Advanced International Journal for Research (AIJFR)
E-ISSN: 3048-7641 ● Website: www.aijfr.com ● Email: editor@aijfr.com

The Relationship Among Perceived AI Effectiveness, Self-Efficacy, and Adaptability of Recruitment Professionals in Selected Cities in Metro Manila

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Abstract

The advancement of Artificial Intelligence (AI) has provided substantial benefits and conveniences in the workplace especially in the Human Resource recruitment function where it has expedited and simplified the hiring process leading to questions on its perceptions and Perceived AI effectiveness. This study aimed to investigate the relationship between Perceived AI Effectiveness, Self-Efficacy, and Adaptability among recruitment professionals in selected cities in Metro Manila. A total of 68 valid recruitment professionals from various companies, recruitment agencies, and talent acquisition firms participated in this study. The data was collected through an online survey and utilized correlational analysis to determine the results. The result of this study shows that Self-Efficacy has a significant positive relationship on Adaptability and Perceived AI Effectiveness. It is also revealed that the Perceived AI Effectiveness provided a moderate positive relationship with adaptability. Findings of this study implies the potential positive connections of AI integration in the recruitment facet citing the need for further support among recruitment employees. Moreover, it also suggested conducting deeper studies to better determine the effects of AI in the workplace.

Keywords: Adaptability, Artificial Intelligence, Job Demands-Resources, Perceived AI Effectiveness, Recruitment Professionals, Self-Efficacy, Social Cognitive Theory, Technology Acceptance Model

1. Introduction

The advancement of Artificial Intelligence (AI) has led to a significant increase in benefits and conveniences, especially in the workplace, to the point of creating a paradigm shift toward how one works, lives, and interacts with the real world. AI streamlines workflows in the workplace, simplifying and eliminating redundant tasks, and promotes strategies for business integration (Almeida et al, 2024).

In the field of human resource (HR) especially in the recruitment facet, AI has changed how the way people management is being done (Patil & Priya, 2024 as cited by Dvouletý et al, 2024). This trend of technological integration can be viewed in the functions of human resources, where, for example, a survey conducted by Engagedly (2023) showed that 45% of the respondents used AI in managing HR. The change has brought in more cost-effectiveness, time-saving, and a higher success rate in hiring (How Artificial Intelligence is Transforming Human Resources and the Workforce, 2024.)

However, along with these benefits are challenges that need to be addressed. For instance, the effectiveness of AI is being questioned by many recruitment professionals who believe that the “human” is still a crucial component in recruitment rather than being fully automated. An example of this can be referenced in a study by Karaboga and Vardalier (2021) where they have noted that despite the expeditious, simplified hiring process, AI, with its inadequacies, may lead to incorrect decisions when hiring candidates. The study also mentioned that while AI may help address decision-making challenges in the future, it is likely to remain as an auxiliary element especially in the process of recruitment. Given the rapid advancement and growing adoption of AI, HR employees now reevaluate themselves—specifically: **(1)** their confidence in performing recruitment tasks, **(2)** their perceived effectiveness of AI in recruitment-related tasks, and **(3)** their capacity to adapt to an ever-evolving workplace, technology-driven workplace.

2. THEORETICAL BACKGROUND

2.1. Theoretical Framework

This study is anchored on Social Cognitive Theory (SCT), the Technology Acceptance Model (TAM), and the Job Demands-Resources (JD-R) to explore the relationship between perceived AI effectiveness, self-efficacy, and adaptability among recruitment professionals.

2.1.1. Social Cognitive Theory (SCT)

Albert Bandura’s Social Cognitive Theory (SCT) is a psychological theory that explains how people learn by watching others. It says that behavior is shaped by a continuous interaction between a person’s personal factors, their behavior, and their environment. Personal factors include beliefs, expectations, and personality. Behavior is the actions a person does. The environment is the surroundings and social context that affect behavior. This three-way interaction is called triadic reciprocality.

A key idea in SCT is self-efficacy. Self-efficacy is a person’s belief in their ability to do a task or handle a situation. Bandura introduced it to explain why people act differently even when they have the same knowledge or skills. People with high self-efficacy are more likely to try hard tasks, keep going when it is difficult, and manage their own motivation. It affects what activities they choose, how much effort they put in, and how well they perform. Success can increase self-efficacy, while repeated failure can lower it.

Research shows self-efficacy is important for motivation, adaptability, and performance. Hadi (2023) found that self-efficacy improves employee performance when motivation and engagement are considered. Mahmud and Khidi (2023) showed a strong link between self-efficacy and career adaptability among diploma students. Xiao and Zheng (2025) found that higher self-efficacy leads to better job satisfaction and well-being. In this study, recruitment professionals with higher self-efficacy are more likely to adapt to new technology and see it as helpful for their work. This fits the study's goal of exploring the relationship between self-efficacy, adaptability, and perceived usefulness of technology.

2.1.2. **Technology Acceptance Model (TAM)**

The Technology Acceptance Model (TAM), developed by Fred D. Davis (1989), was adapted from the Theory of Reasoned Action (TRA) by Martin Fishbein and Icek Ajzen in 1975, which aimed to provide a theoretical framework on understanding and predicting user acceptance and use of technology. TAM expands TRA's focus on behavioral and attitudes to explain and understand technology adoption in both individual and organizational contexts. TAM identifies two (2) key determinants influencing technology adoption: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). Davis (1989) defines PU as "*the degree to which one believes that using a particular system would enhance their job performance*", and PEOU as "*the degree to which a person believes that using a system would be free of effort*." Both of the key determinants in TAM affect the individuals' perception of technology, which influences their behavioral intention and affects actual system use.

According to TAM, when users perceive a system as both useful and easy to use, they develop positive attitudes that encourage adoption, leading to faster and more effective utilization. Furthermore, Davis emphasized the critical role of behavioral intention, shaped by PU and PEOU, in determining actual system usage. These are also influenced by External variables such as user experience, organizational support, training and overall acceptance of using Advance Technological tool such as AI, namely the studies by Su and Li (2021), Lin and Yu (2023), and Wang et al. (2025) have discovered that the interchange and external variables, such as training, users' experiences, and system support, have a significant impact on users' PU & PEOU in an online learning platform, and an actual system utilization. These studies identified that external factors play an important role in how individuals perceive and intend to use technology, which supports Davis' claim that behavioral intention results and is affected by both individual and contextual factors.

