SPECIAL ISSUE ARTICLE OPEN ACCESS

Exploring the Duality of Perceptions: Insights into Uncertainties, Aversion and Appreciation Towards Algorithmic HRM

Anushree Tandon[1] | Amandeep Dhir[2] | Ashish Malik[3] | Pawan Budhwar[4] | Puneet Kaur[5]

[1]Faculty of Social Sciences and Business Studies, University of Eastern Finland & European Forest Institute, Joensuu, Finland | [2]Department of Management, School of Business & Law, University of Agder, Campus Kristiansand, Kristiansand, Norway | [3]Queen's University Belfast, Belfast, UK | [4]Aston Business School, Aston University, Birmingham, UK | [5]Department of Psychosocial Science, University of Bergen, Bergen, Norway

Correspondence: Amandeep Dhir (amandeep.dhir@uia.no)

Received: 28 February 2023 | **Revised:** 13 October 2024 | **Accepted:** 23 October 2024

Funding: This work was supported by the Liikesivistysrahasto (Finnish Foundation for Economic Education), Finland [grant number 220209].

Keywords: algorithmic aversion | algorithmic human resource management | employee | human resources | qualitative

ABSTRACT

The human resource management (HRM) function has witnessed the rapid integration of algorithms into incumbent processes; however, significant employee resistance and aversion to algorithmic decision-making have also been reported. Research on algorithmic HRM practices indicates an underlying duality of perceptual responses by HRM professionals towards this technology. We seek to understand how HRM professionals experience algorithmic HRM use and determine if there are bright sides to its organizational integration. We undertake a qualitative, open-ended study based on written responses to open-ended questions from 58 respondents in the United Kingdom and the United States of America. The data were thematically analyzed using grounded theory, which revealed four themes representing HRM professionals' overarching perspectives on why algorithmic HRM precipitates aversion or appreciation. The first two themes highlight HRM professionals' perceived subjective uncertainty regarding algorithmic HRM and its perceived negative effects on the organization. The third theme acknowledges the positive effect of algorithmic HRM, and the final theme discusses three critical coping strategies (embrace, avoid, and collaborate) that HRM professionals adopt to counteract their experienced fears. Our findings suggest that HRM professionals adopt a cautiously fearful rather than a wholly adverse outlook towards algorithmic HRM, wherein aversion and appreciation appear to emerge simultaneously. We contend this existence of a duality of perceptual responses to algorithmic HRM may be a precursor to setting a harmonious collaboration between humans and algorithms in the HRM domain, contingent on appropriate levels of oversight and governance. Implications for theory and managerial practice are also discussed.

1 | Introduction

Recently, HRM has experienced a transformation driven by the deployment of digital technologies and platforms (Budhwar et al. 2023; S. Kim, Wang, and Boon 2021; Poba-Nzaou, Uwizeyemungu, and Clarke 2020). There is emphatic recognition of the efficiency of algorithms in processing data and performing cognitive tasks normally undertaken by humans (Giermindl et al. 2022). This has led to their increasing use in optimizing HRM decision-making by partially or fully automating incumbent processes (Baiocco et al. 2022; Meijerink et al. 2021) in areas such as task allocation (Baiocco et al. 2022), performance and compensation management (Khoreva et al. 2019; Kinowska and Sienkiewicz 2022; Tong et al. 2021). This integration of algorithms into HRM has led to the development of algorithmic HRM as an emerging field of inquiry. This field involves the narrow application of algorithms to HRM processes, functions, and data, and in our view, algorithmic HRM differs from general algorithmic management in its usages and expectations.

While there is widespread recognition of the benefits algorithmic HRM can bring to organizations, such as, in streamlining HRM operations (see Goods, Veen, and Barratt 2019), there have also been serious concerns raised about its usage. These concerns especially revolve around how it can perpetuate racial and gender bias (Leicht-Deobald et al. 2019) and social inequalities (Bankins et al. 2022) due to data quality, integrity and size, and the complexity of HRM-related consequences (e.g., Tambe, Cappelli, and Yakubovich 2019). These concerns have led scholars to recognize the phenomenon of *algorithmic aversion*. Algorithmic aversion is "a behavior of neglecting algorithmic decisions in favor of one's own decisions or other's decisions, either consciously or unconsciously" (Mahmud et al. 2022, p. 1). In the context of HRM, we contend that such aversion to algorithms could originate from professionals' perceptions of distrust, fear, or lack of confidence (Cheng and Hackett 2021; Prikshat, Malik, and Budhwar 2021) in algorithmic HRM due to the possible bias and detrimental outcomes that it could engender. These outcomes (e.g., see Maasland and Weißmüller 2022; Mahmud et al. 2022) include perceived decrements in fair treatment (Köchling and Wehner 2020) and even job redundancy for HRM professionals (Arslan et al. 2022; Ore and Sposato 2021).

Despite scholars' acknowledgment that fear of and aversion to algorithmic HRM can have severe implications for organizations' use of such technology and the future of work, scant research has been directed toward understanding why these issues exist (Mahmud et al. 2022). This may be due to a combination of reasons. First, there is limited evidence that informs scholars and practitioners about the factors that could reduce the enthusiastic adoption of algorithmic HRM across different HRM functions, such as recruitment (Köchling and Wehner 2020; Park et al. 2021). Second, very little research examining algorithm aversion in real-world professional communities through qualitative methods exists (Mahmud et al. 2022), which means there is significant scope for developing more nuanced insights into the causes of such aversion. In our view, these knowledge gaps are significant since perceptions about the possibility of bias against human agents in new technologies can often determine the failure or success of their adoption (Budhwar et al. 2022; Newman, Fast, and Harmon 2020).

Recognizing these gaps, several scholars (e.g., Köchling and Wehner 2020; Leicht-Deobald et al. 2019; Meijerink et al. 2021; Meijerink and Bondarouk 2023) have called for research that examines how professionals' fear of and aversion to algorithmic decision-making may be reduced, particularly in the context of domains such as HRM. We contend that gaining an in-depth understanding of such aversion is critical for two reasons. First, scholars have reported that negative perceptions of algorithmic HRM use lead workers and HRM professionals to demonstrate *algoactivism* or deliberate sabotage of algorithmic HRM use (Meijerink and Bondarouk 2023). Such negative employee responses to algorithmic HRM use have the potential to severely undermine organizational returns on investments in the deployment of these technologies. Following such suppositions, researchers have recently emphasized the need for qualitative investigations to determine solutions for algorithmic aversion and the underutilization of algorithms (e.g., Neumann et al. 2023; Burton, Stein, and Jensen 2020). We believe that this need is singularly important considering the existing preconceived reservations about the black-box phenomenon of algorithms (i.e., the opacity of their inner workings for the masses; Bartosiak and Modlinski 2022; Meijerink and Bondarouk 2023).

Second, the extensive diffusion of algorithmic HRM rests on HRM professionals acting as agents of change who prepare their organizations and human resources to accept the technologies and their outcomes (Suseno et al. 2022). Hence, gaining a nuanced understanding of factors that could make HRM professionals fearful or averse to algorithmic HRM use is critical. If solutions are to be proposed to counter this aversion or fear, we need to understand if and why such emotional responses persist despite wide-ranging and continual technological advancements being adopted in the workplace. By doing so, we respond to the call to understand HRM professionals' perceptual and emotional responses to algorithmic HRM, with an emphatic focus on investigating why they may resist or be averse to this technological system. We act on the need for nuanced and in-depth research on algorithmic HRM and adopt a qualitative approach to address two research questions (RQs): (1) *Are HRM professionals fearful or averse to algorithmic HRM use in their organizations? If so, what are the reasons for these negative responses and if not what are the reasons for their positive responses?* (2) *What are the outcomes of such fear and aversion toward algorithmic HRM, and how do HRM professionals cope with them?*

To answer these RQs, we collected qualitative data via open-ended, structured interview questionnaires from 58 HRM professionals based in the United Kingdom (UK) and United States of America (USA). Most of these respondents were employed at the managerial level, covering a range of varied functional roles in HRM, such as recruitment, learning and development, performance, and compensation management (see Table 1). These respondents were familiar with algorithmic HRM applications and were asked (a) whether they encountered any fear of or aversion to the use of algorithmic HRM within their organizations and the reasons thereof and (b) their reactions and the coping strategies they utilized in dealing with any experienced fear or aversion. HRM professionals were a viable choice as respondents for this study as they are well-positioned to shape organizational HRM policy and garner other employees' reactions to the same. They, in essence, act as change agents for their organizations (Sarvaiya, Arrowsmith, and Eweje 2021). The data were inductively analyzed using the grounded theory method (Creswell et al. 2007) through iterative coding, which enabled us to assimilate the respondents' voices and translate them into four different themes. These include HRM professionals' perceptual responses of aversion, fear, and even appreciation of algorithmic HRM.

This study contributes to the field of HRM in the following ways . First, it offers an in-depth understanding of why HRM professionals experience a fear of or aversion to algorithmic HRM (either in themselves or from other employees), the outcomes thereof, and the strategies used to cope with the outcomes. By doing so, our first contribution is our response to recent scholarly calls (Cheng and Hackett 2021; Kelan 2023; Mahmud et al. 2022) for further research exploring factors allied to stakeholders' resistance to algorithmic HRM. Recent systematic reviews indicate that only 22 academic studies focusing on algorithmic HRM (Cheng and Hackett 2021) have been published, and algorithmic aversion is less studied in terms of perceptual biases in specific contexts (Choung, Seberger, and David 2023), social dimensions (Bevilacqua and Alashoor 2023), tasks, and high-level organizational factors (Mahmud et al. 2022).

There is limited scholarly information on these topics as algorithmic HRM pertains to a narrow application of algorithms in the modern workplace and is an emergent research issue. The research specifically directed at aversion to algorithmic HRM is relatively scant in comparison to aversion to algorithmic recommendations and decision-making in a general context, which has been the subject of multiple studies (e.g., Köchling and Wehner 2020; McDonnell et al. 2021). Indeed, few qualitative studies (e.g., Neumann et al. 2023) have focused on explicating the reasons or bases for algorithmic aversion or fear—which, in our view, could be a precursor to active resistance toward algorithmic HRM. In this regard, our study goes a long way in undertaking and offering a detailed discussion of professionals' perceptual responses to algorithmic HRM. Our study reveals two reasons (uncertainty and subjectivity of experiences and perceived negative effects on organizations and employees) that may inform HRM professionals' nuanced perceptual responses to algorithmic HRM use, including caution, wariness, fear, and aversion. However, we also find that there is a simultaneous emergence of appreciation for algorithmic HRM that is precipitated by respondents' belief in singularly discussed positive effect on the organization. We believe that such appreciation is a precursor to their acceptance of this technology. To bind the findings together, we employ the stimulus-organism-response (SOR) model to develop a framework explaining perceptual responses to algorithmic HRM use. The SOR is a well-regarded theory that allows scholars to understand the process through which individuals evaluate whether to adopt or avoid a behavior in response to a specific stimulus (Jacoby 2002; Mehrabian and Russell 1974). This framework is an initial attempt to establish a basis for developing more nuanced frameworks linking algorithmic HRM use and employee behavior, both positive and negative.

Second, our study contributes to the literature by revealing a distinct duality of HRM professionals' responses to algorithmic HRM use that encompasses both bright (*appreciation*) and dark (*aversion*) aspects is a marked contribution to this field, especially as we find that the latter (i.e., aversion) seems to have a range of emotional connotations as a response. In our view, aversion may be too strong a word for describing the perceptions of the current workforce, which has witnessed intense and extensive technological advancements in their organizations, particularly in the wake of the COVID-19 pandemic. Instead, we believe algorithmic wariness or caution would be a more apt description for HRM professionals' perceptual response to algorithmic HRM implementation. In addition, some of our respondents also demonstrated appreciation for some aspects of this technology contingent on its selective and well-governed usage. Our findings support prior scholars' (e.g., see Einola and Khoreva 2023; Charlwood and Guenole 2022) contention that a harmonious coexistence between humans and algorithms, with minimal resistance, is possible. However, this potential coexistence is dependent, as mentioned, on algorithmic HRM's selective use and appropriate governance. Further, we align with Moritz et al. (2023) to suggest that algorithmic aversion and appreciation may be two sides of the same coin, thus offering an insight into the potential duality of algorithmic HRM's usage in organizations. In this regard, our proposed framework, which binds this duality under a theoretical aegis, presents an important contribution to this field; it allows scholars to foresee a pathway that translates the deployment of algorithmic HRM into behavioral responses by HRM professionals who are exposed to it.

Third, few studies have focused on investigating the specificities of HRM professionals as a respondent group in aversion literature compared to other respondent groups, such as job applicants (Choung, Seberger, and David 2023) and workers, especially those employed in the gig economy (e.g., Newman, Fast, and Harmon 2020). Since HRM professionals can be effective change agents and are uniquely positioned to ensure the alignment between organizational resources and demands, their experiences exemplify various problematic employee experiences that organizational fora may encounter during algorithmic HRM implementation. Our study findings inform practitioners and scholars about the transformational role that HRM professionals can play in reducing algorithmic HRM aversion. For instance, HRM professionals can deploy strategies that strongly influence employees' positive rumination of the effects of algorithmic HRM use, such that this influence leads to their appreciation of this technology. The results provide valuable insights into practices that could be deployed to alleviate algorithmic aversion and promote HRM professionals' appreciation of algorithmic HRM. Our findings also provide evidence to support the practice of collaborative intelligence (Park et al. 2021; Wilson and Daugherty 2018) in HRM, a nascent field of study with significant implications that may provide organizations with a competitive advantage.

Lastly, the study offers methodological advancement in the field, which has, to date, been limited to mainly conceptual, experiment-based, and quantitative studies. Qualitative approaches can be used to generate nuanced insights in answering the "why" and "how" questions related to HRM professionals' interaction with algorithmic HRM, which is a relatively less examined topic. For this purpose, we utilize the grounded theory approach, which generates a "general explanation for a process, action, or interaction shaped by the views of a large number of participants" (Creswell et al. 2007, p. 249).

The remainder of the manuscript is structured as follows. We begin by offering insight into the state-of-the-art of existing algorithmic HRM and aversion research. This is followed by describing the methodological approach adopted to answer our RQs and the presentation of the study's findings. Binding the findings together under the theoretical underpinnings of the SOR model, we present a framework describing a pathway for explaining the dual perceptual responses that algorithmic HRM use can engender. This is accompanied by a discussion on future research possibilities that scholars can address. Lastly, we present a conclusion, including the implications (both practical and theoretical) and limitations of our research.

2 | Background Literature

2.1 | Algorithmic HRM—Types and Usages

Algorithms reflect an assemblage of different adaptative technologies, such as artificial intelligence (AI) and machine learning approaches designed to read and interpret large sets of data, performing cognitive tasks usually undertaken by humans (Giermindl et al. 2022). Algorithmic HRM is a subset of digital HRM that still lacks broad consensus on its definition due to its nascent origins. Scholars have chosen various ways to define this concept; for instance, Meijerink et al. (2021, p. 2547) define algorithmic HRM as "the use of software algorithms that operate on the basis of digital data to augment HRM-related decisions and/or to automate HRM activities." Cheng and Hackett (2021, p. 8) propose that "HRM algorithms are computer programs of a heuristic nature that use economical input of variables, information, or analytical resources to approximate a theoretical model, enabling an immediate recommendation of screening, selection, training, retention, and other HR functions." Despite the minute variations in scholarly perspectives toward algorithmic HRM, Meijerink et al. (2021) suggest it encompasses three unique features: (a) the creation and use of digital data, (b) software algorithms for processing data that can be combined to establish algorithmic HRM's link with digital HRM, and (c) the full or partial automation of HRM-allied decision-making, which differentiates algorithmic HRM from other technologies included in digital HRM, such as online labor platforms or social media/mobile analytics. In our study, we concur with Meijerink et al.'s (2021) conceptualization of algorithmic HRM and consider AI-assisted HRM as part of the concept.

Algorithms are a group of simple or complex instructions. They are building blocks for technologies like AI and machine learning, which go beyond algorithms to use data to develop human-like logic. As Danner (2018, p. 25) explains, "Algorithms are goal-oriented, cascaded sets of rules that are influenced by external data, triggered by an event or constantly looping, never-ending." In other words, not all algorithms are AI (Puranam 2021). Algorithms are broadly classified into three categories: descriptive, predictive, and prescriptive (Kuhn, Meijerink, and Keegan 2021; Leicht-Deobald et al. 2019). Descriptive algorithms are deployed to support decision-makers (humans) by processing and analyzing data related to workers through statistics such as distribution and mean scores (Langer and König, 2023; Leicht-Deobald et al. 2019). For example, such algorithms may compare worker metrics in performance management. Predictive algorithms typically use more advanced statistics, including regression and data mining, to analyze forecasting data. These algorithms can predict the likelihood of a specific outcome in HRM, such as a prospective candidate's performance or an organization's turnover for a particular period (Leicht-Deobald et al. 2019). Lastly, prescriptive algorithms are used for applications such as scenario planning to decide a course of action based on the prescriptions or decisions produced (Langer and König 2023; Leicht-Deobald et al. 2019).

Algorithms are used globally to quantify, automate, and optimize HRM functions such as staffing, task allocation, and management compensation with little or no human intervention (Lamers et al. 2022). However, confidence in such algorithms' accuracy and efficiency remains questionable. For instance, a survey in the UK (BCS 2020) discovered that about 53% of the public was not confident about any organization's use of algorithms for decision-making in areas related to individuals' welfare, such as social services and education. Further, Medwell (2022) discussed how workers in companies such as Amazon saw algorithms as dehumanizing, overly demanding, and unreasonable in setting performance expectations. Another study (Neudert, Knuutila, and Howard 2020) found that globally, business professionals were slightly more optimistic, with 47% believing automated decision-making to be helpful rather than harmful, albeit with regional variations evident in the analysis.

With the rising integration of digitization in HRM, it is critical to understand the origins of the observable lack of confidence and aversion to the use of algorithmic HRM (Dargnies et al. 2024), particularly as organizations seem to derive profitability from such applications (Lamers et al. 2022). However, academic research investigating the origins of the aversion to and fear of algorithms in HRM still needs to be developed (Cheng and Hackett 2021; Lamers et al. 2022; Scheibmayr and Reichel 2021). Subsequently, we assert that the question of whether algorithmic deployment in business and society is an opportunity or a challenge remains unresolved (Levy, Chasalow, and Riley 2021), and there is a need to understand the duality of responses to this technology's integration in the HRM domain.

2.2 | Algorithmic Aversion

While algorithmic aversion has been studied previously in the context of general decision-making (Mahmud et al. 2022), investigations into the HRM domain are, in the main, limited. Moreover, the limited extant studies offer diverse opinions about how professionals react to algorithmic deployment in HRM functions, which can be contingent on their perception of justice or fairness (Mirowska and Mesnet 2022; Parent-Rocheleau and Parker 2022), organizational outcomes (Moritz et al. 2023), HRM attributions of intent, and algorithmic qualities (Koch-Bayram and Kaibel 2023). Even studies in the general context suggest that employees may be both appreciative of and averse to algorithmic decisions (Moritz et al. 2023), depending on certain factors. For instance, Vassilopoulou et al. (2024) and Langer and König (2023) proposed that the lack of confidence in algorithms used within the HRM domain could be based on their opacity and potential to introduce or mask biases that can perpetuate and disguise social inequalities.

Interestingly, professionals' level of experience has also been found to play a role in determining their perceptual response to algorithmic management. For instance, Allen and Choudhury (2022) determined that professionals with moderate domain experience may find algorithmic advice to be complementary, while professionals with significant experience may reject algorithmic advice because they consider their accountability to be greater for any intended consequences that may arise from following such advice. The latter proposition was also echoed by Wang, Gao, and Agarwal (2023), who found AI to provide greater benefits to employees with extensive task-based experience, wherein junior-level employees were observed to garner greater benefits compared to seniors. Along similar lines, Logg, Minson, and Moore (2019) examined varied individuals' reliance on algorithmic advice and found that professionals rely less on algorithmic advice compared to lay persons.

