A Study of Employee Algorithmic Coping Behavior and Job Performance under Algorithmic Human Resource Management

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Abstract

Algorithmic human resource management is an emerging research field that integrates artificial intelligence technology with human resource management. Although artificial intelligence technology has been widely applied across various functional domains of human resource management, academic research on algorithmic human resource management remains in its infancy, with numerous issues warranting theoretical and empirical investigation. Grounded in structuration theory, this study aims to examine the influence of algorithmic human resource management in the digital intelligence era on employees' cognitive and affective reactions, algorithmic coping behaviors, and their job performance. Specifically, it includes: exploring the impact of algorithmic human resource management on employees' cognitive and affective reactions and its boundary conditions; distilling employees' coping behaviors toward algorithmic human resource management and testing how employees' cognitive and affective reactions influence their selection of algorithmic coping behaviors; and analyzing the effect and underlying mechanisms of algorithmic human resource management on employee job performance. This study will enrich and expand the knowledge system of algorithmic human resource management, provide novel insights for the strategic human resource management domain, and establish a micro-level theoretical foundation for organizations to comprehensively adopt algorithmic human resource management or implement digital human resource management practices.

Full Text

Preamble

Research on Employee Algorithmic Coping Behavior and Job Performance under Algorithmic Human Resource Management

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Abstract

Algorithmic Human Resource Management (HRM) is an emerging research field that integrates artificial intelligence technology with human resource management. Although AI has been widely applied across various functional domains of HRM, academic research on algorithmic HRM remains in its infancy, with numerous issues warranting theoretical and empirical investigation. Grounded in structuration theory, this study aims to examine the impact of algorithmic HRM on employee cognitive and emotional responses, algorithmic coping behaviors, and job performance in the digital intelligence era. Specifically, the research will: explore the effects of algorithmic HRM on employee cognitive and emotional responses and their boundary conditions; identify employee coping behaviors in response to algorithmic HRM and examine how cognitive and emotional responses influence the selection of these coping behaviors; and analyze the impact mechanisms through which algorithmic HRM affects employee job performance. This study will enrich and expand the knowledge system of algorithmic HRM, provide new insights for the strategic HRM field, and establish a micro-theoretical foundation for organizations to fully adopt algorithmic HRM or implement digital HRM practices.

Keywords: algorithmic human resource management, algorithmic management, algorithmic coping behavior, job performance, perceived justice, algorithmic trust

1. Problem Statement

Throughout the evolution of HRM research and practice, technological development has not only transformed HRM tools and methods but has also profoundly influenced its strategic significance and the achievement of organizational objectives. From electronic data processing, e-HRM, information technology, big data, and people analytics to artificial intelligence algorithms, HRM scholars have continuously tracked technological advancements and leveraged technology to assist in HRM decision-making and implementation. However, with the application of algorithmic technology, HRM is shifting from a human decision-making model to a more automated algorithm-driven decision-making model. This transformation represents not merely a technological upgrade but a profound strategic change that redefines the functions and value of HRM. Simultaneously, this transformation affects not only efficiency but also directly impacts employee job performance, laying the foundation for organizations to achieve strategic HRM and gain competitive advantage.

Recently, academics have frequently used the term "Algorithmic Human Resource Management" to unify scholarly perspectives on the increasing adoption of digital technology in HRM (Meijerink et al., 2021; Meijerink & Bondarouk, 2023; Sienkiewicz, 2021). Algorithmic HRM refers to the use of software algorithms based on digital data to enhance HRM-related decisions and/or automate HRM activities (Meijerink et al., 2021). This definition emphasizes three key features: (a) the generation and use of digital data, (b) the deployment of software or AI algorithms to process digital data, and (c) the partial or complete automation of HRM functional decisions. We argue that algorithmic HRM is not simply a technological tool change but a strategic transformation that is altering organizational management models and enhancing enterprise efficiency and performance.

Unlike traditional HRM models, algorithmic HRM not only changes the decision-making subject (from humans to algorithms) but more importantly transforms decision execution methods and the resource allocation logic under data-driven conditions. In practice, AI algorithms characterized by efficiency, optimization, and data-driven approaches are increasingly applied by managers in HRM decision-making (Liu et al., 2022; Wei et al., 2021; Zhao et al., 2020). For example, professional social platforms like LinkedIn and Zhaopin use AI recommendation algorithms to analyze and rank information from tens of millions of job seekers, then combine this with enterprise recruitment needs to personalizedly recommend best-matched talents to corporate clients (Roy et al., 2020). Some companies use natural language processing algorithms to analyze employee data 沉淀 in the workplace to predict turnover likelihood, assisting HR managers and department leaders in taking preventive measures or managing employee attrition (Chowdhury et al., 2023; Silverman & Waller, 2015). These applications not only significantly improve HRM efficiency and scientific rigor but also directly drive employee job performance through more precise data analysis and decision optimization (Huselid, 2018; Strohmeier, 2020).

Within the strategic HRM framework, the potential of algorithmic HRM lies not only in improving HR processes but also in enhancing employee performance. The application of big data and AI algorithms can improve HRM decision quality, making it more objective and scientific (Huselid, 2018; Strohmeier, 2020), and can shift HR functions from operational tasks to strategic and value-creating activities (Ruel et al., 2007; Sienkiewicz, 2021). These advantages are the main drivers for increasing organizational adoption of AI algorithms for HRM and organizational decision-making. Through algorithmic automation and precise analysis, organizations can more effectively predict and measure employee performance, thereby maximizing organizational benefits while enhancing employee job performance.

However, algorithmic HRM not only functions at the efficiency level; its structural impact on organizational management models and employee relationships cannot be ignored. While algorithmic HRM enhances HRM decision-making and execution through digital technology, it also transfers decision-making initiative to robots or computers (Duggan et al., 2020). This practice of delegating HRM decision-making authority to robots or computers executing algorithms may trigger profound changes in roles, responsibilities, cognition, and emotions among various HRM participants, including employees, HR professionals, department managers, senior executives, and corporate policymakers (Kryscynski et al., 2018). While the potential benefits of algorithmic HRM are widely recognized (Parent-Rocheleau & Parker, 2022), scholars have also expressed concerns about potential negative effects, particularly ethical issues that algorithmic decision-making may bring (Duggan et al., 2020; Luo et al., 2022), such as algorithmic discrimination and bias, algorithmic exploitation, algorithmic transparency and explainability, perceived unfairness in algorithmic decisions, algorithm aversion, algorithm appreciation, or algorithmic trust.

Moreover, although algorithmic HRM may be one of the most important future trends in the HRM field, people may instinctively react to emerging and unknown things with suspicion, disbelief, or even resistance (Prahl & Van Swol, 2017; Luo et al., 2022). Some studies support this view, showing that despite algorithmic management being more efficient, accurate, and objective, employees still do not trust algorithmic decision outcomes (Stone et al., 2015; Du, 2022; Li & Chang, 2022). This reflects that while algorithmic HRM drives organizational effectiveness improvement, employees' perceptions of its fairness, transparency, and credibility are also crucial. Literature in human-computer interaction indicates that people's perceptions of algorithmic decisions, especially fairness perceptions, are important (Sundar & Nass, 2001; Jiang et al., 2022; Luo et al., 2022; Pei et al., 2021). Regardless of how algorithmic decisions perform, people's fairness perceptions influence their adoption of them (Lee, 2018; Newman et al., 2020). Compared with HRM decisions made by HR professionals or department managers, we do not fully understand how employees perceive algorithmic decisions, yet employees' views on algorithmic decisions affect their attitudes and emotions toward them, which in turn influence their workplace behaviors and performance. Therefore, understanding and evaluating employees' ethical perceptions (such as fairness perception), emotional reactions (such as algorithmic trust and algorithm aversion), and potential algorithmic coping behaviors (such as adapting to or resisting algorithms) has become very important and necessary. This is also an important prerequisite for comprehensively promoting and applying algorithmic HRM in the HRM field—that is, the internal legitimacy of algorithmic HRM must be widely recognized.