The model has been widely applied across various domains— including business, education, and healthcare. For instance, in Human Resource Management, especially in recruitment and talent acquisition, this theory provided a vital framework for examining professionals' willingness and ability to adapt to the emerging AI-recruitment tools and systems. In the context of this study, when recruitment professionals view AI tools as effective (perceive AI effectiveness) and user-friendly, they are more likely to adopt them, by looking at AI as a resource that enhances efficiency and job performance rather than as a barrier. Conversely, individuals who find it difficult to adapt may resist technology adoption, viewing it as an added challenge rather than a means to productivity.

Building on Davis' foundation, Marikyan and Papagiannidis (2024) provided an updated perspective on TAM, elaborating on its evolution from the Theory of Reasoned Action (TRA) to its extended versions, TAM 2 and TAM 3, which incorporate additional factors such as social influence, perceived enjoyment, and self-efficacy. This development on TAM highlights how the psychological and social factors, like one's self-efficacy, can affect and influence technology adoption, a key intersection relevant to this research, which examines the relationship and influence between self-efficacy, perceived AI effectiveness, and adaptability of recruitment professionals.

2.1.3. **Job Demands-Resources (JD-R)**

While Social Cognitive Theory (SCT) and Technology Acceptance Model (TAM) focus on the individual's ability and technology acceptance, the Job Demands–Resources (JD-R) Model focuses on the environment and employees' productivity in their job. The JD-R model was proposed by Demerouti et al. (2001) as a theoretical framework for understanding why employees experience burnout and motivation, emphasizing that every job consists of two important factors: job demands and job resources. This framework was important in this research as it emphasizes the challenges and support that employees may feel in the workplace, which have an impact on their motivation and performance. In this study, the framework provided a comprehensive understanding of how AI tools function as job resources that can help recruitment professionals improve their self-efficacy and adaptability while handling demanding work conditions.

Job demands refer to the physical, psychological, social, or organizational aspects of a job that require sustained effort and are associated with physiological or psychological costs, such as a high workload, emotional strain, and role ambiguity. For example, in HR, especially for recruitment professionals, there are various job demands such as mass hiring, tight deadlines, and managing multiple client expectations. In contrast, job resources refer to the aspects of the work environment that help employees achieve work goals, reduce job demands, and foster growth & development. For example, for a recruitment professional, these AI tools as job resources could help them in assisting with team structure, defining performance metrics, or creating an intranet for the Human Resources team.

Bakker and Demerouti (2017) later extended the JD-R model, shifting its focus from explaining both negative and positive outcomes, which include burnout and motivation processes such as work engagement. They assumed that job resources are not only a barrier to the influence of high demands but also act as main motivators that foster employee engagement and performance, as they satisfy the basic psychological needs for autonomy, relatedness, and competence, which align with the Self-Determination Theory as a basis for self-motivation and personality integration. When employees have enough resources, they are more likely to remain energetic, committed, and productive. A combination of high demands with a lack of resources may lead to stress, exhaustion, and poor job performance. In this study, AI tools may serve as a job resource that helps recruiters manage demands more efficiently, influencing and enhancing their self-efficacy, adaptability, and perceived effectiveness of AI.

2.2. LITERATURE REVIEW

2.2.1. Artificial Intelligence (AI)

Kumar and Yanamala (2021) defined AI as the ability of machines to replicate or surpass human intelligence, including experience-based learning and reasoning. Not just computer programs but different industries that offer a wide range of products and services are currently utilizing artificial intelligence; hence, making it practically essential to daily life and professional fields (Bewersdorff et al., 2025). According to Zeng (2020), it is a technology used to perform tasks that require some level of intelligence to accomplish—in simpler terms, a tool trained to do what a human can do. The prevalence of Artificial Intelligence in HRM practices is now being utilized to further enhance the capability, diversity, and analysis of candidates who may be part of organizations (Gandolfi et al., 2023). The effectiveness of AI in the field of human resources has been proven especially in recruitment, including resume screening automation, interview process and scheduling, and candidate selection. Studies so far have illustrated that there is a positive outlook on the use of AI in recruitment, citing streamlined, comprehensive, and cost-saving benefits

2.2.2. Perceived AI Effectiveness

Perceived AI Effectiveness is how employees evaluate the usefulness, reliability, and impact of the AI tool they're using derived from their personal experiences and expectations. This assesses an individual's belief that AI is capable of performing a specific task effectively in comparison to a human. Furthermore, it indicates how they perceive AI's usefulness in supporting tasks that call for data processing and human-like decision-making according to a study by Schepman & Rodway, (2020). The use of AI in recruitment to support hiring tasks and recruitment processes is widely viewed as efficient and scalable, as demonstrated by the study conducted by Ahmadi et al. (2024). Furthermore, Almulla and Adam (2025) utilized the Technology Acceptance Model (TAM) to study primary school teachers in Saudi Arabia and explore their perceptions of AI being effective. They found that perceived usefulness (PU) and perceived ease of use (PEU) were significant predictors of their attitudes and behavioral intentions towards AI.

2.2.3. Self-Efficacy

Self-efficacy plays a crucial role in employees' way of dealing problems and tasks in the workplace. Jyoti and Dev (2017) defined self-efficacy as how employees measure their confidence and judgment regarding their ability to successfully execute tasks and overcome workplace challenges. Employees with high self-efficacy tend to exhibit better work performance in task-related and contextual performance, while those with lower self-efficacy may struggle with confidence and engagement. In addition, Job resources, like leadership support and training, are crucial for enhancing self-efficacy, which in turn leads to employees' improved performance and engagement (Bakker and Demerouti, 2017).

2.2.4. **Adaptability**

As the world changes, especially in human resource management (HRM), adaptability has become an essential skill especially in recruitment where there are various technological advancements, multiple AI tools are progressively integrated. According to Johnson and Wilson (2019), adaptability is the capacity of individuals and organizations to adjust and adapt to dynamic changes (internal or external factors), particularly in the modern era where AI and advanced tools are introduced. In the context of recruitment, this includes the changes of AI-Driven tools that are evolving the traditional hiring practices. Smith et al. (2023) emphasized that adaptability includes cognitive, emotional, and behavioral dimensions, which enable employees to process and learn new information, manage emotions professionally, and alter behaviors in evolving and transitioning workplace conditions.

