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AI-Enabled Algorithmic Management and Frontline Employee Job Crafting: The Roles of Control, Support, and Managerial Orientation

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Abstract

Algorithmic management combines functions that regulate work with those that provide information and guidance, yet their distinct psychological and behavioral associations require further examination. Drawing on the Job Demands–Resources framework and a sociotechnical perspective, this study examines algorithmic control and support in relation to frontline employees' job crafting, distinguishing system functions from perceived managerial enactment. Three-wave time-lagged survey data from 547 employees in fast-food chain outlets were analyzed using partial least squares structural equation modeling. Algorithmic support was positively associated with work engagement and negatively associated with exhaustion, whereas algorithmic control showed the opposite pattern. Indirect-effect estimates were consistent with support being associated with greater promotion-focused crafting through engagement and lower prevention-focused crafting through exhaustion. Control was associated with greater prevention-focused crafting through exhaustion and lower promotion-focused crafting through engagement. The support–engagement relationship was stronger at higher perceived managerial decision-support orientation, while the control–exhaustion relationship was stronger at higher perceived enforcement orientation. These findings highlight the value of examining algorithmic functions across both motivational and strain-related pathways and considering how managers enact system outputs. The observational design supports associations consistent with the proposed mechanisms rather than causal conclusions.

Keywords: algorithmic management; algorithmic control; algorithmic support; decision support orientation; enforcement orientation; Job crafting

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1. Introduction

Recent years have witnessed the rapid diffusion of algorithmic management across a wide range of service industries, driven by advances in digital technologies such as big data analytics, artificial intelligence, and real-time monitoring systems (Kadolkar et al., 2025; Kellogg et al., 2019; Parker & Grote, 2022). Algorithmic management refers to the use of algorithmic systems to support or automate the coordination, monitoring, evaluation, and control of work activities (Jarrahi et al., 2021; Kellogg et al., 2019). Digital tools are being employed in organizational settings, covering various functions such as retail, logistics, and fast-food chain operations (Duggan et al., 2020; Meijerink & Bondarouk, 2023), with a particular focus on allocating tasks, monitoring performance, coordinating workflows, and

guiding managerial decision-making through digital dashboards and automated indicators. In fast-food chains, these systems play a central role in core operational tasks. More precisely, algorithms are commonly used to schedule shifts, monitor service speed, track sales performance, standardize procedures, and provide real-time feedback to managers and frontline employees (Möhlmann et al., 2021; Zhang et al., 2025). These systems can improve operational efficiency and consistency while also influencing how employees organize and adapt their work. Hence, algorithmic management has become increasingly influential in shaping both employee behavior and well-being in service-intensive environments.

Concerning employees' behavioral perspective, algorithmic management is characterized by two distinct functions: first, a control mechanism and second, a support function (Jarrahi et al., 2021; Meijerink & Bondarouk, 2023). The control mechanism ensures continuous monitoring, standardized performance metrics, and automated enforcement mechanisms, often triggering stress among employees (Rosenblat & Stark, 2016; Wood et al., 2019). Conversely, these systems also provide guidance, information, and feedback that support coordination, learning, and performance improvement, thereby enabling employees to be more engaged in their work (Faraj et al., 2018; Leonardi, 2011). Thus, the effects of algorithmic management remain theoretically ambiguous and require further examination.

This dual characteristic may either improve or decline workers' well-being. In fact, the adoption of automated work systems can affect employees' perceptions and behavior. Often, such changes in behavior result in changing work boundaries, leading to job crafting (Wrzesniewski & Dutton, 2001). The dark side of algorithmic management demonstrates the effects of controlling mechanisms. For instance, exhaustion associated with Algorithmic control drains employees' mental and emotional resources (Maslach et al., 2001). They tend to exhibit prevention-focused job crafting, i.e., making proactive changes to their work in the form of avoiding problems and risky tasks, preventing losses, and just meeting their set duties (Brenninkmeijer & Hekkert-Koning, 2015). Whereas the positive side posits that work engagement motivated by algorithmic support provides energy and motivation to employees (Bakker & Demerouti, 2007). In response, they tend to exhibit promotion-focused job crafting in the form of trying to achieve growth, learning new skills, and building new relationships to advance their career and fulfill their ambitions (Brenninkmeijer & Hekkert-Koning, 2015; Tims & Bakker, 2010).

While previous studies have examined how algorithmic management shapes job crafting (Liu & Yin, 2024), much of this literature conceptualizes algorithmic management primarily as a control-oriented system, emphasizing monitoring, standardization, and compliance enforcement (Kellogg et al., 2019; Rosenblat & Stark, 2016; Wood et al., 2019). The supportive dimensions of algorithmic management, such as information sharing, task recommendations, feedback, and developmental guidance, remain comparatively underexplored in research on job crafting. Although emerging studies suggest that algorithmic systems can also function as informational and motivational resources that enable learning, coordination, and proactive adaptation (Faraj et al., 2018; Jarrahi et al., 2021; Leonardi, 2011), these supportive functions are rarely integrated into models of job crafting. Furthermore, existing studies have primarily examined boundary conditions related to technological characteristics (Lee et al., 2015; Logg et al., 2019), worker attributes (Dietvorst et al., 2015; Jussupow et al., 2021), or institutional contexts (Kellogg et al., 2019; Möhlmann et al., 2021), rather than the interpretive role of managers in enacting algorithmic management. It remains unclear how employees perceive and respond to their manager's orientation toward the algorithmic management tool, specifically, whether it is used with a decision-support orientation or an enforcement orientation.

Building on research recognizing the enabling and constraining functions of algorithmic management, this study examines algorithmic control and algorithmic support as distinct configurations of work-related system functions. Algorithmic control concerns system-based requirements, monitoring, restrictions, sanctions, and reward allocation, whereas algorithmic support concerns recommendations, information sharing, and gamified performance cues. Drawing on the Job Demands–Resources framework, we examine how these functions are associated with engagement, exhaustion, and different forms of job crafting.

We further distinguish these system functions from employees' perceptions of managerial orientation toward algorithmic management. System functions concern what algorithmic tools do or provide; managerial orientation concerns how managers interpret, communicate, and act on their outputs. For example, the same system-generated performance alert may initiate a contextual coaching discussion or a standardized disciplinary response. Drawing on a sociotechnical perspective, we therefore examine decision-support and enforcement orientations as boundary conditions that may strengthen or weaken employees' responses to algorithmic support and control. This distinction allows us to investigate managerial enactment alongside system functions without assuming that supportive features necessarily receive supportive implementation or that controlling features are uniformly enforced.

