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From Human-AI Confrontation to Human-AI Symbiosis in Society 5.0: Transformation Challenges and Mechanisms

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Artificial Intelligence (AI) is an integral part of Society 5.0. Increasingly large companies are using AI technology to promote digital transformation and assist the human resource management (HRM) process to achieve sustainable talent development. Talent intelligent management system (TIMS), as a typical hybrid intelligent system, brings both opportunities and challenges to the transformation of HRM. Although the use of TIMS has met the expectation of Society 5.0 on replacing repetitive work by digital technology, practical insights are needed to address the potential challenges in human replacement, tacit knowledge of managers and data-driven recommendations, and low interpretability of TIMS recommendations. This article outlines possible solutions to cope with the above challenges. This article shows that the challenges brought by TIMS can be solved by different mechanisms, which cover improving users' trust in TIMS, balancing the rational results and irrational emotions, and enhancing the interpretability of AI algorithms.

BACKGROUND

"Society 5.0" can be defined as a "society of intelligence" with the core view to build a human-centered smart society.[1] In the current wave of digital transformation, talent management has become strategically important, especially for high-tech companies.[2] In line with the expectations of Society 5.0, adopting digital technology for talent management appears to be able to realize a highly inclusive and fair management of talents and thereby achieve sustainable development of talents.[3]

Artificial intelligence (AI), a fundamental component of Society 5.0,[4] though sometimes controversial, has been deployed widely in society and has transformed the business and in general our lives. AI technology, namely talent intelligent management system (TIMS) is increasingly used in in the human resource management (HRM) process. TIMS covers precise personal-job matching, high-potential employees' identification,[5] forward-looking talent retention, organizational diagnosis, and other functions that require human–machine collaboration. This kind of decision-support system, composed out of both humans and intelligent machines (systems) and carries out human–machine interaction with the support of digital intelligent technology, is a hybrid intelligent system.[5]

Digital transformation of HRM via such hybrid intelligent systems can trigger significant changes in the entire process of identifying and maintaining talents. On one hand, the digital transformation in HRM has the potential to improve the alignment between supply and demand of talent, by overcoming the limitations of the interdepartmental silo mentality and relying on various data from different levels of an organization. Companies can also establish a link between internal and external databases, which is valuable for the talent management process and enhance the value of human resources (HR) analytics. On the other hand, these

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significant changes have raised serious discussions. These include the potential replacement of humans and occupations by AI,[7] the crash between experience-based tacit knowledge of HR professional and the data-driven results given by the system,[8] and relatively low interpretability of algorithm-based decisions.[8]

In this article, instead of focusing on the technical side of augmented intelligence, we highlight the HRM transformation challenges and mechanisms. We argue that the emergence of TIMS makes it possible, though challenging, to achieve a balanced symbiosis between humans and machines in the talent management process and help companies reach the expectations of Society 5.0. We further explain what the "intelligent" features of TIMS are and how to manage the challenging digital transformation process in HRM.

TIMS IS TRANSFORMING THE HRM PROCESS

HRM includes six functional areas and mainly focuses on hiring, training, retention, rotation, and dismissal of employees, which can be divided into three general stages, that is, recruitment (new employee entry), management (internal HRM), and turnover management. TIMS provides many automatic and intelligent functions to optimize the HRM process, and improves HR's work efficiency, such as intelligent resume screening, person-job alignment, high-potential talent identification, and employee turnover risk prediction. IBM has claimed that it can predict whether an employee is likely to leave within the next six months at a 95% accuracy rate through its AI platform, which reduces its staff retention costs by $300 million a year.[10]

TIMS is regarded as a hybrid intelligent system applying AI technologies to analyze large-scale data of human talents in organizations.[11] On the strategic level, major HR investments and decisions can be supported by AI via data mining. On the operational level, the HR process can be streamlined by robotic process automation (RPA). Typical algorithms used in TIMS include collaborative filtering, structure-aware attentive neural network,[12] enhanced neural network,[13] long-short term memory,[14] etc. The training of these algorithms requires sufficient historical data and accurate features. However, based on the historical data, the output of the algorithms can also be considered as unfair and uninterpretable, such as Amazon's recruitment discrimination.[15] To solve such ethical issues, fair algorithms and AI ethics are widely studied.[11,16] The comparison between traditional HRM and digital HRM, driven by AI technology (using TIMS), is shown in Figure 1. AI technology, or more broadly speaking, digital technology, not only transfers cumbersome offline processes to online, but also automates repetitive tasks, and even breaks through the boundaries of human cognition and makes prospective predictions possible, as detailed below.