Today, we are in a transitional period. Although emerging digital technologies such as big data, cloud computing, 5G, and AI have spread like wildfire in organizational management decision-making, there is still a long way to go before achieving the goal of fully adopting AI algorithms for HRM decision-making and execution, with many theoretical and practical issues to be resolved (Sienkiewicz, 2021; Luo et al., 2022). Therefore, the current stage is a critical moment for understanding how this technological transformation affects employee cognition, emotion, behavior, and job performance. Consequently, this study will construct a theoretical model of how algorithmic HRM in the digital intelligence era influences employee cognitive and emotional responses, algorithmic coping behaviors, and job performance based on theoretical review and practical observation. By revealing the internal mechanisms of employee cognitive, emotional, and behavioral responses, this study will open the "black box" between algorithmic HRM and performance, accelerate the construction and development of the algorithmic HRM knowledge system, provide new insights for the strategic HRM field, and establish a micro-theoretical foundation for organizations to deeply adopt AI algorithm-based HRM decision-making or implement digital HRM practices.

2.1 Algorithmic Human Resource Management

Algorithmic HRM is not an isolated concept but a product of the continuous evolution and increasing complexity of the socio-technical environment. The interaction between technology and HRM has evolved through early HR information systems, web-based HRM, e-HRM, and virtual HRM stages. Driven by emerging digital technologies such as big data, AI, and cloud computing, more intelligent, automated, and strategic HRM models have emerged, such as intelligent HRM, digital HRM, AI-enhanced HRM, and algorithmic HRM (Kim et al., 2021; Li & Li, 2021; Zhang et al., 2022). This evolution demonstrates that algorithmic HRM is not merely a technological application but a strategic transformation involving management subjects, data-driven resource allocation logic, and multiple other dimensions. Compared with traditional HRM, algorithmic HRM not only achieves breakthroughs in efficiency but also fundamentally changes HRM methods, shifting the decision-making and execution subject from humans to AI algorithms. This transformation brings not only tool improvement but also a disruption in management thinking and strategic practice.

According to Meijerink et al. (2021), algorithmic HRM refers to the use of software algorithms operating on digital data to enhance HR-related decisions and/or automate HRM activities. This concept not only synthesizes insights from various types of digital HRM but also reveals the potential value of algorithmic HRM as a strategic management tool, generating direct impacts not only on efficiency improvement but also providing new pathways for organizational competitive advantage. This shift suggests that algorithmic HRM may have transcended the scope of traditional HRM, becoming an important element for enterprises to enhance performance and competitiveness in the data-driven era. Existing literature has extensively explored different types of digital HRM practices (such as HR analytics, e-HRM, HRM cloud computing, intelligent HRM, AI-based HRM) and the significant relationships between enabling conditions (such as big data, AI) and organizations that depend on these technologies and practices (such as online labor platforms).

The core features of algorithmic HRM can be summarized in three points: (1) the generation and use of digital data, (2) the deployment of software algorithms to process digital data, and (3) the partial or complete automation of HRM functional decisions (Meijerink et al., 2021). Algorithmic HRM emphasizes the use of digital data in HRM to make fully or partially automated decisions based on specific software algorithms. The first two features (i.e., the use of digital data and software algorithms) place algorithmic HRM within the broad domain of digital HRM, while the third feature—the automation of HRM-related decisions—is what distinguishes algorithmic HRM from other forms of digital HRM. This feature endows algorithmic HRM with higher strategic status, enabling it to optimize HRM practices not only at the operational level but also potentially become a management tool that directly influences organizational strategic decision-making.

Despite the strategic potential of algorithmic HRM applications, many unresolved issues remain. Scholars have also found that the positive effects of algorithmic HRM have not been fully realized in all contexts, and in some cases have even brought negative consequences (Stone et al., 2015; Xie et al., 2021). For example, algorithmic unexplainability, insufficient transparency, and potential decision bias may lead to employee distrust and resistance toward algorithmic HRM (Newman et al., 2020; Luo et al., 2022). Therefore, it is necessary to examine algorithmic HRM from the employee perspective (Luo et al., 2022).

Structuration theory provides a powerful framework for understanding the role and mechanisms of algorithmic HRM. The theory posits that in the interaction between humans and technology, human agency always occupies a leading position, while technology serves as a structural attribute playing a supplementary role (Leonardi, 2011). This theory emphasizes the dynamic relationship between technology and humans: although algorithmic HRM plays an important role in automation and efficiency optimization, its successful implementation depends on employee cognition, emotional responses, and adaptive behaviors (Luo et al., 2022; Xie et al., 2021). Therefore, algorithmic HRM must consider not only its technical advantages but also its functional performance in employees' perception, including fairness, transparency, and explainability, especially in relation to performance. Understanding employee cognitive and emotional responses to algorithmic HRM is key to exploring its strategic value. Whether trust or aversion, employee feedback determines the long-term effectiveness and internal legitimacy of algorithmic HRM. Therefore, we need to focus from the employee perspective on their cognitive and emotional responses to algorithmic HRM and potential algorithmic coping behaviors to ensure that algorithmic HRM gains employee recognition and support while enhancing performance.

2.2 Employee Perceived Justice under Algorithmic Human Resource Management

With the explosion of data and development of AI, employers increasingly rely on algorithmic tools for recruiting, selecting, and managing employees. If data and algorithms are used reasonably, they can not only improve management efficiency but also help reduce human bias, making the workplace fairer. However, big data and algorithms also introduce new forms of bias and discrimination risks, triggering widespread academic and practical concern about fairness issues in algorithmic HRM (Zhang et al., 2021). Based on structuration theory, employee perceived justice is not only feedback on technical processes but also an important variable in the interaction between technology and humans, directly influencing employee acceptance of and behavioral choices toward algorithmic HRM.

Current research on algorithmic fairness issues focuses on two aspects: First, the fairness of algorithms themselves. Such research emphasizes formal definitions of algorithmic fairness and uses different metrics to quantify unfairness (bias) in algorithms (Corbett-Davies et al., 2023). These studies typically explore algorithmic statistical bias, group fairness, individual fairness, and procedural fairness by summarizing and evaluating whether different protected attributes (such as gender, race, origin, culture) are treated equally in algorithms (Bellamy et al., 2019). Second, the fairness of algorithmic decision outcomes. Since algorithms follow the same fixed procedures in each run, are not influenced by human emotional factors, and lack subjectivity, they are generally considered to have less decision bias than human decision-makers (Miller & Keiser, 2021; Schildt, 2017; Wilson & Daugherty, 2018; Jiang et al., 2022). However, even if algorithms are objectively fair, if employees believe the decision-making process lacks transparency or fails to adequately consider individual differences, their fairness perceptions will be weakened, thereby affecting employee trust and positive behaviors (Helberger et al., 2020; Newman et al., 2020).