This study makes three contributions. First, building on prior recognition of algorithmic management's enabling and constraining functions, it examines algorithmic control and support simultaneously in frontline service work. Distinguishing these functions allows their associations with employee psychological states and job crafting to be examined separately, rather than combining potentially divergent relationships within an overall algorithmic-management measure. Second, the study develops a JD–R explanation that extends beyond corresponding demand–exhaustion and resource–engagement pathways. Algorithmic support is proposed to be associated with both greater engagement and lower exhaustion, whereas algorithmic control is proposed to be associated with both greater exhaustion and lower engagement. Examining these relationships clarifies how algorithmic functions may be relevant to both motivational and health-impairment processes and, through these processes, to different forms of job crafting. Third, the study distinguishes system functions from employees' perceptions of managerial enactment. By examining decision-support and enforcement orientations as boundary conditions, it investigates whether the psychological associations of algorithmic management vary according to how managers interpret and use system outputs. Together, these contributions provide an integrated account of algorithmic functions, perceived managerial practices, and employee adaptation in franchise-based service work.

2. Theoretical Background and Hypotheses Development

2.1. Job Demand Resource Framework and Algorithmic Management

The integration of algorithmic systems into organizational hierarchies is reshaping how work is allocated, evaluated, and regulated. Algorithmic management (AM) involves systems that coordinate work, provide information, assess performance, and administer work-related requirements and consequences. Previous research already recognizes that these systems can simultaneously constrain and enable employees, combining mechanisms of control with informational, coordinative, and supportive functions (Jarrahi et al., 2021; Kellogg et al., 2019; Meijerink & Bondarouk, 2023). Research has highlighted surveillance, restricted autonomy, and performance pressure in algorithmically managed work (Möhlmann et al., 2021; Rosenblat & Stark, 2016; Wood et al., 2019), while also acknowledging opportunities for guidance and coordination (Jarrahi et al., 2021; Meijerink

& Bondarouk, 2023). The theoretical task is therefore to explain how these recognized functions relate to distinct employee experiences and behaviors, rather than to establish the existence of algorithmic management's duality.

The Job Demands–Resources (JD–R) framework provides a basis for examining these relationships. Job demands are aspects of work that require sustained cognitive, emotional, or physical effort and may incur psychological or physiological costs. Job resources facilitate goal attainment, help employees manage demands, or support learning and development (Demerouti et al., 2001; Bakker & Demerouti, 2017). JD–R theory identifies a health-impairment process linking excessive demands to exhaustion and a motivational process linking resources to engagement (Bakker & Demerouti, 2007). These processes provide complementary explanations of employee experience, without requiring each work characteristic to be associated exclusively with one psychological outcome. Accordingly, algorithmic functions may be relevant to both engagement and exhaustion.

Drawing on this framework, we distinguish algorithmic control from algorithmic support according to the functions employees experience from the system. Algorithmic control comprises restricting, requiring, monitoring, sanctioning, and rewarding functions (Alizadeh et al., 2023). These functions regulate work through system-based instructions, observation, and performance-contingent consequences. Their proposed demand-related role rests on the effort and pressure associated with complying with requirements and remaining subject to evaluation; it does not imply that every control function, including rewarding, is inherently detrimental. Algorithmic support comprises recommendations, information sharing, and gamified performance cues. These functions may help employees prioritize tasks, understand changing requirements, and recognize progress. Its distinction from general job resources lies in the source and work-management function of the resource: recommendations, information, and progress cues are provided through algorithmic systems involved in coordinating or managing work. Algorithmic support is therefore examined as a specific configuration of potential job resources, rather than as an entirely new resource category.

The demand or resource value of these functions is not fixed. Recommendations may reduce uncertainty when employees can use them flexibly, but may become pressuring when treated as compulsory instructions. Similarly, gamified rankings may communicate progress while also intensifying comparison and performance pressure. Distinguishing control and support allows these functions to be examined simultaneously, rather than combining them into an overall AM measure that may obscure different associations with employee psychological states. The distinction also permits examination of whether support is associated with both greater engagement and lower exhaustion, and whether control is associated with both greater exhaustion and lower engagement.

System functions must also be distinguished from their managerial enactment. Algorithmic control and support concern what employees perceive the system does or provides, whereas managerial orientation concerns how employees perceive managers interpret, communicate, and act on its outputs. The same performance alert, for example, may prompt a coaching discussion or a standardized disciplinary response. Thus, a system's provision of supportive information does not necessarily imply supportive managerial use, and the presence of control functions does not determine how rigidly their outputs are enforced. This distinction provides the conceptual basis for examining managerial orientation as a boundary condition of the relationships between algorithmic functions and employee psychological states.

As summarized in Table 1, prior research provides an established foundation for understanding the enabling and constraining functions of algorithmic management. Building on that foundation, this study examines control and support together within a JD–R

model linking algorithmic functions to engagement, exhaustion, and promotion- and prevention-focused job crafting. Its incremental contribution lies in examining their distinct and potentially cross-path associations, alongside managerial enactment as a boundary condition. This approach accommodates motivational and strain-related relationships without assuming that algorithmic support operates only through engagement or that algorithmic control operates only through exhaustion.

Table 1. Synthesis of prior work.

Topic	Dimensions Explored	Key Implications	Limitations	Citation
Algorithmic management (interdisciplinary synthesis)	Algorithmic control in the form of restricting, recommending, recording, rating, replacing, rewarding	Establishes how algorithmic control reshapes direction/evaluation/discipline of work.	Limited micro-level psychological mechanisms and limited conditions under which AM becomes resource-like.	Kellogg et al. (2019).
Algorithmic management (platform governance)	Opaque evaluation, nudges, deactivation threats; indirect control via platform interface.	Shows AM can intensify surveillance and constrain autonomy while maintaining a "flexibility" narrative.	Less attention to supportive/developmental algorithmic functions and formal motivational pathways.	Rosenblat and Stark (2016).
Algorithmic management (platform governance)	Algorithmic control shapes labor process, social relations, market exchange, insecurity, and work quality.	Demonstrates algorithmic control can reduce autonomy and degrade job quality outcomes across regions.	Emphasis on the demand side; limited theorizing of how support features can operate as resources and enable proactive adaptation.	Wood et al. (2019).
Algorithmic management (Algorithmic task allocation)	Uber drivers' coping strategies (guessing, gaming, switching) under AM due to reclaiming autonomy.	Illustrates how AM produces an autonomy-control paradox and prompts adaptive coping/resistance behaviors.	Focused on coping strategies caused by Algorithmic control, neglected the support side of AM	Möhlmann and Zalmanson (2017).
Algorithmic management (integrative via data infrastructures)	Focused on AM's core functions of monitoring, guidance, evaluation, and incentive allocation (can be demand or resource depending on enactment).	Argues effects of AM depend on sociotechnical context and human competencies; not purely deterministic control.	Lacks conceptualizing dual-path psychological mechanisms (e.g., engagement vs. exhaustion) and boundary conditions in a single integrated model.	Jarrahi et al. (2021).
Algorithmic management (algorithmic HRM synthesis)	AM as simultaneously enabling and constraining; links to autonomy and value creation for workers (duality explicitly).	Provides an explicit conceptual basis for treating AM as both demand and resource, motivating dual-path models.	Primarily agenda/conceptual: calls for empirical models that test both sides simultaneously with clear mediators and moderators.	Meijerink and Bondarouk (2023).