Despite the exciting developments of TIMS,[11] published experiences to guide the HRM transformation process are lacking.[18] The Society 5.0 concept advocates replacing repetitive work by digital technology and so enabling people to do more creative work.[17] Although the use of TIMS has largely met this expectation, practical insights are needed to address: the potential challenges in human replacement, tacit knowledge of managers and data-driven recommendations, and low interpretability of TIMS recommendations.

Challenge I: The Controversy About AI Replacing Humans or Occupations

One of the biggest benefits of TIMS is its function to automate some of the daily repetitive basic tasks of HR, such as resume screening, table sorting, producing demographic statistics, etc. Obviously, it leads to more daily HR work but replaces some manual tasks, which were offered by HR department in the past. In fact, the controversy that AI will replace humans always exists. Previous studies have proved AI-enabled automation can potentially replace many occupations, such as manual, routine, and semi routine jobs.[7,8] However, applying AI technologies in organizations may restructure the capacity arrangement and reshape some of the existing job functions. For example, TIMS has been used to execute resume selection, which dramatically reduces the work force in manual resume screening, while it requires different talents in charge of TIMS, in the form of additional capacities in system development and maintenance.

In fact, AI technology empowers human resource analysis, which was originally intended to bring benefits to HRM. It is necessary to find empirical evidence that HR analytics is providing added value to the business. Currently, the lack of empirical evidence has led both researchers and practitioners to speculate that HR analytics is considered a management fad,[9] however anecdotal proof from the HR practice suggests that HR analytics is increasingly picking up momentums in business.[18] We recommend that more evidence is required to support the understanding that HR analytics yields added value to the business.

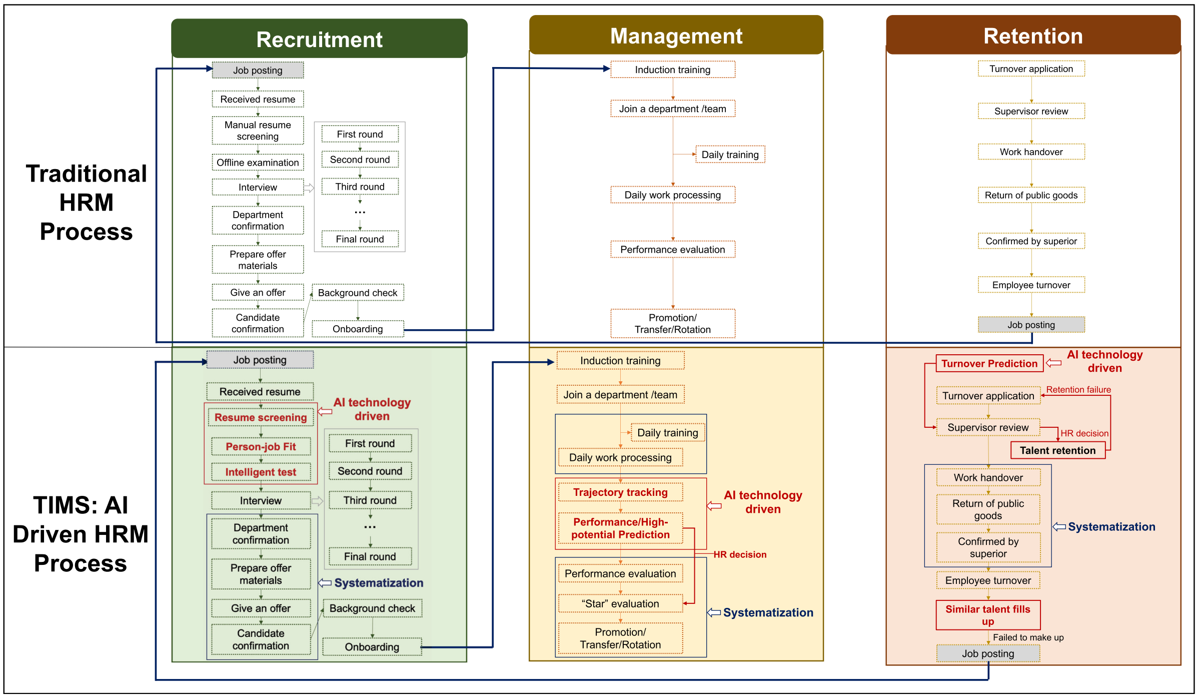

FIGURE 1. Comparison of traditional HRM process and digital HRM process (The special features of digital HRM process are highlighted in red).