Such issues are posited to be significant reasons for the aversion toward algorithmic applications, but studies specific to algorithmic aversion remain scarce. Considering the dearth of research on algorithmic aversion in the HRM domain, we also refer to the literature available in other contexts to explain the possible motivations and factors for this phenomenon. In a recent systematic review, Mahmud et al. (2022) proposed an integrated framework that detailed four elements that could lead to algorithmic aversion: individual factors (e.g., personal or psychological), the nature of the task, the algorithm itself (i.e., its design and delivery), and other high-level factors (e.g., organizational or cultural). However, this review also pointed out that the extant understanding of algorithmic aversion is still constrained by factors such as the need for a comprehensive theoretical framework and an overemphasis on quantitative studies.

Further, a few existing studies have also investigated the factors that could reduce algorithmic HRM aversion. For example, a recent lab-based study on the attitudes of workers and managers toward algorithmic hiring decisions found that algorithmic neutrality toward gender among workers and feedback on decisions among managers reduced aversion (Dargnies et al. 2024). Another study (Lacroux and Martin-Lacroux 2022) found that workers were more averse to algorithmic decision-making than HRM managers in recruitment due to the subjectivity ingrained in this HRM process. Maasland and Weißmüller (2022) determined that HRM personnel were less opposed to delegating unpleasant tasks (e.g., employee dismissal) to algorithms vis-à-vis pleasant ones (e.g., recommending promotions). They also discussed such aversion being contingent on trust in technology-mediated versus human decision-making and HRM professionals' opportunities to pretest the algorithms.

Notably, our literature review (see Appendix I) reveals that aversion or fear experienced by HRM professionals' use of algorithmic HRM remains severely understudied. Moreover, this review especially shows a lack of focus on explaining how HRM professionals view and interact with algorithmic HRM, wherein the extant studies are limited by having adopted a conceptual discursive stance, being based solely in the USA, or focusing only on specific aspects related to algorithmic deployments, such as their association with employee experiences and factors that could reduce algorithmic aversion. Hence, what remains missing is a deliberate and in-depth focus on understanding how and why HRM professionals may feel averse to algorithmic HRM.

Such investigations of algorithmic HRM are sorely needed as this domain has traditionally been dominated by human management and control. Deployment of and dependence on algorithms in this domain may probably be viewed by HRM professionals as intrusive or reductive in light of HRM's "human" aspect. It is also possible that these technologies may be appreciated or preferred by some professionals because of their possibility of reducing any unfairness or bias in the HRM processes. Yet, without a focused investigation on HRM professionals, it is improbable to develop a decent understanding of their appreciation or aversion to algorithmic management.

Further, research indicates that algorithmic aversion may be culturally and contextually dependent. For instance, a recent study (M. Liu et al. 2023) found ridesharing drivers' algorithmic aversion could be explained by their specific experiences regarding previous recommendations by algorithms and peers' actions. The study raised the call for a deeper look into other contextual factors that could explain algorithmic aversion in different settings (M. Liu et al. 2023). Further, N. T. Y. Liu, Kirshner, and Lim (2023) found that algorithmic aversion differed among respondents in the USA and India for two factors: uniqueness neglect (i.e., the consideration of an individual's unique circumstances) and familiarity, but they acknowledged their limited focus on two countries and sectoral specificity (medicine and finance). Similarly, in a recent study, Kelan (2023) also argued that in-depth research is needed to understand the nuances of human–machine interactions during HRM decisional situations. However, these studies (e.g., N. T. Y. Liu, Kirshner, and Lim 2023; M. Liu et al. 2023) have also echoed Mahmud et al.'s (2022) call to imperatively conduct more investigations into algorithmic aversion, particularly regarding factors associated with the individual and contextual environment.

Responding to such scholarly calls, we have conducted a qualitative study to develop in-depth insights into HRM professionals' experience with algorithmic aversion and fear to explicate individual, organizational, and technology-related reasons that may create distrust and resistance to using algorithms in HRM. Our study aims to add contextual and situational insights to the algorithmic aversion literature by focusing specifically on algorithmic HRM applications to understand how HRM professionals feel about this technology. We expect our findings to add significantly to past knowledge through our contextual focus on HRM professionals as respondents and our use of a theoretical lens to develop a framework to encourage further research on algorithmic HRM.

3 | Methodology

3.1 | Approach

We utilized a qualitative approach and leveraged a structured written interview question guide to probe HRM professionals into revealing why they or other employees are fearful of or averse to algorithmic HRM. A qualitative approach was appropriate due to the under-researched state of the chosen topic (Sumpter and Gibson 2022; van den Groenendaal et al. 2022) and the stark shortage of knowledge from the point of view of HRM professionals (especially from different managerial levels). This approach enabled us to conduct an inductive data analysis to develop explanations for the fear of and aversion to algorithmic HRM. Our explanation emerges from our analysis which focused on identifying and classifying the emergent patterns in the interview data (Glaser and Strauss 1999; Mills, Durepos, and Wiebe 2010).

3.2 | Sample and Procedures

The qualitative data collection was based on open-ended interview questions, an approach that scholars have used previously to obtain respondent narratives regarding a phenomenon under investigation (Blaique and Pinnington 2022; Iyanna et al. 2022; Shah, Qayyum, and Lee 2022). This method facilitates respondents' sharing of their experiences, views, and opinions regarding a chosen phenomenon in line with the predefined questions (Shah, Qayyum, and Lee 2022). Furthermore, it allows scholars to understand respondents' cogitation about a phenomenon as their own lived experiences (Blaique and Pinnington 2022) without the limitations that are ordinarily placed by predefined scales. Additionally, open-ended questions allow scholars to obtain rich data that can yield in-depth and nuanced insights into the contextual factors and facets that shape respondents' thoughts and actions.

The qualitative data was collected over 6 months, from August 2022 to February 2023. Initially, a screening survey was run with 952 HRM professionals based in the UK and USA through purposive sampling to identify appropriate participants for the study (see Appendix II for screening survey questions). These HRM professionals came from top, middle, and entry-level management roles. Their job titles spanned from HR assistant to chief HR officer. To identify appropriate participants for this study, the screening questions were focused on the following: (a) a minimum work experience of 2 years, (b) experience employing their organization's use of algorithmic HRM for a minimum of 1 year, and (c) personal exposure to and use of algorithmic HRM in their routine jobs or tasks. The authors reviewed the participants' responses to these questions and shortlisted them based on mutual consent for participation in the main study. Subsequently, 113 suitable participants were identified and considered appropriate for the study of the open-ended questions. In the authors' view, these participants showed sufficient exposure to algorithmic HRM and knowledge of its use for employee management in their routine tasks to discuss how they—and their colleagues—perceived algorithmic HRM.

To collect the actual data (see Appendix II for a list of the open-ended questions), we asked respondents questions about (a) their views on algorithmic HRM application (e.g., areas in which algorithmic HRM should or should not be used), (b) the perceived effect of algorithmic HRM use on organizational processes and outcomes (e.g., in terms of fairness), (c) any experiences of their (or other employees') aversion to or fear of algorithmic HRM and reasons thereof, and (d) the responses and coping strategies they used to deal with these negative feelings. These questions were based on prior literature on algorithmic use (e.g., Burton, Stein, and Jensen 2020; Koch-Bayram and Kaibel 2023), resistance (Kellogg, Valentine, and Christin 2020; Wu et al. 2023), and anxiety and fear (e.g., Budhwar et al. 2022) regarding such technologies in HRM functions. Of the 113 contacted HRM professionals, 58 participated in the study on a first-come-first-serve basis (see detailed profile in Table 1). The respondents, who spent between 30 and 55 min answering the questions, were mainly male (56.9%), aged between 30 and 49 years (65.5%), and came from various industries. The respondents spanned all three (entry, middle, and senior) HRM managerial levels. Most respondents came from middle-management levels (75.8%), and we refer to them as HRM professionals.

3.3 | Analytical Method

We used the grounded theory approach to analyze the data since it is recognized as a systematic and unambiguous method for data analysis and theory development (Kurdi-Nakra and Pak 2022). This approach generates many benefits for researchers, including developing prior theory while emphatically considering context and the phenomenon being studied; and following the obtained data inductively and iteratively (Murphy, Klotz, and Kreiner 2017). We specifically leveraged the Gioia methodology (Gioia, Corley, and Hamilton 2013), which allowed us to present a visual data structure from rigorous analyses focused on developing iterative codes for the obtained data. The Gioia method assumes that an organizational phenomenon is socially constructed (Murphy, Klotz, and Kreiner 2017) by "people [who] know what they are trying to do and can explain their thoughts, intentions, and actions" (Gioia, Corley, and Hamilton 2013, p. 17). However, it is to be noted that the grounded approach cannot be used for confirming, disconfirming, or continually refining a theory; rather, it is for rethinking the bounds of conceptual development (Jeris and Daley 2004).

We followed the standard recommendations for developing a coherent data structure from the analysis in three phases, which aligned with the development of first-order codes, second-order subthemes, and aggregate themes or conceptual dimensions (Gioia, Corley, and Hamilton 2013; Suleiman and Othman 2021). Two authors independently and iteratively developed the first-order codes to cross-validate the findings (van den Groenendaal et al. 2022). They mitigated subjective bias possibilities (Lenka et al. 2018) while engaging in mutual discussion and negotiation at each phase to obtain a consensus on the developing coding structure (Ying et al. 2021). Scholars have previously used similar analytical approaches (Blaique and Pinnington 2022; Kurdi-Nakra and Pak 2022) to gain an in-depth understanding of HRM professionals' responses to under-researched phenomena such as crisis recovery (Sumpter and Gibson 2022) and inclusive HRM (van den Groenendaal et al. 2022).

The study respondents elucidated several issues that underlie the subjective and episodic nature of fear and aversion to algorithms in HRM and the coping strategies they adopt to deal with these phenomena. Using an inductive process, we assimilated the identified issues into aggregate ones (subsequently, themes) presented in the following sections. Then, through an iterative analysis, we derived four themes (see Figure 1), which encompassed 12 subthemes (second-order codes) and 50 issues/topics (first-order codes), representing the factors underlying the fear of, aversion to, and surprisingly, the genesis of appreciation for algorithmic HRM.

4 | Findings

The results suggest that HRM professionals hold diverse opinions about applying algorithmic HRM to support business

TABLE 1 | The demographic profiles of the study respondents ($N = 58$).

Participant ID	Age	Gender	Industry/sector	Job title[a]	Years of experience	Functions performed
P1	37	Female	Insurance	HR Administrator	Between 5 and 20 years	Recruitment
P2	41	Male	Construction	HR (Head)	Between 5 and 20 years	Recruitment and people improvement
P3	39	Male	Construction	Senior Manager (HR-Talent Acquisition)	Between 5 and 20 years	Recruitment
P4	43	Female	Retail	HR Team Leader	Between 5 and 20 years	HR administration
P5	24	Male	Construction	HR Professional	Between 5 and 20 years	Recruitment
P6	27	Male	Retail	Service Supervisor	Between 5 and 20 years	Learning and development (L&D)
P7	37	Male	Government	HR Officer	Between 5 and 20 years	Operations
P8	34	Male	Information technology	HR Supervisor	Between 5 and 20 years	Performance management, L&D, hiring
P9	37	Male	Security	HR Specialist	5 years or less	Recruitment
P10	50	Female	Service	HR Supervisor	Between 5 and 20 years	Recruitment, hiring, training, compensation
P11	37	Male	Business service	HR Manager	Between 5 and 20 years	Recruitment and management
P12	54	Male	Local authorities	Head of Service (HR)	More than 20 years	HR administration and finance
P13	32	Male	Government	HR Officer	5 years or less	L&D
P14	27	Female	Education	HR Administration Assistant	5 years or less	L&D
P15	37	Female	Education	HR Manager	Between 5 and 20 years	Performance management
P16	38	Male	Financial services	HR Director	Between 5 and 20 years	Recruitment
P17	32	Male	Manufacturing	HR Manager	Between 5 and 20 years	Management
P18	28	Male	Insurance	Senior HR Business Partner (HRBP)	Between 5 and 20 years	Recruitment, L&D
P19	34	Female	Government	HR Associate	Between 5 and 20 years	Performance management
P20	39	Female	Science	HR Officer (Talent)	5 years or less	Recruitment
P21	41	Female	Education	HR Assistant	Between 5 and 20 years	Recruitment
P22	34	Female	Financial services	HR Manager	Between 5 and 20 years	Performance management, recruitment
P23	36	Female	Retail	HR Assistant	Between 5 and 20 years	Recruitment

(Continues)

TABLE 1 | (Continued)

Participant ID	Age	Gender	Industry/sector	Job title[a]	Years of experience	Functions performed
P24	39	Male	Education	HR Project Worker (Analysis)	Between 5 and 20 years	Recruitment
P25	34	Male	Financial services	HR Manager	Between 5 and 20 years	HR management
P26	41	Female	Retail	HR Analyst	Between 5 and 20 years	HR IT
P27	51	Female	Law	HR Administrator	Between 5 and 20 years	Recruitment
P28	35	Male	Education	HR (Recruitment Partner)	Between 5 and 20 years	Performance management, recruitment
P29	43	Male	Real estate and property	Head (Talent Management)	Between 5 and 20 years	Recruitment, L&D
P30	41	Male	Healthcare	Senior Officer (HR)	Less than 5 years	Performance management
P31	36	Male	Finance	Director (Talent Acquisition)	Between 5 and 20 years	Performance management, recruitment
P32	69	Male	Information technology	Senior Vice President	More than 20 years	HR management
P33	28	Male	Information technology	HR-Hiring Manager	Between 5 and 20 years	Specialist recruitment
P34	47	Male	Manufacturing	Manager (HR and Quality)	Between 5 and 20 years	Recruitment (specialist roles)
P35	33	Female	Financial services	Manager (Group Learning)	Between 5 and 20 years	L&D
P36	53	Male	Education	HR Director	Between 5 and 20 years	HR administration
P37	39	Female	Manufacturing	People Service Specialist	Less than 5 years	L&D
P38	57	Male	Education	HR Officer	More than 20 years	Recruitment
P39	41	Female	Recreation	HR Manager (Recreation and Leisure)	Between 5 and 20 years	Recruitment, induction, performance management
P40	28	Male	Information technology	HR Executive (Consultant)	Less than 5 years	L&D
P41	32	Female	Police	HR Administrator	Less than 5 years	L&D
P42	32	Male	Retail	Manager (Development and Performance Management)	Between 5 and 20 years	L&D
P43	27	Female	Veterinary	HR Assistant	Between 5 and 20 years	Performance management
P44	33	Male	Public administration	HR Systems Manager and Coordinator	Between 5 and 20 years	Payroll, onboarding, performance management, absence entry and reporting
P45	30	Female	Information technology	HR System Consultant (Certified)	Between 5 and 20 years	Staffing, compensation, and benefits

(Continues)

TABLE 1 | (Continued)

Participant ID	Age	Gender	Industry/sector	Job title[a]	Years of experience	Functions performed
P46	27	Female	Public administration	HR Manager	Between 5 and 20 years	Recruitment
P47	47	Female	Information technology	HR Associate	Between 5 and 20 years	Performance management
P48	56	Female	Service	Senior Manager (HR)	More than 20 years	L&D
P49	29	Male	Transport	HR Manager (Hiring)	Between 5 and 20 years	Performance management, recruitment
P50	37	Male	Healthcare	Director (HR)	Between 5 and 20 years	Management
P51	36	Male	Manufacturing	HR Officer	Between 5 and 20 years	Performance data analysis
P52	45	Male	Education	Chief HR	More than 20 years	Recruitment and hiring
P53	53	Male	Retail	HR Manager	Between 5 and 20 years	Recruit, L&D
P54	39	Female	Healthcare	Assistant Practice Manager	Between 5 and 20 years	HR administration and finance
P55	51	Female	Public sector	HR Assistant	Between 5 and 20 years	People's well-being and safety
P56	37	Male	Healthcare	Manager (HR)	Between 5 and 20 years	Recruitment and hiring, people management
P57	29	Female	Manufacturing	HR Executive	Less than 5 years	Training and development
P58	25	Female	Financial services	HR Manager	Between 5 and 20 years	Performance management, annual reviews, L&D

[a]The titles are self-reported by the respondents and reflect the varied ways in which different industries and companies use terminologies to define job functions.

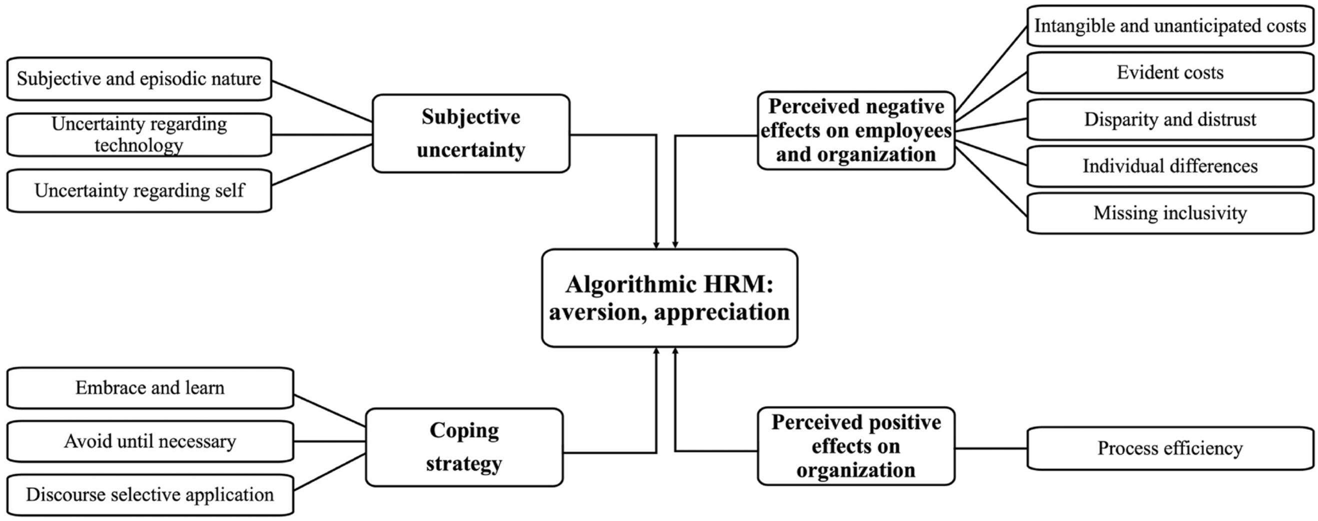

FIGURE 1 | Themes and subthemes derived from data analysis.

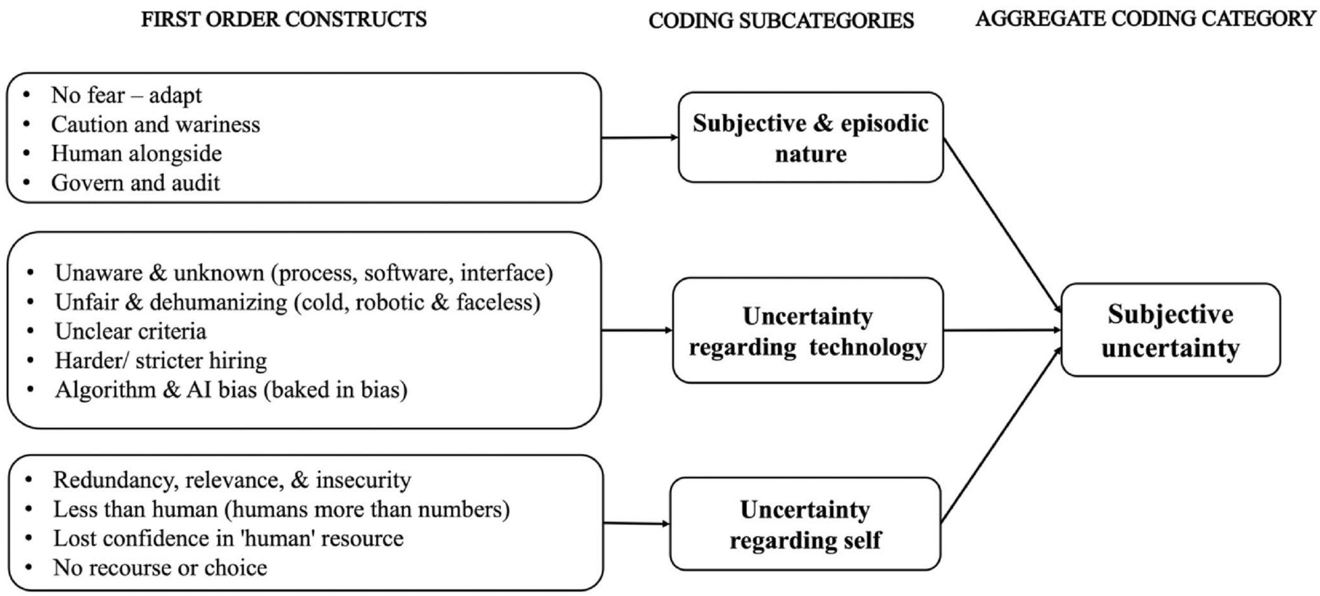

FIGURE 2 | Data structure—subjective uncertainty theme.

functions. Such diversity is evident in the developed themes, which pertain to (a) the subjective reasons or 'bases' for respondents' uncertainty regarding algorithmic HRM use, (b) their perceived negative effects of such usage, (c) the perceived positive effect for organizations, and (d) the coping strategies used to deal with their perceived negative perceptual responses. These themes and the related issues raised by our respondents are consolidated and presented in the following subsections. Appendix III presents quotes that exemplify the premise of our findings categorized under the same thematic structure.