With the advent of AI in the world of HR, adaptability is necessary to navigate and adjust their roles to learn the new tools in recruitment because AI is utilized and assists them in the recruitment process. As many organizations shift and invest in AI, adaptability within HR teams are essential for developing new competencies and skills that provide them an advantage (Sari et al., 2020).

2.2.5. **Self-Efficacy and Adaptability**

Numerous research studies have examined the relationship between Self-Efficacy and Adaptability. Yi et al. (2025) conducted a research study on the Co-Development of Career Adaptability and Academic Self-Efficacy among College students. The study aims to explore the relationship between career adaptability and academic self-efficacy throughout the college year level, using a Four-Wave Longitudinal investigation and Latent Growth Model (LGM). The result of the study states that both the intercepts and slopes of the career adaptability & academic self-efficacy were positively and significantly correlated with a value of $r = 0.70$, $p < 0.01$, suggesting that students with a higher initial level of career adaptability tend to be have a higher initial level of academic self-efficacy. Moreover, a study by Ullah et al. (2019) investigates the correlation between self-efficacy, adaptability, and entrepreneurial intention of the students by deploying a descriptive-correlational research design, and they discovered that self-efficacy has a high and positive correlated to adaptability with a value of $r = 0.639$, $p < 0.01$, indicating that wherever self-efficacy increases, It also increases their ability to adapt. Consequently, Holderman & Wijono (2024) revealed in their study the positive correlation between self-efficacy and adaptability ($r=0.841$, $p<0.01$) among early-career employees revealing that employees with high levels of self-efficacy yields high levels of career adaptability which is one of the key factors towards their career development.

Su and Weng (2024) investigate a study using a convenience sampling method, how self-efficacy influences the social adaptability of Chinese vocational college students, in order to better understand its relationship with social adaptability. The results showed that Self-efficacy is positively correlated with Social Adaptability ($r = 0.807$, $p < 0.01$), meaning a high correlation between the two variables. As students' self-efficacy increased, they were also likely to adapt to social and academic changes.

2.2.6. Self-Efficacy and Perceived AI Effectiveness

Several studies have examined the relationship between self-efficacy and perceived AI effectiveness. Mantik et al. (2024) found that self-efficacy had a significant positive influence on perceived ease of use ($\beta = 0.562$, $p < 0.05$), indicating that individuals with higher confidence in their abilities were more likely to perceive technology as easy to use and adopt it. Similarly, Chen et al. (2024) indicated that AI self-efficacy had a significant positive relationship with attitude towards AI and actual use of AI, suggesting that individuals with increased confidence in their ability to effectively make use of AI tools are more likely to perceive these technologies as comfortable to use and manageable.

In line with these findings, Guipitacio et al. (2025) reported that AI self-efficacy was significantly and positively correlated with attitudes toward AI ($\beta = 0.519$, $p < 0.001$), showing that individuals with higher AI self-efficacy tend to hold more favorable perceptions and attitudes toward AI, reflecting greater openness and confidence in engaging with AI technologies. Furthermore, Pan et al. (2024) revealed that self-efficacy has a positive impact or a significant relationship with perceived ease of use, meaning that users with more confidence in their ability to use the AI coding assistant tools find these tools easier to control and navigate. However, Shata and Hartley (2025) presented contrasting results, revealing that self-efficacy does not significantly influence attitude ($p = 0.113$).This means that an individual's belief in their ability to succeed in a task does not always affect one's attitude or level of comfort toward technology. While many studies found a positive link between self-efficacy and positive perceptions of technology, findings in this area remain inconsistent and may vary across contexts and populations.

Collectively, these studies highlight that individuals with higher self-efficacy generally tend to hold more positive perceptions of AI and technology, perceiving them as easier to use, more comfortable to manage, and more effective overall. Nonetheless, the mixed findings emphasize the need for further exploration of this relationship, particularly in different professional contexts such as recruitment. These insights support the present study's hypothesis that self-efficacy has a significant relationship with perceived AI effectiveness while addressing the gaps found in previous research.

2.2.7. Perceived AI Effectiveness and Adaptability

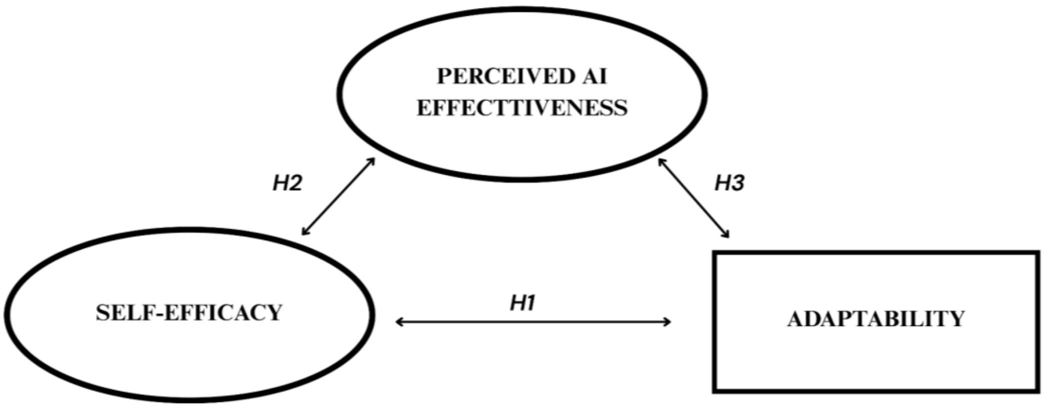
Several studies have examined the relationship between perceived AI effectiveness and adaptability. Gerlich, (2023) conducted research on perceptions and acceptance of AI. The study aims to explore the multifaceted views towards AI in a multi-dimensional study, examining perceived effectiveness of AI, specifically its benefits, efficiency, and accuracy and adaptability to technological change through ex post facto surveys that were correlational, cross-sectional, and non-experimental. They found that perceived effectiveness of AI (benefits, efficiency, and accuracy) and adaptability (usage/acceptance) have a strong positive correlation (0.774). The result indicated that as the perceived effectiveness of AI (benefits, efficiency, and accuracy) increases, the public's adaptability and propensity for usage/acceptance of AI also increases, demonstrating a strong, direct, and positive relationship between these two factors. A study by Dere & Dogan, (2025) which investigates the relationship between teachers' AI use and their flexible thinking skills, explored the connection between positive perceptions of AI and adaptability—their ability to think flexibly in learning using a predictive correlational research design. The results revealed that perceived AI effectiveness has a moderate positive relationship with adaptability ($\beta = 0.34$p, < 0.001).

