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EXPLORING FAT-CAT MODEL OF AI ADOPTION IN AI-ENABLED RECRUITMENT: UNDERSTANDING THE MODERATING ROLE OF AUSTRALIAN RECRUITERS' PERCEPTION

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Article Info

Abstract

Recruitment is being transformed by incorporation of AI, which brings efficiency however also concerns the algorithms' transparency. The effects of AI's FAT-CAT model (explain-ability and augmentation capabilities) on teamwork, hiring, and morality in the Australian hiring process are the focus of this study. Quantitative data was researched and analyzed. To gather data, questionnaire was sent out to various human resources managers and recruiters in various industries in Australia. With a 5% margin of error, the sample size was 178 out of a population of 300. This study used snowball sampling. SPSS was used to analyze data to determine how explain-ability, augmentation, and human-AI adoption affect Australian recruitment. Moreover, moderation of individual perception was also investigated. Findings suggests that explain-ability characteristics marginally affect AI adoption, whereas augmentation features greatly do. AI's promise and problems in recruitment need user-friendly, bias-aware tools and continual recruiter coaching, according to the report. Ensure explain-ability, openness, and empower recruiters with continuing training. Individual perception moderates the association of explainability and augmentation features of AI adoption among Australian recruiters. AI should boost recruiters' skills without replacing human judgement, preserving their crucial position in talent acquisition.

Keywords:
Explain-ability features, Augmentation features, AI Adoption, Recruitment.

Introduction

Artificial Intelligence (AI) implies the use of transformative force in decision making in Human Resource Management to create value for employee, organizations, and customers. The successful AI adoption demands more than just high-tech investment; it stresses the leadership devotion, upskilling of labor force, cultural compliance, and cross-functional alliances (Mohamed, Matimbwa, and Banzi, 2025). Recruitment previously got interest of researchers (Shahzadi & Raja, 2021b) for its knowledge-based applicability in producing effective workforce in knowledge intensive tasks (Shahzadi & Ali, 2021; Shahzadi & Raja, 2021b).

This transition prompts study into how machine intelligence will affect human work and HR management's human-machine partnership dynamics. It examines how AI technology affects candidate selection in recruitment and selection (Harness, 2019). These strategies save time and improve recruitment process. AI may be utilized in recruitment in subsequent ways. For instance, for prediction and analyses, using past data and trends, AI has the knack to forecast those applicants who are more likely to be qualified and efficacious for a job (Malisetty, 2017). For talent acquisition, AI software may use advanced algorithms to explore many social media and job sites, effectively identifying and compiling a diverse pool of possible applicants (Varsha, 2023). For automated interview scheduling, by synching the calendars of all stakeholders, AI software may organize a meeting at the most suitable time for all of them (Yaseen, 2021). For video interview analysis, a framework for "automated video-interview analysis" considers the broad proficiencies of speech recognition, pattern recognition, and the knack to evaluate candidate's aptness (Chen, 2023). For performance management, real-time feedback tools and predictive analysis can be used as an AI application (Mikalef and Gupta, 2021). Additionally, for skills assessment and testing, AI-based skill assessments offer a high degree of validity e.g., objectivity, interpretively, efficiency, scalability, data privacy and biasness (Patel, 2001). For diversity and inclusion, AI based technical audit tools while training for diversity and inclusion can be used as non-technical audit tools. It will help identify and mitigate biases in HR processes (Rodgers et al., 2022).

In addition, for EEO considerations, AI is pprogramed to guarantee adherence to Equal Employment Opportunity philosophies, by producing a suitable applicant pool devoid of demographic biasness. In addition to examining the ethical ramifications of employing AI in selection and recruitment procedures, Hunkenschroer (2022) addresses transparency, impartiality, and bias, with a specific focus on EEO. Moreover, for employee orientation, **s**streamlining the induction procedure for employees can be achieved by providing them with an extensive library of queries, appropriate answer generators, and helpful hints. For employee well-being, mental health chatbots and stress analytics can be used to detect burnout signs and recommends interventions (Margherita and Bua, 2021). For employee career sustainability, the establishment of trust in AI and its effective implementation within an organization are both positively correlated with employee career sustainability (Kong, 2021).

