

Hiring with Algorithms: What Makes Human Resource Personnel Adopt the Artificial Intelligence Recruitment in China?

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ABSTRACT

Manuscript type: Research paper

Research aims: This study examines the factors affecting Artificial Intelligence (AI) recruitment among human resource personnel in China, drawing from an integration of Unified Theory of Acceptance and Use of Technology (UTAUT) 2 and Value-Based Model (VAM).

Design/Methodology/Approach: A quantitative approach using questionnaires was employed. Data collected from 272 HR practitioners in China were analysed using SPSS and AMOS.

Research findings: The results show that performance expectations, effort expectations, social influence and facilitating conditions influence perceived values and adoption of AI recruitment. Perceived values are found to mediate the relationship between the four factors and the adoption of technology.

Research limitations: The study is limited to human resource personnel in China. It uses a cross-sectional design, which can only be able to capture data at one point in time. The use of self-reported data may also introduce bias.

Practical implications: Enterprises should fully leverage social influence by using digital champion approach, besides providing continuous technical support and training. They should also promote how the AI

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recruitment can lead to efficient and effective processes. These measures will boost human resource personnels' perceived value of AI recruitment, thereby significantly strengthening their willingness to adopt and use it effectively.

Originality/Value: This study extends the UTAUT model by integrating VAM, which is applied to an emerging technology, AI recruitment application in China.

Keywords: AI Recruitment, UTAUT, VAM, Perceived Value, China

JEL classification: 030,032,035

1. Introduction

The rapid development of China's economy and market competition has increased the complexity of managing human resources among the Chinese organisations. They are currently dealing with rising recruitment costs encompassing organisational expenses related to hiring, job advertisement, recruiter compensation, background checks and training. In a survey conducted by the China Association for Human Resource Management, it was reported that an enterprise spends in average 5,000 to 7,000 yuan for hiring process. In high-end industries, namely finance and technology, the figure is much higher than the average, especially for positions that require complex screening procedures and multiple rounds of interviews (Zhang et al., 2025). In addition to costs, Chinese organisations are also facing a long hiring cycle, which is around 60 days (LinkedIn, 2022).

Considering these challenges, many of them have started to use artificial intelligence (AI)-enabled recruitment systems to automate their hiring processes (Meshram, 2023). More than 70 per cent of large businesses reported 30 per cent faster hiring cycles with the adoption of emerging technology (Nayak et al., 2024). In Shanghai for example, 91.58 per cent of firms acknowledged the use of AI in recruitment process, with large firms recorded as the primary users (Sun, 2024). The widespread adoption of AI recruitment implies that this technology is no longer positioned as an experimental tool. Instead, it is increasingly being incorporated into the hiring process. Given the growing reliance on AI recruitment, it becomes imperative to understand how HR professionals evaluate and respond to such tools, specifically in regard to perceived value, trustworthiness and willingness to adopt them. Moreover, the use of AI in managing human resource functions remains an ongoing exploration (Islam et al., 2024), with various depths and scopes (Lisa & Talla Simo, 2021). The technology is widely used in the recruitment of fresh graduates

and seasonal workers, which is simpler, as compared to a more senior post of knowledge-intensive vacancies. Further research in this area is thus viable.

Previous literature has predominantly focused on the technical aspects of AI, its' function and applications in human resource (HR) domains. On one hand, many studies have documented the role of AI-enabled recruitment system as a means to simplify the hiring process. For instance, Halid et al. (2024) and Jia and Hou (2024) demonstrate the use of automated resume screening, predictive analytics, chatbots and workforce analytics in human resource management (HRM). They highlight that through such AI-driven applications, HR professionals can focus on higher-value added tasks, human capital planning and decision-making. Technology can support objective assessment in recruitment process, by allowing standardised evaluation of candidate profiles (Mollah et al., 2024). These studies show that the use of AI in recruitment can potentially lead to efficient and data-driven decision-making. On the other hand, there are also studies that report on the challenges associated with AI, particularly on bias and fairness issues. This is due to the fact that AI is trained on historical data, which can perpetuate existing inequalities in society (Akter et al., 2021; Sony, 2025). The algorithm bias can emerge from flawed assumptions and incomplete datasets, which may lead to misclassification and exclusion. There are also studies that explore the roles of managerial and organisational readiness in AI implementation (Sandeep et al., 2024). Several studies have applied theoretical models such as Unified Theory of Acceptance and Use of Technology (UTAUT) and Technology Acceptance Model (TAM) to systematically examine the factors affecting intention to use AI recruitment from the psychological and experiential perspective of recruiters (Almeida et al., 2025; Tanantong & Wongras, 2024; Islam et al., 2024; Alam et al., 2020), and job applicants (Wang & Surienty, 2024). Nevertheless, they focus on countries such as India, Bangladesh and Thailand. While theory such as UTAUT has been employed in the AI-recruitment context, its application may not be able to capture the issue holistically. In AI recruitment, concerns relating to fairness, algorithmic bias and transparency are increasingly salient, highlighting that the technology adoption decisions may not depend solely on functional considerations. Instead, HR professionals may require to simultaneously whether the overall benefits outweigh their potential risks and uncertainties. In China, such concerns are relevant as educational prestige, gender and hierarchical organisational cultures

remain influential in recruitment decisions (Wang & Yu, 2022). In addition, many firms were also reported to have insufficient IT infrastructure that are robust to safeguard the personal data collected, even if the candidate is unsuccessful. For example, in 2019, a database of 33 million profiles of Chinese job seekers containing sensitive personal details such as an individual's username, age, home address, email address, phone number, marital status, job history and salary history was leaked. Hence, integrating perceived value is imperative as it captures recruiters' broader cost-benefit evaluations toward AI recruitment systems. Ignoring perceived values may result in organisations investing heavily in AI recruitment technologies that employees ultimately resist using due to concerns about trust, fairness, or professional consequences.