4.1 | Subjective Uncertainty

We find that the first basis of fear regarding algorithmic HRM originates from HRM professionals' uncertainty and anxiety regarding the technology's applications in HRM processes and subsequently, their self-determined value in the organization (see Figure 2). Furthermore, the findings also suggest that such uncertainty and allied anxiety may only be episodic and subjective, which we believe may be contingent on HRM professionals' awareness and acceptance of algorithms as a critical technology within the HRM domain.

4.1.1 | Subjective and Episodic Nature

Overall, we find that anxiety and uncertainty regarding algorithms are subjective and episodic, which indicates that individuals' contextual evaluation of algorithmic HRM use plays a role in ascertaining their perceptual response to its use. This is in line with limited prior research emphasizing the significance of contextually driven experiences in determining an individual's aversion to algorithms (e.g., see N. T. Y. Liu, Kirshner, and Lim 2023). Moreover, our findings suggest that this subjective nature precedes a range of perceptual responses directed toward algorithms, spanning from fear to caution and wariness. For instance, some HRM professionals acknowledged that "*employees and organizations have some issues to fear from algorithmic HRM*" [P28] (also see P38's and P15's opinions in this regard in Appendix III). Such acknowledgment of fear as a potential response seemed to arise from respondents' views that "*algorithms will take away some manual inputs*" [P30] and that algorithms could be "*skewed to show certain biases*" [P39]. In our view, such responses indicate that rather than an outright fear of algorithmic HRM, HRM professionals harbor a sense of caution and wariness. Our contention is based on multiple respondents' contention (for instance, see P32's statement in Appendix III) that when dealing with algorithmic HRM, employees should "*be wary of them*" [P9] and "*use them with caution*" [P21, P39].

However, other respondents opined that fearing algorithmic HRM is ineffective in the face of rapid technology integration in the domain, which is "*just a fact at this point … [and] it's better to familiarize yourself with it and adapt*" [P1]. For example, when asked if employees should fear algorithmic HRM in any way, a general manager (HRM) working in an IT firm with significant daily use of algorithms stated, "*Absolutely not! … We have a general understanding, which the employee base is well aware of and communicated on periodically that use of algorithms in the HRM is always subject to human/management oversight in any significant or contentious cases*" [P32]. Indeed, our analysis indicates that there seems to be an acknowledgment that "*technology only improves things if used in the right manner*" [P11], wherein the *rightness* of algorithmic HRM usage is indicated to be the key to eliciting and alleviating fear or uncertainty among employees in our respondents' view.

In our respondents' view, the right way of usage stems from ensuring that all employees have proper recourse for gaining substantial awareness of algorithmic HRM as a technology and the processes for appealing or understanding its decisional outcomes. Suggested recourses include using algorithmic HRM "*alongside skilled personnel*" [P22] or "*a team of human HR specialists*" [P19], deploying it "*transparently and in limited circumstances*" [P13] to "*aid human decisions*" [P17], and ensuring that employees have "*the chance to discuss the process further with a human if they think they have been treated unfairly*" [P23]. Moreover, respondents acknowledge that "*it must always be considered that an intervention may be needed*" [P30]. Indeed, some participants suggested that this fear and caution among employees can be reduced through human oversight and auditing (i.e., supervision of the algorithms). The need for human involvement and the capacity to intervene were emphasized as critical factors that influenced respondents' perspectives on algorithmic HRM's capacity to inspire fear or anxiety among their colleagues (for instance, see P12 in Appendix III). One of our respondents, [P3], a senior manager, also suggested that an organization's implementation process could strongly influence employees' view of this technology and said, "*It has to be gradually implemented and in phases. Once such a process is done gradually, employees are more likely to be receptive to it*."

Thus, even in the face of a growing acceptance of algorithmic HRM usage, cautiousness tinged the responses of our sampled HRM professionals, who strongly indicated the need for contextually fueled conditions that could support this technology's effective usage. The conditions pertain to the gradual implementation, governance, and auditing of algorithmic HRM, particularly with having humans-in-the-loop as a necessary condition for assuaging the fear and anxiety that accompanies the deployment of such technology (see P31 in Appendix III). Our findings in this regard align with prior research, which emphasizes the inclusion of humans in decision-making processes in conjunction with algorithmic tools to hold untold benefits (e.g., see Allen and Choudhury 2022; Raisch and Krakowski 2021). These benefits and human insight could be reinforced through a feedback loop between system and user behavior (Kellogg, Valentine, and Christin 2020).

Cumulatively, we infer that uncertainty, fear, caution, and wariness for algorithmic HRM implementation are episodic and subjective. This subjectivity seems to be based on various contextual factors ranging from organizations' methods of implementing algorithmic HRM use, the possibility of human intervention, and the governance of this technology. Our supposition aligns with previous research, which urges varying organizational groups to approach sense-making for intelligent technologies like AI in different ways (Einola and Khoreva 2023). Further, such subjectivity is also based on employees' awareness of the technology and their perceptions about the uncertainties its implementations could create in their work lives, as discussed in the subsequent subthemes.

4.1.2 | Uncertainty Regarding Technology

Uncertainty and a lack of knowledge about the role of algorithmic processes in organizational decisions—particularly those that affect employees—influence respondents' experience of fear of and aversion to algorithmic HRM. For example, P16 opined, "*I think that most employees are unaware of the use of algorithmic HRM*" (see also P49 in Appendix III). Regarding the technology itself, many respondents discussed how "*not all employees understand an algorithm's purpose*" [P10] as they "*often don't have sight of the algorithm and the factors that influence it*" [P45]. This is relatively unsurprising as prior scholars have discussed the apparent *black box* phenomenon of algorithms as a significant barrier to building trust (Langer and König 2023; Mahmud et al. 2022). We believe such responses indicate that a "*fear of the unknown*" [P48] and uncertainty about algorithmic HRM's working processes are at the root of our respondents' adverse opinions regarding its use. Indeed, as P25 stated, "*I think that employees see* [algorithms] *negatively as they do not understand the full processes and methods used*."

Our analysis aligns with limited prior research that suggests employees prefer known human elements over the unknown nature of algorithms due to a perceived lack of explainability and the possibility of biases ingrained in the algorithms themselves (Mirowska and Mesnet 2022; Vassilopoulou et al. 2022). For example, P40 shared her opinions and experience of the potential for algorithms to include biases, even unknowingly (see Appendix III, and also P46 for a similar opinion). The possibility of having baked-in or implicitly included biases in the algorithms before organizational implementation has raised concerns among both academicians (Giermindl et al. 2022) and practitioners

(Nelson, Burton, and Kurth 2023). As a result of mainstream media discussions about such biases and their discriminatory outcomes (e.g., see Dastin 2018; Morse 2020), working professionals may be somewhat aware of possible biases in algorithmic HRM. They may also perceive these technologies to be biased due to uncertain knowledge about their application criteria or parameters. Thus, uncertainty or lack of technical details may promote fear of and aversion to algorithmic HRM unless otherwise substantiated, which was also observed by P53 (see Appendix III).

Moreover, the HRM professionals in our study discussed how the fear of and aversion to algorithms was not just relegated to the technical details but to employees' limited awareness of the nuances, scope, and degree of effect that algorithmic HRM has on their work lives and choices. For instance, as P20 stated, some employees were "*very suspicious of algorithms because they feel they take away choices from people*," and, as P40 noted, algorithms make it "*harder to get hired*." Another respondent [P22] opined that employees may also be uncertain about using algorithms in processes that humans have traditionally handled. She shared, "*Many employees are not clear on how* [an] *algorithm assists in performance rating*" (see also P38's similar opinion in Appendix III). Apart from uncertainty regarding algorithmic HRM's functions, employees also found it difficult to decipher or trust algorithmic outputs, "*software interfaces*" [P41], and "*the criteria we feed* [algorithms] *to speed up processes*" [P1]. Indeed, one respondent [P37] shared that algorithmic HRM use could be significantly challenged "*if people can't understand how we are applying criteria and the reasoning around it*."

Further, the respondents (e.g., see P37 in Appendix III) also noted that such technology-related fear could be related to an employee's degree of exposure to the algorithm. In our view, such limitations link technology-related fear to facets of informational justice (see Section 4.3). Further, the respondents emphatically discussed how the aversion to algorithmic HRM was, perhaps even more, related to employees' beliefs about the technology having "*baked-in biases*" [P13, P28] and being "*faceless*" [P45] or "*soul-less and avoidant of human interaction and understanding*" [P14]. Another employee believed algorithmic HRM creates the "*risk that the individual feels they are being treated like a robot rather than a person*" [P12].

Such perceived dehumanization has been indicated in prior research as a critical reason for algorithmic aversion (Dietvorst, Simmons, and Massey 2015; Koch-Bayram and Kaibel 2023). It is also possible that employees' inherent expectation of personalized interaction with HRM professionals may cause algorithms to be viewed as "*impacting fairness* … [and] *dehumanizing*" [P29] (also see P40 in Appendix III), regardless of the technology's benefits as HRM processes "*need more visible human interaction and depth*" [P38]. However, such personal perceptions may also be linked to the following confidential basis of fear: the respondent professionals' evaluation of their organizational relevance post-algorithmic HRM implementation.

4.1.3 | Uncertainty Regarding Self

Prior research suggests that the use of algorithms and AI-assisted HRM can engender a feeling of cynicism and fear among employees about potential job displacement risks (Tong et al. 2021) and job losses resulting from automation (e.g., Ore and Sposato 2021; Pereira et al. 2021; Varma, Dawkins, and Chaudhuri 2023). Our respondents echo such scholarly contentions. As P53 succinctly stated, "*If algorithms can take person X's job, could mine be next? I don't currently have an answer for that!*" More notably, such feelings may arise more frequently among employees engaged in data-heavy administrative tasks that could be easily automated, such as holiday calculation, payroll, and attendance management (for instance, see the opinions of P44, a manager in a public-sector organization, in Appendix III).

Additionally, a few respondents shared how employees "*felt less than human because of the algorithm*" [P10] (also see P34 in Appendix III). They believe that "*automation runs the risk of eliminating the need for people*" [P24], and algorithmic HRM treats "*humans as numbers and not individuals who are all different*" [P26]. Such negative impressions about algorithmic HRM have inculcated a lack of confidence in the *humanness* of HRM among employees, as this technology "*can take out the human aspects of human resources*" [P9], thus possibly reducing employees' trust in HRM and their organizations.

Additionally, algorithmic HRM seems to generate substantial aversion and fear as employees dread becoming irrelevant in the face of increasing algorithmic use in their organizations and deliberate on "*how it may affect their own role or job security*" [P4]. We contend that such responses indicate employees' experience of uncertainty regarding their future and relevance in their employing organizations. For example, P7 stated, "*I think employees often worry about algorithms and technology replacing their role*" (also see P4 in Appendix III). Our finding garners some support from a recent study that concluded that employees' exposure to knowledge about receiving AI-generated performance feedback negatively affected their trust in the quality of feedback and heightened their perceived risk of job displacement (Tong et al. 2021). This finding also aligns with the propositions that Parent-Rocheleau and Parker (2022) advanced about the negative effect of algorithmic management on work design aspects, including job security and task significance. Indeed, the fear of decreased human relevance was echoed by several respondents. They remarked that employees were acutely aware, due to the automation of all or some parts of their job description, that they "*might have issues about job security due to redundancies*" [P11].

This was a particularly substantial concern among older employees who lack the technical exposure of their younger counterparts and "*do not seek out an automated system to resolve their queries*" [P55]. While prior research has discussed possible redundancies as an implication of algorithmic and AI-assisted HRM (Arslan et al. 2022; Budhwar et al. 2023; Meijerink and Bondarouk 2023), our study solidifies these issues as foundational to employees' fear of and aversion to these technologies.

Our analysis showed that employees' worries and fears were further compounded by uncertainty regarding possible complaint handling, grievance, or appeals processes that could be initiated against algorithmic decisions. P4 suggested that such fears could be mitigated by demystifying the algorithm's inner workings and "*having an appeal process in place*." Such mitigation strategies also align with prior research, which indicates that reducing the opacity of algorithmic management may have far-reaching implications in building trust and acceptance toward these technologies (e.g., see Langer and König 2023).

An interesting point to note was our respondents' acknowledgment that employees' fear of their future careers and organizational value had a distinct silver lining—that of nudging them to learn the nuances of new technologies (for instance, see P48's opinion in Appendix III). Thus, we opine that it is plausible that such fear of job security and personal relevance could be a positive reinforcement that encourages employees to familiarize themselves with algorithmic HRM. This raises implications for the critical role of organizations in leveraging this nudge and offering support to employees' efforts to learn and develop their skills.

4.2 | Perceived Negative Effects on Organization and Employee

Our respondents prolifically discussed various negative consequences that, in their view, could arise due to algorithmic HRM deployment and acknowledged these as the reasons why they remain cautious of this technology. We categorized these reasons under five subthemes (see Figure 3). These include the unanticipated and evident costs of using algorithmic HRM, perceived disparity, loss of inclusivity in the organizational environment, and individual differences. From our sampled HRM professionals' perspective, these are the costs or risks (both tangible and intangible) arising post-implementation of algorithmic HRM and a key cause of their aversive tendencies for the same.

More importantly, these factors shape their perceptions of the cost of failure, as it were, of using algorithms in HRM. Of these, the intangible and unanticipated costs relate to personnel-related outcomes, such as employee frustration. These costs were perhaps not accounted for as probable concerns arising from algorithmic HRM use, but they have detrimental connotations for organizational processes and employees' working efficiency. The evident costs, on the other hand, relate to the monetary or financial costs arising from algorithmic HRM.

4.2.1 | Intangible and Unanticipated Costs

The possibility of missing out on potential talent while recruiting based on algorithmic suggestions was frequently raised as a negative effect or reason for being cautious of algorithmic HRM use. Many respondents noted that while algorithms made it easier to screen job applicants, especially if the applicant pool was big, it was easy to ignore an applicant who did not meet all or scored low on the predetermined criteria. Without human oversight, such exclusion could lead HRM professionals to miss talented potential workforce members. For instance, P31 emphasized that algorithms were not designed to "*capture important parts of the CV of applicants that may be relevant and considered by a human recruiter*" (see also P21's similar thoughts in Appendix III). Our findings echo observations made by prior scholars (Allen and Choudhury 2022; Bankins et al. 2022), who

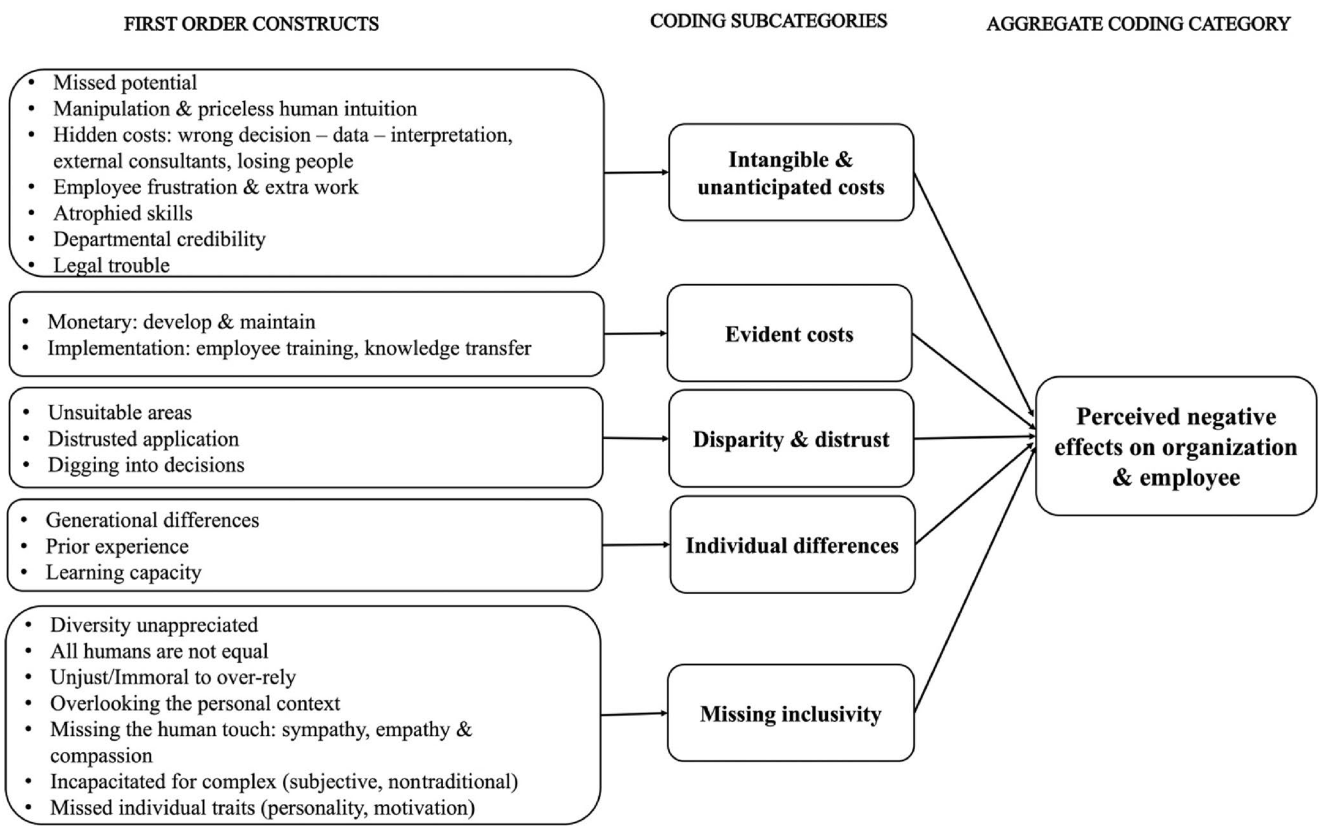

FIGURE 3 | Data structure—perceived negative effects theme.

also highlight missing relevant data as a shortcoming of AI-assisted HRM decision-making.

Interestingly, a few HRM professionals also acknowledged that job applicants' awareness of algorithmic use could lead them to *game the system* by including recognized keywords in their CVs and applications. Our respondents identified that applicants could use tactics like falsely listing skills and keywords to showcase one's suitability for a job, to manipulate algorithms as such tactics are beyond an algorithm's detecting abilities. Such plausible actions were of concern particularly while recruiting younger, more tech-savvy applicants (see the observations shared by P51 and P29 in Appendix III). In our view, such manipulation could lead HRM professionals to disregard other potentially better-suited candidates—an unanticipated and significant potential regret for HRM professionals linked to another possible loss—that of *priceless* human intuition.