Begum et al. (2025) conducted research on cognitive flexibility's role in adapting to climate change: AI- driven educational strategies for developing adaptive thinking with the aim of exploring the place of cognitive flexibility in strengthening adaptive thinking and problem solving, also highlighting AI-powered education as a tool to enhance the aforementioned capabilities. The findings showed that the β (Beta Coefficient) of perceived usefulness of AI—an individual's belief in the capability of AI in performing tasks—is 0.648 ($p < 0.01$), which illustrated a significant positive relationship with adaptive thinking, which is essentially a measure of adaptability. The study's results demonstrate that a higher perceived AI usefulness correlates with greater capability to think adaptively.

2.3. THE HYPOTHESIZED MODEL

This conceptual framework is designed to investigate the relationships among Perceived AI Effectiveness, Self-Efficacy, and Adaptability of recruitment professionals in selected cities in Metro Manila. It aims to examine how these constructs are associated within the context of AI use in recruitment.

The variables are positioned on the same weight level, as the study focuses on their relationships rather than assigning strict independent or dependent roles. The arrows represent the hypothesized relationships and do not imply causation. Self-Efficacy and Perceived AI Effectiveness are treated as latent variables measured through multiple items, while Adaptability is a manifest variable measured through specific indicators.



*THE RELATIONSHIP AMONG **PERCEIVED AI EFFECTIVENESS, SELF-EFFICACY, AND ADAPTABILITY** AMONG RECRUITMENT PROFESSIONALS IN SELECTED CITIES IN METRO MANILA*

H1: Perceived AI effectiveness has a significant relationship on self-efficacy among recruitment professionals.

H2: Perceived AI effectiveness has a significant relationship on adaptability among recruitment professionals

H3: Self-efficacy has a significant relationship on adaptability among recruitment professionals.

3. METHOD

3.1. Research Design

This study utilized both descriptive and correlational research designs. By utilizing descriptive design, the study aimed to gain a detailed and a deeper understanding of how recruitment professionals perceive and experience AI in terms of using and integrating it in their work processes. It also helps to see the clear view of trends and patterns that relate to their perceived AI effectiveness, self-efficacy, and adaptability. Also, employing a correlational design helped the study to observe the relationship between the key variables by discerning how each variable relates to the other variables without creating a cause-and-effect relationship. This approach enables the researchers to look for the relationship between perceived AI effectiveness, self-efficacy, and adaptability without introducing any form of manipulation or control.

To deepen the understanding of the relationship of the key variables, the study applied a non-experimental descriptive and correlational design, which plays an important role in the study. The descriptive design helped to look for the current conditions related to the key variable among recruitment professionals. Before examining how the variables relate to each other, each one was clearly defined. Alongside the descriptive design, a correlational design was also utilized, as it helps determine the relationship between the variables in terms of their nature and strength. It also offers valuable and important insights of how the factors interact and correlate with one another in a real-life set-up, even though it doesn’t propose a causal relationship.

3.2. Subjects and Study Site

The study targeted recruitment professionals from various companies, recruitment agencies, and talent acquisition firms (Manila, Quezon City, Makati, Taguig, Pasig, Pasay, and Mandaluyong). Respondents' participation was voluntary, with no monetary or material incentives involved. Data cleansing was applied to remove the data collected from those who did not meet the criteria.

A total of 68 active recruitment professionals were surveyed, meeting the minimum requirements for Correlational Analysis despite a larger sample size suggested by calculations. Among the 68 respondents, the majority were aged 20-30 years old (67.60%), Female (69.10%). Most had 1-2 years of experience in recruitment (36.80%), and the duration of using AI was 1 year (41.20%), with Quezon City as the common area of the respondents (30.90%),

3.3. Instrumentation

The survey questionnaire used is composed of four (4) major parts, namely:

(a) Part I – Demographic profile of the respondents;

(b) Part II – Perceived AI Effectiveness, adapted from the study of Schepman and Rodway (2020), which is composed of eleven (11) questions;

(c) Part III – Self-Efficacy, adapted from the study of Koopmans et. al. (2013), which is composed of nine (9) questions; and

(d) Part IV – Adaptability, adapted from the studies of Martin et al. (University of Sydney) and Morales-García et. al. (2023), which is composed of ten (10) questions.

3.4. Data Gathering Procedure

The data gathering process followed a systematic sequence to ensure ethical and organized data collection. Initially, the researchers prepared the final research proposal and secured an approval from the Office of the Dean of the College Department to conduct the study. Once clearance was granted, formal request letters were sent to the HR departments of participating companies to seek permission to administer the research instrument.

Upon approval, the researchers distributed an Informed Consent Form to all qualified participants, ensuring that participation is voluntary and that confidentiality is maintained. The primary data collection tool was a structured questionnaire designed to measure perceived AI effectiveness, self-efficacy, and adaptability. Questionnaires were distributed electronically via Google Forms, allowing respondents to complete them conveniently within 10–15 minutes.

The Data collection took place from July to November 2025. Upon completion, all responses were reviewed, organized, and analyzed using the appropriate statistical tools—specifically Correlational Analysis —which evaluated the relationships between the study variables.

3.5. Ethical Consideration

This study utilized an adapted questionnaire from various authors. Emails were sent to the respective authors asking for their consent to properly use their respective research instruments, stating the intention and modifying it to be relevant to the group's study. Consequently, the researchers also sent out letters to the companies' HR departments seeking their permission for them to be included in the group's research through the survey. Potential companies were assured that confidentiality will be maintained and that whatever information employees provided were only used for this study. Should there be a need to emphasize the information given, aliases were utilized to protect the identity of the respondents.