Table 1. *Cont.*

Topic	Dimensions Explored	Key Implications	Limitations	Citation
Algorithmic management	Algorithmic surveillance and evaluation; perceived transparency; justice and quitting intentions (demand, with transparency as condition that can mitigate harm).	Shows that "how AM is experienced," e.g., transparency, shapes fairness perceptions and downstream outcomes.	Addresses fairness more than motivation/strain mechanisms; does not specify supportive AM features that activate engagement.	Bujold et al. (2022).
Algorithmic management (Algorithmic HRM control)	Allocation/coordination; performance management; rewards; compliance features.	Systematizes how AM operationalizes HRM control functions through apps and metrics.	Focus is largely control/HRM governance; resource-oriented AM functions and employee motivational pathways remain underdeveloped.	Duggan et al. (2023).
Algorithmic management (JD–R theory + managerial orientation as boundary condition)	Algorithmic support (recommendations, information sharing, gamification) as job resources. Algorithmic control (restricting, requiring, monitoring, sanctioning, rewarding) as job demands.	Empirically reconciles AM duality by testing both resource and demand pathways simultaneously, explaining when AM motivates vs. strains workers via managerial enactment.	(To acknowledge) context-bound sample); future work can test across occupations/platform vs. traditional work and incorporate objective system logs.	This study

2.2. Algorithmic Management and Job Crafting

Job crafting captures the ways in which employees reshape their work to align with personal goals, values, and situational demands. Early concepts emphasized that employees actively redefine task boundaries, work relationships, and the meaning of their roles in response to changing work conditions (Wrzesniewski & Dutton, 2001). It is a self-initiated regulatory process through which individuals modify aspects of their jobs to better fit their preferences and constraints (Tims et al., 2012). Importantly, job crafting is not uniformly growth-oriented; rather, employees may engage in distinct forms of crafting depending on whether they are motivated by opportunity seeking or by the need to avoid adverse outcomes (Mäkikangas et al., 2017; Rudolph et al., 2017).

To capture this distinction, Lichtenthaler and Fischbach (2019) differentiated between promotion-focused job crafting and prevention-focused job crafting. Promotion-focused job crafting reflects behaviors oriented toward growth, advancement, and the pursuit of gains, such as seeking challenges, acquiring new skills, or expanding task scope. Prevention-focused job crafting, by contrast, reflects behaviors oriented toward protection and loss avoidance, such as reducing hindering demands, limiting emotionally taxing interactions, or narrowing task boundaries. This distinction is particularly relevant in work contexts shaped by algorithmic systems, where employees continuously interpret system-generated cues regarding acceptable performance, risk, and opportunity.

Within algorithmically managed work environments, algorithmic control is one of the important conditions shaping employees' crafting behavior. Algorithmic control relies on mechanisms such as continuous monitoring, standardized task requirements, automated evaluations, and system-driven sanctions to enforce compliance and performance consistency (Alizadeh et al., 2023; Kellogg et al., 2019). Prior research shows that such systems heighten surveillance intensity, constrain discretion, and increase workers' sensitivity to

performance deviations (Rosenblat & Stark, 2016; Wood et al., 2019). These features create a work environment in which employees perceive higher risk and feel pressure to avoid mistakes and deviations. Under such conditions, employees are likely to craft their jobs defensively to protect themselves from negative consequences associated with algorithmic evaluation. This may involve minimizing task complexity, avoiding discretionary challenges, limiting emotionally demanding interactions, or adhering strictly to prescribed routines to reduce exposure to algorithmic penalties. These behaviors are consistent with prevention-focused job crafting, as they reflect safeguarding resources and avoiding loss rather than pursuing growth. Accordingly, we propose:

H1. *Algorithmic control is positively associated with prevention-focused job crafting.*

In contrast, algorithmic support represents a qualitatively different configuration of algorithmic management. Supportive algorithmic features such as task recommendations, information sharing, real-time performance feedback, developmental cues and game-like interfaces can clarify work priorities, reduce ambiguity, and highlight opportunities for improvement (Jarrahi et al., 2021; Leonardi, 2011). Empirical evidence from Human-AI settings suggests that access to timely algorithmic guidance and performance information enables workers to experiment with new approaches, refine skills, and proactively shape their work trajectories (Liu & Yin, 2024). Moreover, algorithmic systems that make progress visible and recognize positive performance create an environment in which effort is potentially rewarding. Such systems communicate opportunity-oriented signals that encourage employees to expand their roles, pursue learning, and invest in capability development. In these contexts, job crafting becomes a way of advancement and self-development rather than risk mitigation. These behaviors align closely with promotion-focused job crafting, which emphasizes growth, aspiration, and the pursuit of gains. Thus, we propose:

H2. *Algorithmic support is positively associated with promotion-focused job crafting.*

2.3. Mediating Role of Work Engagement

Work engagement is a positive, fulfilling work-related psychological state characterized by vigor, dedication, and absorption (Schaufeli et al., 2002, 2006). Engaged employees experience energy, meaningful involvement, and concentration in their work. Within the JD–R framework, engagement represents a motivational process through which job resources are associated with proactive and developmental behavior (Bakker & Demerouti, 2007; Christian et al., 2011). Algorithmic support may contribute to this process by providing resources that help employees understand requirements, coordinate activities, and accomplish work goals. Its motivational relevance therefore rests on the usefulness of its functions, rather than on the assumption that algorithmic technologies are inherently engaging.

Algorithmic information sharing provides performance information, work-related updates, and cues about changing priorities. Such information can reduce ambiguity and help employees align their efforts with task requirements. Clear and timely information may support effective work regulation and meaningful involvement, consistent with the JD–R motivational process (Bakker & Demerouti, 2007, 2017). Algorithmic recommendations may similarly help employees identify their next task, evaluate possible actions, or recognize opportunities for improvement. By assisting prioritization and coordination, these functions may make it easier to sustain attention and involvement in work (Jarrahi et al., 2021; Parker & Grote, 2022). These arguments concern information and guidance supplied by the system; the way managers interpret and enact those outputs is a separate boundary condition.