Algorithmic fairness and transparency are key to influencing employee trust. According to structuration theory, employee perceived justice of algorithmic HRM is not a passive acceptance process but a core factor in employee-technology interaction. For example, if employees can understand the basis and logic of algorithmic decisions, their fairness perception will be enhanced, thereby increasing their trust in algorithms and adaptive behaviors. Conversely, if the algorithmic decision-making process is too opaque or unexplainable to employees, they may develop distrust and resistance toward algorithms (Lambrecht & Tucker, 2019; Sundar & Nass, 2001). Therefore, in the design and application of algorithmic HRM, enhancing fairness and transparency can not only increase the system's internal legitimacy but also help mobilize employees' subjective initiative, pushing their behaviors in positive directions.

2.3 Employee Emotional Responses under Algorithmic Human Resource Management

Despite algorithms' superior speed, accuracy, and objectivity compared to human decision-making, people's trust and acceptance of algorithms are often lower than expected (Edwards et al., 2000; Wilson & Daugherty, 2018). Research shows that evidence-based algorithms can make more accurate future predictions than humans, yet when deciding whether to adopt human predictions or statistical algorithms, people often choose human predictions (Dietvorst et al., 2015). For example, recruiters trust themselves more than algorithmic recommendations (Highhouse, 2008; Newman et al., 2020), patients prefer doctors' diagnoses over medical AI results (Longoni et al., 2019), and employees are unwilling to trust AI-recommended training programs and products (Castelo et al., 2019). This phenomenon of trusting human decisions more than algorithmic decisions is called "algorithm aversion," while the phenomenon of believing algorithmic decisions are superior to human decisions is called "algorithm appreciation" or "algorithmic trust."

Algorithm aversion manifests as human reluctance to use or trust algorithms (or AI products), which may result from negative experiences or perceptions of algorithm use (Dietvorst et al., 2018; Li & Chang, 2022). People develop algorithm aversion for various reasons: (1) People instinctively reject and distrust new technologies they have not used; they typically believe humans are imperfect and making mistakes is normal, but machines should be perfect and should not make mistakes (Prahl & Van Swol, 2017). (2) People's pursuit of autonomy. If people do not understand how algorithms work and cannot interact with them in friendly ways but must directly accept algorithmic recommendations, this reduces their sense of control, leading to algorithm aversion (Dietvorst et al., 2018; Prahl & Van Swol, 2017). (3) Limitations of algorithms themselves. Human nature lies in sociality; people can observe various details through interactive communication in social situations, while algorithmic opacity and unexplainability strengthen the distance between humans and algorithms. Compared with algorithmic decisions, people more easily understand decisions from humans (Yeomans et al., 2019). Additionally, some studies have explored factors causing algorithm aversion, such as algorithm characteristics (Berger et al., 2021) and unfairness perception (Newman et al., 2020).

The phenomenon where people are more willing to accept advice from algorithms than from other humans is called algorithm appreciation (Logg et al., 2019). Similar to algorithm appreciation is algorithmic trust, which refers to the degree of trust people have in the accuracy and fairness of algorithmic decisions (Alexander et al., 2018). Reasons for trusting algorithms include: (1) Personal or others' experience using and trusting certain algorithms. For example, people check rating results based on user reviews before shopping or choosing restaurants. (2) Algorithms have certain humanized, personalized features that make people happy to accept them. For example, shopping website recommendation algorithms have obvious personalized features. (3) Algorithms have strong anti-interference capabilities and make more objective and efficient decisions. Some studies have explored antecedents of algorithmic trust, including personality traits, cultural factors, age, and gender (Hoff & Bashir, 2015).

Given that algorithms are increasingly applied in HRM activities and processes, studying people's trust in algorithms has become increasingly important and urgent. Factors influencing algorithmic trust include decision process transparency, algorithmic accuracy, and fairness of algorithmic decisions. Organizations can ensure fair and accurate management decisions and enhance employee trust in algorithmic decisions by maintaining transparency in algorithm use, ensuring algorithm design aims to eliminate bias, and regularly reviewing and auditing algorithms. When employees tend to believe algorithmic decisions are fair and accurate, they are more likely to trust algorithms, which plays an important role in enhancing employee engagement, satisfaction, and job performance.

The balance between algorithmic trust and aversion and their impact on employee behavior and performance has received preliminary attention in psychology and information systems (Alexander et al., 2018; Dietvorst et al., 2018; Logg et al., 2019). However, people's emotional responses to algorithms depend not only on the technical advantages of algorithms themselves but also on multiple factors including employee cognition, cultural background, and personality traits. Therefore, how to increase employee trust in algorithms and reduce algorithm aversion in organizations is a key issue for the long-term success of algorithmic HRM.

2.4 Employee Coping Behaviors under Algorithmic Human Resource Management

Through reviewing existing literature, this study finds that in the context of algorithmic management in the digital intelligence era, employees or platform workers mainly exhibit three coping behaviors when facing algorithmic HRM: algorithm adaptation, algorithm resistance, and algorithm manipulation (Cheng & Foley, 2019; Kellogg et al., 2020; Liu et al., 2022; Xi & Deng, 2021; Xie et al., 2021). These behaviors both reflect employees' agency when facing technological change and reveal different emotional and cognitive responses to algorithmic HRM.

First, algorithm adaptation behavior. When facing algorithmic HRM decisions, as the relatively weaker and managed party, employees may proactively take actions to understand and adapt to algorithmic decisions. Algorithm adaptation behavior refers to employees actively learning how to work within algorithmic constraints, finding ways to optimize their work performance according to algorithmic standards to meet algorithm-set criteria. Based on platform-based organizations, Jarrahi and Sutherland (2019) found that most platform workers understand and internalize the work standards and norms conveyed by algorithmic management as their own value judgments, then behave according to algorithmic instructions to meet platform expectations. Algorithm adaptation behavior can be seen as an active response and adaptation to algorithmic HRM, helping employees better understand the system and work within it. Research shows that enhancing algorithmic transparency and helping employees understand how algorithms make decisions can strengthen employee trust in algorithmic decisions and increase their adaptive behaviors (Liu et al., 2022). Algorithm adaptation behavior not only enhances employee performance but also promotes the internal legitimacy of algorithmic HRM—employee recognition and support for the system is one of the key factors for the success of algorithmic HRM (Bhave et al., 2020).

Second, algorithm resistance behavior. Algorithm resistance behavior refers to employees' actions of refusing, opposing, or resisting algorithmic HRM decisions. This behavior may manifest as questioning algorithmic accuracy or directly resisting its decision outcomes (Jarrahi & Sutherland, 2019). For example, employees may express dissatisfaction by circumventing algorithmic monitoring or challenging the validity of algorithmic decisions. In algorithmic HRM practice, if employees believe the algorithmic system does not accurately reflect their performance or contributions, they may request manual review of ratings. Additionally, if employees believe algorithmic systems exhibit bias in providing training or promotion opportunities, they may resist algorithmic HRM decision outcomes. Meanwhile, when employees express concerns about privacy and personal information protection or concerns about algorithmic system transparency and accountability, they may also develop algorithm resistance behaviors (Bhave et al., 2020). Although algorithm resistance behavior can be seen as a negative reaction to algorithmic HRM, it may also indicate employees' concerns about the fairness or accuracy of algorithmic HRM decisions, potentially prompting organizations to improve decision-making processes in algorithm design and application, thereby enhancing employee fairness perception and system transparency.