Upon approval, the surveys were administered electronically via Google Forms. Participants were given the choice to use either their personal or work email addresses, depending on their access preferences and company policies regarding Google-based platforms. On the Google forms. it included the participation rights such as their rights to decline participating, withdraw at any time at the study without incurring penalties and obtain the results of the study. Furthermore, it will also ensure the participants' information were anonymous and the data is treated with integrity and without manipulation. All collected data from the forms are strictly confidential, and none of the personal identifiers appeared in any public published material and were only used for response tracking. Only the research team and academic adviser had access to the data and it was safely kept and stored. Once the study is done, all the identifying information will be permanently deleted and erased, in order to avoid identifying any specific respondent, the results were provided in aggregate form. The researcher affirmed that no information will be manipulated, controlled, misused and that all the data will be treated ethically and objectively.

3.6. Data Analysis

Quantitative data from the study will be analyzed using Jamovi. Descriptive statistics will summarize respondents' demographics, years of experience in AI, years of using AI in their work, and perceptions of the variables, while Likert-scale items will assess perceptions of the variables. Purposive sampling will be used to ensure that the data comes from the intended respondents.

A correlational analysis will examine the relationships among perceived AI effectiveness, self-efficacy, and adaptability among Metro Manila recruitment professionals. The study aims to examine the relationships among perceived AI effectiveness, self-efficacy, and adaptability among Metro Manila recruitment professionals and if they are able to accommodate and manage the use of AI in their line of work with little to no hesitations and setbacks.

4. RESULTS

Results from the Questionnaire were collected from recruitment professionals in various companies, recruitment agencies, and talent acquisition firms in selected cities in Metro Manila, which consist of Manila, Quezon City, Makati, Taguig, Pasay, and Mandaluyong. The study aimed to examine the relationship among Self-Efficacy, Adaptability, and Perceived AI Effectiveness. Out of the 81 respondents, 68 were deemed valid and usable for the Data. Results were shown in the form of Tables.

Demographic Characteristics of the Respondents (n-68)

Presented below are the demographic characteristics of the respondents based on Age, Sex, Work Location, Years of Experience, Current Role in HR using AI in their Work, and Years of using AI.

Table 1. Age

Profile	**n**	**%**
Age		
20-30	46	67.60%
30-40	15	22.10%
40-50	6	8.80%
50 Above	1	1.50%

The statistics presented here reveals that the respondents' age group of 20-30 years old are the highest, making up 67.60% of the total population sample.

Table 2. Sex

Profile	**n**	**%**
Sex		
Male	21	30.90%
Female	47	69.10%

The majority of respondents in this study are female, comprising 47 (69.10%) of the total population, while the remaining 21 (30.10%) are male.

Table 3. Work Location

Profile	**n**	**%**
Work Location		
Makati	13	19.10%
Taguig	18	26.50%
Pasig	5	7.40%
Quezon City	21	30.90%
Mandaluyong	3	4.40%
Pasay	4	5.90%
Manila	4	5.90%

For the work location, most of the respondents are based in Quezon City, accounting for 30.90% of the total population of this study.

Table 4. Years of Experience

Profile	**n**	**%**
Years of Experience		
1 - 2 years	25	36.80%
3-5 years	24	35.30%
More than 5 years	19	27.90%

Their years of experience have a balanced distribution, with 36.80% falling within the 1-2 year range, 35.30% within the 3-5 year range, and 27.90% exceeding 5 years.

Table 5. Using AI in your work

Profile	n	%
Using AI in your work		
Yes	68	100.00%

All respondents claimed that they use AI in their work (100%) citing its prevalent use especially in the modern recruitment workplace.

Table 6. AI Use Duration (Years)

Profile	n	%
AI Use Duration (Years)		
1	28	41.20%
2	19	27.90%
3	7	10.30%
4	6	8.80%
5	4	5.90%
6	1	1.50%
7	1	1.50%
8	1	1.50%
10	1	1.50%

For the AI use duration, the majority have been using AI for 1 year comprising 41. 2% of the respondents.

Table 7. Current Role in HR

Profile	n	%
Current Role in HR		
Recruiter	43	63.24%
Onboarding Specialist	4	5.88%
Team Lead	9	13.24%
Manager	5	7.35%
HR Director	2	2.94%
HR Recruitment & Onboarding Specialist	1	1.47%
Sourcing Specialist	1	1.47%
Talent Acquisition Partner	1	1.47%
Sourcer	1	1.47%
Head, Talent Resourcing	1	1.47%

The majority of the respondents in this study have a current role of being a recruiter, comprising 63.20%.

Confirmatory Factor Analysis

Table 8. Confirmatory Factor Analysis

Construct	CODE	Factor Loading	p-value	Cronbach's Alpha (CA)
PAIE				0.899
	PAIE1	0.58	<.001	

	PAIE 2	0.70	<.001	
	PAIE 3	0.86	<.001	
	PAIE 4	0.74	<.001	
	PAIE 5	0.63	<.001	
	PAIE 6	0.71	<.001	
	PAIE 7	0.76	<.001	
	PAIE 8	0.63	<.001	
	PAIE 9	0.78	<.001	
	PAIE 10	0.69	<.001	
	PAIE 11	0.73	<.001	
SE				0.870
	SE1	0.749	<.001	
	SE2	0.818	<.001	
	SE3	0.85	<.001	
	SE4	0.741	<.001	
	SE5	0.662	<.001	
	SE6	0.83	<.001	

	SE7	0.802	<.001	
	SE8	0.645	<.001	
	SE9	0.743	<.001	
AD				0.893
	AD1	0.838	<.001	
	AD2	0.736	<.001	
	AD3	0.658	<.001	
	AD4	0.847	<.001	
	AD5	0.778	<.001	
	AD6	0.742	<.001	
	AD7	0.768	<.001	
	AD8	0.682	<.001	
	AD9	0.777	<.001	
	AD10	0.75	<.001	

Table 7. shows the study's Confirmatory Factor Analysis (CFA), which tested the measurement model. To evaluate the convergent validity, construct reliability, and internal consistency of the indicators that form the constructs (PAIE, SE, and AD), factor loadings (latent variable coefficients) and their significance levels are utilized.

Using Cronbach's alpha (CA), it demonstrates that internal consistency was strong for all constructs—PAIE (0.899), SE (0.87), and AD (0.893), exceeding the ideal Cronbach's alpha threshold of 0.7 ensuring that items are reliably measuring the same construct. Further supporting convergent validity, factor loadings for the indicator items ranged from 0.58 to 0.86, all of which were highly significant ($p < 0.001$), affirming that items strongly load onto their intended constructs.