Quite a few respondents argued that algorithmic HRM use is complicated because it "*lacks human intuition*" [P50], and there is a possibility "*that it will make a judgment that a human wouldn't*" [P20]. For instance, P24 noted how "*some employees fear that without human oversight some nuances could be missed, and the ideal candidate excluded purely on academic or predetermined grounds*." These HRM professionals resisted relying on algorithms to avoid the loss of human intuition while evaluating other employees and prospects. For example, P51 (see Appendix III) highlighted the drawbacks of algorithmic HRM to make decisions without human intervention. Similar situations and negative perceptions regarding the effects of algorithmic HRM cause employees to "*find it frustrating*" [P30] to deal with the technology and its fallouts (see Appendix III for details of an incident shared by P15 in this regard). Moreover, the fallouts of such negative effects, either due to incorrect choice of algorithmic parameters, data input, or interpretation, also include employees' undertaking extra work to correct or avoid the situation. For instance, P7, a manager working in a government body, stated, "*A business may find themselves having humans checking things, and with wages, it becomes a double cost*."

Our analysis also identifies substantial inconspicuous risks associated with the perceived failures of algorithmic HRM, which raises the question as to whether this technology is beneficial in the long run for every organization. Respondent P13 emphasized that algorithm-related fallouts "*lower the confidence in not only our abilities but the credibility of our department*." Further, P28 spoke of the "*atrophy of skills for human managers when dealing with issues*," resulting in a loss of valuable soft skills for managing employees. In the same line of thought, a few respondents (for instance, see P46 in Appendix III) highlighted another hidden negative effect employers have now begun to consider—the possibility of "*discrimination lawsuits*" [P13].

Moreover, for some HRM professionals, hiring external staff, such as "*external IT technicians to sort out problems*" [P25], and managing internal staff retention and engagement also become hidden but expensive costs, especially while transitioning to the use of algorithmic HRM (see P42's opinion in Appendix III). Leveraging existing research (Dietvorst, Simmons, and Massey 2015), we contend that such detrimental effects are significant intangible costs for HRM, which thrives on employees' trust as an organizational function. Indeed, P15 shared a thought that succinctly reflects the critical issues in this subtheme: "*Should we put our trust in it, and does it make us lazy when it comes to making important decisions for a company? These are all serious questions that employers need to be asking themselves.*"

4.2.2 | Evident Costs

Our respondents argue that implementing algorithmic HRM is an exercise with axiomatic monetary costs, which affect the organization's desire to realize its maximum possible benefits, regardless of employees' reactions. The technology's initial deployment is perhaps the most evident cost, as shared by P18 (see Appendix III). Additional accompaniments to these initial costs could include "*customization costs*" [P2] to improve suitability for the organization and establishing "*a team of qualified personnel to maintain it and make changes—IT maintenance, developers, etc.*" [P31].

Further, the "*cost of training existing staff across a complex HRM service, to use the systems and processes being implemented*" [P44] was also a substantial add-on cost that contributed to HRM professionals' hardships, particularly if employees' resistance to such implementation culminated in their failure to "*update it regularly and accurately*" [P44] as it could cause the system to be abandoned. As P51 noted, if their employers "*decide to not spend the money to upgrade or pay to get things straightened up, it goes aside*." We believe these represent the *sunk costs* of status quo bias (H. W. Kim and Kankanhalli 2009), which may drive HRM professionals to maximize their algorithmic use as a recovery strategy to gain back the costs of its implementation (see P18's opinion in Appendix III).

4.2.3 | Disparity and Distrust

Most of our respondents discussed how employees' most significant source of fear and caution originated in misgivings about the functional processes for which algorithmic HRM was used, as it could significantly affect employees' perceptions of fair treatment. We saw a variety of dissenting opinions on this issue. For example, P33 believed that "*hiring wouldn't be a great way to use an algorithm, as there's more to people than just a CV or an application form*." Contrarily, P54 proposed algorithmic HRM as a promising approach for "*processes such as screening candidates' CVs and matching them to the job*." Similarly, concerns about using algorithms to support HRM operations at specific management levels (e.g., recruiting for entry-level or top-level) and functional domains (e.g., performance management for salespersons vs. administrative workers) were raised.

Such uncertainty regarding the basic usage patterns of algorithmic HRM could contribute to developing a distrustful aura toward this technology. For instance, one respondent [P15] discussed how "*there is a lack of trust with the notion of the algorithm and the intentions of the user of this mechanism*" (see also P38 in Appendix III). This distrust was further compounded by employees' belief that algorithmic decisions went unchecked, without intensive human scrutiny—a problem that disconcerted even some of our HRM professionals (for instance, see P17 in Appendix III). Another respondent, [P3] (see Appendix III), discussed how algorithms could be the make-or-break point for employees without humans' decisional review, which could lead to a perception of unfairness in considering nuances. We believe that such distrust about the influence and application of algorithms is a strong underlying reason for employees' subconscious preference for human decision-making and algorithmic aversion. Indeed, past scholars have acknowledged employee reactions (e.g., Tambe, Cappelli, and Yakubovich 2019) to be a significant challenge that has plagued the introduction of AI and algorithms to the HRM domain. Our findings lend credence to the same.

4.2.4 | Individual Differences

A few respondents emphasized that some of their colleagues found it difficult to perform according to the parameters incorporated in this technology. Their discussion centered on the possibility that for some employees, aversion and resistance to algorithmic HRM may not be based on their view of technology as malicious but simply because of their limitations in acclimatizing to it. In this regard, three aspects emerged: generational differences, prior technical experience, and individual learning capacity.

Regarding generational differences, respondents (e.g., see P42's shared experience in Appendix III) unsurprisingly pointed out that their senior colleagues had the most trouble adapting to algorithmic HRM use. Discussing their experience, P28 mentioned "*older employees [age-wise] struggle with any kind of new technology and are often suspicious of this sort of software*." On the other hand, younger employees were generally considered to "*be more aware*" [P55] of the technology as they "*have been used to technology throughout their lives, and it is second nature to them*" [P28]. Further emphasizing such generational differences, P41 discussed the preference for algorithmic HRM among "*younger employees in our office who prefer the non-interaction and the ability to resolve things quickly through our software*." Similar propositions have been put forth by Allen and Choudhury (2022) and Wang, Gao, and Agarwal (2023) although their explanations for this anomaly varied. While Allen and Choudhury (2022) proffered that senior employees remain averse to algorithmic advice due to their own perceived accountability for the consequences, Wang, Gao, and Agarwal (2023) found senior employees demonstrated lower trust in the technology engendered by their ability to identify imperfections or faults in algorithmic outputs.

Further cementing the significance of individual differences in experiencing algorithmic aversion, we find such differences are also subject to the type and area of employees' work experience (e.g., task description, sector) as they "*needed to have a strong understanding of IT before using it*" [P54]. This observation finds some support in recent studies that found domain (Allen and Choudhury 2022) and task-based experience (Wang, Gao, and Agarwal 2023) to have a conditional influence on employees' performance in algorithm-augmented workplaces. P44 also shared his experience regarding the effect of technical knowledge on algorithmic appreciation that aligns with such extant research (see Appendix III). Another facet that our respondents (e.g., see P8 in Appendix III) mentioned was individuals' intrinsic learning capacity or technical savviness, which determined their appreciation of or aversion to algorithmic use. For instance, [P42] agreed that "*a challenge we still face is with employees who are not tech savvy*" and noted that this issue often occurred with "*older colleagues [who] tend to need extra support*."

4.2.5 | Missing Inclusivity

Another crucial negative connotation of algorithmic HRM raised by our respondents was their belief that this technology could undermine their diversity, equality, and inclusion initiatives. Echoing prior studies (e.g., Kelan 2023), our analysis indicates that HRM professionals—and their colleagues—seem to perceive that algorithms could reduce organizational considerations of diversity, nonconformance, and personal contexts that affect human performance. For example, P27 opined that an algorithm "*treats humans as numbers and not individuals who are all different*" (see also P40 in Appendix III). In our view, these opinions imply that diversity might not be appreciated in an algorithm-driven environment, which is a significant factor that may underlie algorithmic aversion in HRM.

Such aversive opinions may be further exacerbated if there is an overreliance on using algorithmic decisions, which is seen to contribute to a "*lack of organization transparency*" [P17] and "*affect [the] morality of decision-making processes*" [P28]—thus again raising significant deleterious implications for perceptions of organizational justice, as also shared by P51 (see Appendix III). Moreover, HRM professionals discussed how they and other supervisors were acutely aware of algorithms' limitations in accounting for subjective and personal contexts while using their outputs for HRM-related decisions.

Multiple respondents opined that there are "*certain intangibles, which cannot be detected from data alone, and you can't get a personality from a set of data*" [P40, P21]; therefore, algorithms are inferior in assessing humans who "*are emotional and complex creatures*" [P40]. Organizations are team-based environments with complex interpersonal dynamics, wherein specific roles emphatically require HRM professionals to "*factor in traits like passion, motivation, and drive*" [P22]. Algorithms' inability to account for subjective parameters like an employee's fit into "*office dynamics and team spirit*" [P21] or how they "*hold themselves and interact with you*" [P7] is seen by HRM professionals as a serious shortcoming and a reason for their caution regarding the use of algorithmic HRM (e.g., see P40's discussion on this aspect in Appendix III).

Similarly, P31 discussed how "*specific personal circumstances should also be accounted for, which is more difficult to do with an algorithmic system*." These personal circumstances are critical when assessing employee performance. Their absence on account of algorithmic limitations is an especially noted challenge in the HR community, whose duties "*require subjective thinking*" [P4] (see also P26's shared experience in Appendix III). Further, some respondents reprised a link between employees' feeling excluded in their algorithm-augmented workplace with algorithmic limitations that created technology-related uncertainties (see Section 4.1.1). In this aspect, they discussed how algorithm-driven organizations could even see a decline in employees' establishing a connection with their organization, perhaps even their citizenship. For instance, P13 pointed out that the use of algorithms can make processes less human. As a result, employees do not feel connected to the team, and it can make a moment such as a layoff much harder and colder as it came from a 'bot'.

Such situations negatively influence employees' interpersonal relationships and are also compounded by their perception that algorithms amputate human elements of "*sympathy*" [P37], "*empathy*" [P12], and "*nuance and compassion*" [P28]. These missing human components have led some HRM professionals to resist algorithms as "*they have no feelings, no compassion; they can't think or adapt to the situation*" [P58].

4.3 | Perceived Positive Effects on an Organization

Even though the discussions emphasized the negative effects of algorithmic HRM, our respondents simultaneously acknowledged that this technology had the potential to be "*a significant asset*" [P32, P56] (see also P51 in Appendix III). Furthermore, our analysis showed that algorithmic HRMs' benefits fall under the broad category of process efficiency and justice, which was improved in multiple ways (see Figure 4).

The main benefits were building process efficiencies, streamlining processes, and integrating the tenets of organizational justice in the form of impartiality, fairness, and parity, mainly when it is essential to make "*quick decisions with data that are evidence-based and results-driven*" [P14]. For instance, P16 found algorithms to be highly beneficial for recruiting as they "*facilitate efficient use of hiring manager and candidate time by ensuring suitable fit*." At the same time, P12 emphasized that when used appropriately, algorithms could ensure a "*consistency of treatment throughout the organization*."

Similarly, P3 agreed that "*equality of treatment across all levels is fair when using such algorithms*," and P8 stated, "*I think that the algorithms actually enhance equality in decision making*," indicating that algorithmic HRM can ensure equality of outcomes for all employees (see also P38's opinion on this aspect in Appendix III). This viewpoint indicates that algorithmic HRM can improve the justice and fairness of HRM processes if appropriately structured and governed. It also aligns with the discussion of the first theme (see Section 4.1.1), which highlighted auditing and governance as key factors that could play a role in alleviating the fear of and aversion to algorithmic HRM.

These opinions suggest HRM professionals believe that algorithmic HRM holds positive connotations for enhancing organizational (distributive and procedural) justice perceptions as algorithms do not "*play favorites*" [P8]. Thus, we partially support the findings of Araujo et al. (2023) and Bankins et al. (2022), who found similar results for automated and AI-assisted decision-making in varied domains. While these prior findings relate primarily to general decision-making context, our findings emphatically cement the importance of justice perceptions with regards to algorithmic HRM. Lastly, some respondents declared that algorithmic HRM could enable employees to be creative when dealing with complex scenarios, which aligns with the propositions of Bogert, Schecter, and Watson (2021) regarding algorithmic appreciation while engaging in difficult tasks. For instance, P45 indicated that algorithmic HRM "*can free up teams to focus on the more important items and the scenarios that need more attention than others*," and P52 observed how this tool "*can free up time spent on mundane tasks, therefore making existing jobs more interesting*." This finding correlates with a recent study suggesting that AI can rehumanize workplaces because it frees up employees' time and facilitates more employee engagement in creative tasks (Einola and Khoreva 2023).

Based on these findings, we contend that our respondents' recognition of such positive effects of algorithmic HRM use could indicate that alongside aversion, caution, and fear, a possible emotional response to these technologies could be *algorithmic appreciation* (see Bogert, Schecter, and Watson 2021; Choung, Seberger, and David 2023; Logg, Minson, and Moore 2019). Our supposition is supported by prior scholarly work on other technologies and platforms, such as social media, which recognizes that technology has both a bright and dark side (e.g., see Baccarella et al. 2018). However, our work deviates from the findings of Logg, Minson, and Moore (2019), which suggested that professionals could demonstrate algorithmic aversion, and finds that in the context of HRM professionals, a budding appreciation is emergent among employees in middle-level management regarding the benefits that algorithms bring to HRM processes. These employees can be postulated to have a moderate level of experience in their domain, and as such, our findings add support to scholarly works that determined that employees with significant domain and task-based experience could benefit from algorithmic support (e.g., see Allen and Choudhury 2022; Wang, Gao, and Agarwal 2023).

We proffer the plausibility that aversion and appreciation may exist as a duality and occur as a response to the same evaluative

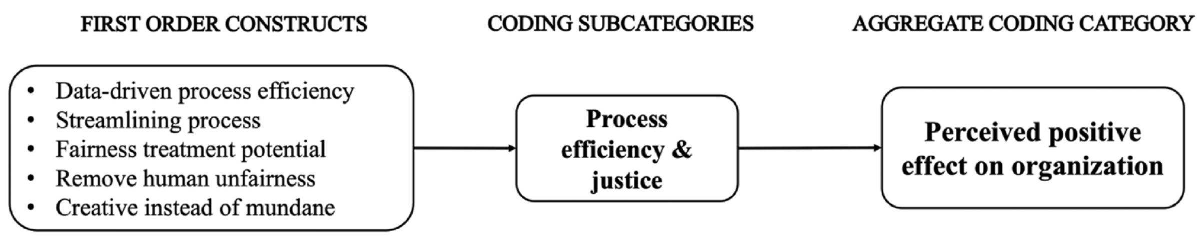

FIGURE 4 | Data structure—perceived positive effect theme.

process that algorithmic HRM may be subject to. Our contention finds strong support in the work of Tong et al. (2021), who determined that using AI to provide employees with feedback could produce significant value for organizations. However, they also found that the disclosure of AI as a source of such feedback could destroy the generated value as it could reduce employees' trust in the feedback quality and lead them to consider the possibility of job displacement. The emergent recognition of such a duality presents a valuable area of inquiry for future research.

4.4 | Coping Strategy

Our respondents' discussion on the fear of and caution toward algorithmic HRM also focused on understanding how employees respond to these negative perceptual responses. We determined three coping strategies (see Figure 5)—positive (embrace), negative (avoid), and the middle ground (collaborate)—wherein the last seems to be the way forward for most of our respondents.

4.4.1 | Embrace and Learn

Recognizing that fear and aversion were often "*based on a lack of knowledge*" [P7], study respondents suggested that despite demonstrating algorithmic aversion, most employees displayed a self-driven initiative to learn more about the technology to alleviate their apprehensions (e.g., see the opinions shared by P33 and P35 for this aspect in Appendix III). Such initiatives transcended functional boundaries, as our respondents indicated that employees across departments were seen to work closely with "*implementation consultants to learn and understand*" [P26] the use and effect of algorithmic HRM. Senior management supported these efforts, and those with expertise in algorithms were "*able to help less experienced members to learn and develop on understanding better*" [P6].

Our study indicates that a solid readiness for change accompanies fear as HRM professionals understand that, given its capacity for conserving resources (i.e., time and money), the integration of algorithmic HRM is likely to increase in the future. Past research on AI-assisted HRM adoption (Suseno et al. 2022) has also shown change readiness to facilitate employees' adoption behavior indirectly. We expect a similar effect in the case of algorithmic aversion, perhaps in concert with employees' technical know-how and individual determinants, such as the desire to learn and regulatory focus. However, for such readiness to practically translate into reduced algorithmic aversion, "*organizations need to be open and provide training and understanding*" [P33], for example, by providing "*additional training seminars*" [P29] to support professionals' efforts.

4.4.2 | Avoid Until Necessary

We found that some HRM professionals avoided using algorithmic HRM unless the situation necessitated its use, or they suggested that it was only "*safe to use them for generating mundane items*" [P13]. For instance, P15 observed, "*We have some members of staff that try to avoid the use of technology as much as they can*" and pondered if such avoidance originated from these colleagues' beliefs about "*being observed in terms of their technology use*" (see also P11's opinions detailed in Appendix III). Similarly, respondents also discussed how they did not "*use algorithmic systems militantly*" [P24] and observed that their colleagues "*just do the minimum*" [P30] with the technology without really considering the systems' suggestions. However, such unenthusiastic opinions reflected only a minority of respondents. In contrast, the majority emphasized a response strategy aimed at integrating the best of technology and human characteristics, as discussed in the next subsection.

4.4.3 | Discourse Selective Application (Collaborate)

Most respondents understood the value of algorithmic HRM. Still, they suggested that retaining the *human touch* of HRM

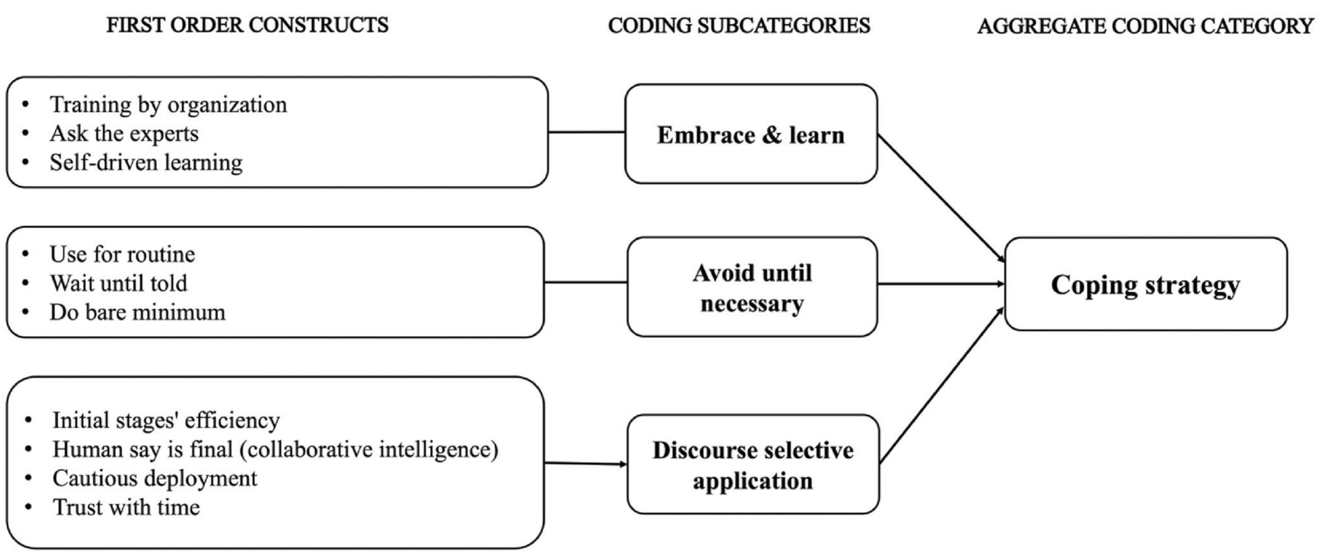

FIGURE 5 | Data structure—coping strategy theme.

functions would be a viable solution for reducing employees' fear of and aversion to this technology. An overwhelming number of our respondents suggested the need to establish guidelines that appropriately converge human and algorithmic decision-making, and we find two main reasons for this suggestion. First, HRM professionals believe collaborative decision-making would enable the retention of the *human touch* of HRM functions that could substantially address the negative employee perceptions we discussed in the preceding sections and reduce the fear of and aversion to this technology. For instance, acknowledging the benefits of algorithms in HRM, P31 stated, "*These must be used with caution. Senior leaders must ensure that algorithms are fit-for-purpose, and they should be critically evaluated on a regular basis*."