Third, algorithm manipulation behavior. Algorithm manipulation behavior refers to employees proactively taking measures or actions that can influence algorithmic HRM decision outcomes. In platform-based organizations, Jarrahi and Sutherland (2019) found that platform workers may privately contact customers to give positive reviews to improve their ratings; in e-commerce research, stores may give customers coupons to encourage positive reviews to improve merchant ratings. In the HRM field, employees also manipulate their online presence or social media activities to present a more favorable image in recruitment decision algorithmic systems (Xie et al., 2021). For example, employees may artificially improve their online reputation by purchasing followers or positive reviews, or managing their social media profiles to present a more professional image. This behavioral approach may create preferences for certain employees in algorithms and undermine the effectiveness and fairness of recruitment decisions. Additionally, employees may manipulate their work hours or artificially increase their productivity metrics to present a more favorable image to algorithmic performance management systems. Furthermore, algorithm manipulation behavior in HRM may also occur when employees attempt to undermine algorithmic system effectiveness. For example, employees may deliberately provide false or misleading information to algorithmic systems to distort results. Compared with face-to-face communication with supervisors, employees in management decision contexts may selectively present themselves and may even engage in impression management to shape a "thousand-faced self" (Colbert et al., 2016). Aware that they may be in a "panopticon" of constant surveillance, employees may more intensely express themselves and engage in "impression management" toward algorithms (Xie et al., 2021). Algorithm manipulation behavior reveals vulnerabilities in algorithmic management system design and implementation; if organizations cannot timely address this behavior, it may lead to algorithmic management system abuse.

Overall, employee coping behaviors are closely related to their cognitive and emotional responses to algorithmic HRM (Colbert et al., 2016). Adaptive behavior reflects employee acceptance and trust of algorithmic systems, while resistance and manipulation behaviors may result from employee reactions to algorithmic opacity, bias, or unfair decisions. By strengthening algorithmic transparency, fairness, and explainability, organizations can effectively reduce resistance and manipulation behaviors and enhance employee adaptive behaviors, thereby realizing the strategic value of algorithmic HRM.

2.5 Algorithmic Human Resource Management and Employee Job Performance

Although existing literature has made beneficial explorations of whether algorithmic decisions affect employee job performance, insufficient attention has been paid to whether and how algorithmic HRM enhances employee job performance. This paper argues that the impact of algorithmic HRM on employee job performance may have two sides.

On one hand, algorithmic HRM may help enhance employee job performance. Algorithmic decision-making is believed to improve employees' decision-making capabilities, freeing them from trivial tasks to focus on more important work, enhancing creative abilities, and thereby improving employee and organizational productivity (Wilson & Daugherty, 2018). Kim et al. (2021) found that in educational tutoring services, AI-generated diagnoses can help tutors adapt to students' learning needs. Luo et al. (2021), based on actual sales training data, demonstrated that AI-assisted sales agent management methods can improve the job performance of sales agents originally ranked in the middle. From a complementary perspective, Tang et al. (2022) studied how the introduction of organizational AI technology and employee conscientiousness can complementarily and positively affect employee job performance. They found that AI technology introduction can improve employee job performance to some extent, but for highly conscientious employees, AI technology introduction does not enhance their job performance.

On the other hand, algorithmic HRM may also negatively affect employee job performance. Stieglitz et al. (2022) focused on social loafing—the phenomenon where individuals work less time on collective tasks than on individual tasks. Their research shows that in virtual collaboration, participants tend to shift responsibility to virtual service managers, potentially exhibiting social loafing that reduces job performance. Fügener et al. (2022) argue that AI advice helps individual performance but reduces humans' unique knowledge, and as group size increases, this reduced diversity damages group performance. Meanwhile, Fügener et al. (2022) found that when humans delegate work to AI, if humans cannot correctly assess their own abilities, leading to poor delegation strategies, AI algorithms cannot improve performance. Additionally, over-reliance on algorithms in decision-making processes may lead to lack of human interaction, reduced employee autonomy and sense of control, and may decrease employee work motivation. If employees feel the performance evaluation system is unfair or lacks transparency, they may lose motivation and no longer invest in their work.

3. Research Framework

As AI algorithm technology becomes widely applied in HRM practice and decision-making, academia and practice are increasingly concerned with how employees perceive and evaluate algorithmic HRM, whether they trust or averse algorithmic decisions, and what algorithmic coping behaviors they may adopt. These issues are not only key points in algorithmic HRM research but also decisive factors in whether algorithmic HRM can support the achievement of organizational strategic objectives. Answering these questions is also critical for organizations to implement algorithmic HRM and promote digital management practices.

This study aims to construct a theoretical model of how algorithmic HRM in the digital intelligence era influences employee cognitive and emotional responses, algorithmic coping behaviors, and job performance. Based on the structuration theory perspective, this study views algorithmic HRM not only as a technological tool but as a dynamic interactive process—employee subjective cognition and emotional responses determine whether algorithmic HRM can truly achieve its effectiveness. In this framework, employee trust in, aversion to, and resulting coping behaviors from algorithms directly relate to the effectiveness and legitimacy of algorithmic HRM in organizations, thereby profoundly affecting organizational competitiveness. By exploring the mechanisms through which algorithmic HRM influences employee cognition, emotion, and behavior, this study promotes and deepens our understanding of the algorithmic HRM knowledge system, establishes a micro-theoretical foundation for organizations to fully adopt AI algorithm-based HRM or implement digital management practices, provides new insights for the strategic HRM field, and deepens the understanding of the micro-foundations of how algorithmic HRM enhances organizational competitive advantage. Specifically, this study addresses three core questions: (1) How do algorithmic HRM decisions affect employee cognitive and emotional responses, and what are the boundary conditions? This question will focus on exploring how factors such as transparency, fairness, and explainability of algorithmic HRM affect employee perceptions and emotional responses (such as trust and aversion), and further examine boundary conditions in different decision contexts. (2) What coping behaviors do employees adopt in algorithmic HRM, and how do cognitive and emotional responses influence their choice of coping behaviors? This question will deeply analyze employee adaptive, resistant, and manipulative coping behaviors and reveal the mediating role of cognition and emotion in employees' selection of these behaviors. From the structuration theory perspective, employee behavioral responses are not passive reactions to algorithms but active interactions with technology, especially under the influence of perceptions of algorithmic fairness and control, employees will choose different behavioral strategies to adapt to or resist algorithmic HRM. (3)

How does algorithmic HRM indirectly affect job performance through employee cognition, emotion, and behavior? By analyzing how employee cognition and emotion drive behavioral choices and subsequently affect job performance, this study will provide theoretical support for the positive or negative effects of algorithmic HRM on organizational performance. Structuration theory emphasizes that technological influence must ultimately be manifested through employee behavior, so the behavioral paths of employees under different emotional and cognitive responses become key factors in whether algorithmic HRM enhances or weakens organizational performance. Figure 1 [Figure 1: see original paper] shows the theoretical framework of this study.

3.1 Study 1: The Impact of Algorithmic Human Resource Management on Employee Cognition and Emotion and Their Boundary Conditions

The application of AI algorithms in HRM can not only improve the objectivity of personnel decisions, reduce HR managers' administrative tasks, and improve management efficiency, but also promote the automation of HRM decision-making (Meijerink et al., 2021). In particular, the application of algorithmic HRM—that is, using algorithms to automate certain HRM practices—has been seen as an important pathway to realizing the strategic potential of HRM. However, employees' perceptions of and reactions to algorithmic HRM may not align with managers' expectations (Tambe et al., 2019; Liu et al., 2022; Xie et al., 2021). Study 1 will explore and examine employee cognitive and emotional responses to algorithmic HRM and the boundary conditions affecting these responses. Figure 2 [Figure 2: see original paper] shows the theoretical model of Study 1.