Challenge II: The Crash Between Experience-Based Tacit Knowledge of HR Professional and the Data-Driven Results Given by the Machine (TIMS)

There is no absolute relationship between humans and machines or HR professionals and TIMS in our context, but it is about finding a cognitive balance. The experience from employees is captured in a large amount of training data obtained by the TIMS. Such data are used to generate a series of insights and reversely assist HR professionals' decisions. This process can be a virtuous circle. However, when the data driven TIMS, an intelligent tool based on AI, entered the HRM process, usually its performance is largely under the expectation (such as the widely discussed Amazon recruitment discrimination problem). In technology anthropomorphism, when machines can replace humans to automate and intelligentize certain tasks, human with more experience and tacit knowledge will be more prone to generate egocentric biases.[8] For example, HR professionals and managers usually perform the advanced cognitive work largely based on their experience-based tacit knowledge. In this process, when the results given by the TIMS are inconsistent with their own experiences, cognitive dissonance typically occurs. In order to achieve a cognitive balance again, they need to make efforts to obtain additional information related to the TIMS recommendations. Managers with a strong ability to balance their own experience-based tacit knowledge and data-driven results recommended by TIMS are more likely to find a balance in interacting with TIMS and they are more likely to accept this inconsistency.

Challenge III: Currently Relatively Low Interpretability of Algorithm-Based Decisions

Intuitive interpretability of results and the responsible AI require computations, a fair process, and transparent design. However, sometimes insights obtained from TIMS can be based on an entirely "black-box" AI technologies, whose inner working mechanisms are likely not fully understood and managed by HR professionals. As a result, they understand neither the process of the HR recommendations by the TIMS, nor the managerial actions to taken based on the recommendations. For example, turnover prediction is a typical function of TIMS driven by supervised machine learning algorithms. If a manager is notified that one subordinate considered as a high-potential talent is currently predicted to have a 95% possibility to resign next month, it will undoubtedly drop a bomb on the manager and hence leads to the questions "why" or "what should I do." However, the machine might not be able to clarify the complete computation process or provide flow-up advice. Therefore, the actual HR process is largely hindered by the lack of interpretability of the recommendations. These challenges lead to the following transformation mechanisms via a case study of TIMS.

METHODOLOGY

In this project, we interviewed various stakeholders with different experiences with TIMS in a large high-tech company headquartered in Asia, including three designers, three developers, three HR managers, and five general HR professionals, to explore how to achieve a better human-AI symbiosis. Among them, 57% were male and 43% were female, with an average age of 36 years. All designers and developers involved in the design and development of TIMS function modules. They have at least five years of working experiences in their current positions, including four senior engineers, who are extremely familiar with each feature improvement process of TIMS. The three HR managers with rich HRM experience are all mid-level managers, as users of TIMS, they have a comprehensive understanding of its functions. The interviewed five regular employees working in five different departments. They have a liaison role between their own department and the HR department and often use the basic functionality of the TIMS.

The interviews consisted of three phases in total. First, we contacted the respondents and explain our research objective on understanding how humans work with TIMS. Second, we designed interview questions based on the literature and our research objectives. To address the challenges mentioned above, we divided the questions into three categories, each with six specific questions (see Appendix 1 for details). To fit for the purpose, we asked HR managers and general HR professionals *"for what type of work do you mainly use TIMS and to what functions are you exposed to,"* while for designers and developers, we asked *"which functions of TIMS have you participated in designing or developing."*

Finally, we summarize the interview results, which indicate the challenges brought by TIMS that have been solved by different mechanisms: improving users' trust in TIMS, balancing the rational results and irrational emotions, and enhancing the interpretability of AI algorithms. The detailed interview findings are summarized in Appendix 2.

