Research on Employee Work Behavior Characteristics in the AI Interview and Evaluation System under the Human-Robot Collaboration Mode: Based on the Job Characteristics Model

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Abstract. Human-robot Collaboration (HRC) is the pivotal product under technology development. And AI interviews, as a new human resource product, have certain research significance. Based on the job characteristic model, this article takes human resource professionals engaging in recruitment as the research object. It uses a combination of interviews and big data analysis to study the intrinsic mechanisms empirically and influencing factors of AI interview and evaluation systems in HRC applications. The result shows that most HR professionals are willing to use AI for interviews, but their willingness varies depending on the industry, job position, age, and education level. The research findings will provide a theoretical basis and practical guidance for HR professionals in optimizing talent selection, work behaviors, and work modes.

Keywords: job characteristic model, AI interviews, human-robot collaboration, and human resources management.

1 Introduction

With the deepening of Informatization, there is a growing demand for artificial intelligence in the workplace. With the arrival of the metaverse era, new virtual and real integrated internet applications, which integrate various new technologies, have emerged, and human-robot collaboration will usher in a new era of work style. In the metaverse era, the core feature is an immersive experience, and the marginal cost of information replication can be neglected. While considering ecological richness and diversity, evolving transactions have mutual impacts[1].

Earlier, Gartner proposed two key emerging AI technologies, deep learning, and machine learning, which will be widely adopted in the future. According to a study by Accenture's AI report[2], not only is AI expanding human capabilities, but humans are constantly optimizing the performance of intelligent technology. At the same time,

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about 63% of company executives surveyed in job positions involving HRC expect AI to create more job opportunities for companies in the next three years.

In recent years, local governments and large enterprises hold the view that the significance of talent acquisition is on the rise. However, when conducting large-scale talent screening, companies have encountered many challenges, such as the inability to quickly conduct massive talent screenings in a short period, the deviation of recruitment results due to the inconsistency of interviewers' cognition during interview assessment, and the high cost of large-scale initial interviews. Considering the rigor of talent acquisition, AI interview robots have been carefully applied to the interview scene after in-depth exploration and analysis of psychological research. Therefore, this study mainly focuses on the collaboration process between AI interview robots and human resource professionals and specifically digs into the following questions:

- Do most human resource professionals have the willingness to engage in HRC?
- Are there significant differences in the willingness to engage in HRC among human resource professionals with individual characteristic variables?
- What is the relationship between job variables?
- What are the specific situations of various incremental HRC intentions?

2 Background

The metaverse is a relatively new area of research, and there is relatively limited research on human-robot collaboration in the field of human resource management. However, the application of human-robot collaboration and similar products are widespread.

Robot journalists that have emerged in the media industry have become an extension of human intelligence, bringing revolutionary changes to the news gathering and editing process as well as the role of journalists. Moreover, the internet provides vast development space for robot journalists. Human-robot collaboration is a major trend in the current field of artificial intelligent development. Robot journalists can free journalists from redundant and repetitive work, enabling them to conduct high-quality news reporting[3].

AI recruiters are enhanced and iterated using multi-modal language algorithms that extend beyond written language, encompassing nonverbal cues like facial expressions, hand gestures, body posture, vocal tone, and other modes of communication. The algorithm can achieve up to a 90% matching rate with human judgment[4]. However, the fairness of AI recruiters is still questioned in the early stage of application for job applicants, especially in terms of the image and language style of the recruiters. In addition, most AI recruiters require follow-up questions, while the experience of job applicants varies greatly in the interview process.

Today's AI interview tools rely on multimode data analysis and perform neural network computations on a data matrix containing 365 features. And big data experts will verified it to ensure its scientific research level in machine learning. Compared with earlier AI interview tools that were mainly in English, existing tools have also overcome the technical bottleneck in the semantics of Chinese. The latest model was built in a highly rigorous environment, based on tens of thousands of real data, and evaluated

through interactive experience-based standards, achieving extremely high reliability and validity.

Langer et al.[5]believe that unfamiliar interactions with technology during AI interviews may trigger fear and anxiety in job applicants, which is a sense of insecurity, accompanied by uncertainty about how to judge the current situation and how to perform. They conducted experiments to verify this hypothesis by randomly conducting video or AI interviews with job applicants. The results showed that compared with video interviews, job applicants who underwent AI interviews felt higher levels of insecurity. However, instead of candidates' professional performance under coaching and self-hiding state during interview, recruiters prefer choosing candidates based on their performance with higher efficiency and authenticity.