Algorithmic HRM explainability refers to the degree to which decisions and outcomes generated by HRM algorithms can be understood and explained by stakeholders (such as employees and department managers) (Langer & König, 2023). This is an important issue because it directly affects employees' perception and evaluation of whether HRM decisions are fair. If employees cannot understand the logic and basis behind algorithmic decisions, they may question the fairness and justice of the entire decision-making process. Conversely, if the algorithmic HRM decision-making process is transparent and employees can understand its logic, basis, and standards, they are more likely to hold positive views of the decision-making process and believe the decisions are fair (Wesche et al., 2024). Chinese scholars Zhou et al. (2022) propose that algorithmic opacity (such as proprietary, non-public data and algorithms) increases employees' perceived unfairness of algorithms. Therefore, explainability and transparency are very important for building employee trust through algorithmic HRM and improving employee work engagement. When employees feel the process is fair and their contributions and interests are considered, they are more likely to be motivated by decisions, work more efficiently, and invest more in their work.

For organizations, ensuring the explainability of algorithmic HRM decision outcomes and process transparency is crucial. This can be achieved by adopting two-way interactive and communication mechanisms that involve employees in the algorithmic decision-making process, including: clearly explaining how algorithms work and the basis for algorithmic decisions, and regularly reviewing and updating algorithms; helping employees understand how algorithms work and how they consider employee performance evaluation and performance data. Additionally, organizations can consider employee appeals and preferences in algorithmic decision-making, soliciting and reasonably adopting employee opinions and suggestions (Du, 2022). Some studies show that if user perspectives can be integrated into algorithms, users are more willing to accept and follow algorithmic decision results and recommendations (Kawaguchi, 2021). In summary, the explainability and transparency of algorithmic HRM are crucial for shaping employees' perception of algorithmic decision fairness. By ensuring transparent decision-making processes and helping employees understand the reasons behind decisions, employees may have higher levels of fairness perception. Therefore, we preliminarily propose the following proposition:

Proposition 1: The stronger the explainability and higher the transparency of algorithmic HRM decision processes and outcomes, the higher employees' perceived justice of algorithmic HRM.

In fact, algorithmic HRM is trained and predicted based on historical data—that is, using sample data to train algorithms to predict events and make decisions (Sienkiewicz, 2021). Therefore, employees' concerns about the source, quality, and collection methods of sample data may directly affect their trust in algorithmic HRM decision outcomes. Algorithms typically operate in a "black box," meaning algorithmic process opacity prevents employees from clearly understanding their working principles and accuracy (Cheng & Hackett, 2021). This opacity exacerbates employees' trust crisis in algorithmic HRM and triggers accountability issues in algorithmic decision-making (Tambe et al., 2019). Some scholars compare real-time behavior tracking, feedback, and evaluation to traditional Taylorist surveillance, arguing that algorithmic management can be seen as an intrusive form of control over employees (Bhave et al., 2020; Xi & Deng, 2021). This form of control conflicts with trends toward giving employees more autonomy and flexible working hours. Therefore, attention must be paid to trust issues that algorithmic HRM brings to employees.

Cognitive appraisal theory posits that individuals' attitudes and behaviors toward an object or situation are influenced by their sense of justice and control. In organizational contexts, employee perceived justice is crucial for building trust. In the context of algorithmic HRM, employees' fairness perception of algorithm use in HRM affects their attitudes and emotional responses toward algorithm use. Employee fairness perception in algorithmic HRM is influenced by multiple factors, including algorithmic transparency, algorithmic accuracy, and consistency of algorithmic outcomes (Jiang et al., 2022). If employees believe the process and outcomes of algorithmic HRM are fair, they are more likely to trust algorithms and hold positive attitudes toward the continued use of algorithms in HRM.

Conversely, if employees believe the process and outcomes of algorithmic HRM decisions lack fairness, they may hold negative attitudes toward organizational adoption of AI algorithms for HRM, even developing algorithm aversion. Algorithm aversion not only reduces the effectiveness and efficiency of HRM processes but also negatively affects employee job satisfaction, engagement, and job performance. Shin (2020) found that employees' fairness perception of algorithms can positively influence their trust in algorithms. Therefore, we preliminarily propose the following proposition:

Proposition 2: The higher employees' perceived justice of algorithmic HRM, the higher their trust in algorithmic decision outcomes; conversely, it leads to employee algorithm aversion.

It is generally believed that human problem-processing modes are more flexible and humanized, while algorithmic problem-processing appears mechanical and emotionless (Du, 2022). In many people's view, algorithms including AI are just tools that can play important roles in analyzing and processing data but cannot handle personalized problems or special situations. Lee (2018), through online experimental research, showed that when facing mechanical, repetitive work tasks like work allocation and scheduling, algorithmic decisions and human decisions are considered equally fair and trustworthy, triggering similar positive emotions; among them, human managers' fairness and trustworthiness are attributed to managerial authority, while algorithmic fairness and trustworthiness are attributed to perceived efficiency and objectivity.

However, when involving more humanized tasks such as recruitment and job evaluation, algorithmic decisions are considered less fair and trustworthy than human decisions and trigger more negative emotions. The reason for this result is that people believe algorithms lack intuition and subjective judgment capabilities, reducing the fairness and credibility of their judgments.

Moreover, humans are emotional and social beings; emotions play important roles in human decision-making. Although algorithms are more reliable in objective prediction or judgment, employees typically believe algorithms lack emotions and human flexible adaptability. Castelo et al. (2019), through online experimental research, found that when dealing with subjective matters (such as dating advice), people prefer to listen to human advice, but when dealing with objective matters (such as economic advice), they tend to accept algorithmic advice. Even when recognizing that algorithms perform better than humans, people still tend to adopt human advice for subjective matters. However, when people believe algorithms possess advanced emotions similar to humans, this perception strongly influences their acceptance of algorithms. Longoni and Cian (2022) reached similar conclusions, finding that compared with objective tasks, people perceive algorithms as less credible and reliable for subjective tasks.

Therefore, we can preliminarily propose the following proposition:

Proposition 3a: In algorithmic HRM task contexts, compared with personalized, subjective, high-impact tasks (such as promotion, performance evaluation, dismissal), if decision tasks are mechanical, repetitive, objective, or low-impact (such as work scheduling, task allocation), employees have higher perceived justice and algorithmic trust levels and lower algorithm aversion.

From an individual perspective, autonomy means that individuals' behaviors, choices, and decisions are initiated and controlled by themselves (Deci & Ryan, 2012). Even with automated assistance systems, humans have a clear desire for self-control. Research shows that even when automated assistance tools make fewer errors and self-reliance yields fewer benefits, some people still insist on their own choices, demonstrating a strong desire to maintain personal control (Dzindolet et al., 2002). If individuals do not understand how algorithms work and cannot interact with them in friendly ways but must directly accept algorithmic decision outcomes, this clearly reduces their sense of control, leading to algorithm aversion (Du, 2022). However, if individuals have some sense of control over algorithm operation and decision-making, algorithm aversion decreases. Dietvorst et al. (2018) argue that if individuals can modify and correct predictions from algorithms considered imperfect, even if the modification process and extent are strictly limited, individuals will be more satisfied with the algorithmic prediction process and more willing to trust algorithms.