These suggestions originated from respondents' belief that due to the very nature of HRM, which needs to account for personal context, "*sometimes a human touch within a face-to-face interview is required*" [P4], and algorithms "*should be there as an aid, but the final say should come from experienced staff using their skills to make the correct decisions*" (for instance, see P44's stance on this aspect in Appendix III). The consensus for collaborative decision-making was especially evident for recruitment processes as this required a subjective and qualitative assessment of candidates. Indeed, one of our respondents [P29] emphasized the need to have the final say among humans in HRM functions (see Appendix III for their response regarding this aspect).

Second, a collaborative approach would allow HRM professionals and employees to build trust in algorithmic HRM decisions. As [P31] stated, "*people need to build trust in the algorithms*," which can facilitate their acceptance of the associated effects of algorithmic HRM use over time. To establish this basis for trust and belief, an algorithm should be "*used to augment human decision making*" [P17], and "*to save time and resources*" [P23]. Our findings suggest that augmentation and benefits would be derived more strongly by applying algorithmic HRM in the initial stages, such as recruitment, performance reviews, and absence management. This suggestion aligns partially with the suggestions of Tong et al. (2021) to introduce AI-generated feedback to employees in a tiered fashion, although they refer to employees' tenure with an organization as the precipitating factor in this regard. However, in our respondents' voice, even such discrete implementation was still accompanied by one caveat—the final decision should remain in human hands. As some respondents (P53, P21) discussed, one way to build such trust and retain HRM's *human touch* would be to ensure the soundness of algorithmic vis-a-vis human decision-making (see Appendix III for the full statements), especially at the end of HRM processes culminating in decisions that ultimately affect humans.

We believe these suggestions closely align with scholars' (Chowdhury et al. 2022, 2023; Wilson and Daugherty 2018) propositions for promoting collaborative intelligence such that organizations can combine and utilize the capabilities of humans and machines. We concur with past findings that it is possible for a *collaborative tandem* (Einola and Khoreva 2023) to exist wherein HRM can integrate algorithmic processing with human qualities, such as creativity and intuition, to establish unparalleled business process efficiency. A quote by P24 succinctly sums up our contention: "*We all want to work more efficiently, and I believe algorithms can help us achieve this—they will never be a replacement for humans, but I firmly believe they can work in harmony with us*."

5 | Discussion

Generally, the results present evidence regarding HRM professionals' belief that algorithmic HRM can be beneficial. However, what is debatable is the range and scope at which these benefits can be realized without encountering a substantial amount of aversion or fear attributable to the perceived negative effects of using these technologies. We further find that, overall, HRM professionals harbor a "cautiously fearful and not wholly averse" outlook on algorithmic HRM. This is a significant deviation from past research, which has mainly discussed algorithmic aversion and fear without any shades of appreciation in its midst (e.g., Mahmud et al. 2022; Lacroux and Martin-Lacroux 2022).

We diverge from past research to suggest that aversion to and fear of algorithmic HRM may be Janus-faced (e.g., Arnold 2003; Tong et al. 2021). While most HRM professionals remain wary of algorithmic HRM's application, some have also begun to partially accept this technology's deployment while discussing avenues for its selective and human-inclusive applications to reduce their wariness. However, such responses differ based on the individually perceived effects of algorithmic HRM use, whether positive or negative. Those focusing on the positive effects that algorithmic HRM has on organizational processes showed appreciation, albeit they did not explicitly discuss their own agency while highlighting these benefits. Yet, their responses lead us to posit that for such appreciative HRM professionals, algorithmic HRM may be a handy tool for strengthening their work agency and performance by leveraging its proffered advantages.

Moreover, this duality of responses, based on individual evaluations that our study uncovered, indicates a transition in HRM professionals' mindset toward acknowledging algorithmic HRM's diverse benefits despite lingering caution regarding its varied perceived pitfalls. Such a transition offers us an optimistic outlook on the more widespread integration and acceptance of algorithmic HRM. This observation is particularly important considering the growth of AI and algorithmic applications in traditionally human-dominant aspects such as monitoring employees' performance, compliance, and even their emotions (Mantello and Ho 2023). We believe that, in time, more HRM professionals will adopt a positive outlook on algorithmic HRM, leading to its wider dissemination within different organizations.

Nonetheless, our findings suggest that such adoption is contingent on developing more transparency, knowledge, and aptitude surrounding algorithmic HRM to preempt HRM professionals' extremely cautious approach toward this technology. This is in alignment with prior studies that have also indicated that aversion to algorithmic HRM could be reduced by incorporating human feedback (Dargnies et al. 2024; Kawaguchi 2021) and overcoming the perceived opacity to inculcate trust (e.g., see Vassilopoulou et al. 2022; Langer and König 2023; Mirowska and Mesnet 2022). Such actions could be undertaken through several means, such as developing financial outlays before using algorithmic HRM, ensuring appropriate governance and an auditing structure for its deployment, and adopting human-in-the-loop decisional systems.

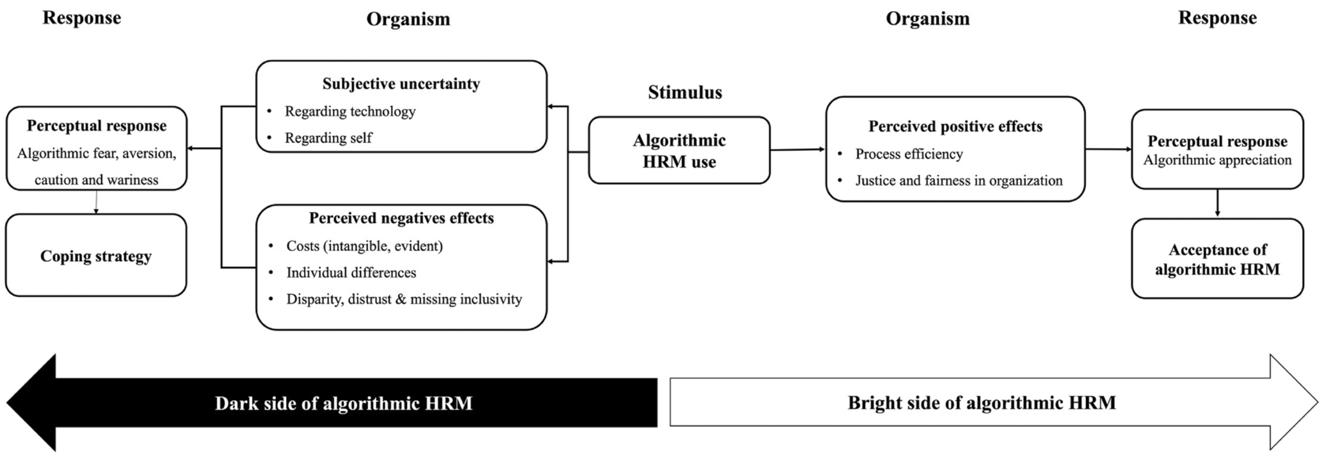

FIGURE 6 | Proposed framework for the aversion–appreciation duality of algorithmic HRM.

These measures could go a long way in reducing the negative effects discussed by our respondents, such as perceived costs and distrust. Yet, before using such measures, organizations and HRM professionals need to understand how and why employees develop a cautious or fearful stance toward algorithmic HRM. To this purpose, we assimilate our findings and propose a framework (see Figure 6) to explain the mechanisms underlying the responses of HRM professionals toward algorithmic HRM.

5.1 | The Duality of Algorithmic HRM: Aversion–Appreciation Framework

To proffer an explanation for the duality of perceptual responses to algorithmic HRM use, we leverage the SOR model—a neo-behavioristic framework that comprises three elements: stimulus (S), organism (O), and response (R; Tandon et al. 2021, 2022; Mehrabian and Russell 1974). The stimulus is an external environmental trigger that activates individuals' (i.e., organisms') cognitive and emotional processes, leading them to cogitate on adopting a specific response (Tandon et al. 2021, 2022; Malik et al. 2023).

Stimulus: We presume that the use of algorithmic HRM is a key stimulus that induces HRM professionals to ruminate on how it affects their work agency and role, as well as their organization. This stimulus, in our view, pertains to the processes that algorithmic HRM is used for in the organization for HRM as a function.

Organism: The stimulus created by the use of algorithmic HRM leads HRM professionals to ruminate on this technology and the effects of its use. Based on our findings, we proffer that such rumination may take two directions based on the individual (see Figure 6). These directions represent the duality of responses that can originate from employees' exposure to and use of algorithmic HRM.

The first direction represents the dark side of algorithmic HRM. It takes individuals on a pathway that leads them to focus on two aspects. The first aspect relates to the subjective uncertainties that algorithmic HRM use creates for themselves as employees (Section 4.1). These uncertainties, although subjective and episodic in nature, seem to also be linked to the second aspect of rumination—the negative effects that HRM professionals perceive to originate from algorithmic HRM use (Section 4.2). These negative effects encompass both monetary and nonmonetary aspects, wherein the latter focus on dynamic and contemporary problems such as maintaining inclusivity, trust, and parity within organizational relationships. We believe that these subjective uncertainties and perceived negative effects represent the dark aspects of employees' rumination originating from the stimulus, that is, algorithmic HRM use. In our view, these two aspects form the reasons why our sampled HRM professional experienced the perceptual response of fear, caution, and wariness toward algorithmic HRM.

The second direction HRM professionals' rumination can take is an innately positive one (Section 4.3) and represents the bright side of algorithmic HRM as it focuses their attention on the many perceived benefits of using algorithmic HRM. As per our findings, these positive effects relate to streamlining processes for maximum efficiency, justice, and fairness—definitive reasons for not fearing algorithmic HRM use. Interestingly, our findings indicate that some HRM professionals have also begun to appreciate how algorithmic HRM can facilitate creative work performances by automating mundane tasks. This finding has profound connotations. It indicates the genesis of recognition among HRM professionals that algorithmic automation may in fact help humans achieve higher goals.

Response: These two ruminative directions, emerging from our findings, induce HRM professionals to adopt either of two perceptual responses—appreciation or aversion—depending on whether they focus on the perceived positive or negative effects of algorithmic HRM use.

This allows us to consider the two sides to algorithmic HRM use—positive (bright) and negative (dark)—that may co-occur. Indeed, we contend that the duality of perceptual responses to algorithmic HRM originates from the same evaluative process.

On the one hand, employees who focus on the negatives, in our view, showcase varied perceptual responses ranging from fear to caution and wariness based on their rumination on the subjective uncertainties and perceived negatives (or reasons) not to use algorithmic HRM. We believe that these perceptual responses are precursors to resistance behavior and, if left unaddressed, could lead HRM professionals to lean toward adopting active resistance tactics, such as algoactivism (Kellogg, Valentine, and Christin 2020).

Moreover, we believe that the perceptual response of fear or caution influences the professionals' adoption of specific coping strategies as a behavioral response (Section 4.4). For instance, professionals who embrace the embrace-and-learn coping strategy could evaluate their position in the organization as complementary to algorithmic HRM and not perceive diminished self-relevance. Such employees may even experience algorithmic appreciation over time by focusing on algorithmic HRM's benefits. On the contrary, professionals who are more advanced in age or struggle with algorithmic use could perceive a higher risk to their job security and adopt avoidance as a coping strategy.

On the other hand, those who focus on the positive effects of algorithmic HRM use showcase appreciation of these technologies, which, in our view, is a precursor to acceptance as a behavioral response. Such acceptance of algorithmic HRM use, especially from HRM professionals, who can be seen as agents of change, can be an emphatic influence through which other employees' perceived negative effects of algorithmic HRM could be attenuated or eliminated.

Thus, our framework presents duality-centric pathways that explain how the same base of factors, centered in the use of algorithmic HRM by individuals and the organization, could lead to two forms of perceptual responses.

5.2 | Future Research Possibilities

To enhance our understanding of algorithmic HRM and the perceptual, emotional, and behavioral responses of HRM professionals who encounter its usage, we propose certain future research possibilities developed based on our understanding of the literature and the respondents' voices. We implore scholars to undertake mixed-method and longitudinal research approaches to explore the connotations of the subsequently mentioned issues to build a more robust and nuanced framework for explaining algorithmic HRM use behaviors and perceptual responses.

Stimuli: Based on our respondents' discussion, we propose future investigations into two specific aspects as potential stimuli related to algorithmic HRM use: the area for which it is applied (e.g., for recruitment or performance management) and the criteria used to ensure that the application does not impinge on the *humanness* of HRM processes (e.g., having appeals processes in place). We implore future scholars to undertake more exhaustive research into the cognitive and affective stimuli, unrelated specifically to algorithmic HRM, that could evoke HRM professionals' rumination on its use. For instance, future scholars could explicate how an employee's self-motivation and regulatory focus (i.e., prevention or promotion focus; Brockner and Higgins 2001) could endear them toward algorithmic HRM. Moreover, exploring HRM professionals' prejudices, such as cynicism or anxiety related to technology use in a function that is human-dominant, may also be critical internal stimuli to explore. Further, it is human nature to share experiences and assimilate information from such shared experiences. Thus, scholars could also turn their attention to understanding if there exists a filter bubble effect that attunes HRM professionals, and perhaps other employees, to only a certain range of perceptual and emotional responses to algorithmic HRM.

Organism: Leveraging our findings and recent research (e.g., Duggan et al. 2023; Edwards et al. 2024), we propose the need to examine contextual factors that could influence HRM professionals' rumination about and behaviors toward algorithmic HRM. For instance, through our findings, we propose the need to examine if employees' aversion to or fear of algorithmic HRM could be alleviated in the presence and visibility of a robust governance, auditing, and oversight structure (see Sections 4.4.1 and 4.3) with a straightforward human-in-the-loop design. One reason could be that such a system design would capacitate humans to identify clear intervention possibilities in algorithmic decision-making and retain their sense of humanness and context-inclusive decision-making in the HRM processes.

Indeed, recent research has also contended that such a design could engender greater trust among all corporate employees in the algorithmic system (e.g., see Meissner and Keding 2021). With the lapse of time, such contextual influences could prompt HRM professionals (as well as other employees) to view algorithmic HRM in a more positive light and perhaps enhance the possibility of more congenial human–machine collaboration. For example, such collaboration could strengthen the contextual influence of employees' trust in the organization and the technology.

Simultaneously, we implore scholars to decipher the nuances of any functional benefits derived from algorithmic HRM in varied processes such as compensation or performance management. For instance, scholars could study if algorithmic HRM's appreciation is seen in cases of automated prompt acceptance of compensation requests for work expenses instead of purely human decision-making. Such nuanced knowledge could go a long way in helping HRM professionals understand the processes wherein algorithmic HRM may yield the most return on investment and processual benefits.

Duality of responses: While our study was initially geared toward understanding the more negative or dark side of algorithmic HRM (i.e., fear and aversion), our results showed respondents' acknowledgment of a distinct positive or bright aspect to using this technological system. Consequently, we argue that accounting purely for resistance through a conceptual model would be ineffectual in considering users' comprehensive evaluation of and perceptions toward algorithmic HRM. Thus, based on our findings, we propose that algorithmic HRM use can be enabled *and* hindered by factors evaluated by its users simultaneously. Since the way employees make sense of the stimuli that influence their work environment has been found to influence their well-being (Edwards et al. 2024) and work engagement (Parent-Rocheleau et al. 2024), it is important that the duality of their responses be critically examined.

Subsequently, we propose that a more nuanced approach toward understanding employees' responses to algorithmic

HRM systems needs to be developed, considering that both aversion and appreciation may occur based on their evaluation of the same factors. Similar observations have been put forth by Meissner and Keding (2021), who emphasized that individual decision-making styles can lead different users of an IT system (such as AI) to formulate their responses uniquely, even when the system-related inputs are the same. So, it is plausible to say that an individual's filtering and perception of information after interacting with an IT system is the deciding factor in their view of the system as having a negative or positive effect. A recent study by Li et al. (2024) also supports our contention. This study examined cab drivers' work engagement during algorithmic management through challenge-hindrance appraisals and found these appraisals have a significant mediating effect. Through their findings, the authors (Li et al. 2024) emphasized that algorithmic management could be simultaneously experienced as both positive and negative. In another recent work, Duggan et al. (2023) examined gig workers' experience of algorithmic HRM. They discussed how this technology can both capacitate and restrict workers, considering the volatility of contextual factors. Thus, we propose that future scholars emphatically consider the duality of algorithmic HRM use and evaluation while developing their research frameworks.

In addition to the SOR-related factors discussed above, we leverage our findings to propose a few conditional and temporal influences that could dampen or enhance the relationships between algorithmic HRM use, HRM professionals, and their organizations, as well as other employees. In our view, these influences could act as possible mediators or moderators between stimuli, organisms, and responses.

Conditional and temporal influences: Our findings indicated that caution or fear toward algorithmic HRM might be reduced with continual exposure, increased awareness of its benefits or detriments, and organizational support in its transparent, ethical use. Subsequently, we propose that future scholars investigate how algorithmic HRM's perceived effects on human agency and job autonomy influence employees' behavioral and perceptual responses over time while accounting for organizations' supportive and ethical use of this technology. Such studies are particularly important in light of limited past research which has indicated that algorithmic HRM can increase and decrease workers' autonomy (Meijerink and Bondarouk 2023) and motivation (Edwards et al. 2024). Thus, temporally oriented information on the factors that simulate both positive and negative effects on employees' overall experience, well-being, organizational relevance, security, and autonomy is highly valuable.

Likewise, scholars should also focus attention on the thresholds at which HRM professionals (or even other employees) may consider the negative costs of algorithmic HRM to outweigh any perceived effects of its implementation or vice versa. This information would be valuable in assisting organizations in developing strategies to keep HRM professionals from reaching and crossing such thresholds. Scholars could also focus attention on whether and to what degree an appeals or grievance process implemented to include human feedback for improving algorithmic management (i.e., for a human-in-the-loop design) influences these professionals' rumination, behavioral, and perceptual responses.

6 | Conclusion

While algorithms are increasingly used to support HRM, scholarly debates focus on the automation–augmentation paradox (Raisch and Krakowski 2021) to explain the best approach for optimizing the interactions between humans and algorithms. However, we believe such efforts will succeed only if humans keep an open mind toward algorithms and are not preinclined to resist their adoption. Furthermore, prior scholars' contentions that the benefits of technology for HRM can be genuinely unlocked by developing nontechnical resources, such as an innovation mindset among employees (Chowdhury et al. 2023), also lend credence to our belief. Motivated by this thought and the scantness of literature on algorithmic HRM aversion, we conducted a qualitative study to understand (RQ1) if HRM professionals are fearful or averse to algorithmic HRM use in their organizations and the reasons thereof and (RQ2) the outcomes of this experienced fear and aversion along with the strategies HRM professional employ to cope with its deployment.

In response to the first question, HRM professionals and their colleagues are not wholly opposed to algorithmic HRM and instead have adopted a cautious stance toward this technology. The reasons for this caution and fear were attributed to their uncertainties about their place in an algorithm-driven organization as well as the perceived negative effects of this technology's use for HRM processes and the overall organization, for example, in creating disparity, unanticipated costs, and overlooking individual differences in work behaviors.

These findings lend insights into the proxy view of technology theorization (Kim, Wang, and Boon 2021), which places emphatic importance on the role users play in determining the implementation, adoption, and acceptance of technologies. In essence, users' agency and responses (behavioral and cognitive) have a significant influence on how technology's effects are perceived post-implementation (Kim, Wang, and Boon 2021). Our findings signify that HRM professionals believe that their agency is affected to a certain degree due to the use of algorithmic HRM, which subsequently informs their perceptual and behavioral response of caution, fear, and aversion and consequently, their coping strategies. Furthermore, we also contend that these professionals' perceptual responses arising from their evaluation of how algorithmic HRM influences them and their organizations are, ultimately, the reasons for their possible resistance to this technology. However, some employees discuss being appreciative of this technology's many evident benefits and contributions toward improving HRM processes. At the same time, many wary employees remain open to learning about algorithms and embrace their use in HRM despite their wariness. Thus, we find a duality exists for professionals' perceptual and behavioral responses to algorithmic HRM deployment in the workplace.