3 Methods

3.1 Definition of Work Model:

This study adopts a commonly used model in the industry, the Job Characteristics Model, which is currently a highly influential model in the research on the essence of work and the practice of work design. And it has become the core method of work design. This model covers five core job characteristic dimensions, including skill variety, task identity, task significance, autonomy, and feedback[6].

Job characteristics can be divided into two aspects: job demands and job resources. Job demands refer to the continuous physical or mental effort or skills required, which are related to physical and mental exhaustion, such as work-related negative emotions, workload, and job pressure. On the contrary, job resources refer to the resources that can facilitate work completion, stimulate positive emotions, and motivate individual growth and development, such as social support, salary, and fair opportunities[7]. This study will use the job characteristic indicators proposed by Jicun Xu and Li Zhang as research indicators.

3.2 Research Object:

This study takes human resource professionals with great demand for interviews as sample, uses different levels of probability sampling to distribute questionnaires, and simultaneously selects some personnel for interviews. Two hundred questionnaires were distributed, and 186 valid questionnaires were collected, with a recovery rate of 93%.

3.3 Research Hypotheses:

Based on the Job Characteristics Model, this study investigates human resource professionals' use of AI interview tools. This study applies SPSS to quantitatively analyze individual and job characteristics' impact on human-robot collaboration. The following hypotheses are proposed:

- Hypothesis 1: Most human resource professionals are willing to engage in human-robot collaboration.
- Hypothesis 2: There are significant differences in individual characteristic variables among human resource professionals in their willingness to engage in human-robot collaboration.
- Hypothesis 3: Due to related variables, there are significant differences in the willingness to engage in human-robot collaboration among human resource professionals in different industries.
- Hypothesis 4: The descriptive analysis model can successfully analyze the factors that increase the willingness of human resource professionals to engage in human-robot collaboration.

3.4 Interview Outline:

Questionnaire construction: The scale adopts the Likert five-point scoring method, with scores ranging from "strongly disagree" to "strongly agree," with 1 to 5 points, respectively. Based on the actual human resource positions, the relevant settings were made around the five dimensions of the work system, and a questionnaire survey and interviews were conducted within Sichuan Province to form the final data.

Interview Approach: The study conducted in-depth interviews with human resources professionals, focusing on skill variety, job identity, job significance, autonomy, and feedback. To obtain targeted information, interviews focused on the core skills HR professionals need to master and their overall participation in work tasks. Regarding job significance, the study conducted cognitive investigations at various levels, distinguishing between managers and employees on the importance of work to interview. For managers, we focused on their decisive role in work cognition. And for employees, we explored the importance of work from the perspective of colleagues, the company, and their cognitive situation. Regarding skill variety, we set up actual case materials during the interview to discuss the complexity of skills, knowledge requirements, and the necessary technology for work.

4 Results

4.1 Reliability Analysis

Table 1. Cronbach's α Coefficient Table

Cronbach's α coefficient	Standardized Cronbach's α coefficient	Number of items	Sample size
0.822	0.829	5	186

The Table 1 above shows the results of the Cronbach's α coefficient, including the values of Cronbach's α coefficient, standardized Cronbach's α coefficient, number of items, and sample size to measure the validity and reliability of data.

- Cronbach's α coefficient evaluates whether the collected data are reliable and can identify unreasonable questions or careless responses.
- Standardized Cronbach's α coefficient converts different scale scores to a uniform measurement. When the scale scores have different units, such as analyzing 5-point and 10-point scales together, standardization can be used.
- Number of items are the number of variables involved in the reliability analysis calculation.

The Cronbach's α coefficient value of the model is 0.822, indicating that the questionnaire has good reliability.

Table 2. Reliability Analysis Conclusion

No.	Analysis Item	Correlation with overall score after deletion	Cronbach's α coefficient after deletion	Conclusion
1	Skill Variety	0.683	0.769	Good
2	Task Identity	0.563	0.809	Good
3	Autonomy	0.592	0.795	Good
4	Job Significance	0.636	0.781	Good
5	Feedback	0.639	0.784	Good

As shown in Table 2, the reference criteria for item selection are based on the correlation with the overall score after deletion is less than 0.3. If so, whether the Cronbach's α coefficient after deleting the item is higher than the original coefficient. According to this, the conclusion is that all the selected items have strong reliability.

4.2 Validity Analysis

In the validity analysis, the following variables were used: skill variety, task identity, autonomy, feedback, and task significance. Firstly, KMO and Bartlett's tests were conducted.