Human-computer interaction literature points out that if opportunities for interaction with algorithms or automated machines can be provided, enabling understanding of algorithmic or machine decision-making processes and information expression forms, even if no changes can be made to how algorithms or machines themselves operate, people trust algorithms or machines more (Hoff & Bashir, 2015). Additionally, research on platform workers found that if platform workers can participate in the design and improvement process of algorithmic management, their uncertainty perception of algorithmic management significantly decreases, thereby reducing negative effects of algorithmic management (Buhmann et al., 2020). Zhou et al. (2022) propose that platform workers' work participation can weaken the positive relationship between algorithmic opacity and perceived algorithmic unfairness. Therefore, we can preliminarily propose the following proposition:

Proposition 3b: In algorithmic HRM task contexts, if employees can participate in algorithmic decision-making, employees have higher perceived justice and algorithmic trust levels and lower algorithm aversion under algorithmic HRM.

3.2 Study 2: The Influence of Employee Cognitive and Emotional Responses on Algorithmic Coping Behaviors

Algorithmic HRM has become an important research hotspot in the HRM field. However, despite this, significant gaps remain in existing literature regarding employee coping behaviors under algorithmic HRM. Based on this, exploring how employees cope with algorithmic HRM from the employee perspective is crucial for fully leveraging the positive effects of algorithmic HRM (Cheng & Foley, 2019; Kellogg et al., 2020; Liu et al., 2022; Xie et al., 2021).

Drawing on previous research, this study proposes that employees may exhibit three algorithmic coping behaviors when facing algorithmic HRM: proactively adapting to algorithmic HRM—that is, employees adjust their behaviors to meet algorithmic requirements by understanding how algorithms work. For example, employees learn how to optimize their work performance within the algorithmic framework to meet algorithm-set performance standards (Colbert et al., 2016; Kellogg et al., 2020); resisting algorithmic HRM—that is, employees take resistant actions by obstructing organizational data collection or directly ignoring algorithmic decision outcomes to express distrust or dissatisfaction with algorithmic decisions. For example, employees may question algorithmic effectiveness or even resist by avoiding algorithmic management (Jarrahi & Sutherland, 2019; Kellogg et al., 2020; Zhou et al., 2022); manipulating algorithmic HRM—that is, employees attempt to influence algorithmic decision outcomes through "currying favor" or "impression management." For example, employees may adjust their behaviors or provide misleading information to manipulate algorithmic decisions to obtain favorable performance evaluations or other outcomes (Kellogg et al., 2020; Xie et al., 2021).

Study 2 aims to explore how employees' cognitive and emotional responses to algorithmic HRM affect their choice of coping behaviors. Specifically, employees' fairness perception (cognitive response) and algorithmic trust or aversion (emotional response) toward algorithmic HRM will significantly influence which coping behaviors they adopt. Figure 3 [Figure 3: see original paper] shows the theoretical model of Study 2, detailing the relationship between employee cognitive and emotional responses and coping behaviors. This will help us deeply understand employee response mechanisms to algorithmic HRM and provide a more comprehensive perspective for organizations when implementing algorithmic HRM.

Employee perceived justice of algorithmic HRM importantly influences their responsive behaviors to algorithms in the workplace (Wei et al., 2021; Zhou et al., 2022). Fairness perception directly affects employees' willingness to accept or reject algorithmic decision outcomes. If employees believe algorithmic HRM decision processes and outcomes are fair, they are more likely to accept and comply with algorithmic decisions, proactively adopt algorithm adaptation behaviors, rather than resist or attempt to bypass these decisions. However, if employees believe algorithmic HRM decision processes or outcomes are unfair, they are more likely to resist, question, or even challenge these decisions (Zhou et al., 2022).

Cognitive appraisal theory posits that individuals' emotional and behavioral responses to stressful situations are determined by how they perceive and interpret these situations (Lazarus, 1991). In the context of algorithmic HRM, employees can participate in the evaluation process to determine the fairness of algorithmic outcomes. If employees believe algorithmic outcomes align with their goals and expectations, they are more likely to consider algorithmic decisions fair and hold positive attitudes toward algorithms. However, if employees believe algorithmic outcomes violate their rights or expectations, they may consider algorithmic decisions unfair and adopt resistant behaviors. For example, if algorithms have unfair impacts on employee performance evaluations, compensation, or promotion, employees are likely to show dissatisfaction and engage in behaviors that undermine algorithm implementation. Additionally, research shows that when using AI algorithms for HRM decisions (such as recruitment), low levels of interactional justice perception increase the likelihood of applicants suing companies that use algorithmic decision-making systems (Acikgoz et al., 2020). Similarly, Zhou et al. (2022) propose that individuals' perceived algorithmic unfairness increases their algorithmic resistance behaviors. Therefore, this study can preliminarily propose the following proposition:

Proposition 4a: In algorithmic HRM contexts, employee perceived justice influences their adopted algorithmic coping behaviors. Specifically, if employees believe algorithmic HRM decision processes or outcomes are fair, they are more likely to adopt algorithm adaptation or manipulation behaviors; conversely, if employees believe algorithmic HRM decision processes or outcomes are unfair, they are more likely to adopt algorithm resistance behaviors.

Employee trust in or aversion to algorithmic HRM decisions may also importantly influence their adopted algorithmic coping behaviors. Employees who trust algorithmic HRM decisions typically show higher acceptance, are willing to adopt algorithmic recommendations, and actively adapt to algorithm use. For example, when employees believe algorithmic decision processes are fair and accurate, they increase trust in algorithms and are likely to hold open attitudes toward algorithmic decisions, and are more likely to adopt behaviors consistent with algorithmic decision processes, such as using algorithms to help their work or seeking to understand algorithmic decision processes. Distrust in algorithmic decisions leads employees to resist algorithm use and adopt more defensive approaches to algorithmic decisions, possibly engaging in behaviors aimed at undermining algorithmic decision processes, such as ignoring algorithmic recommendations or working to subvert algorithmic decision outcomes, like seeking human decision-makers to overturn algorithmic decisions. Meanwhile, aversion to algorithmic HRM decisions often leads to negative reactions such as resistance, avoidance, or rejection of algorithmic solutions. Research shows that when employees understand the underlying decision-making process, the algorithms used, and their limitations, they may feel algorithmic decisions are just and unbiased; in such cases, they are more likely to trust algorithmic decisions and thus may be more willing to accept algorithmic solutions (Yeomans et al., 2019).

Therefore, this study can preliminarily propose the following proposition:

Proposition 4b: In algorithmic HRM contexts, employees who trust algorithms are more likely to adopt algorithm adaptation or manipulation behaviors, while employees who averse algorithms are more likely to adopt algorithm resistance behaviors.

3.3 Study 3: The Impact of Algorithmic Human Resource Management on Employee Job Performance

In HRM practice, organizations' main purpose for adopting AI algorithms is to reduce costs and improve efficiency. Therefore, organizations expect algorithmic HRM to enhance employee job performance. However, existing research has not fully explored how algorithmic HRM enhances employee job performance. Study 3 will focus on the impact of algorithmic HRM on employee job performance. Figure 4 [Figure 4: see original paper] shows the theoretical model of Study 3.

Employee job performance typically includes two components: in-role performance and extra-role performance. Generally, in-role performance refers to employees' task performance in fulfilling formal duties, such as task quality and efficiency; extra-role performance covers voluntary behaviors beyond duties, such as helping colleagues and supporting teams, typically reflecting organizational citizenship behavior.