MECHANISM TO TRANSFORM FROM HUMAN-AI CONFRONTATION TO HUMAN-AI SYMBIOSIS

Based on the TIMS in practice and the interview data, our case study demonstrates that, processwise, the transformation from human-AI confrontation to human-AI symbiosis needs to go through three phases: 1) *an enabling phase*, 2) *a running-in phase, and* 3) *a symbiosis phase*, as detailed below.

Enabling Phase: Establishing Trust

Trust is the basis for effective and efficient system use. Trust in this context includes the belief that machines can only take over part of the tasks of humans, rather than all of them, and humans can learn and grow together with machines. Regarding this, most users have reached a consensus, they indicate that *"I don't think that the machine (TIMS) can replace my occupation. I have my own value in the work. I can deal with more complexed cognitive tasks, such as formulating a plan to solve a HR problem in some specific projects. When I make a decision, the results obtained from the TIMS also can be used referred to improve my opinion. If the result obtained from the machine is more convincing with detailed explanations of it, I would be more willing to believe and use it."* The interview data also reveals such trust can be generated through system usage training. Trained HR professionals can make use of TIMS to conduct resume screening, a basic repetitive task in general. The improved efficiency made HR professionals gradually rely on the machine, which in turn leads to trust. One user remarked *"The collaboration between humans and machines is inevitable. Simple tasks replaced by machines also require a small amount of manual review before they can be accepted. But with more frequent interactions, machines learn from human experience, so as a result, users will trust it more."* For example, although robotic interviewers have been put into HR practice, face-to-face interviews are still inevitable. Companies will even conduct multiple rounds of face-to-face interviews to ensure that the right employees are recruited. This form of cooperation between humans and machines will enable machine results to be integrated into human work experience, thereby HR professionals can clearly recognize what can be handled by AI, what should be handled by them, and when they can be combined. In this way, a trust relationship can be established.

Running-in Phase: Balancing Data-Driven Results and User Experience

The use of TIMS can bring new tensions to managing human-AI interactions in the organization. TIMS generally demonstrates rational objective result that gained from real data (such as performance prediction, high-potential talent prediction, etc.), but sometimes it is counterintuitive and contradicting with managers' experiences. Through the interview, 91% of managers think TIMS can provide accurate results. However, when they face counterintuitive results, 59% of them will be prone to their own experiences, while only 37% of the respondents have stated to combine rational results with their experience-based intuition. They indicated "*When making decisions, I refer to the objective results given by the system. Generally, when I encounter results given by TIMS that are consistent with my experience, I tend to make judgments based on the objective results. However, when the objective results are counterintuitive, I will be more inclined to judge from my own experience. If the objective result is different from my own experience, but there is only marginal difference or it has a detailed explanation, I will combine the objective results with my intuition in an attempt to make my decision-making more accurate.*" This result represents that the confrontation and fusion about human wisdom and AI tools' anthropomorphic wisdom are coexisting. For example, in the talent development management process, TIMS has changed the original cumbersome way of manual work, which not only improves efficiency, but also provides a predictive function that assists decision-making.

In generally, it is always challenging for HR professionals (managers) to identify the most talented employees in the early stage of the employment and train them in advance. However, the empowerment of the machine (TIMS) not only allows multiple tasks to be paralleled, but also enables HR professionals to obtain some unobvious insights based on a large-pool historical data, such as predicting who is the employee with high potentials, which will prevent talent loss to some extents. In this digital process, HR's ability to balance data-driven results with experience-based tacit knowledge is important and necessary. Take performance prediction as an example, our interviews suggest that HR decision-making is typically based on the results given by TIMS and supplemented by their own experience. As one developer puts it "*We still position the result of TIMS as an "assistance" role. Managers can make a priori judgment based on their own experience, and the result of TIMS can be used as a posterior. If there is an inconsistency, some managers will ask us for a more detailed explanation, while other managers may directly judge based on their own experiences.*" When generating inconsistencies between data-driven results and HR professional's experience, the HR professional should reevaluate the situation by considering more objective data. In other words, the data-driven and hence objective results of TIMS can play a key role in auxiliary supervision, as such, it provides better assistance to managers to achieve more accurate decision-making.