We determine that the limited openness HRM professionals display in appreciating algorithmic HRM remains contingent on its deployment in a highly selective manner that ensures human oversight and governance in place to preempt any fallouts. This stance, echoed by respondents showcasing wariness and fear of algorithmic HRM, clarifies their adopted coping strategies addressed by RQ2 of our study. In response to RQ2, we found that our respondents relied on three strategies that ranged from avoidance to embracing the technology, with respondents also advocating for the selective application of algorithmic HRM in a manner that establishes a harmonious collaboration between humans and machines. Our findings elucidate substantial and vital implications for scholars and practitioners who are interested in mapping the future directions of algorithmic HRM, which we will discuss subsequently.

6.1 | Theoretical Implications

We offer a fivefold contribution to theory through our results. First, a qualitative approach enabled us to delve deeply into HRM professionals' experiences with fear of and aversion to algorithms—an understudied field that needs concentrated academic research (Mahmud et al. 2022; Meijerink et al. 2021; Meijerink and Bondarouk 2023). Our findings offer an in-depth insight into the individual and organization-related negative effects and uncertainties that lead employees to develop algorithmic aversion and fear of its widespread use. One of the most important implications for scholars that we raise through our findings pertains to the effect of algorithmic HRM on diversity, equality, and inclusion strategies, especially in the context of psychologically vulnerable (e.g., those dealing with mental health issues) and neurodiverse workforces that may be more susceptible to organizational biases (e.g., see Walkowiak 2023).

Second, our proposed framework constitutes a significant step forward in establishing a new perspective on algorithmic HRM-related aversion and appreciation—and the duality thereof. We conceptualize that algorithmic aversion and appreciation arise from the same process that organizational employees (HRM professionals in our case) adopt to evaluate algorithmic HRM. These two phenomena of appreciation and aversion, in our view, represent a duality and may be considered two sides of the same coin, that is, perceptual responses to the implementation of algorithmic HRM in organizations. Our acknowledgment of the perceived positive effects of algorithmic HRM and its subsequent appreciation behavior adds to the extant HRM literature by consolidating perspectives from the information systems domain. Past research on other technologies in the information systems domain (e.g., Honora, Memar Zadeh, and Haggerty 2024) has also suggested that individual or organizational adoption of technological platforms can have both bright and dark aspects that subsequently engender varied responses from the adopters. Our consideration of this aspect of technology adds to the theoretical underpinnings in our HRM-oriented study of algorithmic management. It will hopefully bring two concepts (aversion and appreciation), which have hitherto been studied separately, under the same aegis as perceptual responses to algorithmic management.

We surmise that HRM professionals (and perhaps other employees) acknowledge the positive effects (i.e., benefits) of algorithmic HRM well enough to move in a positive direction instead of toward pure aversion. Subsequently, we call for robust longitudinal qualitative studies that examine the individual, organizational, and technology-related factors that could affect employees' rumination on algorithmic HRM use and, in turn, their aversion and appreciation of this technology. Our findings and the proposed framework add in-depth and contextual insights regarding employees' perceptual responses to algorithmic HRM adoption to extend past knowledge and push boundaries for future scholarly investigations. We also raise the call for deciphering the minutia of changes in these dimensions of our framework over time, as also discussed in Section 5.2.

Third, our study emphasizes that algorithmic aversion may be a continuum of emotional responses, ranging from fear to wariness, instead of a discrete stance that employees adopt in response to perceived negative effects created by technological integration. We implore scholars to focus on the conceptual (particularly the emotional and psychological) nuances and stages of algorithmic aversion, perhaps by using seminal frameworks like the diffusion of innovation model and technology resistance frameworks (e.g., see Samhan 2018). Explicating these stages could help scholars identify specific stimuli that prompt HRM professionals' reasoning processes of appreciating or being aversive to algorithmic HRM through more novel frameworks such as behavioral reasoning theory (Claudy, Garcia, and O'Driscoll 2015). Given the dearth of theoretical grounding in algorithmic aversion research (Mahmud et al. 2022), we believe such approaches would add substantial knowledge to the current literature.

Fourth, we concur with the recent research (e.g., Einola and Khoreva 2023) contending algorithms' and AI's capacity to introduce elements of dehumanization in HRM functions in niche and unique ways. Since our findings indicate employees' inclination to embrace selective algorithmic HRM applications and collaborative intelligence approaches, it would be beneficial to conduct more in-depth studies to decipher how algorithms could be used in conjunction with higher levels of human touch in automated and augmented processes. Doing so will clear the path for a more harmonious coexistence between these two. Such attempts could make in-roads to resolve the automation–augmentation paradox and understand the instances of mismatch between algorithm use and human expectations.

Lastly, our respondents frequently alluded to performance and recruitment-related processes while discussing the shortfalls and frustrations related to algorithmic HRM use. Subsequently, we believe that resolving these processes' challenges could contribute significantly to showing employees the value of algorithmic HRM. In this regard, researchers could develop in-depth and nuanced approaches for these prospective assessments using knowledge from other fields, such as natural language processing and neurolinguistics, to create a more personal profile addressing candidate psychology and technical skills.

6.2 | Practical Implications

For practitioners, we offer three implications. First, as our findings show algorithmic HRM aversion to being contingent on individual differences amidst a generally cautious perspective, we strongly urge practitioners to develop targeted and recurring interventions to overcome the negativity. To ensure their effectiveness and appreciation within organizations, we suggest their development should leverage human-in-the-loop design, wherein functional managers and frontline employees should also be included in the design, testing, and implementation of interventions (also see Charlwood and Guenole 2022). Moreover, HRM professionals' experience with HRM and organizational processes should be accounted for while designing algorithms used in their organizations. Such design may ensure that the algorithms being used to automate HRM processes are uniquely attuned to the needs of the employees and the organization, thereby offering a way to alleviate any perceived disparity or distrust.

Further, algorithmic HRM development and use should also account for employees' prior domain experience (e.g., see Allen and Choudhury 2022), current context, and ability to facilitate knowledge transfer to this IT system. Such considerations may dispel employees' concerns regarding algorithms' inability to address inclusivity and situational factors affecting employees. Concurrently, HRM professionals should offer intensive formal training programs and informal peer support for older and less technologically savvy employees. The same could also be directed toward employees with more nontraditional backgrounds and subjective task descriptions to encourage an "embrace and learn" approach among all employees. Interventions in this regard could include, for example, creating workplace teams that bring together inexperienced and experienced employees to encourage knowledge sharing about complementing the strengths of algorithmic HRM with human skills. Such interventions, we believe, could go a long way in reducing employees' experienced uncertainties, fear, and aversion and, perhaps, in inculcating algorithmic appreciation.

Second, we focus on the respondents' proposition to selectively apply algorithmic HRM. We propose conducting extensive interorganizational mapping exercises to examine the processes wherein algorithmic HRM would be prone to a more positive employee embrace. This map, for example, could develop green, yellow, and red zones of algorithmic HRM implementation through a participatory approach with employees and HRM professionals. It would indicate where employees would be comfortable with fully deploying integrated algorithm-driven processes (green), partially integrating algorithms with substantial human oversight and final decision-making (yellow), or altogether avoiding algorithms (red).

However, such an exercise would require substantial interorganizational coordination. So, we also encourage HRM professionals to take a step back and assess their organizations' readiness and capacity to streamline coordination among different departments. This would lay the way for HRM professionals, as well as other employees, to work together and reimagine workflows that use algorithmic HRM for the most optimal outcomes. This may also allow current employees to consider how prospective ones may fit into the new work scenarios and process flows and, in turn, develop preemptive inputs for the algorithms to consider if used during recruitment and selection processes. Such an effort, though specific to organizations, could preempt employees' adoption of workaround strategies and instead foster a more friendly outlook toward algorithms. This could significantly assist organizations in saving resources invested in developing algorithmic systems, enhancing their technological infrastructure, and developing critical employee skills.

Lastly, our respondents' discussion about the unanticipated costs of algorithmic HRM leads us to question whether organizations' readiness for algorithmic HRM truly considers all possible avenues of this technology's effects on individuals and their organizations. We especially call attention to the organizations that are not dominant users of technology or have recently embarked on adopting algorithmic management. These organizations need to consider how to use algorithmic HRM to optimize employee creativity, performance, and decision-making while also ensuring that technology use does not impinge on employees' perceived work autonomy and job security. For this purpose, it might be beneficial for organizations to use recently developed frameworks, such as the AI capability framework (Chowdhury et al. 2023), to reassess their algorithm use strategies, considering the issues raised by our respondents.

However, such strategic initiatives in organizations must be accompanied by the establishment of transparent auditing, governance, and grievance structures to deal with any incidents of perceived injustice by current and prospective employees. Such an initiative would be a significant step in giving employees across all organizational levels a chance to express their reservations with algorithmic decision-making. In our view, it would also reduce employee uncertainties and perceptions of the algorithm as a threat to their careers while establishing trust in organizations' ethical and benevolent use of this technology.

In conclusion, the appropriate use of algorithmic HRM could contribute to developing content and a thriving workforce with opportunities to engage in creative and challenging tasks. To this end, it is essential to introduce counteractive measures to negate algorithmic aversion and uncertainty-driven fear.

6.3 | Limitations and Future Research

Despite our attempts to ensure a robust research design, our study is limited by certain constraints that should be addressed in upcoming studies. First, our sample was limited to the UK and the USA, which are mature and developed economies with significant infrastructure to support technology integration in organizations. The findings apply mainly to our subject pool and may not be generalizable to other samples or contexts. Thus, it would be interesting to examine if similar issues are raised by HRM professionals in other countries that are culturally different and relatively less developed or technologically advanced than the UK and USA, for example, India or Turkey. Comparative studies should also consider the connotations of culture as a viable area of inquiry, as indicated by Mahmud et al. (2022).

Second, we focused on HRM professionals as respondents and did not examine intergroup differences between the various management levels that the respondents belonged to or those between HRM and other functions. We believe there is significant potential for investigating the cross-functional and intergroup differences in professionals' aversion toward algorithmic HRM. Therefore, we urge scholars to develop research designs incorporating different groups with varied management levels of HRM professionals and of HRM with other departments to understand the thresholds of and areas vulnerable to algorithmic HRM aversion, fear, and uncertainty. Additionally, as we found the extant literature on algorithmic HRM and aversion limited, we did not consider segregating our respondents according to their organizational hierarchy. However, through our analysis, we find that it would be beneficial to conduct dyadic or triadic qualitative and longitudinal investigations with members from different management levels to understand how (and if) temporality and hierarchy affect algorithmic HRM aversion and what could be done to establish a consonance among them.

Lastly, we acknowledge that despite our efforts to introduce objectivity in the coding process, we cannot entirely exclude the possibility of researchers' subjective bias, which is a limitation of our approach. Further, our use of grounded theory is limited in its ability to refine our findings as it is recommended for the conceptual development of varied phenomena. Hence, future scholars should validate our results with more qualitative and mixed-method research approaches, including focus group studies and personal interviews, which could be combined with survey-based or experimental research to develop more nuanced insights into algorithmic HRM.

Disclosure

The authors have nothing to report.

Ethics Statement

Necessary approvals were obtained.

Consent

Informed consent was received.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

References

Allen, R. T., and P. Choudhury. 2022. "Algorithm-Augmented Work and Domain Experience: The Countervailing Forces of Ability and Aversion." *Organization Science* 33, no. 1: 149–169. https://doi.org/10.1287/ORSC.2021.1554.

Araujo, T., A. Brosius, A. C. Goldberg, J. Möller, and C. de Vreese. 2023. "Humans vs. AI: The Role of Trust, Political Attitudes, and Individual Characteristics on Perceptions About Automated Decision Making Across Europe." *International Journal of Communication* 17, no. 28: 6222–6249.

Arnold, M. 2003. "On the Phenomenology of Technology: The "Janus-Faces" of Mobile Phones." *Information and Organization* 13, no. 4: 231–256.

Arslan, A., C. Cooper, Z. Khan, I. Golgeci, and I. Ali. 2022. "Artificial Intelligence and Human Workers Interaction at Team Level: A Conceptual Assessment of the Challenges and Potential HRM Strategies." *International Journal of Manpower* 43, no. 1: 75–88. https://doi.org/10.1108/IJM-01-2021-0052.

Baccarella, C. V., T. F. Wagner, J. H. Kietzmann, and I. P. McCarthy. 2018. "Social Media? It's Serious! Understanding the Dark Side of Social Media." *European Management Journal* 36: 431–438. https://doi.org/10.1016/j.emj.2018.07.002.

Baiocco, S., E. Fernández-Macías, U. Rani, and A. Pesole. 2022. "The Algorithmic Management of Work and Its Implications in Different Contexts." [No. 2022/02.] JRC Working Papers Series on Labour, Education and Technology. https://www.ilo.org/wcmsp5/groups/public/---ed_emp/documents/publication/wcms_849220.pdf.

Bankins, S., P. Formosa, Y. Griep, and D. Richards. 2022. "AI Decision Making With Dignity? Contrasting Workers' Justice Perceptions of Human and AI Decision Making in a Human Resource Management Context." *Information Systems Frontiers* 24, no. 3: 857–875. https://doi.org/10.1007/s10796-021-10223-8.

Bartosiak, M. L., and A. Modlinski. 2022. "Fired by an Algorithm? Exploration of Conformism With Biased Intelligent Decision Support Systems in the Context of Workplace Discipline." *Career Development International* 27: 601–615. https://doi.org/10.1108/CDI-06-2022-0170.

Barati, M., and B. Ansari. 2022. "Effects of Algorithmic Control on Power Asymmetry and Inequality Within Organizations." *Journal of Management Control* 33: 525–544. https://doi.org/10.1007/s00187-022-00347-6.

BCS. 2020. "The Public Don't Trust Computer Algorithms to Make Decisions About Them, Survey Finds." *BCS: The Chartered Institute for IT*, September 8, 2020. https://www.bcs.org/articles-opinion-and-research/the-public-dont-trust-computer-algorithms-to-make-decisions-about-them-survey-finds/.

Bevilacqua, M., and T. Alashoor. 2023. "The Social and Moral Dimensions of Algorithm Aversion." *Academy of Management Proceedings* 2023, no. 1: 18721.

Blaique, L., and A. H. Pinnington. 2022. "Occupational Commitment of Women Working in SET: The Impact of Coping Self-Efficacy and Mentoring." *Human Resource Management Journal* 32, no. 3: 555–583. https://doi.org/10.1111/1748-8583.12405.

Bogert, E., A. Schecter, and R. T. Watson. 2021. "Humans Rely More on Algorithms Than Social Influence as a Task Becomes More Difficult." *Scientific Reports* 11, no. 1: 8028.

Brockner, J., and E. T. Higgins. 2001. "Regulatory Focus Theory: Implications for the Study of Emotions at Work." *Organizational Behavior and Human Decision Processes* 86, no. 1: 35–66.

Budhwar, P., S. Chowdhury, G. Wood, et al. 2023. "HRM in the Age of Generative AI: Perspectives and Research Direction on ChatGPT." *Human Resource Management Journal* 33, no. 3: 606–659.

Budhwar, P., A. Malik, M. T. T. de Silva, and P. Thevisuthan. 2022. "Artificial Intelligence—Challenges and Opportunities for International HRM: A Review and Research Agenda." *International Journal of Human Resource Management* 33, no. 6: 1065–1097. https://doi.org/10.1080/09585192.2022.2035161.

Burton, J. W., M. K. Stein, and T. B. Jensen. 2020. "A Systematic Review of Algorithm Aversion in Augmented Decision Making." *Journal of Behavioral Decision Making* 33, no. 2: 220–239. https://doi.org/10.1002/bdm.2155.

Charlwood, A., and N. Guenole. 2022. "Can HR Adapt to the Paradoxes of Artificial Intelligence?" *Human Resource Management Journal* 32, no. 4: 729–742.

Cheng, M. M., and R. D. Hackett. 2021. "A Critical Review of Algorithms in HRM: Definition, Theory, and Practice." *Human Resource Management Review* 31, no. 1: 100698. https://doi.org/10.1016/j.hrmr.2019.100698.

Cheng, M., and C. Foley. 2019. "Algorithmic Management: The Case of Airbnb." *International Journal of Hospitality Management* 83: 33–36. https://doi.org/10.1016/j.ijhm.2019.04.009.

Choung, H., J. S. Seberger, and P. David. 2023. "When AI Is Perceived to Be Fairer Than a Human: Understanding Perceptions of Algorithmic Decisions in a Job Application Context." *International Journal of Human–Computer Interaction*: 1–18.

Chowdhury, S., P. Budhwar, P. K. Dey, S. Joel-Edgar, and A. Abadie. 2022. "AI-Employee Collaboration and Business Performance: Integrating Knowledge-Based View, Socio-Technical Systems and Organizational Socialization Framework." *Journal of Business Research* 144, no. January: 31–49. https://doi.org/10.1016/j.jbusres.2022.01.069.

Chowdhury, S., P. Dey, S. Joel-Edgar, et al. 2023. "Unlocking the Value of Artificial Intelligence in Human Resource Management Through AI Capability Framework." *Human Resource Management Review* 33, no. 1: 100899. https://doi.org/10.1016/j.hrmr.2022.100899.

Claudy, M. C., R. Garcia, and A. O'Driscoll. 2015. "Consumer Resistance to Innovation—A Behavioral Reasoning Perspective." *Journal of the Academy of Marketing Science* 43, no. 4: 528–544. https://doi.org/10.1007/s11747-014-0399-0.

Creswell, J. W., W. E. Hanson, V. L. Clark Plano, and A. Morales. 2007. "Qualitative Research Designs: Selection and Implementation." *Counseling Psychologist* 35, no. 2: 236–264. https://doi.org/10.1177/0011000006287390.

Danner, G. E. 2018. *The Executive's How-to Guide to Automation: Mastering AI & Algorithm-Driven Business*. 1st ed. Cham, Switzerland: Springer Nature Switzerland AG.

Dargnies, M.-P., R. Hakimov, D. Kübler, W. Berlin, T. U. Berlin, and G. Weizsäcker. 2024. "Aversion to Hiring Algorithms: Transparency, Gender Profiling, and Self-Confidence." *Rationality and Competition Discussion Paper Series* 334. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4238275.

Dastin, J. 2018. "Amazon Scraps Secret AI Recruiting Tool That Showed Bias Against Women." *Reuters*, October 11, 2018. https://www.reuters.com/article/us-amazon-com-jobs-automation-insight-idUSKCN1MK08G.

Dietvorst, B. J., J. P. Simmons, and C. Massey. 2015. "Algorithm Aversion: People Erroneously Avoid Algorithms After Seeing Them Err." *Journal of Experimental Psychology: General* 144, no. 1: 114–126. https://doi.org/10.1037/xge0000033.

Duggan, J., R. Carbery, A. McDonnell, and U. Sherman. 2023. "Algorithmic HRM Control in the Gig Economy: The App-Worker Perspective." *Human Resource Management* 62, no. 6: 883–899.

Edwards, M. R., E. Zubielevitch, T. Okimoto, S. Parker, and F. Anseel. 2024. "Managerial Control or Feedback Provision: How Perceptions of Algorithmic HR Systems Shape Employee Motivation, Behavior, and Well-Being." *Human Resource Management* 63: 691–710. https://doi.org/10.1002/hrm.22218.

Einola, K., and V. Khoreva. 2023. "Best Friend or Broken Tool? Exploring the Co-Existence of Humans and Artificial Intelligence in the Workplace Ecosystem." *Human Resource Management* 62, no. 1: 117–135. https://doi.org/10.1002/hrm.22147.

Giermindl, L. M., F. Strich, O. Christ, U. Leicht-Deobald, and A. Redzepi. 2022. "The Dark Sides of People Analytics: Reviewing the Perils for Organizations and Employees." *European Journal of Information Systems* 31, no. 3: 410–435. https://doi.org/10.1080/0960085X.2021.1927213.