This research looks at the perceptions of people who are involved in recruitment processes towards AI adoption in their job scopes. Differ from majority of studies in the area, this study extends the UTAUT model by incorporating VAM in determining the factors influencing them to adopt AI-recruitment. Incorporating VAM is important since AI not only offers potential benefits, yet it is also associated with risks. Hence, recruiters' evaluation of the balance between perceived advantages and potential risks, which is referring to "perceived values" may act as a driver that determine their acceptance towards AI (Kim et al., 2007; Al-Abdullatiff, 2023). While technology adoption decisions are often made at the organisational level, this study focuses on the individual level, specifically HR professionals who are involved in recruitment processes. This is due to the fact that extensive research in information systems suggests that employees' willingness to use technology is a critical determinant of its actual adoption and effective utilisation (Venkatesh, 2022). Findings from this study are expected to supplement the existing literature by providing insights into AI recruitment in China. It also extends the UTAUT model by including perceived values as a mediating variable. The understanding of the determinant factors will help organisations and developers of technology in China when providing an AI recruitment environment.

This paper is organised as follows. Section 2 reviews the existing literature which helps identify research gaps and build conceptual framework of this study. Section 3 describes the methodology adopted in this study, namely the sampling frame, data collection techniques and data analysis approaches. Section 4 provides report on data analysis, while Section 5 discusses the results of this study. Section 6 concludes by providing the implications of the research as well as its limitations and suggestions for future research.

2. Literature Review

2.1 *AI in Recruitment*

The purpose of recruitment is to obtain enough qualified candidates in a timely manner and employ the right candidate from the pool. To achieve this objective, organisations are required to quickly and effectively identify high quality candidates, irrespective of their geographical location. In traditional settings, the recruitment process is time-consuming, requiring substantial administrative efforts (Michailidis, 2018). Today, AI has increasingly been used in various business functions, including HRM, in numerous industries across the globe. In the recruitment process, AI has been introduced as a tool to screen resumes, schedule interviews and conduct preliminary evaluations, enhancing efficiency and reducing operational costs (Allal-Cherif et al., 2021).

AI is considered a “unique” technological tool as compared to others, since it is claimed to be equipped with intelligent capabilities. This characteristic allows the technology to function autonomously by relying on the information collected and processed through its interactions with the surroundings (Gonzalez-Garcia et al., 2017). The use of AI in recruitment process varies to some degree. At the basic level, AI is used as a chatbot, which communicates with applicants through text messages, social media and any other preferred channels 24/7 (Upadhyay & Khandelwal, 2018). L’Oreal for instance, utilises the “Mya Systems” chatbot to ask questions, verify credentials and respond to job applicants queries on company culture, policy and benefits (Lisa & Tally Simo, 2021). Through this process, the chatbot pre-screens the job applicants and identifies whether they are suitable for the role. Given that the number of job applicants have increased due to online advertisements and online submissions, Upadhyay and Khandelwal (2018) highlight that HR professionals are experiencing difficulties in finding the most suitable talents. Thus, the offers provided by AI in recruitment help make the process more efficient, as it can be completed within a shorter time. While an HR professional spends 45 minutes on screening, scheduling and conducting interviews, AI can complete the whole procedure in under five minutes.

Despite the benefits of AI in recruitment, previous studies have also highlighted various concerns in using such technology (Rigotti & Fosch-Villaronga, 2024; Hunkenschroer, & Luetge, 2022; Khair et al., 2020). Some of the key concerns include biases in the data that are used to train algorithms which are subject to fairness, ethical

and legal issues. Since AI relies on previous datasets, the trained model tends to be built based on biased algorithms, which may result in AI favouring a certain group of candidates. For example, Amazon encountered this problem, as the algorithm used was built based on performance data which was dominated by white male employees. This resulted in AI assigning higher scores to male white applicants. These ethical and fairness concerns show the importance of incorporating perceived value. Despite the efficiency offered by AI recruitment, recruiters may simultaneously associate the technology with risks, reducing the overall value evaluations of the technology. Hence, perceived value becomes an important mechanism through which recruiters balance expected benefits against potential sacrifices or uncertainties. Another growing concern is the use of AI in recruitment has also affected society's trust in the companies that utilise them, as AI algorithms are not transparent to the public (Figueroa-Armijos et al., 2022). In line with this, Mirowska and Mesnet (2022) found that job applicants prefer to keep humans in the recruitment process loop, although humans have inherent biases, since such biases are perceived as more familiar and predictable compared to the uncertainty and opacity often associated with algorithmic decision-making. In some literature, it is also highlighted that the use of AI in recruitment differs between the types of jobs as well as positions (Lisa & Talla Simo, 2021).

2.2 Underpinning Theory and Conceptual Development

A major aspect of understanding the adoption of AI-based recruitment tools involves looking at the theories that explain how people and organisations take up new technologies. One of the most frequently applied models in technology adoption research is the Unified Theory of Acceptance and Use of Technology (UTAUT), which was created by Venkatesh et al. (2003). UTAUT integrates several earlier theories on technology acceptance, such as the Technology Acceptance Model (TAM), the Theory of Planned Behaviour (TPB), and the Diffusion of Innovations (DOI). UTAUT states that four main factors, namely performance expectancy, effort expectancy, social influence, and facilitating conditions impact an individual's behavioural intention (intent to use) and usage behaviour in adopting new technology. This theory has been used in various technology adoption studies, including AI-recruitment (Tanantong & Wongras, 2025; Lee et al., 2021; Alam et al. 2020). Notably, these studies identify different sets of significant determinants, suggesting that the factors influencing AI recruitment adoption are context

dependent. This variation indicates that institutional, cultural, and labour market conditions shape adoption dynamics, thereby justifying the application and empirical validation of this model within the Chinese context. While different factors emerge in various studies, this model ensures 70 per cent accuracy (Venkatesh et al., 2003) in analysing behaviour-related technology usage, indicating the model as a reliable framework.

While UTAUT is a robust model which is commonly utilised to examine an individual's acceptance of new technologies, the factors are limited to predicting an individual's decision-making process in accepting or rejecting new technologies. To address this limitation, this study adopts the value-added model (VAM) which incorporates the concept of perceived values. Kim et al. (2007) highlights perceived values as an important predictor of usage intention and acceptance. This variable is described as "a cost-benefit" paradigm that represents the individuals' decision to accept or to reject is depending on whether the cost of uncertainty is lower than the benefits that they can obtain. Considering that AI-recruitment does not only offer potential benefits but also associated with risks (Figuerola-Armijos et al., 2022), this study extends the UTAUT model by including perceived values. Therefore, in this study, perceived values help capture how decision-makers evaluate the overall worth of AI recruitment relative to its costs, risks, and consequences. In organisational settings, particularly HR, people do not adopt AI simply because it exists or is efficient; they adopt it because they believe it creates net value.