For the KMO test, the value is 0.81, indicating that the degree is appropriate. For Bartlett's test, if the significance level is less than 0.05, the null hypothesis is rejected, indicating that factor analysis can be performed. Conversely, if the null hypothesis is not rejected, it suggests that these variables may independently provide some information and are not suitable for factor analysis.

Table 3. KMO Test and Bartlett's Test

KMO value		0.81
Bartlett's test of sphericity	Approximate Chi-square value	323.478
	df	10
	P	0.000***

Note: ***、**、* represent significance levels of 1%, 5%, and 10% respectively.

Total Variance Explained						
	Eigenvalue			Rotated variance explained		
Component	Eigenvalue	Variance explained (%)	Cumulative percentage (%)	Eigenvalue	Eigenvalue Variance explained (%)	Cumulative percentage (%)
1	2.973	59.5	59.5	2.973	59.5	59.5
2	0.689	13.8	73.2			
3	0.548	11	84.2			
4	0.465	9.3	93.5			
5	0.326	6.5	100			

As can be seen from Table 3, the KMO value is 0.81, and the result of the Bartlett's sphericity test shows a significant *P* value of 0.000***, indicating a significant level of correlation among variables which rejects the null hypothesis. Therefore, the factor analysis is valid and appropriate, and has been verified through the validity test.

4.3 Variable Analysis Using the Entropy Method

Table 4. Weight Calculation Results

Entropy Weight Method			
Item	Entropy Value e	Information Utility Value d	Weight (%)
Skill Variety	0.989	0.011	10.066
Task Significance	0.956	0.044	39.751
Task Identity	0.984	0.016	14.804
Autonomy	0.977	0.023	20.685
Feedback	0.984	0.016	14.695

The Table 4 shows the weight calculation results of the entropy weight method and analyzes the weights of each indicator.

4.4 Intelligent Analysis:

The weight calculation results of the entropy weight method show that the weight of Skill Variety is 10.066%, the weight of Task Significance is 39.751%, the weight of Task Identity is 14.804%, the weight of Autonomy is 20.685%, and the weight of Feedback is 14.695%. Among them, the indicator with the highest weight is Task Significance (39.751%), and the one with the lowest weight is Skill Variety (10.066%).

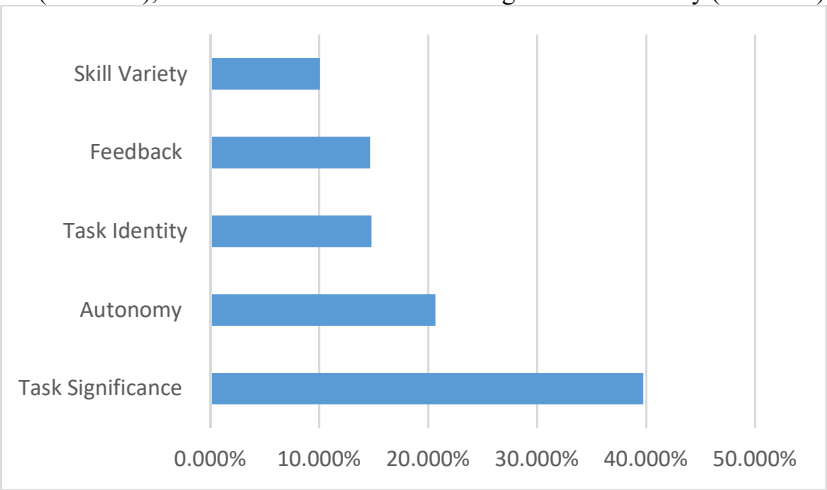

Fig. 1. Histogram of Indicator Significance

It can be seen from Fig.1.that the significance ranking of indicators in a descending order under a histogram format. And overall score are also shown in Table 5 below.

Table 5. Overall Score Table

Row Index	Comprehensive Evaluation	Ranking
1	0.4952498394156396	92
2	0.3642682906111323	166
3	0.3642682906111323	164
4	0.2635787303300028	181
5	0.3642682906111323	165
6	0.3642682906111323	167
7	0.4729460507974273	99
8	0.4382830197717498	129
9	0.6292556307472577	13
10	0.38136882443596914	149
11	0.3642682906111323	163
12	0.38136882443596914	150
13	0.5152092944792206	86
14	0.4435388988732344	126
15	0.2635787303300028	180