The instrument exhibits reliability and validity. More specifically, the high Cronbach's alpha values of 0.899, 0.87, and 0.893 for PAIE, SE, and AD, respectively, show strong internal consistency (reliability). Similarly, the significant factor loadings indicate that the respondents interpreted the measurement items as intended, which establishes the construct validity of the instrument.

The Relationship of Self-Efficacy, Adaptability, and Perceived AI Effectiveness

Table 9. *Summary of Hypothesis Testing*

Correlation	r	df	p-value	Strength	Description	Interpretation
SE <-> AD	0.880***	66	<.001	high	significant	H1 is supported.
SE <-> PAIE	0.764***	66	<.001	high	significant	H2 is supported.
PAIE <-> AD	0.679***	66	<.001	moderate	significant	H3 is supported.

Note. * p < .05, ** p < .01, *** p < .001

Size of Correlation	Interpretation
.90 to 1.00 (-.90 to -1.00)	Very high positive (negative) correlation
.70 to 0.90 (-.70 to -.90)	High positive (negative) correlation
.50 to 0.70 (-.50 to -.70)	Moderate positive (negative) correlation
.30 to .50 (-.30 to -.50)	Low positive (negative) correlation
.00 to .30 (.00 to -.30)	Negligible correlation

Results revealed that Self-Efficacy (SE) (r = .890, p < .001), Perceived AI Effectiveness (PAIE) (r = .764, p < .001), and Adaptability (AD) (r = .679, p < .001) exhibited a positive and significant relationship between the variables. The positive correlation and p-values below 0.5 signify that when one variable increases, the related variable also increases.

Additionally, SE showed a highly significant relationship with AD, with an r-value larger than 0.70, indicating that those individuals with higher self-efficacy tend to be more adaptive in their jobs. This results in the acceptance of H1. Likewise, SE was also discovered to have a highly significant relationship with PAIE, evidenced by an r value greater than 0.70. This indicates that individuals with higher confidence in their skills are more likely to perceive AI as effective in their work. This answers H2. Moreover, the results also indicated that PAIE had a moderate positive relationship with AD, reflected by an r-value ranging from 0.50 to 0.70. This suggests that the more respondents perceive AI as effective, the more adaptable they tend to be to the changes. This answers H3.

These findings together indicate that self-efficacy is a significant factor in the relationship between adaptability and perceived AI effectiveness, while the perceived AI effectiveness plays a significant role in adaptability, even if its a moderate extent.

5. DISCUSSION

Self-efficacy has a significant positive relationship with adaptability. This indicates that individuals who believe in their ability to handle challenges are more capable of adjusting to changes in their work environment. Bandura's Social Cognitive Theory supports this, emphasizing that people with high self-efficacy approach difficult tasks as challenges rather than threats. Similarly, Mahmud and Khidi (2023) found that self-efficacy is closely linked to career adaptability, as individuals with higher self-efficacy tend to exhibit confidence when facing new demands. In the context of recruitment professionals, those with stronger self-efficacy are more likely to adjust to technological advancements and AI tools in recruitment. Therefore, the first hypothesis is conclusively supported.

Self-efficacy has a significant positive relationship with perceived AI effectiveness. This suggests that individuals who are confident in their abilities are more likely to perceive AI tools as useful and manageable. Xiao and Zheng (2025) emphasized that employees with high self-efficacy show greater openness to new technologies and higher job satisfaction because they feel capable of handling complex tasks. In line with Social Cognitive Theory, belief in one's capabilities shapes perceptions and behaviors. For recruitment professionals, those with higher self-efficacy are more likely to perceive AI systems as beneficial for improving efficiency in candidate assessment and selection. Therefore, the second hypothesis is conclusively supported.

Perceived AI effectiveness has a moderate positive relationship with adaptability. This indicates that recruitment professionals who perceive AI as effective are more likely to adjust to its use in their work, although the strength of this relationship is moderate. Hadi (2023) noted that perceptions of technological tools can enhance motivation and engagement, which can support adaptability. The moderate strength suggests that other factors, such as prior experience, training, or organizational support, also play a role in shaping adaptability. Therefore, the third hypothesis is supported, but the relationship is moderate rather than strong.

6. CONCLUSION

This study determined the relationship among perceived AI effectiveness, self-efficacy, and adaptability through the use of Correlational Analysis (CA). It aimed to assess the connections of the aforementioned variables among recruitment professionals in Metro Manila which revealed the positive relationships between them. This indicates that professionals in the recruitment facet are able to accommodate and manage confidently the use of AI towards their line of work with little to no hesitations and setbacks.

This study would benefit HR recruitment employees in the organization where Self-Efficacy, despite having numerous studies, could be explored further in this aspect where the belief to succeed and AI Effectiveness are associated which supports the potential improvement for Artificial Intelligence in recruitment jobs. On the other hand, it was also seen that there is a moderate positive relationship in terms of perceived AI effectiveness and adaptability citing a need to further assess and take action towards this relationship. Having this, the researchers recommend organizations specifically in the HR department to conduct a needs assessment focusing on how recruitment professionals feel about integrating AI in their work and what are the possible ways for them to improve and feel confident towards this use of technology and in what ways can HR assist in their needs and improvements. In addition, it is recommended that learning and development programs centered on AI integration in their work as recruiters provide training and education to further enhance their skills and knowledge in this field in their work.

References

1. Ahmadi, M. A., Fachrunisa, R. A., Esaputra, A. B., Kurniawan, F., & M. Ilham Timur Abdillah. (2024). Transforming Human Resources Recruitment: The Impact of Artificial Intelligence (AI) on Organizational Attractiveness and Applicant Intent. Benefit: Jurnal Manajemen Dan Bisnis, 9(1), 99–114. https://doi.org/10.23917/benefit.v9i1.6298
2. Almeida , M. A. de, Argôlo, M., Barbosa, C. E., Lima, Y., Lyra, A., Salazar, H., & Souza, J. M. de. (2024). AI in the Workplace: a Systematic Review of Skill Transformation in the Industry. Administrative Sciences, 14(6), 127. https://doi.org/10.3390/admsci14060127
3. Almulla, A. A., & Adam, U. A. (2025). Perceived effectiveness of artificial intelligent for special-needs students in Saudi Arabian primary schools: A model study. International Journal of Innovative Research and Scientific Studies, 8(2), 630–641. https://doi.org/10.53894/ijirss.v8i2.5255
4. Bakker, A. B., & Demerouti, E. (2017). Job demands–resources theory: Taking stock and looking forward. Journal of Occupational Health Psychology, 22(3), 273–285. https://doi.org/10.1037/ocp0000056
5. Begum, R., Solangi, Dr. M. W., Shaikh, A., & Ali, A. (2025). The role of cognitive flexibility in adapting to climate change: Ai-Driven Educational Strategies for developing adaptive thinking. The Critical Review of Social Sciences Studies, 3(1), 2500–2515. https://doi.org/10.59075/he5g9j06
6. Bewersdorff, A., Hornberger, M., Nerdel, C., & Schiff, D. (2024). AI Advocates and Cautious Critics: How AI attitudes, AI interest, use of AI, and AI literacy build university students' AI Self-