Gamified features, including points, rankings, and progress indicators, may also make performance and progress more visible. Research on gamification identifies potential benefits for motivation and involvement, although these benefits depend on the elements used and their context (Hamari et al., 2014; Mekler et al., 2017). Accordingly, gamification is treated as a potential resource rather than as uniformly beneficial. Progress cues may support involvement when they provide useful feedback, while competitive rankings or demanding targets may also create pressure. Taken together, information sharing, recommendations, and gamified cues are expected to be positively associated with engagement when experienced as useful work resources.

Algorithmic support may also be associated with lower exhaustion. Timely updates and recommendations can reduce uncertainty, unnecessary task switching, and avoidable effort in planning and coordinating work. In frontline service settings, where employees must respond to changing customer demands, these functions may help make demanding work more manageable. This expectation follows the JD–R proposition that resources can facilitate goal attainment and help employees manage job demands (Bakker & Demerouti, 2017). Thus, support may be relevant to both stronger motivational involvement and lower strain, rather than exclusively to engagement. Accordingly, we propose:

H3. *Algorithmic support is positively associated with work engagement and negatively associated with work exhaustion.*

Engaged employees have the energy and motivation to pursue growth-oriented changes in their work. Promotion-focused job crafting involves seeking resources, developing capabilities, and undertaking challenges (Lichtenthaler & Fischbach, 2019). Employees who experience their work as meaningful and stimulating may therefore be more inclined to invest effort in these activities. In algorithmically managed settings, engagement may support employees' willingness to use available information and guidance to refine work processes, seek feedback, and develop new skills. The proposed mediation mechanism is that algorithmic support provides potentially useful work resources, engagement reflects employees' motivational involvement, and promotion-focused crafting represents their subsequent investment in developmental changes. Based on this reasoning, we propose:

H4. *Work engagement mediates the relationship between algorithmic support and promotion-focused job crafting.*

Engagement may also provide a pathway linking algorithmic control to lower promotion-focused job crafting. System-based restrictions, mandatory instructions, and continuous monitoring may narrow perceived discretion and shift attention toward compliance and avoiding performance deviations (Kellogg et al., 2019; Rosenblat & Stark, 2016; Wood et al., 2019). When experienced as pressuring or restrictive, these functions may be associated with lower engagement, alongside the exhaustion pathway developed in Section 2.4. Lower engagement may, in turn, be associated with less willingness to invest effort in learning, resource seeking, and discretionary challenges. The study therefore also examines the negative indirect relationship between algorithmic control and promotion-focused job crafting through engagement. This cross-path analysis complements the proposed support–engagement pathway without assuming that control and support are opposite ends of a single construct.

2.4. Mediating Role of Exhaustion

Exhaustion represents a central aspect of work-related strain and reflects depletion associated with sustained exposure to demanding work conditions (Demerouti et al., 2001;

Maslach et al., 2001). Employees experiencing exhaustion may feel drained and find it difficult to sustain their usual work effort. Within the JD–R framework, exhaustion forms part of the health-impairment process through which demanding job characteristics are associated with strain and subsequent behavioral responses (Bakker & Demerouti, 2017). In algorithmically managed work, this process provides a basis for examining whether system-based control is associated with employees' perceived depletion and their efforts to reduce hindering demands.

Algorithmic control comprises functions that regulate work through restrictions, mandatory instructions, monitoring, sanctions, and performance-contingent rewards (Alizadeh et al., 2023). Continuous monitoring and system-based requirements may increase the effort needed to maintain compliance, while evaluation and potential sanctions may heighten concern about performance deviations (Kellogg et al., 2019; Parent-Rocheleau & Parker, 2022). Employees may consequently devote cognitive effort to tracking requirements and interpreting evaluation criteria, alongside the emotional effort involved in managing perceived pressure. These experiences are consistent with a demand-related association between algorithmic control and exhaustion. However, control functions are not assumed to produce strain uniformly. Their implications depend on the demands employees experience, including the intensity of monitoring, rigidity of requirements, and consequences attached to performance.

Algorithmic control may also be negatively associated with engagement. When employees experience system-based requirements as restrictive, their attention may shift toward compliance and avoiding mistakes rather than exercising initiative or pursuing meaningful challenges. Limited discretion and persistent evaluation pressure may therefore be associated with reduced motivational involvement as well as greater depletion (Kellogg et al., 2019; Wood et al., 2019). This cross-path argument complements the health-impairment mechanism: control may be relevant to both exhaustion and engagement, rather than exclusively to strain. Accordingly, we propose:

H5. *Algorithmic control is positively associated with exhaustion and negatively associated with work engagement.*

Resource conservation provides a basis for understanding employees' behavioral responses to exhaustion (Hobfoll, 1989). When depleted, employees may prioritize adjustments that reduce further demands and protect their remaining resources. Prevention-focused job crafting includes efforts to reduce hindering demands, such as limiting emotionally taxing interactions or making work mentally less intense (Lichtenthaler & Fischbach, 2019). These adjustments remain employee-initiated changes to work; they should not be equated automatically with passive withdrawal, strict compliance, or disengagement. In algorithmically managed service work, employees experiencing exhaustion may seek to reduce difficult interactions, simplify demanding aspects of their work, or limit prolonged concentration requirements. Such changes may serve a protective function by making work more manageable.

The proposed mediation mechanism therefore links employees' experience of system-based control to exhaustion and, subsequently, to efforts to reduce hindering demands. A positive association with prevention-focused crafting does not necessarily indicate undesirable behavior: protective adjustments may be adaptive responses to demanding conditions. Based on this reasoning, we propose:

H6. *Work Exhaustion mediates the relationship between algorithmic control and prevention-focused job crafting.*

Exhaustion also provides a basis for examining an additional indirect relationship between algorithmic support and prevention-focused job crafting. Recommendations and timely information may help employees anticipate changing requirements, prioritize tasks, and reduce avoidable effort. Consistent with the resource function described in JD–R theory, such support may be associated with lower exhaustion by helping employees manage work demands (Bakker & Demerouti, 2017). Lower exhaustion may, in turn, be associated with less need to reduce hindering demands through prevention-focused crafting. The study therefore also examines a negative indirect relationship between algorithmic support and prevention-focused job crafting through exhaustion. This relationship concerns differences in the perceived need for protective adjustments, rather than evidence that lower prevention-focused crafting is inherently preferable.

2.5. Moderating Role of Managerial Orientation

Algorithmic systems provide information and regulate work, but their outputs are frequently interpreted and implemented through human managers. A sociotechnical perspective emphasizes that employees' experiences reflect the relationship between technical arrangements and the social practices through which those arrangements are enacted (Leonardi, 2011; Orlikowski, 2000; Trist & Bamforth, 1951). We therefore distinguish algorithmic control and support, which concern system functions, from managerial orientation, which concerns employees' perceptions of how managers interpret, communicate, and act on algorithmic outputs. Related research at the corporate-governance level examines sustainability-linked executive compensation in conjunction with board, audit, and reporting arrangements (Mubeen et al., 2026); this provides broader context for incentive alignment, rather than direct evidence about frontline employees or algorithmic systems.