5 Conclusion

Hypothesis 1: Most human resource professionals are willing to engage in human-robot collaboration. According to interviews, industries such as finance, automobile, real estate, the internet, and government agencies all need AI interview tools. Takes the AI system of Liepin as an example. Based on repeated operations in the market, the system has the basic conditions of fluency, safety, and stability. It also has authoritative certifications such as ISO certification, human resource service license, and National Copyright Administration computer software copyright. In the actual application process, it can perform customized interviews, generate intelligent evaluations and save much time by rapidly eliminating unqualified candidates. In the structured and semi-structured interview process, various AI tools can assist in intelligent recommendations for the topic, which also saves time for HR professionals. During the interview, we learned that most HR professionals are willing to use human-robot collaboration for AI interviews based on their evaluation. As a result, AI interviews can significantly reduce the investment of workforce and resources in the initial screening. In terms of interview report acquisition, AI reports can evaluate the dimensions that need to be assessed in the initial interview, such as appearance, temperament, and verbal fluency. It can also score competency modules by setting dimensions such as drive, teamwork, communication and coordination skills for questioning and evaluation.

Hypothesis 2: There are significant differences in individual characteristic variables among human resource professionals in their willingness to engage in human-robot collaboration. During the interview, we found that HR professionals are more cautious than other employees regarding the importance of job interviews. This is also in line with the results of the survey questionnaire, in which it shows that this item accounts for the largest proportion in the task importance module. Furthermore, we learned from the interview that the willingness of management teams to use AI is slightly lower than that of ordinary employees, and they would have more considerations. In contrast, ordinary employees consider more about job autonomy and integrity. Therefore, there are significant differences in individual characteristic variables, and the second hypothesis is established.

Hypothesis 3: Due to related variables, there are significant differences in the willingness to engage in human-robot collaboration among human resource professionals in different industries. Based on the interview results involving HR professionals in the government agencies, finance, automotive, real estate, fast-moving consumer goods, and Internet industries, we found that the higher job skill requirements, such as cross-departmental collaboration and communication, strong organizational coordination ability, and large-scale data statistics after the interview, and the more timely job feedback is required, the higher willingness to collaborate with AI. In real-life scenarios, finance, fast-moving consumer goods, and Internet industries have the largest user base and the broadest application of AI in actual interviews.

Hypothesis 4: The descriptive analysis model can successfully analyze the factors that increase the willingness of human resource professionals to engage in human-robot collaboration.

5.1 The algorithm configuration used was:

- Algorithm: Categorical Summary
- Variables: Grouping variable: {Job level}; Summary variable: {AI usage willingness}
- Parameters: Summary type: {Mean}

5.2 The analysis results are as follows:

The Categorical Summary calculates results based on the data aggregation statistics.

Table 6. Group summary table

Job level	AI usage willingness
Employee	2.870
Manager	3.647

The Table 6 provides an overview of outcomes of variables inclination towards using AI. The results indicate that HR professionals at the managerial level are more likely to accept HRC based on the considerations of task importance and job autonomy requirements in job characteristics. At the same time, because managers have stronger organizational and coordination abilities, they are more willing to cooperate with AI.

5.3 Algorithm Configuration:

- Algorithm: Category summary
- Variables: Grouping variables: {Gender, Age, Education, Job Level}; Summarized variable: {AI usage willingness}
- Parameters: Summary type: {Mean}

Table 7. Group Summary Table

Gender	Age	Education	Job Level	AI usage willingness
Male	22.0	Bachelor's Degree	Employee	2.5555555555555554
	23.0	Bachelor's Degree	Employee	2.8
	24.0	Bachelor's Degree	Employee	3.0
		Master's Degree	Manager	4.0
	25.0	College Degree	Employee	2.5
		Bachelor's Degree	Employee	3.111111111111111
	26.0	College Degree	Employee	2.5
		Bachelor's Degree	Employee	2.7777777777777777
	27.0	College Degree	Employee	3.0
		Bachelor's Degree	Employee	2.875
	28.0	College Degree	Employee	3.0
		Bachelor's Degree	Employee	2.75
		Master's Degree	Manager	4.0