Explainability (FAT) and augmentation (CAT) features of FAT-CAT model encourage ethics and confidence in recruitment process. Explain-ability in AI adoption refers to comprehending and interpreting AI system decisions. It lets applicants comprehend the reasons why they were chosen or refused, it also helps cultivating trust and objectivity (Amodei, Olah, Steinhardt, Christiano, Schulman, & Mané, 2016).

In contrary, augmentation features of AI adoption use AI to encourage human recruiters instead of substituting them with AI. Miller (2020) found that AI automates the interview organizing and resume screening. It consequently facilitates recruiters to focus on mounting relationships. It is critical to assess how much explainable AI is, hence, to enhance fairness, trust, and openness in hiring practices. AI may also be benefited for other tasks e.g., resume screening and applicants fitting, while lucratively leveraging human proficiencies.

A variety of industries are extensively using AI as a latest trend in recruitment process (Nugent and Scott-Parker, 2022). AI cannot inevitably swap humans, rather it complements the complex, recurring, and time-laborious jobs (Mikalef and Gupta, 2021). Consequently, Black & van Esch (2020) contemplates AI technology as the foremost new-fangled component of Digital Recruiting 3.0. AI adoption is also influenced by the recruiters' perception of AI adoption for AI-enabled recruitment. Therefore, the study objectives are:

RO1: To examine the impact of explain-ability features on AI adoption among Australian recruiters.

RO2: To examine the impact of augmentation features on AI among Australian recruiters.

RO3: To inspect the moderating impact of individual perception on the relationship between explain-ability features and AI adoption among Australian recruiters.

RO4: To inspect the moderating impact of individual perception on the relationship between augmentation features and AI adoption among Australian recruiters.

Literature Review:

The Technology Acceptance Model (TAM) is a well-known framework used to analyze the adoption of new information technology (Davis, 1989). As determinants of technology adoption, the model pinpoints two key beliefs that impact users' behavioral intention to use technology. Perceived usefulness is the extent to which a person believes that a technical tool will help them carry out their responsibilities more effectively. The degree of difficulty that a person anticipates a certain technological job to entail is known as perceived simplicity of usage.

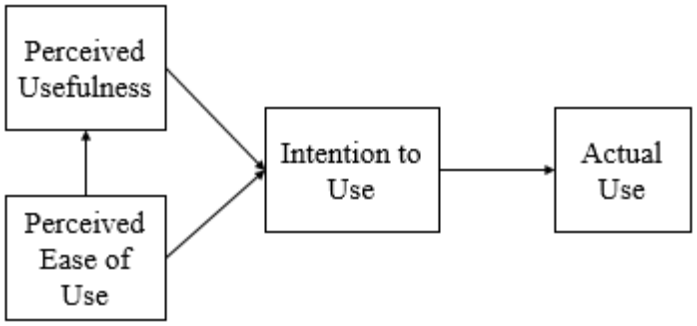

Figure 1: TAM Model (Marikyan, 2023)

FAT-CAT Model of AI Adoption in AI-Enabled Recruitment:

Artificial intelligence adoption refers to the use and integration of these technologies (Lee and Cha, 2023). It comprises putting AI tools and systems into place to automate tasks, increase the effectiveness of the hiring process, and improve decision-making. It also involves adapting organizational structures and practices to AI-driven changes while ensuring that staff members receive sufficient education and training.

The tools of AI-enabled recruitment are altering the conventional mode of recruitment processes (Horodyski, 2023). AI, or artificial intelligence, is the term for human intelligence displayed by machines. Candidates may find it challenging to distinguish between human and AI actions during interviews or surveys because of AI tools which are settled to mimic brainy human activities e.g., speech recognition, graphic perception, and even mobile conversations (e.g., AI-driven chatbots). AI is one of the utmost cutting-edge HR technologies to date, and it can be highly effective, particularly in the hiring process. Time-consuming tasks are cut down or eliminated, resume evaluations are streamlined and automated, candidates' current abilities and job needs are more effectively and efficiently matched, and prompt decision-making is made possible (Vedapradha et al., 2019). Any AI-based verdicts or recommendations must be based on the initial inputs (e.g., scope) that the programmers' set before the interaction with the potential applicant; neither humans nor other AI tools should add inputs during the interaction phase. This is necessary to fully utilize AI in the hiring process. AI has shown effectiveness in diverse fields, e.g., speech recognition, natural linguistic processing, visual perception, and speech-to-text transformation.