This distinction is important because system functions do not determine their managerial enactment. An algorithmic dashboard may provide recommendations and performance information, while a manager uses those outputs either to explore problems collaboratively or to demand compliance without contextual discussion. Similarly, monitoring data may be interpreted as evidence of a need for staffing or training adjustments, or as an automatic basis for disciplinary action. Managerial orientation is therefore proposed as a boundary condition rather than an additional measure of the system's supportive or controlling functions.

Decision-support orientation captures employees' perceptions that managers treat algorithmic outputs as informational inputs for contextual judgment, coaching, and collaborative problem solving. This orientation draws on the distinction between developmental and administrative uses of performance information and the broader idea that technology can complement human judgment (Boswell & Boudreau, 2000; Raisch & Krakowski, 2021). Algorithmic support may offer useful recommendations and information, but employees must be able to understand and apply these resources. When managers discuss the information, consider individual circumstances, and help employees translate recommendations into feasible actions, the supportive functions become more usable and relevant to task accomplishment. Such enactment may strengthen the motivational association between algorithmic support and work engagement. Accordingly, we propose:

H7. *Managers' decision-support orientation strengthens the positive relationship between algorithmic support and work engagement.*

Enforcement orientation captures employees' perceptions that managers treat algorithmic outputs as authoritative prescriptions for compliance and standardized action. Research on algorithmic control suggests that system-based evaluation can constrain discretion and increase employees' exposure to performance demands (Kellogg et al., 2019;

Möhlmann et al., 2021). Enforcement-oriented enactment may reinforce these demands by reducing opportunities to discuss contextual circumstances, negotiate feasible responses, or question system-generated judgments. Employees experiencing algorithmic control under this orientation may therefore perceive greater pressure to comply with requirements and avoid adverse consequences. Within the JD–R health-impairment process, these conditions are expected to strengthen the positive association between algorithmic control and exhaustion. Accordingly, we propose:

H8. *Managers' enforcement orientation strengthens the positive relationship between algorithmic control and work exhaustion.*

Decision-support and enforcement orientations are treated as separate dimensions rather than opposite ends of a single continuum. Employees may perceive that a manager uses algorithmic information developmentally in some situations while enforcing system-based requirements in others. The proposed moderation relationships therefore concern the distinct contribution of each orientation, without assuming that high decision-support orientation necessarily implies low enforcement orientation.

Job Demands–Resources theory posits that job demands primarily influence behavior through exhaustion, whereas job resources operate through engagement. Extending this logic to algorithmic management implies that algorithmic control and support affect job crafting indirectly via exhaustion and engagement, respectively. Importantly, sociotechnical perspectives indicate that managerial orientation toward algorithmic management shapes how these demand- and resource-based mechanisms are activated. As a result, the indirect effects of algorithmic control and support on prevention- and promotion-focused job crafting are likely to vary depending on whether managers enact algorithmic systems in an enforcement-oriented or decision-support-oriented manner. Accordingly, we propose moderated mediation hypotheses that link algorithmic control to prevention-focused job crafting through exhaustion and algorithmic support to promotion-focused job crafting through engagement, conditional on managerial orientation (Figure 1).

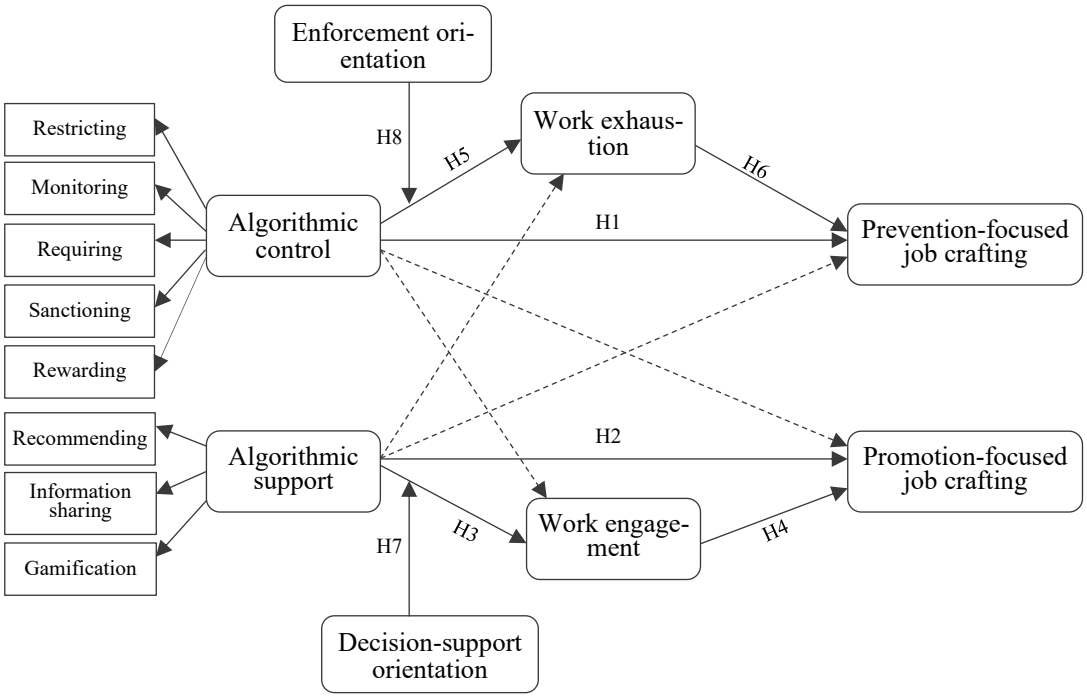


Figure 1. Conceptual Model.

H9a. *Managerial orientation toward algorithmic management moderates the job-demand mechanism linking algorithmic control to prevention-focused job crafting via exhaustion.*

H9b. *Managerial orientation toward algorithmic management moderates the job-resource mechanism linking algorithmic support to promotion-focused job crafting via engagement.*

3. Research Design

This study adopted an employee-focused survey methodology to examine how algorithmic management tools influence employee behavior in service organizations. Fast-food chain outlets increasingly rely on algorithmic systems for managerial decision-making, monitoring, and control. Employee-centered studies are widely used to evaluate how individuals interact with technology-enabled management systems and how such interactions shape work experiences and engagement (Kellogg et al., 2019; Kujala, 2003). Prior research emphasizes that employee involvement and perceptions are critical for the effective functioning and acceptance of information systems, particularly in digitally managed workplaces (Barki & Hartwick, 1994; Jarrahi et al., 2021). Empirical assessment of employees' responses is therefore essential for understanding whether algorithmic tools facilitate supportive human–AI collaboration or intensify control and resistance in everyday work settings (Meijerink & Bondarouk, 2023).

