your field of study?** *

Check all that apply.

- [ ] Bachelor of Accounting (Information System) with Honours
- [ ] Bachelor of Accounting with Honours
- [ ] Bachelor of Applied History
- [ ] Bachelor of International Business Management (Hons)
- [ ] Bachelor of International Affairs Management (Hons)
- [ ] Bachelor of Public Management (Hons)
- [ ] Bachelor of Media Technology (Hons)
- [ ] Bachelor of Industrial Statistics (Hons)
- [ ] Bachelor of Social Work Management (Hons)
- [ ] Bachelor of Education (Hons) (Guidance and Counselling)
- [ ] Bachelor of Agribusiness Management (Hons)
- [ ] Bachelor of Operations Management (Hons)
- [ ] Bachelor of Banking (Hons)
- [ ] Bachelor of Muamalat Administration (Hons)
- [ ] Bachelor of Technology Management (BTechMgt) (Hons)
- [ ] Bachelor of Human Resource Management (Hons)
- [ ] Bachelor of Risk Management and Insurance (Hons)
- [ ] Bachelor of Business Administration (Logistics & Transportation) (Hons)
- [ ] Bachelor of Finance (Hons)
- [ ] Bachelor of Islamic Finance and Banking (Hons)
- [ ] Bachelor of Entrepreneurship (Hons)
- [ ] Bachelor of Law (Hons)
- [ ] Bachelor of Business Administration (Hons)
- [ ] Bachelor of Tourism Management (Hons)
- [ ] Bachelor of Hospitality Management (Hons)
- [ ] Bachelor of Business Mathematics (Hons)
- [ ] Bachelor of Multimedia (Hons)
- [ ] Bachelor of Accounting (Hons)
- [ ] Bachelor of Economics (Hons)
- [ ] Bachelor of Counselling (Hons)
- [ ] Bachelor of Communication (Hons)
- [ ] Bachelor of Science (Hons) Decision Science
- [ ] Other: ____________________

4. **1(d). What year of study are you currently in?**

Mark only one oval.

- First Year
- Second Year
- Third Year
- Fourth Year and Above

5. **1(e). Have you ever applied for a job using an AI-driven recruitment system?** *

Mark only one oval.

- Yes
- No

6. **1(f). How often do you encounter AI in job recruitment processes?**

Mark only one oval.

- Always
- Often
- Sometimes
- Rarely
- Never

Section 2: Awareness of AI in Recruitment

Instructions: Please indicate your level of agreement with the following statements. (Likert Scale: 1 = Strongly Disagree, 5 = Strongly Agree)

7. 2(a). I am aware that AI is being used in job recruitment processes. *

Mark only one oval.

	1	2	3	4	5	
Stron	◯	◯	◯	◯	◯	Strongly Agree

8. 2(b). I understand how AI evaluates job applications and resumes. *

Mark only one oval.

	1	2	3	4	5	
Stron	◯	◯	◯	◯	◯	Strongly Agree

9. 2(c). I have seen or read about companies using AI for hiring decisions. *

Mark only one oval.

	1	2	3	4	5	
Stron	◯	◯	◯	◯	◯	Strongly Agree

10. 2(d). I am familiar with AI tools such as resume screening and automated interviews. *

Mark only one oval.

	1	2	3	4	5	
Stron	◯	◯	◯	◯	◯	Strongly Agree

11. 2(e) I know both the benefits and risks of AI-driven recruitment systems. *

Mark only one oval.

	1	2	3	4	5	
Stron	◯	◯	◯	◯	◯	Strongly Agree

Section 3: Trust in AI Decision-Making

Instructions: Please indicate your level of agreement with the following statements. (Likert Scale: 1 = Strongly Disagree, 5 = Strongly Agree)

12. 3(a). I trust AI to make unbiased hiring decisions. *

Mark only one oval.

	1	2	3	4	5	
Stron	◯	◯	◯	◯	◯	Strongly Agree

13. 3(b). I believe AI can accurately evaluate my qualifications for a job. *

Mark only one oval.

	1	2	3	4	5	
Stron	◯	◯	◯	◯	◯	Strongly Agree

14. 3(c). I feel comfortable with AI making decisions about candidate selection. *

Mark only one oval.

	1	2	3	4	5	
Stron	◯	◯	◯	◯	◯	Strongly Agree

15. 3(d). AI recruitment systems can effectively reduce human bias in hiring. *

Mark only one oval.

	1	2	3	4	5	
Stron	◯	◯	◯	◯	◯	Strongly Agree

16. 3(e). I believe AI can correctly match job applicants with suitable roles. *

Mark only one oval.

	1	2	3	4	5	
Stron	◯	◯	◯	◯	◯	Strongly Agree

17. 3(f). AI-based hiring decisions should always be reviewed by a human. *

Mark only one oval.

	1	2	3	4	5	
Stron	◯	◯	◯	◯	◯	Strongly Agree

Section 4: Perceived Fairness of AI in Recruitment

Instructions: Please indicate your level of agreement with the following statements. (Likert Scale: 1 = Strongly Disagree, 5 = Strongly Agree)

18. 4(a). AI ensures a fair evaluation of all job applicants. *

Mark only one oval.

	1	2	3	4	5	
Stron	◯	◯	◯	◯	◯	Strongly Agree

19. 4(b). The use of AI in recruitment reduces discrimination and bias. *

Mark only one oval.

	1	2	3	4	5	
Stron	◯	◯	◯	◯	◯	Strongly Agree

20. 4(c). AI recruitment processes are transparent and accountable. *

Mark only one oval.

	1	2	3	4	5	
Stron	◯	◯	◯	◯	◯	Strongly Agree

21. 4(d). I believe AI-based hiring systems treat all candidates equally. *

Mark only one oval.

	1	2	3	4	5	
Stron	◯	◯	◯	◯	◯	Strongly Agree

22. 4 (e). AI decision-making in hiring should be explainable to applicants *

Mark only one oval.

	1	2	3	4	5	
Stron	◯	◯	◯	◯	◯	Strongly Agree

23. 4(f). AI recruitment can sometimes be unfair due to data biases. *

Mark only one oval.

	1	2	3	4	5	
Stron	◯	◯	◯	◯	◯	Strongly Agree

Section 5: Willingness to Apply for Jobs through AI-Driven Systems

Instructions: Please indicate your level of agreement with the following statements. (Likert Scale: 1 = Strongly Disagree, 5 = Strongly Agree)

24. 5(a). I am willing to apply for jobs that use AI-driven recruitment systems. *

Mark only one oval.

	1	2	3	4	5	
Stron	◯	◯	◯	◯	◯	Strongly Agree

25. 5(b). The presence of AI in hiring would not discourage me from applying. *

Mark only one oval.

	1	2	3	4	5	
Stron	◯	◯	◯	◯	◯	Strongly Agree

26. 5(c). I prefer companies that use AI for recruitment over those that don’t. *

Mark only one oval.

	1	2	3	4	5	
Stron	◯	◯	◯	◯	◯	Strongly Agree

27. 5(d). I feel comfortable with AI analyzing my job application. *

Mark only one oval.

	1	2	3	4	5	
Stron	◯	◯	◯	◯	◯	Strongly Agree

28. 5(e). I would participate in an AI-driven interview or assessment. *

Mark only one oval.

	1	2	3	4	5	
Stron	◯	◯	◯	◯	◯	Strongly Agree

29. 5(f). AI-driven recruitment would improve my chances of getting a job. *

Mark only one oval.

	1	2	3	4	5	
Stron	◯	◯	◯	◯	◯	Strongly Agree