	29.0	College Degree	Employee	3.0
		Bachelor's Degree	Employee	2.5
		Bachelor's Degree	Manager	3.0
		Master's Degree	Manager	3.0
	30.0	Bachelor's Degree	Employee	3.0
	32.0	Master's Degree	Manager	4.0
	33.0	Bachelor's Degree	Employee	3.0
	34.0	Bachelor's Degree	Employee	2.5
		Master's Degree	Manager	3.5
		PhD	Manager	4.0
	35.0	PhD	Manager	3.0
	36.0	Bachelor's Degree	Employee	3.0
	37.0	Bachelor's Degree	Employee	3.0
		PhD	Manager	4.0
	38.0	Bachelor's Degree	Employee	3.0
	39.0	Bachelor's Degree	Employee	3.0
		Master's Degree	Manager	4.0
		PhD	Manager	4.0
	40.0	PhD	Manager	4.0
	41.0	Master's Degree	Manager	4.0
	43.0	Bachelor's Degree	Employee	3.5
Female	20.0	Bachelor's Degree	Employee	3.0
	22.0	Bachelor's Degree	Employee	3.0
	23.0	Bachelor's Degree	Employee	3.0
	24.0	Bachelor's Degree	Employee	3.0
	25.0	College Degree	Employee	3.0
		Bachelor's Degree	Employee	2.8125
	26.0	College Degree	Employee	3.0
		Bachelor's Degree	Employee	3.0
		Bachelor's Degree	Manager3.0	
	27.0	Bachelor's Degree	Employee	2.9411764705882355
	28.0	Bachelor's Degree	Employee	2.875
	29.0	Bachelor's Degree	Employee	2.75
		Bachelor's Degree	Manager	4.0
	33.0	Bachelor's Degree	Employee	3.0
	36.0	Bachelor's Degree	Employee	2.6666666666666665
	37.0	Master's Degree	Manager	3.0
	38.0	Bachelor's Degree	Employee	3.0
	44.0	Bachelor's Degree	Employee	3.0
	45.0	Bachelor's Degree	Employee	2.0

Table 8. Group Summary Table

Gender	AI Usage willingness
Male	2.970
Female	2.908

Table 9. Group Summary Table

Education	AI Usage willingness
College Degree	2.818
Bachelor's Degree	2.882
Master's Degree	3.667
PhD	3.800

The Table 7-Table 9 summarizes the variables AI usage willingness. The results show that HR professionals with different gender, age, and educational background have different levels of willingness to use AI, depending on the importance of their job tasks, the efficiency of job autonomy, the task completeness and closed-loop task monitoring, and the different skill requirements. Among them, the age group of 30-35 has the highest acceptance rate, and there is little difference between men and women. The data on educational background shows that the higher the educational level, the higher the willingness to use AI.

6 Discussion

6.1 Research Results

Work characteristics have a significant positive impact on the willingness of human resource professionals to use human-robot collaboration. Based on the analysis of massive data on the entire network, big data can provide enterprises with industry-wide talent market analysis, real-time updates on industry trends, predict employee turnover intentions based on industry trends, employee behaviors, and other information, and providing human resource departments with more objective talent architecture decision-making references[8]. Furthermore, from the perspective of job variety and job identity, AI interview tools based on job characteristic models can assist human resource management in enriching the additional knowledge required in job positions and also provide functions such as massively inviting candidates and interviewing, conducting group interviews and automatic queuing systems, automatic grouping, and automatic generating talent assessment reports after interviews, greatly saving HR professionals' time in performing transactional work. At the same time, based on the large data sample and standardized processes, it plays a guiding role in the work identity of HR professionals.

Industry differences in the job characteristic model have a significant relationship with employees' willingness. Based on different dimensions under different work characteristics in different industries, there is a demand for willingness that focuses on their actual scenarios. Also, due to differences in individuals' educational levels, there are differences in the importance of work and the degree of completeness evaluation.

6.2 Insights for HR management

Create a comprehensive growth path for HR avoids no sense of accomplishment caused by the emergence of AI tools. In the interview, the interviewees will consider the substitutability of their own work value and evaluate the work richness and difficulty when using AI tools. Thus, we can consider more about the development direction of HR, like job rotation through OD, BP, and COE-related positions in large Internet companies. In the financial industry, HR professionals also need to coordinate with business development to rotate through different positions to gain various abilities, which benefits them from overall competency and literacy.

Guidance can be given based on the comprehensiveness of HR development during the feedback process. In the feedback process, many companies evaluate based on the performance level. However, in most cases, they only focus on formality and evaluate results without considering the applicability of the feedback. At the same time, HR professionals may have negative self-perception or weak motivation due to a lack of feedback or incomplete feedback, which is not conducive to their overall development in the future.

The direction of autonomy, a strict interview process, rigorous screening criteria, and unified interview evaluation dimensions can effectively regulate the behavior of HR professionals, avoid differences in results due to individual preferences or different personal perceptions, and cause adverse effects on employer brand evaluation and candidate perception.

6.3 Limitation

Data limitations: This study has certain limitations due to the restricted data and sample size, which may lead to regional bias or incomplete information. A broader population can be selected for more comprehensive analysis in future studies if possible.

Scale design: The study adopted the mature Likert scoring method for scale selection, and some references from foreign individuals were also consulted. However, there may be specific cultural differences in the data sample.

7 Reference

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