According to Vedapradha et al., (2019), the subsequent AI-enabled hiring tools have been unified into the hiring process: The US-based startup "Hirevue" analyzes audiovisual interviews of job applicants using video intelligence, giving employers additional information to help them make decisions more quickly. In support of HRM, the National Aeronautics and Space Administration (NASA) revealed that 86% of HR tasks could be accomplished without human interaction when they used AI-enhanced HR processes (Davenport & Ronanki, 2018).

Successful AI adoption can result in industry-wide and business transformations, increased productivity, and a competitive edge. Numerous studies validate the ability of algorithms to swiftly evaluate resumes and classify ultimate candidates (Chen, 2023). Furthermore, companies hire chatbots to greet applicants, assist interview scheduling, and engage them in humanistic dialogues (Hogg, 2019). Such customized AI tools enable the evolution to a contemporary recruitment procedure e.g., Unilever cut hiring time by 30% by employing AI-powered hiring programs to ensure diversity inclusion. IBM also leverages AI set of rules to match best applicant, screen resumes, and do a predictive analysis (Danoch, 2024).

The existing body of research has frequently concentrated on recruitment tools or techniques that are based on artificial intelligence (AI), rather than offering an inclusive overview of the techniques in which AI is revolutionizing the recruitment industry. The FAT-CAT model of AI adoption is a conceptual framework that explains how different perceived characteristics of artificial intelligence influence its acceptance, particularly in HR and recruitment settings. AI adoption depends on the balance between FAT (fairness, accountability, and transparency) and CAT (complexity, anxiety, trust) features. FAT features

are the attributes of explainability while, the CAT features are the attributes of augmentation features of AI adoption. Recruiters go for AI-enabled recruitment when it's equally trustworthy and capable of progressing their selection processes (Lee and Cha, 2023).

Explainability (FAT) Feature of AI (XAI) Adoption:

Explain-ability refers to the capacity to comprehend the reasoning behind the decisions or outputs of an AI system. It is the capacity to elucidate the mechanisms by which an algorithm operates and the rationales behind the generation of outcomes. It is a powerful tool to enhance performance of AI models (Mersha, Yigezu, Tonja, Shakil, Iskander, Kolesnikova, and Kalita, 2025). XAI consists of comprehending what prompted the AI to select a particular option? Which characteristics was it deemed most essential? From what data did the AI acquire knowledge, and how has this influenced its output? To what extent is the AI susceptible to biases inherent in the data or its design, and what strategies can be implemented to mitigate these risks?

It was clarified by the Defense Advanced Research Projects Agency in the figure shown below:

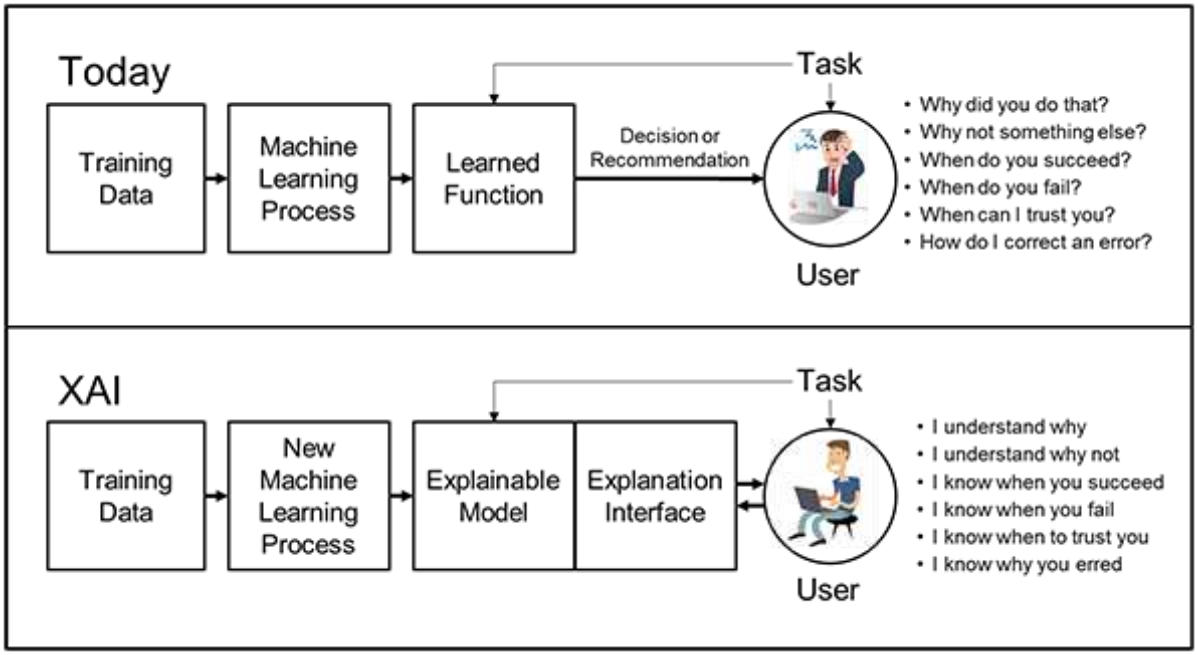

Figure 2: Explain-ability Feature of AI (XAI) (Gunning, 2016)

The implementation of explain-ability techniques may prove advantageous in the reduction of hazards associated with deployed systems or the improvement of progress forecasting in AI. As stated by Rauker (2023). These may encompass, yet are not restricted to, educating users on fundamental concepts such as algorithms, models, and data. Lee & Cha (2023) has exhibited that the FAT model presents transparency about explain-ability. FAT model is conceptualized and operationalized as fairness, accountability, and transparency. Fairness is the impartial (e.g., race, gender, religion etc.) considerations in the recruitment process (Ochmann, 2019) which ensures inclusiveness. **Accountability** ensures

shielding the security and secrecy of confidential information (Diakopoulos, 2016) while **transparency** is in decision-making process stipulates translucent explanations for choices.

Augmentation (CAT) Features of AI Adoption:

The augmentation feature supports the human-robot alliance to point out the role of AI in strengthening their talents (Johnson, 2021). Whereas the standard procedures for data augmentation may mess up the contextual coherence, noise, lack of control, and overfitting (Mersha, et al., 2025). AI's augmentation feature is based on three mechanisms: complexity, anxiety, and trust (Lee & Cha, 2023). These components constitute the later portion of the FAT-CAT paradigm, which pertains to AI explain-ability and augmentation. Incorporating AI into the decision-making process may increase its **complexity** since managing an AI-generated system requires the utilization of its own resources. While the AI recruitment system shrinks the volume of data that needs to be processed, its operation may increase in complexity if recruiter training is required. Although AI-based recruitment systems have the capability to eliminate ineligible candidates, they also require recruiters to invest significant time and effort in coordinating their personal and professional lives (Van Esch, 2019). The rationality of AI decision-making can only then be deemed acceptable. **Anxiety** emerges during the recruitment process when the scorer's ambiguity potentially introduces regrettable partiality. Employers who have solely been privy to the algorithm's objectivity may be less concerned about losing qualified candidates. By using an augmented AI system that integrates equity by alerting users to the bias at work, anxiety can be reduced (Shahzadi, Ali, and Arshad, 2019), claims (Ochmann, 2019).

When an AI system is **trusted**, it means that it is dependable and aligned with the organization's benefits. Because recruiters must evaluate candidates based on incomplete information sources, like resumes or curriculum vitae, the hiring process is inherently unpredictable. By incorporating the explainability techniques and language models in the data augmentation, the gap amid improving model performance and retaining interpretability (Mersha, et al., 2025) will be reduced. To lower the dangers and uncertainties that could arise from inadequate knowledge, Arrieta's (2020) study investigated how well AI tools can inspire confidence in algorithms. According to several studies, improving coordination is necessary to create a positive relationship between people and AI (Lee and Cha, 2023). Both parties may lessen each other's limitations, which will lead to better decision-making. The study's hypotheses are as follows:

H1: There is a favorable association of explain-ability features and AI adoption among Australian recruiters.

H2: There is a favorable association of augmentation features and AI adoption among Australian recruiters.

Individual/Recruiters' Perception in Shaping AI-Adoption:

The application of AI technologies to various recruitment roles is called AI-enabled recruitment. AI may simply facilitate the automated communication using chat bots or more vigorously optimize the

selection process to detect high-potential applicants. Predictive analytics and neuroscience tools surrogate HR professionals to curtail human biasness and improve applicants' emotional, cognitive, and behavioral attributes to improve selection decisions. AI is progressively beneficial in automating recurring recruitment activities e.g., resume assessment, interview scheduling, and feedback provision, while likewise evaluating the current employees to reinforce more informed hiring decisions. To appeal more talent, recruiters displaying jobs on social media, nevertheless this surge in applications eventually made classifying the best-fit candidates ever more challenging for HR (Michailidis, 2018).