Gioia, D. A., K. G. Corley, and A. L. Hamilton. 2013. "Seeking Qualitative Rigor in Inductive Research: Notes on the Gioia Methodology." *Organizational Research Methods* 16, no. 1: 15–31. https://doi.org/10.1177/1094428112452151.

Glaser, B. G., and A. L. Strauss. 1999. *The Discovery of Grounded Theory: Strategies for Qualitative Research*. New York: Routledge. https://doi.org/10.4324/9780203793206.

Goods, C., A. Veen, and T. Barratt. 2019. "'Is Your Gig any Good?' Analyzing Job Quality in the Australian Platform-Based Food-Delivery Sector." *Journal of Industrial Relations* 61, no. 4: 502–527. https://doi.org/10.1177/0022185618817069.

Honora, A., M. Memar Zadeh, and N. Haggerty. 2024. "The Bittersweet of Consumer–Human Brand Relationships in the Social Media Context." *Psychology & Marketing* 41, no. 3: 547–574. https://doi.org/10.1002/mar.21932.

Iyanna, S., P. Kaur, P. Ractham, S. Talwar, and A. K. M. Najmul Islam. 2022. "Digital Transformation of Healthcare Sector. What Is Impeding Adoption and Continued Usage of Technology-Driven Innovations by End-Users?" *Journal of Business Research* 153: 150–161. https://doi.org/10.1016/j.jbusres.2022.08.007.

Jacoby, J. 2002. "Stimulus-Organism-Response Reconsidered: An Evolutionary Step in Modeling (Consumer) Behavior." *Journal of Consumer Psychology* 12, no. 1: 51–57.

Jeris, L., and B. J. Daley. 2004. "Orienteering for Boundary Spanning: Reflections on the Journey to Date and Suggestions for Moving Forward." *Advances in Developing Human Resources* 6, no. 1: 101–115.

Kawaguchi, K. 2021. "When Will Workers Follow an Algorithm? A Field Experiment With a Retail Business." *Management Science* 67, no. 3: 1670–1695. https://doi.org/10.1287/mnsc.2020.3599.

Kelan, E. K. 2023. "Algorithmic Inclusion: Shaping the Predictive Algorithms of Artificial Intelligence in Hiring." *Human Resource Management Journal* 34, no. 3: 694–707. https://doi.org/10.1111/1748-8583.12511.

Kellogg, K. C., M. A. Valentine, and A. Christin. 2020. "Algorithms at Work: The New Contested Terrain of Control." *Academy of Management Annals* 14, no. 1: 366–410. https://doi.org/10.5465/annals.2018.0174.

Khoreva, V., V. Vaiman, T. Bondarouk, and S. Salojärvi. 2019. "Exploring the Influence of Digitalization on Global Talent Management." In *AOM 2019: Understanding the Inclusive Organization—79th Annual Meeting of the Academy of Management, 2018*. Briarcliff Manor, NY: Academy of Management.

Kim, H. W., and A. Kankanhalli. 2009. "Investigating User Resistance to Information Systems Implementation: A Status Quo Bias Perspective." *MIS Quarterly* 33: 567–582.

Kim, S., Y. Wang, and C. Boon. 2021. "Sixty Years of Research on Technology and Human Resource Management: Looking Back and Looking Forward." *Human Resource Management* 60, no. 1: 229–247. https://doi.org/10.1002/hrm.22049.

Kinowska, H., and Ł. J. Sienkiewicz. 2022. "Influence of Algorithmic Management Practices on Workplace Well-Being—Evidence From European Organizations." *Information Technology & People* 36: 21–42. https://doi.org/10.1108/itp-02-2022-0079.

Koch-Bayram, I. F., and C. Kaibel. 2023. "Algorithms in Personnel Selection, Applicants' Attributions About Organizations' Intents and Organizational Attractiveness: An Experimental Study." *Human Resource Management Journal* 34, no. 3: 733–752. https://doi.org/10.1111/1748-8583.12528.

Köchling, A., and M. C. Wehner. 2020. "Discriminated by an Algorithm: A Systematic Review of Discrimination and Fairness by Algorithmic Decision-Making in the Context of HR Recruitment and

HR Development." *Business Research* 13, no. 3: 795–848. https://doi.org/10.1007/s40685-020-00134-w.

Kuhn, K. M., J. Meijerink, and A. Keegan. 2021. "Human Resource Management and the Gig Economy: Challenges and Opportunities at the Intersection Between Organizational HR Decision-Makers and Digital Labor Platforms." *Research in Personnel and Human Resources Management* 39: 1–46. https://doi.org/10.1108/S0742-730120210000039001.

Kurdi-Nakra, H., and J. Pak. 2022. "Exploring the Socio-Political Dynamics of Front-Line managers' HR Involvement: A Qualitative Approach." *Human Resource Management* 62: 615–636. https://doi.org/10.1002/hrm.22150.

Lacroux, A., and C. Martin-Lacroux. 2022. "Should I Trust the Artificial Intelligence to Recruit? Recruiters' Perceptions and Behavior When Faced With Algorithm-Based Recommendation Systems During Resume Screening." *Frontiers in Psychology* 13: 895997. https://doi.org/10.3389/fpsyg.2022.895997.

Lamers, L., J. Meijerink, G. Jansen, and M. Boon. 2022. "A Capability Approach to Worker Dignity Under Algorithmic Management." *Ethics and Information Technology* 24, no. 1: 10. https://doi.org/10.1007/s10676-022-09637-y.

Langer, M., and C. J. König. 2023. "Introducing a Multi-Stakeholder Perspective on Opacity, Transparency and Strategies to Reduce Opacity in Algorithm-Based Human Resource Management." *Human Resource Management Review* 33: 100881. https://doi.org/10.1016/j.hrmr.2021.100881.

Leicht-Deobald, U., T. Busch, C. Schank, et al. 2019. "The Challenges of Algorithm-Based HR Decision-Making for Personal Integrity." *Journal of Business Ethics* 160, no. 2: 377–392. https://doi.org/10.1007/s10551-019-04204-w.

Lenka, S., V. Parida, D. R. Sjödin, and J. Wincent. 2018. "Exploring the Microfoundations of Servitization: How Individual Actions Overcome Organizational Resistance." *Journal of Business Research* 88: 328–336. https://doi.org/10.1016/j.jbusres.2017.11.021.

Levy, K., K. E. Chasalow, and S. Riley. 2021. "Algorithms and Decision-Making in the Public Sector." *Annual Review of Law and Social Science* 17: 309–334. https://www.annualreviews.org/.

Li, W., Y. Lu, P. Hu, and S. Gupta. 2024. "Work Engagement of Online Car-Hailing Drivers: The Effects of Platforms' Algorithmic Management." *Information Technology & People* 37, no. 3: 1423–1448. https://doi.org/10.1108/ITP-02-2022-0122.

Liu, M., X. Tang, S. Xia, S. Zhang, and Y. Zhu. 2023. "Algorithm Aversion: Evidence From Ridesharing Drivers." *Management Science*. https://doi.org/10.1287/mnsc.2022.02475.

Liu, N. T. Y., S. N. Kirshner, and E. T. K. Lim. 2023. "Is Algorithm Aversion WEIRD? A Cross-Country Comparison of Individual-Differences and Algorithm Aversion." *Journal of Retailing and Consumer Services* 72: 103259. https://doi.org/10.1016/j.jretconser.2023.103259.

Logg, J. M., J. A. Minson, and D. A. Moore. 2019. "Algorithm Appreciation: People Prefer Algorithmic to Human Judgment." *Organizational Behavior and Human Decision Processes* 151, no. December 2018: 90–103. https://doi.org/10.1016/j.obhdp.2018.12.005.

Maasland, C., and K. S. Weißmüller. 2022. "Blame the Machine? Insights From an Experiment on Algorithm Aversion and Blame Avoidance in Computer-Aided Human Resource Management." *Frontiers in Psychology* 13: 779028. https://doi.org/10.3389/fpsyg.2022.779028.

Mahmud, H., A. K. M. N. Islam, S. I. Ahmed, and K. Smolander. 2022. "What Influences Algorithmic Decision-Making? A Systematic Literature Review on Algorithm Aversion." *Technological Forecasting and Social Change* 175: 121390. https://doi.org/10.1016/j.techfore.2021.121390.

Malik, A., P. Budhwar, H. Mohan, and N. R. Srikanth. 2023. "Employee Experience—The Missing Link for Engaging Employees: Insights From an MNE's AI-Based HR Ecosystem." *Human Resource Management* 62, no. 1: 97–115.

Mantello, P., and M. T. Ho. 2023. "Emotional AI and the Future of Wellbeing in the Post-Pandemic Workplace." *AI & Society* 39: 1883–1889. https://doi.org/10.1007/s00146-023-01639-8.

McDonnell, A., R. Carbery, J. Burgess, and U. Sherman. 2021. "Technologically Mediated Human Resource Management in the Gig Economy." *International Journal of Human Resource Management* 32, no. 19: 3995–4015. https://doi.org/10.1080/09585192.2021.1986109.

Medwell, J. 2022. "When the Algorithm Is Your Boss." *Tribune*, January 30, 2022. https://tribunemag.co.uk/2022/01/amazon-algorithm-human-resource-management-tech-worker-surveillance.

Mehrabian, A., and J. A. Russell. 1974. *An Approach to Environmental Psychology*. Cambridge, MA: MIT Press.

Meijerink, J., and T. Bondarouk. 2023. "The Duality of Algorithmic Management: Toward a Research Agenda on HRM Algorithms, Autonomy and Value Creation." *Human Resource Management Review* 22: 100876. https://doi.org/10.1016/j.hrmr.2021.100876.

Meijerink, J., M. Boons, A. Keegan, and J. Marler. 2021. "Algorithmic Human Resource Management: Synthesizing Developments and Cross-Disciplinary Insights on Digital HRM." *International Journal of Human Resource Management* 32, no. 12: 2545–2562. https://doi.org/10.1080/09585192.2021.1925326.

Meissner, P., and C. Keding. 2021. "The Human Factor in AI-Based Decision-Making." *MIT Sloan Management Review* 63, no. 1: 1–5.

Mills, A., G. Durepos, and E. Wiebe. 2010. "Longitudinal Research." In *Encyclopedia of Case Study Research*. Thousand Oaks, CA: SAGE. https://doi.org/10.4135/9781412957397.n196.

Mirowska, A., and L. Mesnet. 2022. "Preferring the Devil You Know: Potential Applicant Reactions to Artificial Intelligence Evaluation of Interviews." *Human Resource Management Journal* 32, no. 2: 364–383. https://doi.org/10.1111/1748-8583.12393.

Moritz, J. M., L. Pomrehn, H. Steinmetz, and M. Wehner. 2023. "A Meta-Analysis and Review About the (Un)fairness Perceptions of Algorithmic Decision-Making." *Academy of Management Proceedings* 2023, no. 1: 15483.

Morse, J. 2020. "People Are Fighting Algorithms for a More Just and Equitable Future. You Can, Too." *Mashable.Com*, September 4, 2020. https://mashable.com/article/police-facial-recognition-algorithms-activism.

Murphy, C., A. C. Klotz, and G. E. Kreiner. 2017. "Blue Skies and Black Boxes: The Promise (And Practice) of Grounded Theory in Human Resource Management Research." *Human Resource Management Review* 27, no. 2: 291–305.

Nelson, S. M., S. W. Burton, and H. A. Kurth. 2023. "The Purpose, Prevalence, and Legal Pitfalls of AI in Workforce Management." *Westlaw Today*, July 26, 2023. https://www.huntonak.com/images/content/9/2/v2/92220/the-purpose-prevalence-and-legal-pitfalls-of-ai-in-workforce-man.pdf.

Neudert, L.-M., A. Knuutila, and P. N. Howard. 2020. "Global Attitudes Towards AI, Machine Learning & Automated Decision Making: Implications for Involving Artificial Intelligence in Public Service and Good Governance." *Oxford Commission on AI and Good Governance*. https://www.oii.ox.ac.uk/news-events/reports/global-attitudes-towards-ai-machine-learning-automated-decision-making-implications-for-involving-artificial-intelligence-in-public-service-and-good-governance/.

Neumann, M., A. S. M. Niessen, P. P. Hurks, and R. R. Meijer. 2023. "Holistic and Mechanical Combination in Psychological Assessment: Why Algorithms Are Underutilized and What Is Needed to Increase Their Use." *International Journal of Selection and Assessment* 31, no. 2: 267–285.

Newman, D. T., N. J. Fast, and D. J. Harmon. 2020. "When Eliminating Bias Isn't Fair: Algorithmic Reductionism and Procedural Justice in Human Resource Decisions." *Organizational Behavior and Human Decision Processes* 160: 149–167. https://doi.org/10.1016/j.obhdp.2020.03.008.

Ore, O., and M. Sposato. 2021. "Opportunities and Risks of Artificial Intelligence in Recruitment and Selection." *International Journal of Organizational Analysis* 30: 1771–1782. https://doi.org/10.1108/IJOA-07-2020-2291.

Orhan, M. A., I. Khelladi, S. Castellano, and S. Singh. 2022. "Work Experience on Algorithm-Based Platforms: The Bright and Dark Sides of Turking." *Technological Forecasting and Social Change* 183: 121907. https://doi.org/10.1016/j.techfore.2022.121907.

Parent-Rocheleau, X., and S. K. Parker. 2022. "Algorithms as Work Designers: How Algorithmic Management Influences the Design of Jobs." *Human Resource Management Review* 32, no. 3: 100838. https://doi.org/10.1016/j.hrmr.2021.100838.

Parent-Rocheleau, X., S. K. Parker, A. Bujold, and M. C. Gaudet. 2024. "Creation of the Algorithmic Management Questionnaire: A Six-Phase Scale Development Process." *Human Resource Management* 63, no. 1: 25–44.

Park, H., D. Ahn, K. Hosanagar, and J. Lee. 2021. "Human–AI Interaction in Human Resource Management: Understanding Why Employees Resist Algorithmic Evaluation at Workplaces and How to Mitigate Burdens." In *CHI Conference on Human Factors in Computing Systems (CHI '21)*. New York, NY: Association for Computing Machinery. https://doi.org/10.1145/3411764.3445304.

Pereira, V., E. Hadjielias, M. Christofi, and D. Vrontis. 2021. "A Systematic Literature Review on the Impact of Artificial Intelligence on Workplace Outcomes: A Multi-Process Perspective." *Human Resource Management Review* 33: 100857. https://doi.org/10.1016/j.hrmr.2021.100857.

Poba-Nzaou, P., S. Uwizeyemungu, and C. Clarke. 2020. "Patterns Underlying Required HR and IT Competencies: A Content and Cluster Analysis of Advertisements of HR Manager Positions." *International Journal of Human Resource Management* 31, no. 16: 2065–2088. https://doi.org/10.1080/09585192.2018.1424019.

Prikshat, V., A. Malik, and P. Budhwar. 2021. "AI-Augmented HRM: Antecedents, Assimilation and Multilevel Consequences." *Human Resource Management Review* 33: 100860. https://doi.org/10.1016/j.hrmr.2021.100860.

Puranam, P. 2021. "Human–AI Collaborative Decision-Making as an Organization Design Problem." *Journal of Organization Design* 10, no. 2: 75–80. https://doi.org/10.1007/s41469-021-00095-2.

Rodgers, W., J. M. Murray, A. Stefanidis, W. Y. Degbey, and S. Y. Tarba. 2023. "An Artificial Intelligence Algorithmic Approach to Ethical Decision-Making in Human Resource Management Processes." *Human Resource Management Review* 33, 100925. https://doi.org/10.1016/j.hrmr.2022.100925.

Raisch, S., and S. Krakowski. 2021. "Artificial Intelligence and Management: The Automation–Augmentation Paradox." *Academy of Management Review* 46, no. 1: 192–210. https://doi.org/10.5465/2018.0072.

Samhan, B. 2018. "Revisiting Technology Resistance: Current Insights and Future Directions." *Australasian Journal of Information Systems* 22: 1–11. https://doi.org/10.3127/ajis.v22i0.1655.

Sarvaiya, H., J. Arrowsmith, and G. Eweje. 2021. "Exploring HRM Involvement in CSR: Variation of Ulrich's HR Roles by Organisational Context." *International Journal of Human Resource Management* 32, no. 21: 4429–4462.

Scheibmayr, I., and A. Reichel. 2021. "Bringing the Algorithmic HR Manager In: Behavioral Responses to Algorithmic HRM." *Academy of Management Proceedings* 2021: 15863.

Shah, A. M., A. Qayyum, and K. Y. Lee. 2022. "Customers' Dining Choice Using Meal Ordering Apps: Insights From China and Indonesia." *Asia Pacific Journal of Marketing and Logistics* 35: 1443–1473. https://doi.org/10.1108/APJML-11-2021-0828.

Suleiman, N., and Z. B. Othman. 2021. "Forensic Accounting Investigation of Public Sector Corruption in Nigeria: The Gioia Methodology." *Qualitative Report* 26, no. 3: 1021–1032. https://doi.org/10.46743/2160-3715/2021.3907.

Sumpter, D. M. D., and C. B. Gibson. 2022. "Riding the Wave to Recovery: Relational Energy as an HR Managerial Resource for Employees During Crisis Recovery." *Human Resource Management* 62: 581–613. https://doi.org/10.1002/hrm.22117.

Suseno, Y., C. Chang, M. Hudik, and E. S. Fang. 2022. "Beliefs, Anxiety and Change Readiness for Artificial Intelligence Adoption Among Human Resource Managers: The Moderating Role of High-Performance Work Systems." *International Journal of Human Resource Management* 33, no. 6: 1209–1236. https://doi.org/10.1080/09585192.2021.1931408.

Tambe, P., P. Cappelli, and V. Yakubovich. 2019. "Artificial Intelligence in Human Resources Management: Challenges and a Path Forward." *California Management Review* 61, no. 4: 15–42.

Tandon, A., A. Dhir, S. Talwar, P. Kaur, and M. Mäntymäki. 2022. "Social Media Induced Fear of Missing out (FoMO) and Phubbing: Behavioural, Relational and Psychological Outcomes." *Technological Forecasting and Social Change* 174: 121149.

Tandon, A., F. Jabeen, S. Talwar, M. Sakashita, and A. Dhir. 2021. "Facilitators and Inhibitors of Organic Food Buying Behavior." *Food Quality and Preference* 88: 104077.

Tong, S., N. Jia, X. Luo, and Z. Fang. 2021. "The Janus Face of Artificial Intelligence Feedback: Deployment Versus Disclosure Effects on Employee Performance." *Strategic Management Journal* 42, no. 9: 1600–1631. https://doi.org/10.1002/smj.3322.

Tomprou, M., and M. K. Lee. 2022. "Employment Relationships In Algorithmic Management: A Psychological Contract Perspective." *Computers in Human Behavior* 126: 106997. https://doi.org/10.1016/j.chb.2021.106997.

van den Groenendaal, S. M. E., C. Freese, R. F. Poell, and D. T. A. M. Kooij. 2022. "Inclusive Human Resource Management in Freelancers' Employment Relationships: The Role of Organizational Needs and Freelancers' Psychological Contracts." *Human Resource Management Journal* 33: 224–240. https://doi.org/10.1111/1748-8583.12432.

Varma, A., C. Dawkins, and K. Chaudhuri. 2023. "Artificial Intelligence and People Management: A Critical Assessment Through the Ethical Lens." *Human Resource Management Review* 33, no. 1: 100923.

Vassilopoulou, J., O. Kyriakidou, M. F. Özbilgin, and D. Groutsis. 2022. "Scientism as Illusion in HR Algorithms: Towards a Framework for Algorithmic Hygiene for Bias Proofing." *Human Resource Management Journal* 2021: 1–15. https://doi.org/10.1111/1748-8583.12430.

Vassilopoulou, J., O. Kyriakidou, M. F. Ozbilgin, and D. Groutsis. 2024. "Scientism as Illusio in HR Algorithms: Towards a Framework for Algorithmic Hygiene for Bias Proofing." *Human Resource Management Journal* 34, no. 2: 311–325.