Symbiosis Phase: Enhancing the Interpretability

TIMS prompts managers to make data and algorithm-based decisions. In this process, managers can integrate the completely data-driven results of the machine (TIMS) with their own unique experience, knowledge, and intuition to make better judgments and management actions. In order to achieve long-term human-AI (machine) symbiosis, the key is to improve the interpretability of results given by algorithms. Interestingly, our interviews show that in fact, the interpretability of the results is the goal pursued by both users and developers. Almost all users pointed out that "*I hope that when I see the results provided by the machine, I will not only see a comprehensive indicator, but also a detailed explanation supporting it. I need to know the reason why this is the case and not just this fact. If the results obtained by TIMS are well interpretable, I will be more aware of the angle from which I should approach the actual problems or I can make more accurate and well-founded decisions, so that it is more convenient for me to explain to my subordinates why take this decision.*"

The turnover prediction function provided by TIMS is a concrete example as shown in Figure 2 with two turnover prediction results with different levels of interpretability. Specifically, the low interpretability interface only displays the total turnover risk value and a few explanatory indicators, which is a typical example of low interpretability. When the manager faces such results, s/he will have many questions about it, such as why these indicator values represent a high risk of leaving. One interviewee raised the question "*What is the source of the data behind some indicators? Or how to ensure the reliability of the indicator structure itself? Almost all AI systems have this problem. They do not provide data sources, nor do they provide data guarantees, they only state probability and confidence, which cannot be used as the sole basis for decision-making. If only based on the data-driven results, I think some employee evaluations are not accurate. Furthermore, I cannot know the criteria and basis of evaluation, thus, the entire result of this entry has lost my trust.*"

Correspondingly, the highly interpretability interface is shown on the right side of Figure 2. This forecast report contains more explanatory indicators and gives the reference points (i.e., the normal reference rang in the current example) based on the existing employee distribution in the organization, so that the manager and the HR professional have more information to

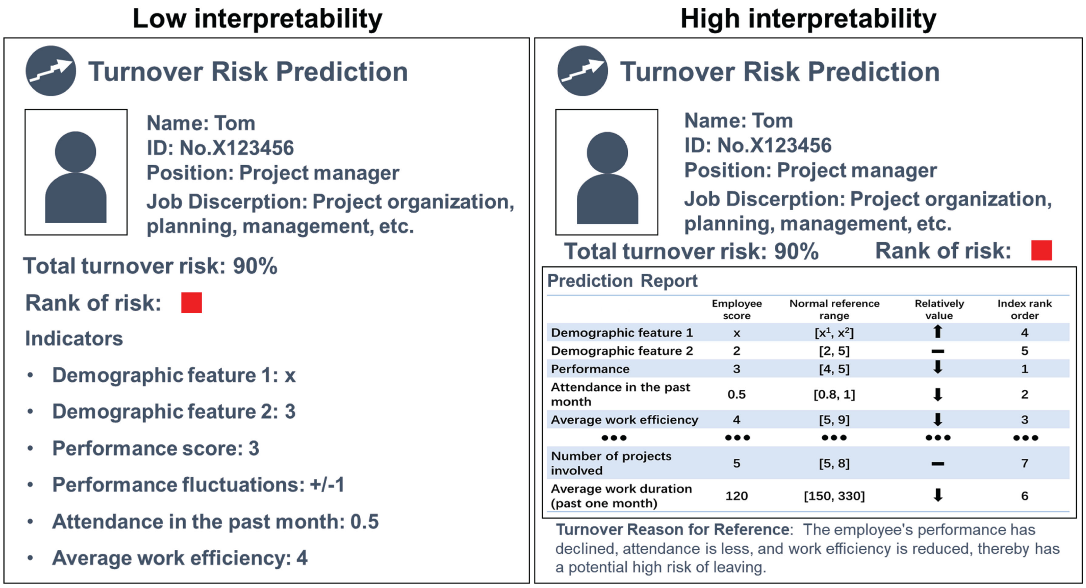

FIGURE 2. Interpretability of data-driven results (low versus high).

consider. In addition, it gives a possible turnover reason for reference to support the manager. If the functions with richer interpretable indicators are more recognized and appreciated by managers, the usage rate of TIMS will increase. According to the field data from our focal company, it can be found that after the *T1* (updating turnover prediction function with highly interpretability), TIMS utilization rate has increased significantly, as shown in Figure 3. In addition, enhancing the interpretability of the results will also further boost managers' trust in the machine and make them more receptive to integrate these results in daily HR decision-making.