The UTAUT is widely applied since it is a unified model that cartels a diversity of variables from eight major theories i.e., Theory of Reasoned Action, Technology Acceptance Model, Motivational Model, Theory of Planned Behavior, Decomposed Theory of Planned Behavior, Model of PC Utilization, Innovation Diffusion Theory, and Social Cognitive Theory (Alam, Dhar, and Munira, 2020). It is suggested that overall, four primary factors serve as key determinants of technology use i.e., effort expectancy, performance expectancy, and social influence. These factors unswervingly impact behavioral intention, though facilitating conditions directly influence the actual usage behavior (Heikkilä and Smale, 2011). Performance expectancy refers to how much individuals believe the system will improve their work performance. Effort expectancy reflects how easy-going the system is to use. Social influence captures the degree to which individuals feel that others think they should use the system. Facilitating conditions describe the extent to which individuals believe that enough organizational and technical support exists to enable system use (Attuquayefio and Addo, 2014).

Artificial Intelligence (AI) has developed to a level where it can automate extensive divisions of the hiring activity, thereby reshaping the role of recruiters and HR professionals. Despite this advancement, limited research explores recruiters' perceptions of AI (Horodyski, 2023), and little is understood about the factors that drive its use in their workplaces. This study investigates recruiters' intentions to adopt AI by extending the Unified Theory of Acceptance and Use of Technology (UTAUT) to incorporate AI usage frequency and education.

H3: Individual perception *moderates the association of explain-ability features and AI adoption among Australian recruiters.*

H4: Individual perception *moderates the association of augmentation features and AI adoption among Australian recruiters.*

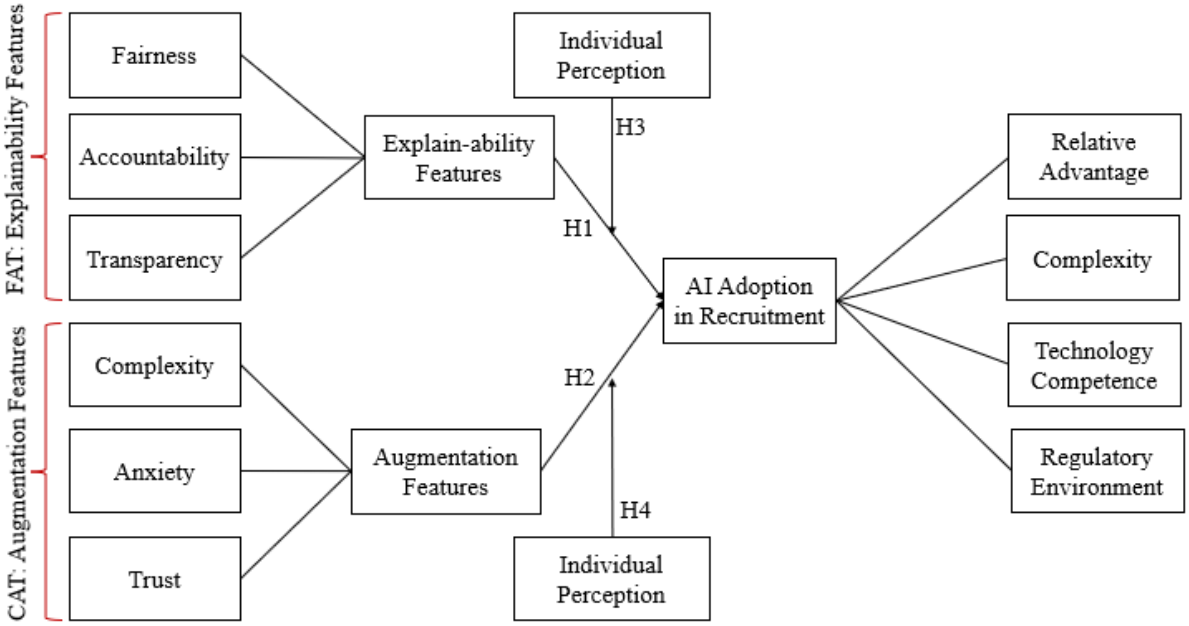

Figure 3: Hypothetical Research Model

METHODOLOGY

Data was gathered from primary sources, including questionnaires given to recruiters and HR managers, as well as secondary sources, including relevant research publications. The unit of analysis, which included recruiters and HR managers from different companies, answered 27 questions on the questionnaire. The survey employed a 7-point Likert scale. "Strongly disagree" (1) and "Strongly agree" (7) are at opposite ends of the scale. The use of AI in recruitment has been impacted by research in the field, specifically by Nawaz (2019) and Lee and Cha (2023), who examined the exchange of human interaction and the explainability and augmentation of AI systems in the recruitment context.