3.1. Sampling Technique and Data Collection

The study used a non-probability recruitment strategy combining purposive selection and participant referrals. Recruitment focused on frontline employees working in fast-food chain outlets in northern China. Outlets were approached through professional and organizational contacts and selected based on accessibility and the use of digital systems for scheduling, task allocation, performance monitoring, or operational coordination. Neither outlets nor employees were randomly selected; consequently, the sample should not be interpreted as representative of all fast-food employees in China.

The final analytical sample comprised 547 employees from 114 outlets belonging to KFC, McDonald's, Wallace and Subway. Multiple respondents reported to the same manager. The details are presented in Table A10. The employee-level analysis did not adjust for outlet or supervisor clustering because identifiers linking respondents to these groups were not retained. Employees sharing an outlet or supervisor may have correlated experiences and responses. Consequently, the independence assumption could not be assessed, and the reported standard errors and significance tests may be affected by unaccounted dependence. This limitation is acknowledged in the discussion.

Within participating outlets, purposive screening identified employees with direct and routine exposure to algorithmic management tools. Eligible respondents were frontline employees whose work involved interacting with these tools or receiving system-generated instructions, recommendations, performance information, or evaluations. Employees without relevant exposure were excluded. Initial invitations were distributed through workplace contacts and employee communication groups. Participants could also forward the invitation to eligible colleagues, introducing a snowball component to recruitment. All referred participants completed the same eligibility screening.

Data were collected in three waves to separate the measurement of predictors, mediators, and outcomes over time. At Time 1, conducted from 6 October to 26 October 2025, respondents completed measures of algorithmic control, algorithmic support, perceived managerial decision-support orientation, perceived managerial enforcement orientation, and demographic characteristics. At Time 2, conducted from 28 November to 23 December 2025, respondents completed measures of work engagement and exhaustion. At

Time 3, conducted from 25 January to 15 February 2026, respondents completed measures of promotion-focused and prevention-focused job crafting. Follow-up invitations were distributed during these collection windows, and the elapsed time between responses therefore varied across participants. This design provided temporal separation consistent with the proposed theoretical ordering but did not establish causal relationships.

Participation was voluntary. Respondents received information about the study and provided informed consent before completing the first questionnaire. They were informed that participation or withdrawal would not affect their employment and that individual responses would not be shared with their managers. A payment of RMB 2 was provided after completion of each survey wave.

To match responses, each participant received a unique study code used throughout the three waves. Contact information required for follow-up invitations and incentive distribution was maintained separately from questionnaire responses. The analytical dataset contained study codes rather than names or contact details. Because contact information was retained for follow-up, participation was confidential rather than fully anonymous. Individual study codes enabled longitudinal matching; they did not, by themselves, identify outlet or supervisor membership

At Time 1, 720 employees completed the questionnaire. Following eligibility and completeness checks, 680 respondents were retained and invited to Time 2. Of these, 612 provided usable, matched responses at Time 2, representing a retention rate of 90.0%. At Time 3, 565 respondents provided usable, matched responses, representing a retention rate of 92.3% relative to Time 2. During final screening, 18 matched cases were excluded because of duplicate records or responses that failed the stated data-quality criteria. The final analytical sample comprised 547 employees with usable responses across all three waves, equivalent to 80.4% of the eligible Time 1 sample.

3.2. Questionnaire

This research adapted some constructs from existing research, and some constructs were developed based on relevant literature. All items were measured using a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. In order to fit the scales in the Algorithmic management and service sector context, the questions were modified a little with the recommendations by an expert panel. As the study was conducted in China, the questionnaire (see Appendices A–C) was translated into Chinese and back-translated into English to assess translation equivalence.

3.2.1. Independent Variables

Algorithmic control (ACON) and algorithmic support (ASUP) served as the independent variables and were modeled as second-order formative constructs. Algorithmic control comprised five lower-order dimensions: algorithmic restricting (3 items), algorithmic requiring (4 items), algorithmic monitoring (4 items), algorithmic rewarding (3 items), and algorithmic sanctioning (4 items). These dimensions were measured using items adapted from Alizadeh et al. (2023).

Algorithmic support comprised three lower-order dimensions: algorithmic gamification (5 items), algorithmic recommending (4 items), and algorithmic information sharing (4 items). The gamification items were developed based on prior research on gamification mechanics in technology-mediated contexts (Hamari et al., 2014; Mekler et al., 2017). The information-sharing items were developed with reference to research on algorithmic coordination and digital information flows, emphasizing the provision of performance information, changing customer demands, and work-relevant updates (Faraj et al., 2018;

Leonardi, 2011). The algorithmic recommendation items were adapted from Alizadeh et al. (2023). All measurement items are presented in Tables A1 and A2.

3.2.2. Mediating Variables

Work engagement and work exhaustion served as mediating variables. Work engagement was measured using nine items covering vigor, dedication, and absorption (Schaufeli et al., 2006). Work exhaustion was assessed using a ten-item adapted measure informed by the burnout and exhaustion literature (Maslach et al., 2001; Demerouti et al., 2001). The administered items cover perceived emotional depletion, physical fatigue, and associated work-related strain symptoms. Accordingly, the measure is described as work exhaustion rather than the standard emotional-exhaustion subscale of the Maslach Burnout Inventory. The complete items are presented in Table A4.

3.2.3. Moderating Variables

Managerial orientation toward algorithmic management was assessed through employees' perceptions of how their managers interpret, communicate, and use algorithmic outputs. Two dimensions were distinguished: decision-support orientation (DS) and enforcement orientation (EN). The referent of these measures is the manager's use of algorithmic information, whereas the referent of algorithmic control and support is the system's work-management functions. Accordingly, enforcement orientation is assessed through employees' perceptions of managers' enforcement-related practices. However, some items describe mandatory responses to algorithmic outputs or limited managerial discretion. Responses may therefore reflect organizational requirements as well as managers' tendencies to enforce algorithmic decisions. The measure is consequently interpreted as perceived enforcement-oriented managerial enactment within organizational constraints, rather than a direct assessment of managers' personal preferences or freely chosen orientations.