TRANSFORMING HRM BY TIMS IN SOCIETY 5.0

In Society 5.0, AI technology has brought both opportunities and challenges to society. Specifically, TIMS is transforming the talent management process in enterprise digital transformation, which liberates people from simple repeatable works but also brings several challenges to HR decision-making. From this article, we outlined possible solutions to cope with the transformation challenges when introducing TIMS in the HRM process in order to transform human-AI confrontation to human-AI symbiosis. Although in this article, we only focus on a demonstration case from a high-tech company, from both research and practice perspectives, the TMIS, the examples, and the proposed mechanisms are applicable to many industries globally, with a high level of generalization. It is undeniable that human-AI symbiosis in Society 5.0 does have a lot of benefits to people. Meanwhile, we acknowledge that for the realization of human-AI symbiosis, machines ought to be more anthropomorphic and intelligent, such as integrating sentiment analysis of job interviews as another input to the predictive model, which may generate new dilemmas and concerns about machines replacing human-labor. Even so, with the deepening development of Society 5.0, the anthropomorphism of machines needs to be developed and maintained by humans and deserves more in-depth research.

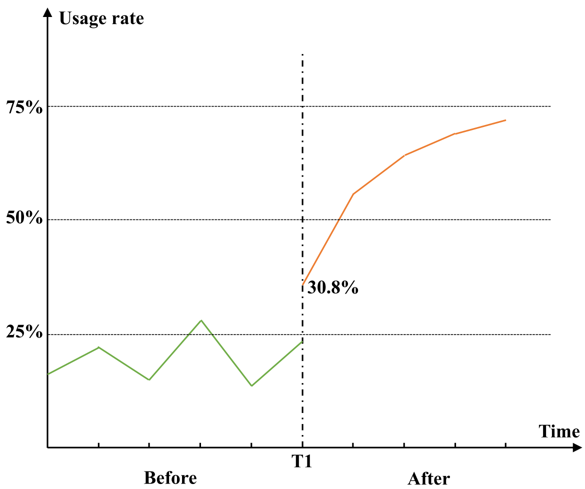

FIGURE 3. Usage rate comparison before and after improving interpretability of TIMS.

APPENDIX 1: INTERVIEW FRAMEWORK

- Total Goal

From perspective of human-AI interactions, we interview users in different background of TIMS (for example, designers, developers, managers, and general employees) to explore how to achieve better human-AI symbiosis when adopting TIMS assists HR decision-making:

- Interview Framework

Appendix 1: Interview Question Design		
Object-oriented	**Conclusion goal**	**Specific questions**
1. Designers 2. Developers 3. HR managers 4. General HR professionals	Trust of HR on AI (TIMS)	1.1 Do you know AI or AI algorithms? (Give an example)
		1.2 Do you know TIMS?
		1.3 What work do you mainly use TIMS for and which functions will be exposed to (for designers or developers, which functions of TIMS have you participated in designing or developing)?
		1.4 To what extent do you think TIMS can help your work (for designers or developers, what do you think these functions can assist HR in doing, and to what extent can it help HR)?
		1.5 To what extent do you trust the results given by TIMS? Why or why not?
		1.6 How much you make use of the recommendations from TIMS in your work?
1. HR managers 2. General HR professionals	Ability of HR to balance rational results and irrational emotions (focus HR)	2.1 How much of your work will require experience, tacit knowledge? While, how much of your work will require summarizing objective data and explicit knowledge?
		2.2 If you are asked to evaluate the quality of TIMS, what is your evaluation standard? (Please use some words or short sentences to summarize)
		2.3 In the process of work, when will you be more emotional? Do you have an emotional bias?
		2.4 What kind of results does TIMS usually give, and how objective is it?
		2.5 In the decision-making process, how much do you rely on the results given by TIMS?
		2.6 What would you do if TIMS gave counter-intuitive results or results that surprised you?
1. Designers 2. Developers 3. HR managers 4. General HR professionals	The interpretability of AI algorithm	3.1 What AI algorithms do you know? Classification algorithm or clustering algorithm?
		3.2 What is your understanding of "interpretability"?
		3.3 Do you think the interpretability will help your work? Why or why not?
		3.4 How interpretable do you think the results given by TIMS are? When there are counter-intuitive results, how much can you understand the results? (for designers or developers, do you think the results given by TIMS are interpretable?)
		3.5 Under what circumstances would you find the results of TIMS more interpretable?
		3.6 What kind of results do you expect from TIMS?