Table 1: Measuring Items

Variables	**Item**	**N**	**Reference**
Explain-ability	Fairness	2	Shin (2021)
	Accountability	2	
	Transparency	2	
Augmentation	Complexity	5	Pan (2021)
	Anxiety	5	Meuter (2003)
	Trust	3	Shin (2021)
Individual Perception	Individual Perception	6	Horodyski (2023)
AI Recruitment System Adoption	AI Recruitment System Adoption	14	Autry (2010); Wang (2010); and Zhu (2006)

Directly engaged in the recruitment process, HR managers and recruiters comprise the target audience. Geographic regions in Australia with high technology adoption constituted the sampling frame. The primary emphasis was on regions renowned for technological advancements and the integration of AI to attract organizations that are probable users of AI for recruitment purposes.

Primarily, snowball sampling was utilized for the sampling process. These individuals possessed practical knowledge of AI tools and technologies and were able to offer insightful commentary on their efficacy, difficulties, and influence on their respective fields of work. Contact was established with them via email, LinkedIn, website searches, and additional social media platforms. With a margin of error of 5%, the sample size was 178 out of a population of 300 (Saunders, 2007).

DATA ANALYSIS

Correlation:

SPSS-26 was used to analyze data (Shahzadi, Ali, and Ejaz (2023). Pearson's correlation coefficient (r) was employed to quantify correlation. It gauges a linear relationship's direction and strength. Its value ranges from -1 to 1. A high negative correlation is shown by r=-1, and a strong positive correlation is shown by r=1. There is no correlation if r=0. R value 0.512 depicts explain-ability and augmentation features are moderately correlated with each other in a direct relationship. Moreover, r value 0.475 depicts that explain-ability feature and AI adoption are also moderately correlated with each other in a direct relationship. Additionally, r value 0.741 depicts that augmentation feature and AI adoption are significantly associated with each other in a positive direction.

Reliability:

To evaluate a measurement tool's or scale's consistency and dependability, reliability analysis was done. Cronbach's alpha, which measures the internal consistency of a set of survey items, was computed to assess the reliability (Shahzadi, Ali, and Arshad, 2024). On a scale of 0 to 1, the values that are closer to 1 indicate greater reliability and agreement. According to Taber (2018), a Cronbach's alpha value of 0.7 is deemed adequate.

Table 2: Cronbach´s Alpha

	No. of Items	**Cronbach´s Alpha**
Explain-ability	6	0.758
Augmentation	13	0.785
Individual Perception	6	0.816
AI adoption	14	0.854

Direct Relationship Analysis:

Multiple regression was used to observe the direct association among variables (Ali & Shahzadi, 2019). The model's ability to use the predicting variables to elucidate the disparity in the response variable, is gauged by two statistics: R and R2. A complete negative correlation is signified by a value of -1, no correlation is embodied by a value of 0, and a perfect positive correlation is characterized by a value of 1.

Table 3: Model Summary & ANOVA Results

Model	**R**	**R Square**	**Adjusted R Square**	**F**	**Sig.**
1	.749[a]	.562	.557	112.144	.001

There is a strong positive association, as indicated by the R=0.749, which is near to 1. A strong positive correlation is regarded as solid proof of a relationship. The coefficient of determination, or R2, illustrates the extent to which the explanatory variables account for the change in the outcome variable. It ranges from 0 to 1, where 0 signifies no variation can be explicated by the model, while 1 signifies that variance can be explicated by the model. R2 = 0.562 indicates that 56.2% of the variation in the response variable can be explained by the regression model using the predictor variables. It indicates a relatively good fit amid the model and the data.

To determine whether there are statistically momentous differences between the means of two or more groups in the data, an Analysis of Variance (ANOVA) was also conducted. The likelihood that the observed differences between groups were the result of chance is indicated by the p value. A p-value of less than 0.05 is preferred (Shahzadi & Ali, 2020). A good fit model is indicated by a p-value of less than 0.05.