Decision-support orientation captures the extent to which employees perceive that their managers use algorithmic information for contextual judgment, coaching, collaborative problem solving, and employee development. Enforcement orientation captures the extent to which employees perceive that their managers treat algorithmic outputs as authoritative prescriptions for compliance and standardized action, with limited contextual discretion. For example, a system-generated performance alert concerns the provision of algorithmic information, while a manager's use of that alert to initiate a supportive discussion or require formal action concerns managerial enactment. The orientations were measured separately rather than treated as opposite ends of a single continuum. This specification permits employees to perceive both developmental and enforcement-oriented uses of algorithmic outputs within the same managerial relationship.

Eight items were developed for each orientation with reference to prior literature on performance-appraisal use, managerial decision processes, and algorithmic management (Boswell & Boudreau, 2000; Möhlmann et al., 2021). These studies provided conceptual guidance for item development; they were not sources of previously validated DS and EN scales. The resulting measures were newly developed for this study. A sample DS item is "When algorithmic dashboards indicate performance changes, my manager uses the information to start a supportive discussion." A sample EN item is "When algorithmic systems flag underperformance, my manager must initiate formal actions regardless of context." The complete items are presented in Tables A7 and A8.

Before the main survey, the questionnaire underwent expert review, translation into Chinese, back-translation into English, and pilot testing. These procedures supported the assessment of item relevance, comprehensibility, and contextual suitability. Expert review and pilot feedback informed the assessment of content suitability, while the main-sample

analyses evaluated the measures' statistical properties. Indicator loadings, internal consistency reliability, and average variance extracted presented in Table 2 were examined to assess indicator reliability, scale reliability, and convergent validity. Discriminant validity was evaluated using HTMT and the Fornell–Larcker criterion, including comparisons with the reflective lower-order dimensions of algorithmic control and support, as reported in Tables 3–5. These comparisons address whether managerial-orientation measures are empirically distinguishable from the system-function measures, although statistical discriminant validity alone cannot resolve conceptual overlap.

Because employees reported both system functions and managerial orientation, the measures capture perceived managerial practices rather than directly observed managerial behavior or managers' self-reported intentions. The evidence is therefore interpreted as initial validation within the present sample and research context. Further validation using independent samples, manager reports, and observations of algorithmic-output use would strengthen confidence in the measures' distinctiveness and applicability.

3.2.4. Dependent Variables

Prevention-focused job crafting was measured using six items assessing the reduction of hindering job demands. Promotion-focused job crafting was measured using 14 items covering increasing structural job resources (5 items), increasing social job resources (5 items), and increasing challenging job demands (4 items). The items were adapted from Tims et al. (2012) and are presented in Tables A5 and A6.

3.3. Expert Review, Translation and Pilot Testing

The questionnaire underwent expert review and pilot testing before the main survey to assess item relevance, clarity, and suitability for frontline employees in algorithmically managed service work. Particular attention was given to the newly developed decision-support orientation and enforcement orientation measures.

The expert panel comprised five members: two researchers specializing in organizational behavior and employee well-being, one researcher specializing in information systems and algorithmic management, one researcher with expertise in survey measurement, and one service-sector practitioner familiar with digital performance-management systems. Panel members received the construct definitions and proposed items and independently assessed their relevance, clarity, and alignment with the intended constructs. They were also asked to identify overlapping content and wording that might confuse algorithmic system functions with managerial enactment.

Following the independent reviews, the research team discussed the comments and revised ambiguous or overly broad wording. For the managerial-orientation items, revisions emphasized the manager as the actor and the interpretation or use of algorithmic outputs as the behavior being assessed. For example, general references to supportive management were made more specific by identifying the manager's response to algorithmic dashboards, alerts, or performance indicators. References to enforcement were clarified by describing whether managers treated system-generated information as a basis for mandatory action or considered contextual circumstances. These revisions were intended to improve conceptual specificity without changing the underlying construct definitions. The panel subsequently reviewed the revised items for consistency with the intended domains.

The English questionnaire was translated into Chinese by a bilingual researcher familiar with organizational research. A second bilingual researcher, who had not consulted the original English version, independently back-translated the Chinese questionnaire into English. The research team compared the original and back-translated versions and resolved differences through discussion with the translators. Particular attention was given

to expressions concerning algorithmic tools, managerial discretion, coaching, and formal action. The resulting Chinese version was reviewed for accessibility to frontline employees.

A pilot survey was administered to 60 frontline employees working in Wallace, Subway, and KFC franchises who had direct experience with algorithmic work-management tools. Pilot participants were recruited separately and were not included in the main analytical sample. After completing the questionnaire, they were invited to comment on unfamiliar terms, ambiguous wording, questionnaire length, and the relevance of the statements to their work. Feedback indicated that concrete references to dashboards, alerts, and performance indicators were easier to interpret than general references to algorithmic outputs. Minor wording changes were therefore made to improve comprehension and maintain consistent terminology.

Preliminary internal consistency and item-level diagnostics were examined for the reflective measures. The pilot assessment considered Cronbach's alpha, corrected item–total correlations, and participant feedback together when identifying items requiring further review. The results for decision-support orientation and enforcement orientation are reported in Table A9. No items were removed solely to increase reliability; decisions concerning wording or retention also considered the coverage of each construct's conceptual domain.

The pilot sample was used primarily to assess feasibility, comprehensibility, and preliminary measurement performance. Its size did not support strong conclusions about the factorial structure or broader validity of the newly developed scales. Indicator reliability, internal consistency reliability, convergent validity, and discriminant validity were subsequently assessed in the main sample. The expert review and pilot procedures therefore provided supporting evidence for content suitability and questionnaire usability, while the main-sample analyses provided initial statistical validation.

4. Data Analysis

Data analysis was conducted using SPSS version 26 for descriptive and demographic statistics, while SmartPLS (version 4.1.0.3) was employed for partial least squares structural equation modeling (PLS-SEM). PLS-SEM was selected because the model includes formative higher-order constructs, multiple mediation and moderation relationships, and a relatively complex structural model. The analysis followed established guidelines for specifying, evaluating, and reporting PLS-SEM models (Guenther et al., 2023; Hair et al., 2019). Moreover, PLS-SEM relies on nonparametric estimation techniques and is robust to violations of data normality (Hair et al., 2019). Prior research also highlights its suitability for theory development and exploratory research settings, even when some data limitations exist (Guenther et al., 2023).

4.1. Common Method Bias

Common method bias (CMB) is a potential concern in survey-based research and should be addressed carefully through research design and analysis (Memon et al., 2023; Podsakoff et al., 2003). To reduce this risk, the study applied several procedural remedies, including a balanced Likert scale, pilot testing, and expert review to improve item clarity and reduce ambiguous wording. Importantly, data were collected across three time points, creating temporal separation among the key constructs. This time-lagged design helps limit consistency bias, common response patterns, and short-term mood effects, thereby lowering the likelihood of CMB. Prior research suggests that temporal separation is one of the most effective procedural techniques for minimizing CMB in self-reported survey research (Conway & Lance, 2010; Memon et al., 2023; Podsakoff et al., 2003). Multicollinearity and

construct validity were assessed separately. These assessments do not establish the absence of common method bias, which remains a limitation of the employee self-report design.