This study argues that, similar to traditional HRM practices, algorithmic HRM can enhance both employee in-role and extra-role job performance through multiple mechanisms. First, improving decision accuracy and efficiency. Algorithmic HRM can enhance in-role performance, such as task performance. Through algorithm application in performance management and decision processes, AI algorithms can quickly and objectively process large amounts of historical data for more accurate performance evaluations, thereby helping employees better complete work tasks and improve their core work performance. Second, using predictive analytics for personalized assessment. Algorithmic HRM, through application of historical data and predictive analytics, can identify factors related to high employee job performance, such as skills, experience, and personality traits, and use this information to make wiser and more objective performance evaluation decisions. Meanwhile, this approach helps enhance extra-role performance (such as helping behavior), because when employees feel fairly and targeted supported, they are often more willing to proactively help others and exhibit behaviors beyond job duties. Third, developing personalized training and development plans. Through analysis of employee characteristics, algorithms can help organizations develop personalized training and development plans, further improving employee work performance and efficiency. This mechanism not only enhances employees' task performance but also strengthens their extra-role performance, such as helping and supporting colleagues, because they are more likely to show loyalty and responsibility to the organization. Fourth, real-time monitoring and personalized feedback. Algorithmic HRM can monitor employee work performance in real time, provide timely feedback to employees, and offer personalized suggestions. This timely feedback and personalized suggestions can help employees identify areas needing improvement and take measures to improve their task performance. Meanwhile, when algorithmic HRM feedback mechanisms are transparent and fair, employees may be more willing to invest extra effort in extra-role performance, such as helping and supporting team members, to further enhance overall organizational effectiveness.

However, the impact of algorithmic HRM on employee job performance may not be direct but may depend on employees' fairness perception and algorithmic trust in algorithmic decisions. For example, when employees feel algorithmic HRM decisions are transparent, explainable, and fair, and they clearly understand how algorithms work and how decisions are made, they are more likely to perform well. Conversely, if employees feel algorithmic HRM decision processes and outcomes are unfair and biased, they may distrust or averse algorithmic HRM, leading to damage to both in-role and extra-role performance, especially showing negative attitudes in work motivation and helping behavior. For example, if employees feel AI algorithm-based performance evaluations overemphasize digital data without considering individual special circumstances, they may lose work motivation, reduce work engagement, and decrease work investment and extra-role behaviors. Therefore, this study can preliminarily propose the following proposition:

Proposition 5a: Algorithmic HRM indirectly affects employee in-role job performance [a1] and extra-role job performance [a2] by influencing employee perceived justice or algorithmic trust.

Studying the relationship between employee coping behaviors toward algorithmic HRM and job performance can provide valuable insights into how algorithmic HRM affects employee job performance. For example, employees adopting algorithm adaptation behaviors means they understand how to work within algorithmic constraints, which typically helps them better complete tasks and thereby improves job performance. Conversely, if employees adopt algorithm resistance behaviors, this may weaken their ability to effectively perform work tasks, leading to decreased job performance. Therefore, by deeply studying different types of algorithmic coping behaviors, organizations can design and implement more effective algorithmic HRM systems that are more acceptable to employees and enhance their performance.

Specifically, algorithm adaptation behavior demonstrates employees' acceptance and compliance with algorithmic decisions. This behavioral strategy can positively affect employee job performance because it allows employees to focus on their tasks and responsibilities without questioning the validity or fairness of algorithmic decision processes and outcomes. Additionally, employees who choose to adapt to algorithmic HRM may benefit from the speed, accuracy, and objectivity of algorithmic decisions, leading to more efficient HRM processes. Meanwhile, employees who adapt to algorithms may also positively affect extra-role performance, because algorithmic objectivity and consistency reduce employee uncertainty, leading to positive attitudes in helping behavior and cooperation.

Proposition 5b: Employee algorithm adaptation behavior positively affects employee in-role job performance [b1] and extra-role job performance [b2].

Algorithm resistance behavior refers to employees' refusal to comply with algorithmic decision outcomes, whether passive or active. Employees may exhibit this behavior if they believe algorithmic HRM is unfair, untrustworthy, or opaque. Employees resisting algorithmic HRM may disengage from work or even actively challenge algorithmic decisions, which may lead to decreased job performance and satisfaction. Additionally, algorithm resistance behavior may also affect extra-role performance; when employees distrust algorithmic HRM, they often also reduce support and helping behaviors toward others and the organization.

Proposition 5c: Employee algorithm resistance behavior negatively affects in-role job performance [c1] and extra-role job performance [c2].

Algorithm manipulation behavior demonstrates employees' proactive learning of algorithms and even searching for algorithmic loopholes, then displaying attitudes and behaviors that meet algorithmic requirements to improve job performance. To some extent or initially, this can deceive algorithms and obtain higher performance ratings. However, this behavioral strategy may damage employees' long-term performance, especially when organizations discover algorithmic loopholes and fix them. Additionally, the self-interested nature of algorithm manipulation behavior may weaken employees' extra-role performance because the focus is on personal interests rather than organizational or colleague helping behaviors. Therefore, this study can preliminarily propose the following propositions:

Proposition 5d1: Employee algorithm manipulation behavior shows an inverted U-shaped relationship with employee in-role job performance;

Proposition 5d2: Employee algorithm manipulation behavior negatively affects employee extra-role job performance.

4.1 Theoretical Contributions

This study reveals how algorithmic HRM affects employee job performance by influencing employee cognition, emotional responses, and coping behaviors. This provides theoretical basis and practical guidance for organizations and managers to adopt AI algorithm-based HRM systems or implement digital management practices. Through the lens of structuration theory, this study emphasizes the role of employees as active agents, demonstrating the importance of employee cognition and emotional responses in the effectiveness of technology application. Furthermore, this study focuses on how individual employees in the digital intelligence era perceive, evaluate, and cope with algorithmic HRM, which will establish a novel micro-foundational theory of algorithmic HRM and summarize the internal cognitive and emotional mechanisms through which organizations and managers can use algorithmic HRM to enhance employee job performance, providing a solid foundation for enterprises in the digital intelligence era to conduct algorithmic HRM. This research not only expands our understanding of algorithmic HRM but also provides a systematic framework revealing its potential unique value in the strategic HRM field.

First, this study provides a new theoretical perspective for deepening and developing the algorithmic HRM knowledge system. Although algorithmic technology has long been applied in business practice, existing literature, especially research exploring the impact of algorithmic HRM on employee behavior and performance, is still in its infancy, particularly empirical research (Liu et al., 2022; Luo et al., 2022). Algorithmic HRM is not merely a simple extension of HRM tools but a strategic transformation that helps organizations improve efficiency and achieve competitive advantage through data and algorithm-driven decision-making. Based on core tenets of structuration theory, this study argues that the effectiveness of algorithmic HRM depends not only on the technology itself but more importantly on employees' acceptance and adaptation capabilities. Therefore, studying algorithmic HRM can not only provide useful insights into how organizations can use algorithmic systems to improve the efficiency and effectiveness of HRM processes but also help organizations understand ways to improve employee engagement and job performance through algorithmic systems, as well as ethical issues arising from algorithmic decision-making in HRM, ultimately enriching the research content of strategic HRM.

Second, this study deeply explores employee cognitive and emotional responses under algorithmic HRM and their impact on employee coping behaviors, advancing micro-foundational theoretical research on algorithmic HRM. The core object of algorithmic HRM is employees; how employees view and evaluate HRM algorithms directly affects their trust in and attitudes toward algorithms, which in turn influences their workplace behaviors and performance, affects organizational adoption of algorithmic decisions, and ultimately affects organizational performance (Lee, 2018; Newman et al., 2020; Jiang et al., 2022). Currently, examining the impact of algorithmic HRM on employees from the individual level is still in its infancy, lacking theoretically oriented research questions that can deeply reflect the context of AI algorithmic decision-making (Luo et al., 2022). By studying employee cognitive and emotional responses to algorithmic HRM and algorithmic coping behaviors, this study reveals how employee adaptive, resistant, and manipulative behaviors mediate the relationship between algorithmic HRM and employee job performance, filling the missing link in the digitalization challenges facing HRM (Dery et al., 2013). Furthermore, within the structuration theory framework, employee cognitive and emotional responses are not merely reactions to algorithmic technology but manifestations of active adaptation or resistance to organizational management structures and technology application environments, while also partially explaining why some digital HRM practices, such as algorithmic HRM implementation, perform well in some cases but not in others. Therefore, this perspective based on employee cognitive and emotional responses compensates for the deficiency in traditional digital HRM research regarding the exploration of individual behavioral mechanisms.