Table 4: Coefficient Table

Hypotheses		**Unstandardized Coefficients**		**Sig.**
		B	Std. Error	
		1.068	.273	.001
H1	ExFtC	.102	.046	.027
H2	AuFtC	.694	.060	.001

The estimated change in the DV for a one-unit increase in the IV is indicated by the "B" values. The requirement is that we maintain the same values for every other variable. These p-values correspond to the t-tests. Since p is less than 0.05, H1 is accepted (β=.102, P=.027). H2 is also accepted (β=.694, P=.001).

Indirect Relationship Analysis:

The indirect hypotheses (moderation) were analyzed for each of the direct relationship hypotheses by using the PROCESS Macro (Preacher and Hayes' Model 1) in SPSS. H3 states that individual perception moderates the relationship between explainability features and AI adoption among Australian recruiters. H3 is accepted. It implies that a recruiter's propensity to embrace AI is influenced by explainability qualities (such transparency, interpretability, and intelligible decision-making) based on their level of work experience. For instance, there may be a bigger positive correlation between explainability traits and AI adoption if recruiters with more individual perception place a higher priority on explainability. On the other hand, when determining whether to use AI technologies, people with less expertise might be less concerned with transparency and, as a result, less swayed by explainability.

H4 is also accepted. This indicates that "among Australian recruiters, individual perception moderates the association of augmentation features and AI adoption." It implies that the influence of augmentation features (such AI's capacity to improve hiring efficiency, aid in decision-making, or lessen manual labor) on AI adoption also differs according to work experience. For instance, there may be a larger positive correlation between augmentation features and adoption if seasoned recruiters are more receptive to utilizing AI that enhances their judgment and aids in better hiring selections. A weaker or different link may result from less experienced recruiters adopting such technologies despite their potential for enhancement or feeling threatened by them. Both values of R and R square have been increased as compared to the direct relationships (Shahzadi & Ali, 2022) which means that moderation exists.

Table 5: Moderation Analysis Using PROCESS Macro (Model 1)

Model	Predictor	B	SE	t	P	LLCI	ULCI
H3	Explainability Features (Ex)	0.355	0.078	4.55	<0.001	0.201	0.509
	Individual Perception (W)	0.127	0.062	2.05	0.042	0.005	0.249
	Int_1	0.414	0.081	2.64	0.003	0.054	0.373
H4	Augmentation Features (Au)	0.018	0.061	.446	<0.001	0.310	0.551
	Individual Perception (W)	0.151	0.091	1.423	0.451	0.004	0.281
	Int_2	0.301	0.046	1.375	0.004	0.044	0.482

Note: B = Unstandardized coefficient; SE = Standard Error; LLCI = Lower-Level Confidence Interval; ULCI = Upper-Level Confidence Interval.

Discussion and Recommendations:

Four hypotheses were designed to meet the study objectives. It is found that H1 is accepted, these findings are consistent with preceding studies (Lee & Cha, 2023), which found that organizations which put forward explainability features in AI systems have more AI adoption rates since it enhances trust. H2 is also accepted, these findings are consistent with the preceding research which accentuated the prominence of augmentation feature of AI adoption in diverse sectors. The acceptance of H3 and H4 reveals an important realization: the use of AI in hiring is influenced by the adopters' human traits,

particularly their degree of work experience, in addition to the functional aspects of the technology, such as explainability and augmentation. These outcomes are aligned with the conclusions of Horodyski (2023).

This study highlights that an effective AI adoption need efforts of both technology and humans. To bridge the variance of potential of AI tools and applicant's trust, recruiters' perception must blend the behavioral intuitions in the FAT-CAT design. Besides, it is recommended to the prospect researchers to further investigate the influence of AI adoption on HRM practices especially in the recruitment process to enrich the FAT-CAT model in the developing economies. The forthcoming research should also perform longitudinal considerations to investigate the sustained value of AI adoption policies and to further discover the added factors which may impact the AI adoption. Auxiliary studies should investigate the impact of user-experience and usability of AI interface to facilitate AI adoption. It will offer significant insights for HR practitioners who are struggling with the AI implementation in recruitment processes. Therefore, impending studies can staunchly focus on the influence of complexity, and uncertainty on AI adoption. Role of metaverse in AI adoption will be an interesting insight into the AI adoption in recruitment.

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