2.2.1 UTAUT and Value-Added Model (VAM) Perspectives

In the context of AI recruitment, integrating UTAUT and VAM is particularly important. This is because although recruiters may perceive the technology as useful in terms of optimising the hiring process, they simultaneously hold concerns relating to algorithmic bias, fairness, transparency, accountability and the potential of over-reliance on automated decision-making. Such concerns may lower the value of AI recruitment among its users. They need to sacrifice on these matters in order for them to reap the benefits of AI recruitment. This shows that relying solely on UTAUT may provide incomplete explanation of AI recruitment adoption, as the model does not explicitly capture how users evaluate ethical and professional trade-offs associated with AI technologies.

Hence, integrating both UTAUT and VAM therefore offers a valuable theoretical contribution as it combines technological

belief factors with broader value evaluations. In AI recruitment environments, HR professionals are not only evaluating whether the technology improves performance or is easy to use, but also whether the benefits outweigh potential ethical, organisational, and professional risks. This integration is particularly relevant in high-stakes HR contexts where recruitment decisions may significantly affect fairness, diversity, and organisational legitimacy.

Based on the integration of the two models, in this study, it is postulated that the four factors – performance expectancy, effort expectancy, social influence and facilitating conditions – will influence perceived values of AI-recruitment, which in turn will determine the adoption of technology (Figure 1). While the original UTAUT model considers gender, age, experience and education as moderating factors between performance expectancy, effort expectancy, social influence and facilitating conditions and usage intention, this study does not incorporate the demographic variables. This is following the results of previous studies on information system used in HR domain which did not find the effects of gender, age, and education as having significant influence (Menant et al., 2021).

Performance Expectancy (PE) refers to the degree to which HR professionals believe that using an AI recruitment tool will help them improve their job performance. In this sense, the use of AI can outperform humans through its abilities in screening job applications and extracting specific skills and personality attributes from a candidate's records, including their social media presence, in a timely manner (Huang et al., 2023; Alam et al., 2020). Incorporating AI into the recruitment process also gives HR professionals more time to do value added tasks, while reducing monotonous jobs (Lisa & Tally Simo, 2021). When HR professionals perceive that AI recruitment can accelerate hiring processes, improve decision quality, and reduce routine workload, they are more likely to evaluate the technology as beneficial relative to its associated costs, thereby enhancing perceived value. At the same time, strong performance-related beliefs also directly motivate the adoption of technology, as they expect it to improve their work outcomes (Al Mamun, 2022). Accordingly, this study proposes the following hypotheses:

H_1 : Performance expectancy is positively related to perceived values

H_2 : Performance expectancy is positively related to AI recruitment adoption

Effort Expectancy (EE) refers to the degree of which the technology is perceived to be used easily. This variable evaluates how user-friendly is the interface, the simplicity of interaction flows, and effort needed to learn the system (Zhao et al., 2025). It is expected that when information system applications or technologies are complex and a challenge to use, users will see it as low value. In this sense, recruiters who find AI applications easy to operate and master are more likely to evaluate the technology as beneficial relative to its costs, thereby increasing perceived value (Delecraz et al., 2022). Moreover, perceived ease of use directly reduces barriers to adoption. Based on this reasoning, the following hypotheses are proposed:

H_3 : Effort expectancy is positively related to perceived values

H_4 : Effort expectancy is positively related to AI-recruitment adoption

Social Influence (SI) refers to the degree to which an individual values the opinions of others from their social environment including peers, superiors, and management when using a new technology. In an organisation, the use of AI-recruitment can be socially influenced by colleagues or superiors promoting AI tools (Rahman et al., 2024). Positive recommendations regarding new technology from colleagues and co-workers or pressures from upper-level management may persuade recruiters to use AI-recruitment (Horodyski, 2023). As they see many people surrounding them promoting or using AI applications, they may also recognise the potential of the technology and appreciate its value. Consequently, recruiters may be more inclined to evaluate AI recruitment as valuable, as social endorsement helps frame the technology as beneficial rather than risky. At the same time, perceived expectations from influential others can directly motivate compliance and adoption behaviour, thereby strengthening intention to use AI recruitment systems. Based on this reasoning, the following hypotheses are proposed:

H_5 : Social influence is positively related to perceived values

H_6 : Social influence is positively related to AI recruitment adoption.

Facilitating conditions (FC) refers to the resources, infrastructure and support needed to use a technology. In the context of AI recruitment systems, facilitating conditions might involve having access to training programmes, technical help, and the appropriate hardware or software setup required to run the system. Previous

literature found that when an organisation offers training classes and ongoing IT assistance related to AI recruitment software, HR professionals are more likely to make use of it (Li, et al., 2021). Facilitating conditions reduce the effort, uncertainty, and resource demands associated with AI recruitment applications, enabling HR professionals to effectively realise the benefits of using the system. As a result, employees are more likely to evaluate AI recruitment systems as worthwhile, thereby enhancing their perceived value. Moreover, the availability of adequate support and infrastructure lowers practical barriers to using the technology. Based on this reasoning, the following hypotheses are proposed:

H_7 : Facilitating condition is positively related to perceived values

H_8 : Facilitating conditions is positively related to AI recruitment adoption

Perceived value refers to an individual's overall evaluation of the utility of an item, such as goods, services or technology, which is relying on their perceptions of the efforts or costs spent and gained benefits (Zeithaml, 1988). It is determined by the trade-off between the benefits gained from the decisions and the efforts required to make the decision (Xie et al. 2021). Various consumer behavioural studies have demonstrated the positive impact of perceived value on individuals' attitudes (Roy 2016; Xie et al. 2021). In the technology acceptance field, Yan et al. (2021) and Sun et al. (2021) have acknowledged the role of perceived values in influencing consumers' intention to adopt FinTech services. Based on this argument, this study proposes that:

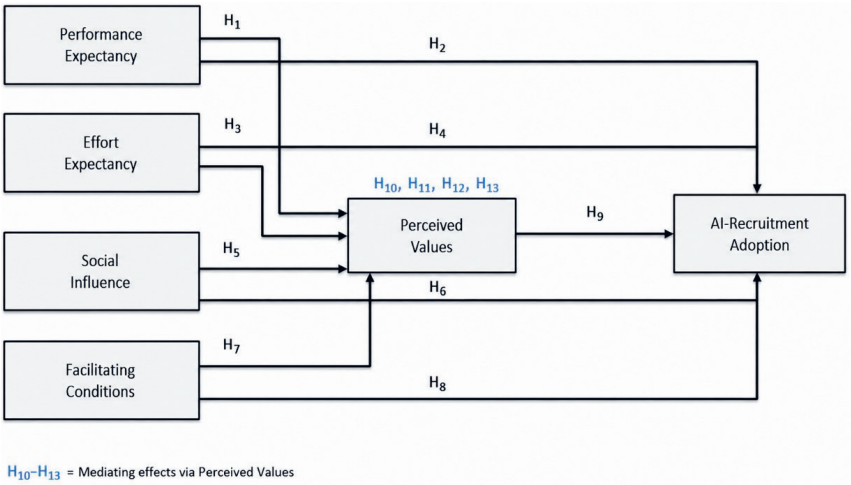
H_9 : Perceived value is positively related to AI recruitment adoption

Although performance expectancy, effort expectancy, social influence, and facilitating conditions are expected to directly influence intention to use AI recruitment systems, this study argues that these effects are also transmitted through perceived value. Perceived value expresses employees' overall evaluation of whether the benefits of AI recruitment outweigh their associated costs and risks. Accordingly, perceived value is positioned as a mediating mechanism that translates belief-based assessments into behavioral intention. Based on this argument, this study proposes that:

H_{10} : The relationship between performance expectancy and AI-recruitment adoption is mediated by perceived values

- H_{11} : The relationship between effort expectancy and AI-recruitment adoption is mediated by perceived values
- H_{12} : The relationship between social influence and AI-recruitment adoption is mediated by perceived values
- H_{13} : The relationship between facilitating conditions and AI-recruitment adoption is mediated by perceived values

Figure 1: Conceptual Framework



3. Research Methodology

3.1 Research Design and Measurements

To test the hypotheses and determine the relationships depicted in Figure 1, this study employed quantitative techniques. A cross-sectional design data collection, measuring attitudes at a single point in time was also utilised. Multiple items from the literature were adapted as measurements, which were used in the online-based structured questionnaire. The items AI-Recruitment Adoption was measured using four items. Perceived value was assessed by items capturing respondents’ overall evaluation of whether the benefits of using AI recruitment outweigh its associated costs and risks. Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions were measured using established items commonly employed in technology adoption research. Measurement items, graded on a 5-point Likert scales ranging from strongly disagree = 1 to strongly agree = 5 were used. Table 1 depicts the operationalisation of constructs. As the items were adapted to capture

the unique characteristics of AI recruitment, expert panel validation was conducted. These items were first validated by three experts in the field, who have substantial experience and knowledge in AI. The evaluation process showed that the level of agreement among the three experts was 91.5 per cent. As the data collection was conducted in China, and the respondents were non-English speakers, this questionnaire was translated into Mandarin, in line with suggestions from Brislin (1970). A pilot study involving 30 respondents was conducted to determine whether the questionnaire was clear, easy to comprehend and can be completed in a given time. Following the pilot study, minor adjustments were made to refine the questionnaire, which was subsequently sent to the respondents.

Table 1: Operationalisation of Constructs

Construct	Measurement item	Source
Performance Expectancy	PE1: I think AI is useful in carrying out recruitment tasks.	Venkatesh et al. (2003), Tanantong and Wongras (2024)
	PE2: I think that AI makes recruitment process faster.	
	PE3: I think AI can increase efficiency of recruitment work.	
	PE4: I think using AI can help analyse candidates more accurately.	
Effort Expectancy	EE1: I would find the AI based recruitment software easy to use.	Venkatesh et al. (2003), Tanantong and Wongras (2024)
	EE2: I think it would be easy to learn how to use the interface of AI based recruitment software.	
	EE3: For me, it will not take long to be skillful in using AI in recruitment.	
	EE4: I think AI in recruitment would be flexible for use.	
Social Influence	SI1: There is proportion of co-workers using the AI recruitment software in my organisation.	Venkatesh et al. (2003), Tanantong and Wongras (2024)
	SI2: Those who use AI in recruitment would have more advantages than those who do not.	
	SI3: People whose opinion I value prefer me to use AI recruitment software.	
	SI4: I think the introduction of AI in recruitment into our company will be trendy in my industry.	

Construct	Measurement item	Source
Facilitating Conditions	FC1: I expect to call a technical support team in case of facing any problems. FC2: I expect that the system would be available in both computer and mobile devices. FC3: I think guidance would be available in AI based recruitment system.	Venkatesh et al. (2003), Tanantong and Wongras (2024)
Perceived Value	PV1: I think that using AI in recruitment is worth investing. PV2: I feel that using AI can remain quality of recruitment process consistently. PV3: I realise that using AI in recruitment will give the organisation the social approves. PV4: I feel that using AI in recruitment will make impression on candidates.	Hosain et al.(2025), (Mori et al.2025)
Adoption of AI-Recruitment	IU1: I use AI tools on regular basis to perform related recruitment tasks. IU2: I effectively integrate AI tools with my work process. IU3: I actively learn practical applications of AI recruitment to implement them. IU4: I use AI in recruitment process to its full potential.	Bhardwaj et al. (2021), Chatterjee et al. (2021)

3.2 Sampling Technique and Populations

The target population for this study is HR professionals working in various sectors. This study employed a purposive sampling technique to recruit participants. Only HR professionals with direct involvement in recruitment process and possess sufficient familiarity with AI recruitment systems are chosen. In this study, purposive sampling is deemed as appropriate techniques since it requires information-rich respondents who are capable of providing informed evaluations of recruitment process and AI usage. Given that the study examines employees' adoption of AI recruitment, it is necessary to target individuals who are directly involved in recruitment decision-making or system use, rather than a random sample of employees who may lack relevant exposure. This approach ensures that the collected data accurately reflects informed perceptions and experiences related to AI recruitment adoption. This will help in ensuring the validity

of findings. Three inclusion criteria were used: 1) participants are 18 years old and above; 2) participants work as full-time HR professionals in recruitment process; 3) participants have experience with AI recruitment tools.

To determine the minimum required sample size, this study used G*Power 3.1 through an a priori power analysis. Assuming a medium effect size ($f^2 = 0.15$), a significance level of $\alpha = 0.05$, and a statistical power of 0.80, the analysis indicated a minimum required sample size of 92 respondents. The final sample size of 272 respondents therefore substantially exceeds the minimum requirement, indicating adequate statistical power for hypothesis testing.