Walkowiak, E. 2023. "Digitalization and Inclusiveness of HRM Practices: The Example of Neurodiversity Initiatives." *Human Resource Management Journal* 2023: 1–21. https://doi.org/10.1111/1748-8583.12499.

Waldkirch, M., E. Bucher, P. K. Schou, and E. Grünwald. 2021. "Controlled by the Algorithm, Coached by the Crowd–How HRM Activities Take Shape on Digital work Platforms in the Gig Economy." *International Journal of Human Resource Management* 32, no. 12: 2643–2682. https://doi.org/10.1080/09585192.2021.1914129.

Wang, W., G. Gao, and R. Agarwal. 2023. "Friend or Foe? Teaming Between Artificial Intelligence and Workers With Variation in

Experience." *Management Science* 70, no. 9: 5753–5775. https://doi.org/10.1287/mnsc.2021.00588.

Wilson, J. H., and P. R. Daugherty. 2018. "Collaborative Intelligence: Humans and AI Are Joining Forces." *Harvard Business Review* 2018, no. July–August: 17.

Wu, X., Q. Liu, H. Qu, and J. Wang. 2023. "The Effect of Algorithmic Management and Workers' Coping Behavior: An Exploratory Qualitative Research of Chinese Food-Delivery Platform." *Tourism Management* 96: 104716.

Ying, T., J. Tang, J. Wen, et al. 2021. "Traveling With Pets: Constraints, Negotiation, and Learned Helplessness." *Tourism Management* 82: 104183. https://doi.org/10.1016/j.tourman.2020.104183.

Appendix I

Brief Snapshot of Prior Literature on Algorithmic Aversion

S. No.	Author	Context	Sample	Method/technique	Focus
1	Rodgers et al. (2023)	General, AI-algorithms	n.a.	Conceptual	Throughput framework-based discussion focused on ethical dimensions of algorithmic decision-making
2	Barati and Ansari (2022)	General, algorithmic control in HRM	n.a.	Conceptual	Commentary on how deploying algorithmic control to complement/substitute traditional methods could amplify power asymmetries and inequalities given large variations in adoption levels and overestimation of benefits (objective and transparent control) based on the control model proposed by Kellogg, Valentine, and Christin (2020)
3	Lamers et al. (2022)	General, software algorithms	n.a.	Conceptual	Propose a framework based on Capability Approach to understand implications of algorthimic management for workers' dignity
4	Orhan et al. (2022)	US, algorithm-based platforms	$N = 401$, Amazon Mturk workers, 44.1% = 25–24 years, 61.8% male, 46.4% = 4 year degree, 68.3% = full time employed, 71% = Caucasian	SEM	Concentrate on workers' experience on Micro-task platforms (MTurk) and phenomenon of turking. Higher turking, significance of task and meaningfulness (bright side) improve personal opportunities for growth and workers' perceived QoL. Excessive work and financial pressure (dark side) reduce workers' self-acceptance and QoL. Both direct and mediating effects uncovered in tested associations
5	Maasland and Weißmüller (2022)	Germany, algorithm-based decision-support system in HRM	$N = 288$, Professional and students, $M_{age} = 28.03$ years (SD = 6.1), 54.2% female, 58.7% = tertiary education	2 × 2 randomly-controlled vignette design, online experiment, Chi square, odds ratio, φ-tests, logistic regression	Examine algorithmic aversion and blame avoidance while using algorithmic-decisions to support HRM functions. Determined that algorithmic aversion is affects by type of HR decisions made by algorithms, user confidence in machines, pretesting opportunities wherein there is a counter-intuitive effect of latter two factors
6	Tomprou and Lee (2022)	US, algorithmic management and employment relationships	Amazon MTurk, Study 1: $N = 239$, 56.5% male, $M_{age} = 37.18$ years (SD = 10.40), 72% = full time employed Study 2: $N = 210$, 64.8% = male, $M_{age} = 37.20$ (SD = 10.75), 76.6% = full time employed Study 3: $N = 334$, 61.7% = male, $M_{age} = 37.27$ (SD = 11.18), 69.2% = full time employed Study 4: $N = 315$, 54% male, $M_{age} = 37.30$ (SD = 11.49), 65.7% = full time employed Study 5: $N = 324$, 57.1% male, $M_{age} = 37.33$ (SD = 10.59) 65.4% = full time employed	Study 1–5: 2 × 2 between-subjects experiments, two-way ANOVA, bivariate correlations	Adopt psychological contract lens to examine how type of agent (algorithm vs. human) influenced perceived commitment employer commitment and psychological contract contingent on type of inducement (relational vs. transactional) 5 studies conducted across recruitment and onboarding and inducement delivery phases. Found significant effect of agent type in case of relational inducement (recruiting and low inducement delivery), greater perceived breach and higher turnover for human agents in case of low delivery
7	Langer and König (2023)	General, algorithm-based HRM	n.a.	Conceptual	Discuss opacity and allied problems/implications for multiple stakeholders (users, developers, affected individuals, deploying organizations/entities and regulators)
8	Meijerink and Bondarouk (2023)	General, HRM algorithms	n.a.	Conceptual	Deliberate on duality of HRM algorithms in context of enhancing/diminishing autonomy and value creation for affected workers
9	Kawaguchi (2021)	Japan (Retail: Japan Railway East), Algorithmic decision-making	$N = 70$ subcontractors (workers)	Algorithm development and model testing, field experiment, analysis for nonexperimental variations	Developed and tested algorithm for dynamic product assortment revenue increment. Examined workers' aversion in taking algorithmic advice and determined importance of individual (e.g., worker regret, advice integration in algorithm) and contextual (e.g., sales volume) factors in mitigating this effect

S. No.	Author	Context	Sample	Method/technique	Focus
10	Cheng and Hackett (2021)	General, algorithmic HRM	Academic articles = 22 Practitioner articles = 122	SLR	Compare status of research vs. practice, discourse less focus on theory integration in algorithmic HRM and its nature as a glass box (heuristics) rather than a black box. Deliberate on causality and adverse impact issues of algorithms in HRM practice and propose research agendas for future
11	McDonnell et al. (2021)	General, gig economy and algorithmic management	n.a.	Narrative discussion (Special issue introduction/Editorial)	Focus overall on technology mediated-HRM and discuss its implications for gig economy workers and HRM
12	Waldkirch et al. (2021)	General, digital labor platforms, algorithmic management	12,091 scraped comments from 1311 authors (workers, Upwork platform)	Text-analysis, in-depth qualitative content analysis (mixed-method)	Explicate five HRM practice related conversations, (a) access and mobility, (b) T&D, (c) scoring and feedback, (d) appraisal and control, (e) platform literacy and support
13	Meijerink et al. (2021)	General, algorithmic HRM	n.a.	Narrative discussion (Special issue introduction/Editorial)	Discuss state of literature and features of algorithmic HRM. Deliberate on relationship with worker status and employment relationships to propose future research propositions
14	Köchling and Wehner (2020)	General, algorithmic decision-making in HRM	Academic articles = 36	SLR (academic articles)	Focus on two HRM functions: recruitment and development, to discuss the issues of discrimination and fairness in algorithms' use and possibilities for future research
15	Newman, Fast, and Harmon (2020)	General, algorithmic decision-making in HRM	Amazon MTurk worker pool (unless otherwise specified), Lab experiments: Study 1: $N = 199$ 41.2% = female, $M_{age} = 32.9$ (SD = 10.3) 76.4% = Caucasian Study 3: $N = 189$, 45% = female, $M_{age} = 35.3$ (SD = 10.5), 79.4% = Caucasian Study 4: $n = 197$ (undergraduate students), 45.7% = female, $M_{age} = 20.9$ (SD = 1.8), 41.6% = Caucasian Study 5: 213 (undergraduate students), 41.3% = female, $M_{age} = 19.9$ (SD = 2.1), 39.9% = Caucasian Large scale experiment (Study 2): $N = 1654$, 66.8% = female, $M_{age} = 38.6$ (SD = 11.4) 42.1% = Caucasian	Four lab experiments: 2 × 2 design, four laboratory experiments, one large-scale randomized experiment in organization (Private university), ANOVA, linear contrast effects, correlations, mediation	Deliberate on issues of algorithmic reductionism (non-consideration of relevant information) and procedural justice or fairness of algorithms vs. managers in HRM decisions (layoff vs. promotions). Determined lesser perceived fairness of algorithmic vs. human decisions and a subjective perception that algorithms violate the workers' procedural justice as they fail to take holistic performance into consideration. This perception occurs across a range of scenarios and can have significant implications for organizational commitment
16	Cheng and Foley (2019)	General, algorithmic management, sharing economy	$N = 545$ (posts from AirBnB hosts)	Thematic analysis	Emergent themes from analysis discussed in detail: (a) algorithm ambiguity, (b) sense of anxiety/frustration, (c) sense of control, (d) experimentation, (e) resistance, (f) manipulation, (g) penalty and rewards
17	Leicht-Deobald et al. (2019)	General, algorithm-based decision-making in HRM	n.a.	Conceptual	Discuss that efficiency brought forth by algorithms may create challenges related to workers' integrity by pushing them more toward compliance. Also indicate possible mitigating influence of factors such as data literacy, awareness of ethics, participatory design use

Note: Articles presented are limited to those published between 2023 (January 26) and 2019.
Abbreviations: general = no country specified/or no country-specific data used, M_{age} = mean age, n.a. = not available/applicable, QoL = quality of life, SD = standard deviation, SLR = systematic literature review, US = United States.

Appendix II

Questions for Respondents

Screening wave questions:

1. How long have you been in the profession of Human Resource (HR) (in years)?
2. Are you aware of Algorithmic HRM (tools for algorithm decision-making in HRM)?
3. Is your company currently using Algorithmic HRM (tools for algorithm decision-making in HRM)?
4. Kindly give the name(s) of the Algorithmic HRM tools that your company is currently using.
5. Are you using Algorithmic HRM tools in your day-to-day work routine?
6. Please explain how you use Algorithmic HR tools in your daily work routine. Give an example and discuss in detail.
7. Is your firm a public or private sector?
8. What is your current job profile in the firm/organization?
9. What is your designation in the firm/organization?
10. What are your core areas of activities in HR (e.g., talent acquisition, talent development, talent retention, performance management)?
11. What key tasks or roles do you perform in your day-to-day work in the current firm/organization?

Interview wave questions:

1. In your opinion, do all employees understand an algorithm's use, function, and decisions in terms of how this technology affects them? Discuss your answer (why or why not) by providing 1–2 examples or real-life incidents that have shaped your thoughts.
2. Do you think that algorithmic HRM has negatively affected employees' views or opinions of the HRM processes in your organization? Kindly discuss 2–3 reasons which, in your opinion, have created such negative perceptions about algorithmic HRM.
3. Do you believe that using algorithms in HRM processes introduces any risks or challenges? Please mention 2–3 risks or challenges and describe how they affect your use of algorithmic HRM.
4. In your opinion, should algorithms be used in all areas/processes of HR or only a few? Please discuss which areas you think algorithmic HRM should be used and why? Support your answer by sharing 1–2 examples or real-life incidents that have shaped your thoughts.
5. Which areas do you think algorithmic HRM should NOT be used and why? Support your answer by sharing 1–2 examples or real-life incidents that have shaped your thoughts.
6. What are the negative costs associated with implementing algorithms in HRM processes? Please discuss your answer by sharing 2–3 specific costs and real-life examples or incidents on which your answer is based.
7. In your opinion, should humans make HRM-related decisions instead of algorithms? Discuss your answer (why or why not) by providing 1–2 examples or real-life incidents that have shaped your thoughts.
8. Do you think the organization and its employees should fear using algorithms in HRM processes? Discuss your answer (why or why not) by providing 2–3 examples or real-life incidents that have shaped your thoughts.
9. How do you respond to and cope with any fear or aversion that you feel about using algorithms in HRM functions? Please discuss your answer by sharing 1–2 examples of your responses or coping strategies.
10. Do you feel that algorithms affect the overall fairness and 'human touch' of HRM processes? Support your answer by sharing 1–2 examples or real-life incidents that have shaped your thoughts.
11. In your opinion, does using algorithms in HRM affect dignity and respect, equality of treatment, or consideration given to all employees? Discuss your answer (why or why not) by providing 1–2 examples or real-life incidents that have shaped your thoughts.
12. Do you think algorithmic HRM can negatively affect the fairness of process outcomes for current employees (e.g., selection, promotions, appraisals, and disciplinary action outcomes)? Discuss your answer (why or why not) in detail by providing 1–2 examples or real-life incidents that have shaped your thoughts.

Appendix III

Evidence Quotes

Theme and subtheme	Quote [respondent]
Uncertainty bases and subjectivity	
Subjective and episodic nature	*Yes, I think it is perfectly understandable for an organization and its employees to fear algorithms in the HRM process. Firstly, it takes away a basic sense of human "agency" in terms of how decisions are made. Secondly, it could create a working culture where everyone is the same, as the qualities they possess are identified by the algorithm. In my opinion, this represents quite a dystopian way of working.* [P38]
	Fear is a strong word, but if poor decisions are made in a company as a result of the poor implementation of these algorithms, then yes, fear and caution should certainly play a role. I'm not saying we should be afraid of technology full stop, but we should certainly find ways to monitor it more closely than has happened in some countries in the last decade. [P15]
	Fear is a strong word, but I think some caution should be taken in using full-scale algorithm-based decisions. I believe it should be there as an aid. Still, the final say should come from experienced staff using their skills to make the correct decisions. [P32]
	There is no need to fear it, as long as there is always room for humans to intervene, to empathize, and to potentially overrule the algorithm's course of action [P12]
	Senior leaders must ensure that algorithms are fit-for-purpose, and they should be critically evaluated on a regular basis. Likewise, P18 stated, *I don't think these should be feared, as with good control and governance these algorithms only improve the existing systems, reducing costs and creating efficiencies.* [P31]
Technology	*To be honest, a lot of the employees that work in my organization probably have never heard the word before, let alone are aware of what it does and its functions.* [P49]
	I just think that the algorithm can be skewed to show certain biases. For example, we wanted it to bring candidates to have a PhD for a position and we noticed that predominantly it was finding male candidates as there were just more of them around and it was showing that bias in the selection process, so few women were being included. We then decided that a master's degree was more than enough, and suddenly, the gender split was much more even, and we were getting the same quality of candidates.
	It dehumanized the process a bit which is making people into data sets as opposed to seeing intangibles that can't be seen from the algorithms perspective. [P40]
	Algorithm use in HR processes has definitely created negative feelings toward the processes in my organization. A good example is job applications, where people feel that a human-directed process is fairer or that AI use misses the nuances and can create discriminatory outcomes. This is because of the basis that algorithms replicate the biases of humans who set up the programming. [P46]
	[If] *it can be demonstrated to the organization that the output of the algorithms is (at the very least) as sound as those made by a human, then that should go a long way toward mitigating the fear.* [P53]
	The challenge of ensuring that people know how an algorithm works ... which would affect [my] use of algorithmic HRM by creating a climate of 'uncertainty' in the HRM process. [P38]
	Employees may just be in charge of a small part of the module and only focusing on that part, rather than understanding the whole algorithm. [P37]
Self	*Some employees are right to fear algorithms as they will replace the humans in completing basic tasks such as monitoring absence and turnover in my current employer.* [P44]
	I think (some) people come to HR with the expectation of the human element. They struggle to understand why the 'human'/discretionary element would be taken away. They see things under this system as rigid and inflexible. They look for a caring attitude but see 'a robot' making decisions. [P34]
	Some organizations and employees are right to fear algorithms if they truly believe they can have a negative impact on their working conditions or security. [P4]
	As an older employee, I fear that my relevance in the company will diminish if I do not continue to embrace this technology. [P48]

Theme and subtheme	Quote [respondent]
Negative impact on organization and employee	
Intangible and unanticipated costs	*Just scanning CVs and looking for keywords, [we] might miss an excellent candidate who has written in an untraditional manner.* [P21]
	A person can easily look perfect on paper but [be] *nothing like that paper in real life, only making things up just to get ahead, and an algorithm cannot pick that up … A human has experienced the process, got a "feel" for the situation, and used intuition and their own life experiences/judgments to help inform their decision. As sophisticated as algorithms now are, there is no replacement for human intuition and, sometimes, a "gut feeling"* [P51]
	[younger people] *have greater experience of HR-based algorithms* [and] *believe that they can manipulate them as they feel they have a greater understanding of them. We recently had an interview with someone that was an almost perfect match, but in person, they were nowhere near the person they portrayed themselves to be.* [P29]
	When the group the algorithm had chosen were called for interviews, it was a very disappointing interview process, and no one was hired in the end. This led to a lot of complaints, general frustration, and someone even leaving the company. What a waste of time and money. [P15]
	Employees may bring legal cases against the organizations if they feel the algorithms discriminate. There's a resulting reputational damage risk to the organization, which is important as my industry relies on public trust. [P46]
	Transitioning people to a new system, which changes their job hours and potentially the jobs they need to be completing, can be difficult for employees to get on board with. [P42]
Evident costs	*We implemented a system for recruitment which cost 10s of thousands of pounds initially, and the wider subscription fee is again around 10 k per year. This cost is very significant, so it is important to obtain value for money.* [P18]
	The systems have paid for themselves and more by the end of a 1–2 year period. [P18]
Disparity and distrust	*I think that there is a current climate of this 'distrust' about algorithms making decisions in any area of HRM, which could be performed by humans.* [P38]
	If people took results blindly without digging into why a decision was reached, then biased and unfair decisions could be reached. [P17]
	One negativity is that employees' belief there is no human input or feelings when decisions are made as a result. They feel it is being robotic and they are treated as not humans. Another reason is that there is no border line. What this means is that where something is on the border line of a decision, for instance 49 when a pass mark of 50 is required, this is placed as fail whereas, a review could mean a pass. Employees have this perception as it relates to their work. And thirdly, employees feel it creates a lonely environment [P3]
Missing inclusivity	[Algorithms] *present the risk that people with different backgrounds from the norm might be excluded as the algorithm is trained to conform to what we would normally expect from most candidates.* *We had a candidate who came in, and we thought they were perfect based on their profile, and the algorithm did too, only to find out that the guy was very arrogant and didn't come across well at all, and was not very team-oriented, so there are other things that matter other than hard data.* [P40]
	If you focus on the algorithms, they don't really understand the aspect of dignity and respect, equality of treatment, or consideration of real people as there are just 1 and 0s. [P51]
	Recently, someone with a great track record had to be disciplined for absence. They had been off with a serious illness and then had to go through an absence meeting escalation on their return due to the algorithm. [P26]

Theme and subtheme	Quote [respondent]
Individual difference	*Several older [age] colleagues did simply not like and could not get on board with the new tool we were implementing, even with people taking time to discuss the advantages of using such a tool*. [P42]
	Some of our employees are field-based and do not use technology—getting them to log into any portal is a task in itself, and I doubt that they understand what algorithms are. However, we have many employees who hold technical roles and have some level of technical understanding of how their data is used or converted using algorithms, which we use to change our portals. [P44]
	Some employees are more technologically savvy than others. I have worked with employees that can barely send an email by themselves and others who have enough knowledge to troubleshoot without assistance. [P8]
Positive organizational impact	
	Mastering these tools and using them to our advantage means smarter, more efficient, and ultimately less stressful ways of tackling the tasks at hand. [P51]
	It [algorithmic HRM] *affects fairness in the decision-making processes but in a good way; it can eliminate the human-caused unfairness*. [P38]
Coping approach	
Embrace and learn	*By becoming proficient I can eliminate fear. It makes the process less scary*. [P35]
	I'm trying more to understand how it works; that's the best way to get over fear—try and understand it. [P33]
Avoid until necessary	"*I do not make use of the HRM algorithm unless told to do so by my superior …* [they] *should not be used to fill positions that a human is filling*."
Discourse selective application	*I think algorithmic HRM improves processing where human input is not required. For straightforward processes, it can be extremely helpful, but for more complex processes, often only partial automation is useful*. [P44]
	At the end stages, a human touch is definitely required. However, where you have 50 resumes and need to make a short list, it is useful. Use them at the start and then take a more traditional approach is the best way forward. [P21]