APPENDIX 2: INTERVIEW RESULTS

Appendix 2: Interview Summary from TIMS Stakeholders in a High-tech Company	
Trust is an important factor in the process of adopting TIMS	Some users have pointed out "I don't think that the machine (TIMS) can replace my occupation. I have my own value in the work. I can deal with more complexed cognitive tasks, such as formulating a plan to solve a HR problem in some specific projects. When I make a decision, the results obtained from the TIMS also can be used referred to improve my opinion. If the result obtained from the machine is more convincing with detailed explanations of it, I would be more willing to believe and use it". Similarly, "The system does help me save time for repetitive tasks, but there are still some decision-making tasks that I need to complete by myself. It is not the case that I don't want to trust TIMS, but sometimes the recommendation is very puzzling. When the system results are consistent with my experience, I trust these results."
	Another user remarked "The collaboration between humans and machines is inevitable. Simple tasks replaced by machines also require a small amount of manual review before they can be accepted. But with more frequent interactions, machines learn from human experience, so as a result, users will trust it more."
	One developer specified that "active users generally believe more in the results given by TIMS. Other users will more or less take these results into account when making decisions or plans. Those who do not trust it will never use it at all. Furthermore, I think that the managers who use TIMS will not only work more efficiently, but also know what they should do more clearly and therefore distinguish themselves from machines. They should control the "AI" and transform it into a powerful support tool, instead of being led by the system's functionality."
Balancing data-driven results and experience	Some users indicated "When making decisions, I refer to the objective results given by the system. Generally, when I encounter results given by TIMS that are consistent with my experience, I tend to make judgments based on the objective results. However, when the objective results are counter-intuitive, I will be more inclined to judge from my own experience. If the objective result is different from my own experience, but there is only marginal difference or it has a detailed explanation, I will combine the objective results with my intuition in an attempt to make my decision-making more accurate."
	Some users also stated that "It is undeniable that the TIMS has helped us improve efficiency of simply repetitive tasks and made us aware of the difference with AI-based recommendations it. Although the current degree of intelligence of the machine cannot completely replace our work, we must adapt to it and carry out a self-transformation. In this way, we can better coordinate with the machine."
	One developer specified "We still position the result of TIMS as an "assistance" role. Managers can make a priori judgment based on their own experience, and the result of TIMS can be used as a posterior. If there is an inconsistency, some managers will ask us for a more detailed explanation, while other managers may directly judge based on their own experiences."
The interpretability of algorithm results from TIMS is necessary	A user raised the question "What is the source of the data behind some indicators? Or how to ensure the reliability of the indicator structure itself? Almost all AI systems have this problem. They do not provide data sources, nor do they provide data guarantees, they only state probability and confidence, which cannot be used as the sole basis for decision-making. If only based on the data-driven results, I think some employee evaluations are not accurate. Furthermore, I can't know the criteria and basis of evaluation, thus, the entire result of this entry has lost my trust."
	Some developers commented "Although only part of the functionality currently performs well in terms of interpretability, it has to be noticed that the improvement of the interpretability of the results is our constant goal. We hope to provide users with more detailed indicators, just like the medical diagnosis report, the indicators and the corresponding threshold range will be clearly given, and the manager will play the role of a doctor and give his (her) judgment based on the diagnosis report. Obviously, the readability and comprehensibility of the diagnostic report are very important."
	Both users and developers believed that the interpretability of results gained from TIMS is necessary. Almost all users pointed out that "I hope that when I see the results provided by the machine, I will not only see a comprehensive indicator, but also a detailed explanation supporting it. I need to know the reason why this is the case and not just this fact. If the results obtained by TIMS are well interpretable, I will be more aware of the angle from which I should approach the actual problems or I can make more accurate and well-founded decisions, so that it is more convenient for me to explain to my subordinates why take this decision."

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