3.3 Data Collection

Questionnaires were distributed to HR professionals actively engaged in recruitment process in China. Participants were recruited through various online platforms, including LinkedIn and Facebook, via a link directing them to an online questionnaire hosted on Wenjuanxing, a local online platform. To ensure that the study was conducted in an ethical and responsible manner, prior to questionnaire distribution, participants received an email containing the description of the study, including the purpose and methods. All participants were also reminded that their participation was voluntary, and their answers were confidential. The survey took about 15 to 20 minutes to be completed. 500 questionnaires were sent out, with 306 returned, indicating 61 per cent response rate. However, 34 invalid responses were detected, and they were excluded from further analysis. With responses from 272 respondents, the sample was deemed sufficient to run the conceptual model developed. Table 2 provides the respondent profiles.

Table 2: Demographic Characteristics of Respondents

Categories	Dimensions	Frequency	Percent (%)
Workplace	Domestic	267	98.2
	Overseas	5	1.8
Gender	Male	105	38.6
	Female	167	61.4
Age	Under 25	26	9.6
	25–34	68	25.0
	35–44	60	22.1
	45–54	105	38.6
	54 and above	13	4.8

Categories	Dimensions	Frequency	Percent (%)
Educational Background	Bachelor	79	29.0
	Master	20	7.4
	Doctor	5	1.8
	Others	168	61.8
Position	Staff	214	78.7
	Supervisor/ Team Leader	37	13.6
	Manager/Department Head	13	4.8
	Director/Executive	8	2.9
Work Experience (Years)	0-3	35	12.9
	3-5	18	6.6
	5-10	48	17.6
	10-15	48	17.6
	15 and above	123	45.2
Industry Type	Agriculture & Food Industry	30	11.0
	Information Technology	8	2.9
	Manufacturing	4	1.5
	Healthcare	135	49.6
	Finance	12	4.4
	Services	19	7.0
	Energy & Utilities	9	3.3
	Consumer Goods Industry	3	1.1
	Others	52	19.1
Organisational Size (Number of Employees)	Fewer than 25	92	33.8
	26-50	45	16.5
	51-200	101	37.1
	201-500	11	4.0
	More than 500	23	8.5

As indicated in Table 2, majority of respondents were employed in local organisations (98.2%) as compared to multinational organisations (1.8%). This suggests that the findings represent perceptions shaped by local organisational and institutional environments. More than 60 per cent of them were females. This is not surprising considering that in China, the recruitment and human resource functions are typically dominated by females (Hu et al., 2022). It was also noted that the largest age group of respondents was between 45 to 54 years old (38.6%), reflecting that they were in the mid-to-late career stage, and were expected to have substantial experience in recruitment processes. In terms of education, only 29 per cent of them possess a bachelor's degree, suggesting that the sample represents a practitioner-oriented workforce, rather than an academically concentrated group. The "Others" category

primarily consisted of respondents possessing diploma qualifications, vocational education, professional certifications, technical training backgrounds, and other non-degree qualifications commonly associated with practitioner-oriented HR positions in China. These categories were grouped together due to relatively small individual frequencies and to simplify the presentation of demographic information.

In this study, a substantial proportion of respondents (49.6%) were from the healthcare sector and may potentially influence the AI recruitment adoption. Given this, an additional post-hoc analysis was conducted to examine whether industry type significantly influences the results. An independent t-test was conducted, and the analysis comparing the two groups – healthcare and non-healthcare showed that there were no statistically significant differences between them (Table 3). This suggests that the findings are unlikely to be substantially driven by industry-specific effects.

Table 3: Post-Hoc Analysis of Industry Type and AI Recruitment Adoption

Variables	Healthcare Industry (n=135)	Non-Healthcare Industries (n=137)	t-value	p-value
	Mean	Mean		
Adoption of AI Recruitment	2.79	2.70	1.124	0.262
Perceived Value	2.95	2.87	0.984	0.326

3.4 Data Analysis

The data was initially imported and organised using the Statistical Package for the Social Sciences (SPSS) version 25. Subsequently, it was analysed using co-variance based structural equation modeling (CBSEM), as the conceptual model was developed using well-established theories (Narimawati & Sarwono, 2024). By using CBSEM, several dependent variables with measurement errors can be estimated simultaneously (Hidayat & Wulandari, 2022). There were two primary phases adopted. In phase one, measurement model was constructed and the factor loadings, internal consistency reliability, convergent validity, and discriminant validity was examined. In the second phase, a structural model was formed based on the measurement model results. This structural model will be used for hypothesis-testing among the variables in the conceptual model.

4. Analysis and Findings

4.1 Measurement Model Analysis

A measurement model incorporating all the constructs in the conceptual framework was evaluated. Two psychometric tests, namely validity and reliability were performed based on the model generated. As represented by Table 4, all the constructs had composite reliability (CR) values of more than 0.7. In addition to composite reliability, this study also assessed the Cronbach’s alpha coefficients. The analysis showed a value of between 0.846 to 0.869, indicating a satisfactory degree of reliability. In addition to composite reliability, this study also evaluated convergent validity, through item outer loadings and average variance extracted (AVE). As shown in Table 3, the outer loadings of all items ranged from 0.650 to 0.882, passing the threshold value of 0.6, indicating each item can effectively measure its corresponding construct. The AVE values of all constructs ranged from 0.579 to 0.654, greater than the cut-off values of 0.5, indicating good convergent validity of each construct (Bentler & Bonett, 1980).

Table 4: Reliability and Validity Constructs

Factors	Item	Outer loading	Cronbach’s alpha	Composite reliability	Average variance extracted
PE	PE1	0.882	0.862	0.865	0.619
	PE2	0.650			
	PE3	0.808			
	PE4	0.789			
EE	EE1	0.844	0.843	0.846	0.579
	EE2	0.715			
	EE3	0.726			
	EE4	0.752			
SI	SI1	0.872	0.853	0.860	0.608
	SI2	0.828			
	SI3	0.699			
	SI4	0.704			
FC	FC1	0.813	0.85	0.850	0.654
	FC2	0.791			
	FC3	0.821			
PV	PV1	0.694	0.866	0.869	0.624
	PV2	0.854			
	PV3	0.790			
	PV4	0.814			

Factors	Item	Outer loading	Cronbach's alpha	Composite reliability	Average variance extracted
AI	IU1	0.834	0.855	0.857	0.601
	IU2	0.728			
	IU3	0.761			
	IU4	0.774			

Notes: PE= Performance Expectancy, EE=Effort Expectancy, SI=Social Influence, FC=Facilitating Conditions, PV= Perceived Values, AI=AI Recruitment Adoption

In this study, discriminant validity was evaluated using the Fornell-Larcker criterion (Fornell & Larcker, 1981). All the scales appeared to have a substantially higher AVE value compared to their correlation with other constructs, providing evidence of discriminant validity (Table 5).