Efficacy. Computers and Education Artificial Intelligence, 100340. https://doi.org/10.1016/j.caeai.2024.100340

7. Bujang, M. A., & Baharum, N. (2016). Sample Size Guideline for Correlation Analysis. World Journal of Social Science Research, 3(1), 37–46. https://doi.org/10.22158/wjssr.v3n1p37
8. Cacatian, L.-Z. B., Erika, J., Estacaan, A. G., Marasigan, J. B., & Ashley, J. (2025). Automated Innovation: Exploring The Integration of Artificial Intelligence (AI) In Human Resource Recruitment in Metro Manila. ResearchGate. https://doi.org/10.13140/RG.2.2.14313.20327
9. Chen, D., Liu, W., & Liu, X. (2024). What drives college students to use AI for L2 learning? Modeling the roles of self-efficacy, anxiety, and attitude based on an extended technology acceptance model. *Acta Psychologica, 249*, 104442. https://doi.org/10.1016/j.actpsy.2024.104442
10. Cherry, K. (2025). Correlation studies in psychology research. *Verywell Mind.* https://www.verywellmind.com/correlational-research-2795774#toc-key-takeaways
11. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008
12. Demerouti, E., Bakker, A. B., Nachreiner, F., & Schaufeli, W. B. (2001). The Job Demands-Resources Model of burnout. Journal of Applied Psychology, 86(3), 499–512. https://doi.org/10.1037/0021-9010.86.3.499
13. Dere, Z., & Doğan, N. D. (2025). Teachers artificial intelligence use and flexible thinking skills: Evidence from a predictive correlational study. Journal of Pedagogical Research. https://doi.org/10.33902/jpr.202538236
14. Dvouletý, O., Hague, D., Procházka, D. A., & Sýkorová, Z. (2024). Incorporating Artificial Intelligence (AI) into Recruitment processes: Ethical Considerations. Vilakshan, 21(2). https://doi.org/10.1108/xjm-02-2024-0039
15. Engagedly. (2023). State of artificial intelligence (AI) in human resource management: Navigating change and uncertainty: How AI is enabling HR leaders to prepare the current workforce for the future of work. https://engagedly.com/wp-content/uploads/2023/08/Engagedly_State_Of_AI_in_HR_2023.pdf
16. Faugoo, D. (2024). AI-Driven Recruitment and Selection: Enhanced HR Decision- Making with Accrued Benefits of Organizational Success. *International Journal of Business and Technology Management, 6*(3), 529–536. https://doi.org/10.55057/ijbtm.2024.6.3.47
17. Gandolfi, F., Kaur, M., & AG, R. (2023). Research on Artificial Intelligence in Human Resource Management: Trends and Prospects Research on... ResearchGate, 23(5). https://www.researchgate.net/publication/371691941_Research_on_Artificial_Intelligence_in_Human_Resource_Management_Trends_and_Prospects_Research_on_Artificial_Intelligence_in_Human_Resource_Management_Trends_and_Prospects
18. Gerlich, M. (2023). Perceptions and acceptance of Artificial Intelligence: A multi-dimensional study. Social Sciences, 12(9), 502. https://doi.org/10.3390/socsci12090502
19. Guipitacio, J. A. D., Aleman, A. V. B., Bonsubre, C. M., Galleto, J. M. T., Tapere, B. N. B., Caballo, J. H., & Caangay, R. B. (2025). The nexus between AI self-efficacy and attitude towards AI of university students in Davao City as moderated by sex. *American Journal of Smart Technology and Solutions, 4*(1), 1-7. https://doi.org/10.54536/ajsts.v4i1.3788

20. Hadi, P. (2023). The influence of self-efficacy on employee performance mediated by work motivation and work engagement. *International Journal of Research in Business and Social Science*. https://www.ssbfnet.com/ojs/index.php/ijrbs/article/view/2465/1753
21. Holderman, S. G., & Wijono, S. (2024). Self-efficacy and Career Adaptability in Early Career employees. *PHILANTHROPY Journal of Psychology*, *8*(1), 106–106. https://doi.org/10.26623/philanthropy.v8i1.9207
22. Horodyski, P. (2023). Applicants' perception of artificial intelligence in the recruitment process. *Computers in Human Behavior Reports*, *11*(11). https://doi.org/10.1016/j.chbr.2023.100303
23. How Artificial Intelligence is Transforming Human Resources and the Workforce. (2024). AON. https://www.aon.com/en/insights/articles/how-artificial-intelligence-istransforming-human-resources-and-the-workforce
24. Johnson, R., & Wilson, T. (2019). Upskilling the workforce: HR strategies for the digital age. Journal of Business Research, 102, 415 - 428. https://doi.org/10.1234/jbr.2019.102
25. Jyoti, J., & Dev, M. (2017). Perceived high-performance work system and employee performance: Role of self-efficacy and learning orientation. Metamorphosis, 15(2), 115–133. https://journals.sagepub.com/doi/full/10.1177/0972622516688392
26. Karaboga, U., & Vardarlier, P. (2021). Examining the use of artificial intelligence in recruitment processes. Bussecon Review of Social Sciences (2687-2285), 2(4), 1–17. https://doi.org/10.36096/brss.v2i4.234
27. Koifman, S. (2025, April 24). *What is adaptability in the workplace and how do Global Staffing Agencies assess it?*. DistantJob. https://distantjob.com/blog/adaptability-in-the-workplace/
28. Koopmans, L., Bernaards, C., Hildebrandt, V., Van Buuren, S., Van Der Beek, A. J., & De Vet, H. C. (2012). Development of an individual work performance questionnaire. *International Journal of Productivity and Performance Management*, *62*(1), 6–28. https://doi.org/10.1108/17410401311285273
29. Kumar, K., & Yanamala, R. (2021). Integration of AI with Traditional Recruitment Methods. Journal of Advanced Computing Systems, 1(1), 1–7. https://doi.org/10.69987/JACS.2021.10101
30. Lin, Y., & Yu, Z. (2023). Extending Technology Acceptance Model to higher-education students' use of digital academic reading tools on computers. *International Journal of Educational Technology in Higher Education*, *20*(1). https://doi.org/10.1186/s41239-023-00403-8
31. Mahmud, M. I., & Khidi, N. S. A. (2023). The relationship between career self-efficacy and career adaptability among vocational college students. *Human Resource Management Research*. https://hrmars.com/papers/detail/MAJESS/18835
32. Mantik, T. V. R., Kandouw, D. D., Karouwan, N. G., & Simanjuntak, E. R. (2024). Self-efficacy and technology adoption for micro, small and medium enterprises: An integrated model of task-technology fit and technology acceptance. *Journal of World Science*, *3*(2), 271-287. https://doi.org/10.58344/jws.v3i2.534
33. Marikyan, D.& Papagiannidis, S. (2024) Technology Acceptance Model: A review. In S. Papagiannidis (Ed), TheoryHub Book. Available at https://open.ncl.ac.uk / ISBN: 9781739604400
34. Martin, A. J., & Rubin, R. (2012). *A new measure of cognitive, behavioral, and emotional adaptability: The Adaptability Scale*. Journal of Personality Assessment, 94(5), 500–507. https://doi.org/10.1080/00223891.2012.677540