Third, this study promotes understanding of employee coping behavior models under algorithmic HRM. By proposing these three employee coping behaviors—adaptation, resistance, and manipulation—this study fills theoretical gaps in existing literature regarding how employees cope with algorithmic management.

Combining these coping behaviors with job performance, this study reveals the mechanisms through which employees influence HRM system success or failure through different behavioral patterns, especially in terms of algorithm implementation effectiveness. This model reflects the dynamic relationship between technology and humans in structuration theory—that is, the effectiveness of technology application varies depending on employee acceptance and behavioral choices. This theoretical framework provides theoretical support for understanding employee-algorithm interaction and offers practical guidance for organizations to design more effective algorithmic HRM systems.

Fourth, this study deeply explores how algorithmic HRM functions in HRM practice from the structuration theory perspective, addressing the complexity of algorithm application in existing HRM literature. Structuration theory posits that although technology plays a key role in organizations, the role of employees as active agents cannot be ignored; technology's influence largely depends on employees' cognition and adaptation capabilities (Leonardi, 2011). Therefore, in the algorithmic HRM context, this means employees' acceptance and adaptation capabilities will directly affect the effectiveness of algorithmic HRM. Therefore, research must not only focus on how AI algorithm technology changes HRM processes but also on how employees adapt to, evaluate, or even resist algorithmic HRM (Xie et al., 2021). For example, employees may choose to resist or manipulate algorithms based on distrust, which not only affects individual job performance but also challenges the legitimacy of the entire HRM system. This study explores how employees perceive and evaluate algorithmic HRM—that is, studying employee perceived justice, algorithmic trust, and algorithm aversion toward algorithmic HRM; it also explores what behaviors employees may adopt to cope with algorithmic HRM and how these algorithmic coping behaviors affect employee job performance. Therefore, studying algorithmic HRM from the structuration theory perspective also partially responds to the four challenges Tambe et al. (2019) proposed for AI adoption in HRM: the complexity of HRM phenomena, usage limitations due to small data volumes, explainability issues related to fairness and other ethical and legal constraints, and negative employee reactions to data-based algorithmic management decisions.

Finally, this study conducts an in-depth and comprehensive exploration of fairness and explainability issues in algorithmic HRM, focusing on analyzing how these factors affect employee algorithmic trust and job performance. This study systematically reveals ethical issues that algorithms may generate in decision-making processes, especially challenges in algorithmic discrimination, bias, and transparency. This research emphasizes that although algorithms can improve HRM efficiency, their decision transparency and explainability directly affect employee trust in algorithms and work motivation. If employees cannot understand the basis of algorithmic decisions or perceive them as unfair, then even if algorithms themselves have high efficiency and objectivity, they may trigger employee resistance and affect organizational performance. The study points out that improving algorithmic HRM transparency and explainability is crucial for enhancing employee trust, especially in HRM practice, which not only helps improve employee work engagement and performance but also enhances organizational acceptance and legitimacy of algorithmic systems. To effectively address these technical and ethical challenges, this study further proposes increasing employee participation in algorithm design and application processes to reduce algorithmic system opacity and lack of control. Additionally, the study recommends regularly reviewing algorithmic fairness and accuracy to ensure compliance with ethical and legal standards, thereby reducing potential conflicts caused by algorithmic bias or discrimination. In summary, through systematic analysis of algorithmic fairness, transparency, and explainability issues, this study provides a more nuanced framework to guide organizations on how to more effectively implement algorithmic HRM during digital transformation. These research findings not only provide new ideas for improving employee trust in algorithmic HRM but also offer practical guidance for organizations to balance efficiency and ethics in technology application.

4.2 Future Research Directions

In addition to the above theoretical implications, this paper proposes the following research directions, hoping future research can further expand and improve theory and practice in the algorithmic HRM field. First, deepen understanding of the impact mechanisms of algorithmic HRM on multi-dimensional employee performance. Future research can adopt diverse research methods, using field experiments, longitudinal studies, and case analyses to more comprehensively validate the effects of algorithmic HRM. These methods can capture employee behavioral dynamics in algorithm-driven management contexts, helping reveal the immediate and long-term impacts of algorithmic HRM on employee performance. For example, longitudinal studies can provide profound insights into the continuous effects of algorithmic HRM on employee cognition, emotion, and behavior, offering solid empirical support for theoretical development in algorithmic HRM (Bhave et al., 2020; Kellogg et al., 2020). Additionally, case analyses can reveal specific contexts of enterprise algorithmic HRM implementation, providing references for management practices in different organizational sizes and industry backgrounds.

Second, explore the differential impacts of different types of algorithmic HRM systems on employee reactions. Future research can distinguish the unique characteristics of predictive algorithms and evaluative algorithms and their impact paths on employee cognition, emotion, and behavior. Predictive algorithms focusing on behavior trend forecasting may significantly affect employee fairness perception and trust levels, while evaluative algorithms focusing on performance evaluation may lead to differential employee reactions in emphasis on in-role performance (such as task performance) and extra-role performance (such as helping behavior) (Meijerink et al., 2021). Studying the relative advantages and limitations of these algorithm types will help understand best practice strategies for algorithmic HRM in specific contexts and provide targeted guidance for optimizing performance management.

Third, focus on the moderating role of employee individual characteristics and cultural backgrounds in algorithmic HRM. The individual differences perspective is important for revealing diverse employee reaction patterns to algorithmic management. For example, future research can examine the influence of personality traits (such as extraversion, openness) on employee adaptation to and trust in algorithmic decision systems. Employees high in extraversion or openness may be more inclined to accept and trust algorithm-driven decisions, while those high in conservatism may more easily exhibit resistant behaviors (Dietvorst et al., 2015). Additionally, as algorithmic HRM promotes globally, cross-cultural research becomes particularly important. Future research can explore how employee acceptance and reaction patterns to algorithmic management differ across cultural backgrounds, examining how cultural differences affect the effectiveness of algorithmic HRM. This perspective not only helps build a universal algorithmic HRM theoretical framework but also provides culturally sensitive management recommendations for international enterprises implementing algorithmic HRM in different cultural environments.

Finally, focus on ethical and governance issues in algorithmic HRM. While improving efficiency and performance, ensuring the fairness, transparency, and compliance of algorithmic HRM is an important challenge for enterprises implementing this management practice. Future research can explore how to enhance employee trust in algorithmic decisions through institutional design from an organizational governance perspective. For example, increasing employee participation in algorithm system design and application processes, establishing decision feedback mechanisms, and regularly reviewing algorithms to reduce bias and discrimination (Helberger et al., 2020; Newman et al., 2020). This governance-structure-focused research can not only optimize the management effectiveness of algorithmic HRM but also enhance its legitimacy and social acceptance, providing stable ethical and legal foundations for enterprise HRM in the digital intelligence era.

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Note: Figure translations are in progress. See original paper for figures.