Table 5: Descriptive Statistics and Correlation Analysis

	M	SD	PE	EE	SI	FC	PV	IU
PE	2.90	1.11	0.787					
EE	2.93	1.13	0.247***	0.761				
SI	2.98	1.09	0.289***	0.376***	0.779			
FC	2.93	1.19	0.322***	0.382***	0.339***	0.808		
PV	2.91	1.07	0.389***	0.430***	0.450***	0.423***	0.790	
AI	2.74	1.08	0.448***	0.502***	0.541***	0.513***	0.570***	0.775

Notes: PE= Performance Expectancy, EE=Effort Expectancy, SI=Social Influence, FC=Facilitating Conditions, PV= Perceived Values, AI=AI Recruitment Adoption; Values on the diagonal are the square roots of AVE (in parentheses); * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

In addition to Fornell-Larcker criterion, this study also evaluated the discriminant validity using HTMT. All HTMT values between constructs are significantly lower than 0.90, indicating that there is clear distinctiveness between constructs, and no conceptual overlap exists (Henseler et al., 2015). The HTMT values between constructs range from 0.248 to 0.571, with generally low values, which further verifies the independence and discriminant validity of each variable in this study

Table 6: HTMT Analysis

	PE	EE	SI	FC	AI	PV
PE	-					
EE	0.248	-				
SI	0.288	0.377	-			
FC	0.322	0.382	0.339	-		
AI	0.449	0.502	0.541	0.513	-	
PV	0.389	0.431	0.451	0.424	0.571	-

Notes: PE= Performance Expectancy, EE=Effort Expectancy, SI=Social Influence, FC=Facilitating Conditions, PV= Perceived Values, AI=AI Recruitment Adoption

The result of the measurement model showed that various validity and reliability criteria were satisfied. Therefore, the measurement model can be used to examine the structural model and its associated hypotheses.

4.2 Structural Model Analysis

The structural equation model was estimated using AMOS 28.0 with the maximum likelihood method. The model fit indices (Table 7) meet or exceed the recommended thresholds: $\chi^2/df=1.731$ (<3.0), SRMR=0.042 (<0.08), RMSEA=0.052 (<0.08), IFI=0.954, TLI=0.945, CFI=0.953 (>0.90), indicating a good fit between the hypothetical model and the observed data. The R^2 value for PV is 0.421, indicating that PE, EE, SI, and FC collectively explain 42.1% of the variance in PV, which demonstrates a moderate explanatory power. The R^2 value for AI Recruitment Adoption is 0.640, indicating that PE, EE, SI, FC, and PV jointly account for 64.0 per cent of the variance in AI, reflecting a substantial level of explanatory power and suggesting that the model exhibits strong predictive capability.

To examine the hypotheses, this study analysed the size of standardised path coefficients (β), the standard error (SE), t -Values (t), and their respective significance levels (p -values). Table 7 shows the results of direct hypotheses testing. As indicated in Table 7, performance expectancy ($\beta = 0.214$, $SE = 0.052$, $t = 3.289$, $p = 0.001$), effort expectancy ($\beta = 0.213$, $SE = 0.061$, $t = 2.91$, $p = 0.004$), social influence ($\beta = 0.246$, $SE = 0.063$, $t = 3.471$, $p < 0.001$), and facilitating conditions ($\beta = 0.217$, $SE = 0.056$, $t = 3.0$, $p = 0.003$), were positively significant to perceived values. These results indicated that H_1 , H_3 , H_5 and H_7 were supported. In addition, performance expectancy ($\beta = 0.182$, $SE = 0.058$, $t = 3.183$, $p = 0.001$), effort expectancy ($\beta = 0.194$, SE

= 0.068, $t = 3.004$, $p = 0.003$), social influence ($\beta = 0.256$, $SE = 0.072$, $t = 4.041$, $p < 0.001$), and facilitating conditions ($\beta = 0.235$, $SE = 0.063$, $t = 3.662$, $p = 0.001$), were positively significant to AI recruitment adoption. These results indicate that H_2 , H_4 , H_6 and H_8 were supported. This study also demonstrated a significant relationship between perceived values and AI recruitment adoption ($\beta = 0.226$, $SE = 0.089$, $t = 3.251$, $p = 0.001$), supporting H_9 .

Table 7: Direct Hypothesis Testing

Hypothesis	Path	Estimate	S.E.	C.R.	P	Result
H1	PE→PV	0.214	0.052	3.289	0.001	Supported
H2	PE→IU	0.182	0.058	3.183	0.001	Supported
H3	EE→PV	0.213	0.061	2.910	0.004	Supported
H4	EE→IU	0.194	0.068	3.004	0.003	Supported
H5	SI→PV	0.246	0.063	3.471	***	Supported
H6	SI→IU	0.256	0.072	4.041	***	Supported
H7	FC→PV	0.217	0.056	3.000	0.003	Supported
H8	FC→IU	0.235	0.063	3.662	***	Supported
H9	PV→IU	0.226	0.089	3.251	0.001	Supported

Notes: PE= Performance Expectancy, EE=Effort Expectancy, SI=Social Influence, FC=Facilitating Conditions, PV= Perceived Values, AI=AI Recruitment Adoption; Model fit criteria: $\chi^2/df < 3.00$; SRMR < 0.08; RMSEA < 0.08; IFI > 0.90; TLI > 0.90; CFI > 0.90. "****" indicates $p < 0.001$.