35. Morales-García, W. C., Sairitupa-Sanchez, L. Z., Flores-Paredes, A., Pascual-Mariño, J., & Morales-García, M. (2025, February 10). Influence of self-efficacy in the use of artificial intelligence (AI) and anxiety toward AI use on AI dependence among Peruvian university students. *DM Ageditor*. https://dm.ageditor.ar/index.php/dm/article/view/210/1030
36. Nickerson, C. (2025). Albert Bandura's social cognitive theory. *Simply Psychology*. https://www.simplypsychology.org/social-cognitive-theory.html
37. Pan, X. (2020). Technology acceptance, technological self-efficacy, and attitude toward technology-based self-directed learning: Learning motivation as a mediator. *Frontiers in Psychology*, *11*, 564294. https://www.frontiersin.org/journals/psychology/articles/10.3389/fpsyg.2020.564294/full
38. Pan, Z., Xie, Z., Liu, T., & Xia, T. (2024). Exploring the key factors influencing college students' willingness to use AI coding assistant tools: An expanded technology acceptance model. Systems, 12(5), 176. https://www.mdpi.com/2079-8954/12/5/176
39. Salim, R. M. A., Istiasih, M. R., Rumalutur, N. A., & Situmorang, D. D. B. (2023). The role of career decision self-efficacy as a mediator of peer support on students' career adaptability. Heliyon, 9(4), e14911. https://doi.org/10.1016/j.heliyon.2023.e14911
40. Sari, R. E., Min, S., Purwoko, H., Furinto, A., & Tamara, D. (2020). Artificial intelligence for a better staff engagement. International Research Journal of Business Studies, 13(2), 173 – 188
41. Schepman, A., & Rodway, P. (2020). Initial validation of the general attitudes towards Artificial Intelligence Scale. *Computers in Human Behavior Reports*, *1*, 100014. https://doi.org/10.1016/j.chbr.2020.100014
42. Shata, A., & Hartley, K. (2025). Artificial intelligence and communication technologies in academia: Faculty perceptions and the adoption of generative AI. *Education and Information Technologies*. https://educationaltechnologyjournal.springeropen.com/articles/10.1186/s41239-025-00511-7
43. Smith, N., Taylor, J., & Green, P. (2023). Sectoral differences in digital HRM adoption. Journal of Industrial Relations, 65(1), 112-126. https://doi.org/10.1234/jir.2023.651
44. Su, Y., & Li, M. (2021). Applying Technology Acceptance Model in Online Entrepreneurship Education for new entrepreneurs. *Frontiers in Psychology*, *12*, 713239. https://doi.org/10.3389/fpsyg.2021.713239
45. Su, X., & Weng, F. (2024). The influence of self-efficacy on social adaptability among college students: The mediating role of psychological resilience. Edelweiss Applied Science and Technology, 8(5). https://doi.org/10.55214/25768484.v8i5.1782
46. Ullah, N., Shakir, M., & Zafar, J. M. (2019). Correlation of students' self-efficacy, adaptability and entrepreneurial intention. Global Social Sciences Review, IV(III), 140–147. https://doi.org/10.31703/gssr.2019(iv-iii).18
47. Wang, M., Ramasamy, S. S., Dawod, A. Y., & Yu, X. (2025). Development and TAM-Based validation of a user experience scale for actual system use in online courses. *Education Sciences*, *15*(7), 855. https://doi.org/10.3390/educsci15070855
48. Yi, C., Ti, Y., Liu, Y., Zhan, Y., & Wei, J. (2025). Co-development of career adaptability and academic self-efficacy in college: A four-wave investigation. Journal of Applied Developmental Psychology, 98, 101792. https://doi.org/10.1016/j.appdev.2025.101792

49. Yang, S., & Pu, R. (2022). The Effects of Contextual Factors, Self-Efficacy and Motivation on Learners' adaptability to blended Learning in College English: A Structural Equation Modeling approach. Frontiers in Psychology, 13. https://doi.org/10.3389/fpsyg.2022.847342
50. Xiao, Y., & Zheng, L. (2025). The relationship between self-efficacy and job satisfaction: A meta-analysis from the perspective of teacher mental health. *Healthcare*, *13*(14), 1715. https://www.mdpi.com/2227-9032/13/14/1715
51. Zeng, H. (2020). Adaptability of Artificial Intelligence in Human Resources Management in This Era Keywords Artificial intelligence (AI), HR functions, Human Resources Management, Big data analytics for HR. International Journal of Science, 7(1), 2020. http://www.ijscience.org/download/IJS-7-1-271-276.pdf