The bias-corrected bootstrapping method (5,000 samples, 95% confidence interval) was used to test the mediating effect of perceived value between performance expectancy, effort expectancy, social influence, facilitating conditions and AI recruitment adoption. Perceived value mediates the effects of performance expectancy (indirect effect = 0.048, 95% CI = [0.017, 0.108], $p = 0.004$), effort expectancy (indirect effect = 0.048, 95% CI = [0.014, 0.114], $p = 0.014$), social influence (indirect effect = 0.056, 95% CI = [0.017, 0.122], $p = 0.006$), and facilitating conditions (indirect effect = 0.049, 95% CI = [0.011, 0.117], $p = 0.015$) on AI recruitment adoption, supporting Hypotheses H_{10} , H_{11} , H_{12} , and H_{13} . These findings indicate that while the four antecedents directly influence intention to use, they also exert indirect effects through perceived value, suggesting that perceived value plays a partial mediating role. In essence, beliefs regarding performance benefits, ease of use, social endorsement, and facilitating conditions enhance adoption of AI recruitment systems

by strengthening respondents’ overall value evaluations of the technology.

The partial mediation of perceived values and high R^2 value (AI recruitment adoption) shows that performance expectancy, social influence and facilitating conditions do not influence adoption solely through recruiters’ evaluation of the value of the technology. Instead, these variables also affect the AI recruitment adoption directly. This implies that HR professionals adopt AI recruitment technology although the value assessments are not fully established, specifically in business environments where the digitalisation efforts are strongly promoted by the national agenda or institutionally embedded. The findings are particularly relevant in the Chinese organisational context, where collectivist cultural values and hierarchical organisational structures may strengthen normative pressures toward technology adoption. For example, social influence may operate not only because recruiters genuinely perceive AI recruitment systems as valuable, but also because management expectations, peer usage, and organisational policies encourage conformity toward digital transformation initiatives. Consequently, AI recruitment adoption appears to be simultaneously value-driven and socially reinforced.

Table 8: Mediating Path Coefficients

Hypothesis	Path	Estimate	Lower	Upper	P	Result
H_{10}	PE→PV→IU	0.048	0.017	0.108	0.004	Supported
H_{11}	EE→PV→IU	0.048	0.014	0.114	0.014	Supported
H_{12}	SI→PV→IU	0.056	0.017	0.122	0.006	Supported
H_{13}	FC→PV→IU	0.049	0.011	0.117	0.015	Supported

5. Discussion

This study extends the existing literature by providing empirical evidence on AI recruitment adoption in the context of Chinese firms. The findings demonstrate that performance expectancy, effort expectancy, social influence, and facilitating conditions significantly shape AI recruitment adoption, both directly and indirectly through perceived value. The findings highlight that adoption decisions in AI-enabled recruitment are not purely technology-driven but are embedded in value evaluations, social surroundings and psychological beliefs.

The significant effects of performance expectancy on both perceived value and AI recruitment adoption indicate that

Chinese HR professionals strongly associate AI recruitment with productivity gains, speed, and improved matching quality. This finding is consistent with previous studies conducted in Bangladesh (Islam et al., 2024). In the Chinese environment, the labour market is characterised as highly competitive and organisations typically receive large volumes of applications (Wang & Yu, 2022). In order to grab skillful and talented employees, they need to efficiently process the applications within a tight timeline. In such situations, technologies that demonstrably improve task performance are more likely to be evaluated as valuable and worthy of adoption. Therefore, while many firms are aware of the potential drawbacks and ethical issues linked to the AI recruitment process, the clear benefits and the fast-paced competition for recruits outweigh these concerns.

The positive effects of effort expectancy on perceived value and intention underscore the importance of usability in AI recruitment systems. This is consistent with previous literature in AI environment (Horoydoski, 2023). Given the demographic profile consists of a substantial proportion of respondents who do not hold formal university degrees, and are between the ages of 45 to 55, this finding is expected. For these users, intuitive interfaces and ease of handling the AI recruitment applications become particularly important. To them, complex or technical demanding systems may appear disruptive rather supportive (Nguyen et al., 2024). This reflects that AI recruitment technologies are valued not for their sophistication alone, but for their accessibility and immediate contribution to work efficiency. The substantial significant effect of effort expectancy on AI recruitment adoption may also relate to the issue of interface familiarity and workflow compatibility, rather than solely technological complexity. Since almost 40 per cent of the respondents were between 45 and 54 years old, ease of use may be interpreted differently. Instead of perceiving technology itself as a barrier, the older recruiters may be concerned about whether the technology aligns with established work routines and recruitment practices. Since these age group of HR professionals typically have accumulated extensive work experience over many years, technologies that demand them to adjust their behaviour or work practices may introduce unfamiliar interactions, which can be disrupted. Consequently, user-friendly interfaces, intuitive navigation, and seamless integration into existing HR workflows become particularly important in shaping positive evaluations toward AI recruitment systems.

This study also found a strong direct and indirect effect of social influence on AI recruitment adoption, in line with Alam et al. (2020) and Chatterjee et al. (2021). As Chinese cultural context is attributed by collectivism culture, respect for hierarchy, and sensitivity to social norms (Li et al, 2025), HR professionals are particularly attentive to the attitudes and behaviours of their peers, supervisors, and senior management when deciding to use AI or not in their job functions. The mediation through perceived value suggests that social influence does more than exert compliance pressure. Instead, it actively shapes how AI recruitment is evaluated. When AI tools are endorsed or visibly used by influential people in organisations, they are framed as legitimate, beneficial, and aligned with organisational expectations, thereby enhancing perceived value and reducing uncertainty associated with algorithmic decision-making.

The significant role of facilitating conditions, both directly and indirectly via perceived value, highlights the importance of organisational or institutional readiness in AI recruitment adoption. This finding is in line with previous UTAUT studies. Chinese government is investing significantly in digitalisation (Zong & Guan, 2025). They have gradually integrated emerging technologies such as AI, cloud computing, and blockchain for their economy and society (Wang, 2024). In the environment where the digitalisation is heavily emphasised by the government, the presence of training programmes, technical support, and adequate infrastructure signals that AI recruitment is a strategic investment. Such signals enhance employees' confidence that the technology can be effectively used and supported over time, thereby increasing its perceived value and encouraging intention to use.

6. Implications and Conclusions

6.1 Theoretical Implications

This study extends the UTAUT model by incorporating perceived values as a mediating variable. The findings confirm the viability of combining UTAUT factors with perceived values in AI adoption research, specifically in the context of recruitment. The results demonstrate perceived values to be a significant mediator in predicting how performance expectancy, effort expectancy, social influence and facilitating conditions affect recruiters' acceptance of AI adoption in performing their job functions. The more recruiters perceived AI as valuable tools, with benefits outweighing risks, the more willing they were to adopt them. This yields a theoretical

implication, as it highlights perceived value as a powerful determinant in the context of AI recruitment technology acceptance. In AI recruitment, where concerns about fairness, accountability, and professional risk are salient, HR professionals appear to rely on perceived value to integrate expected benefits, effort considerations, social endorsement, and organisational support into a single judgment that guides adoption decisions. This finding extends prior AI recruitment research by demonstrating that adoption is not solely belief-driven but value-driven, especially in high-stakes HR functions. It is important that, in future investigations in the context of human resource management, consider the perceived value component as a mediating variable for adopting AI-based tools.

These findings, therefore, suggest the potential for a modified VAM-UTAUT framework in future AI adoption research, specifically those that involve high-risk professional environments. While traditional UTAUT model primarily focuses on cognitive and behavioural beliefs such as usefulness, effort expectancy, social influence, and facilitating conditions, the VAM model demonstrates the importance of perceived value in translating the technological beliefs into actual adoption. Integrating value-based perspectives with traditional technology acceptance frameworks may provide a more comprehensive theoretical explanation of AI adoption behavior in ethically sensitive and high-stakes organisational environments.

6.2 *Practical Implications*

The findings of this study provide several practical implications for organisations seeking to implement or scale AI-enabled recruitment systems, particularly within the Chinese organisational context.

First, to cultivate the use of AI recruitment, organisations should demonstrate how such technology could improve job performance, such as shortening hiring cycles, improving candidate matching accuracy and reducing administrative workload. Managers can communicate the benefits through piloting the system or benchmarking exercise. Highlighting the efficiency in a measurable manner would help recruiters translate the technological capabilities into perceived tangible value, strengthening their decisions to adopt. To outweigh the benefits more than the risks, organisations need to follow strictly on data privacy rules and publicly highlight the use of AI security certifications and appropriate data processing procedures so that the HR professionals have confidence in using them.

Second, the significant role of effort expectancy and its indirect effect through perceived value underscore the importance of

usability-oriented system design. Given that AI is an emerging tool and is evolving quickly; and there are various generations in the workforce with different levels of technological savviness, it is important for organisations to avoid purchasing overly complex or technically demanding systems. Instead, they should prioritise solutions that can be integrated seamlessly into existing processes. For technology providers or developers, they should also consider designing user-friendly products that are able to address privacy and security concerns of HR professionals.

Third, since social influence plays a critical role in shaping both perceived value and intention to use AI recruitment systems, visible endorsement from senior management, HR leaders, and respected peers can substantially enhance acceptance. Organisations should therefore encourage top-down support so that HR professionals are more likely to perceive them as legitimate, beneficial, and aligned with organisational norms. Besides top-down approach, establishment of digital champion roles whereby selected HR personnel who are familiar with AI recruitment technology is appointed as internal mentors and advocates for the adoption may also be embraced. This individual can demonstrate practical applications of AI tools, provide informal continuous practical guidance, share successful usage experiences, and help reduce uncertainties associated with AI-enabled recruitment processes. This approach may be sound in the Chinese organisational context, since they value collectivist culture.

Fourth, the significant impact of facilitating conditions highlights the necessity of organisational readiness. To ensure the AI recruitment adoption among HR professionals, organisations must up-skill recruiters. By providing adequate training programs, organisations can reduce uncertainties and perceived risks, which indirectly will help increase the value of using AI. Given that substantial experienced HR professionals may consist of older generations, organisations should prioritise “digital bridging” strategies when embracing AI recruitment technologies. They should extend beyond conventional technical support by providing practical hands-on, simplified training modules, guided demonstrations and continuous assisted learning approaches that will help in familiarising employees with the technology. Additionally, organisations should also prioritise highly intuitive and user-friendly AI recruitment interfaces when selecting the AI recruitment technology in the market. A system that emphasis usability, familiarity, and workflow compatibility may help reduce

psychological resistance and improve long-term adoption among experienced HR personnel.

6.3 *Limitations of the Study and Suggestions for Future Research*

This study has several limitations that should be acknowledged. First, the sample was restricted to HR professionals working in China. Hence, caution should be exercised when generalising the findings to other geographical contexts, where institutional environments and recruitment practices may differ.

Second, the study employed a cross-sectional research design, which limits the ability to capture changes in recruiters' perceptions and behaviours over time. Owing to this, the study may not be able to capture the long-term effects of AI recruitment use. Future studies may therefore benefit from longitudinal designs to better understand the impact of AI recruitment applications, when the technology becomes more embedded into organisational processes.

Third, since the data were collected through self-reported questionnaires, the findings may subject to common method bias and social desirability effects. Respondents may provide answers that they perceived socially acceptable, rather than their truly attitudes. Future research therefore could be enhanced with data collected from multiple sources.

In addition, the absence of qualitative data limits the ability to explore the underlying factors of AI recruitment adoption much deeper. Future studies, hence, could adopt mixed-method approaches, such as interviews or case studies, to gain richer insights.

6.4 *Conclusion*

Drawing on the UTAUT framework and VAM, this study empirically examines the factors influencing the adoption of AI recruitment applications among HR professionals in China. The findings demonstrate that performance expectancy, effort expectancy, social influence, and facilitating conditions significantly influence intention to use AI recruitment, both directly and indirectly through perceived value, which plays a partial mediating role. These results highlight that AI recruitment adoption is not driven solely by technological capability, but by HR professionals' broader evaluations of value, usability, social legitimacy, and organisational support.

This study not only contributes to the literature by focusing on China which have different contextual and cultural settings, yet it also extends existing knowledge by testing the integration

of two theories which are UTAUT and VAM in the context of AI recruitment. The findings show the applicability of integrating both theories in the context of AI recruitment. It also offers practical insights for organisations, AI technology developers, and HR practitioners by emphasising the importance of designing user-friendly systems, leveraging social endorsement, and providing adequate organisational support to enhance perceived value and adoption willingness.

Despite the limitations related to sample scope and research design, this study provides meaningful theoretical and practical contributions to understanding AI recruitment adoption in China. Future research is encouraged to expand the scope across regions, employ longitudinal and mixed-method designs. Such efforts will help advance knowledge on AI recruitment and support the sustainable integration of AI technologies into HR practices.

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