4.2. Demographics

The sample consists of 51.9% male and 48.1% female respondents, with a mean age of 33 years, an average work experience of 9 years, and approximately 44 working hours per week. 42% respondents at least have High school degree, 23% have vocational diploma and 35% have a bachelor's degree. As far as the job role is concerned, 30.2% were crew members, 19.7% were order takers, 30.2% were kitchen staff, and 19.9% were maintenance staff.

4.3. Construct Reliability

Construct reliability was assessed using Cronbach's alpha (α) and composite reliability (CR), as recommended in PLS-SEM research (Hair et al., 2019). Cronbach's alpha evaluates internal consistency based on inter-item correlations, while composite reliability provides a more accurate estimate by considering the individual indicator loadings. Values above 0.70 for both measures indicate satisfactory reliability. The results presented in Table 2 show that all constructs exceeded the recommended threshold, confirming adequate internal consistency and reliability of the measurement model.

Table 2. Construct reliability and validity.

Construct	Item	Loadings	A	CR	AVE
Algorithmic control (ACON)					
Algorithmic Rewarding (RW)			0.830	0.896	0.743
	RW1	0.864			
	RW2	0.829			
	RW3	0.891			
Algorithmic Restricting (RS)			0.836	0.900	0.750
	RS1	0.880			
	RS2	0.886			
	RS3	0.831			
Algorithmic Requiring (RQ)			0.867	0.909	0.715
	RQ1	0.881			
	RQ2	0.850			
	RQ3	0.813			
	RQ4	0.837			
Algorithmic Monitoring (MO)			0.858	0.904	0.702
	MO1	0.876			
	MO2	0.820			
	MO3	0.828			
	MO4	0.826			
Algorithmic sanctioning (SA)			0.849	0.903	0.701
	SA1	0.845			
	SA2	0.835			
	SA3	0.822			
	SA4	0.850			
Algorithmic Support (ASUP)					
Recommendations (RC)			0.882	0.918	0.737
	RC1	0.852			
	RC2	0.879			
	RC3	0.843			
	RC4	0.860			

Table 2. *Cont.*

Construct	Item	Loadings	A	CR	AVE
Information sharing (IS)			0.869	0.909	0.715
	IS1	0.827			
	IS2	0.851			
	IS3	0.840			
	IS4	0.863			
Gamification (AG)			0.887	0.917	0.689
	AG1	0.810			
	AG2	0.836			
	AG3	0.835			
	AG4	0.834			
	AG5	0.836			
Work Engagement (ENG)			0.950	0.958	0.715
	ENG1	0.833			
	ENG2	0.833			
	ENG3	0.864			
	ENG4	0.842			
	ENG5	0.847			
	ENG6	0.852			
	ENG7	0.837			
	ENG8	0.865			
	ENG9	0.836			
Work Exhaustion (EXH)			0.941	0.961	0.713
	EXH1	0.813			
	EXH2	0.847			
	EXH3	0.840			
	EXH4	0.861			
	EXH5	0.829			
	EXH6	0.849			
	EXH7	0.851			
	EXH8	0.845			
	EXH9	0.847			
	EXH10	0.859			
Managerial Decision-support orientation (DS)			0.928	0.940	0.661
	DS1	0.845			
	DS2	0.817			
	DS3	0.808			
	DS4	0.801			
	DS5	0.804			
	DS6	0.798			
	DS7	0.803			
	DS8	0.828			
Managerial Enforcement orientation (EN)			0.960	0.966	0.781
	EN1	0.889			
	EN2	0.890			
	EN3	0.875			
	EN4	0.899			
	EN5	0.863			
	EN6	0.872			
	EN7	0.897			
	EN8	0.881			

Table 2. *Cont.*

Construct	Item	Loadings	A	CR	AVE
Prevention-focused job crafting (PRE)			0.932	0.946	0.746
	PRE1	0.869			
	PRE2	0.865			
	PRE3	0.867			
	PRE4	0.870			
	PRE5	0.846			
	PRE6	0.865			
Promotion-focused job crafting (PRO)			0.959	0.968	0.687
	PRO1	0.831			
	PRO2	0.816			
	PRO3	0.820			
	PRO4	0.808			
	PRO5	0.840			
	PRO6	0.840			
	PRO7	0.845			
	PRO8	0.825			
	PRO9	0.833			
	PRO10	0.816			
	PRO11	0.846			
	PRO12	0.811			
	PRO13	0.818			
	PRO14	0.852			

4.4. Discriminant Validity (DV)

Discriminant validity assesses whether the constructs in the model are empirically distinct from one another. In this study, discriminant validity was evaluated using both the heterotrait–monotrait (HTMT) ratio presented in Table 3 and the Fornell–Larcker criterion presented in Table 4. According to the Fornell–Larcker criterion, the square root of each construct's average variance extracted (AVE) should be greater than its correlations with other constructs, indicating adequate discriminant validity (Fornell & Larcker, 1981). In addition, the HTMT ratio was examined as a more stringent test. HTMT values below 0.85 (or 0.90 for conceptually similar constructs) suggest sufficient discriminant validity (Henseler et al., 2015).

Table 3. Heterotrait–Monotrait Ratio.

	AG	DS	EN	ENG	IS	MO	PRE	RC	RQ	RS	RW	SA	EXH	PRO
AG														
DS	0.045													
EN	0.046	0.068												
ENG	0.414	0.038	0.053											
IS	0.069	0.082	0.067	0.320										
MO	0.108	0.036	0.057	0.212	0.061									
PRE	0.149	0.035	0.087	0.354	0.207	0.109								
RC	0.052	0.039	0.036	0.274	0.079	0.073	0.198							
RQ	0.038	0.048	0.091	0.225	0.056	0.031	0.202	0.032						
RS	0.043	0.033	0.071	0.121	0.055	0.051	0.144	0.057	0.054					
RW	0.049	0.038	0.076	0.225	0.037	0.044	0.253	0.055	0.024	0.024				
SA	0.052	0.114	0.041	0.178	0.029	0.061	0.178	0.086	0.070	0.053	0.069			
EXH	0.275	0.073	0.065	0.461	0.269	0.211	0.599	0.212	0.221	0.192	0.188	0.239		
PRO	0.355	0.040	0.033	0.687	0.321	0.115	0.280	0.284	0.143	0.096	0.159	0.112	0.370	

Table 4. Fornell–Larcker.

	AG	DS	EN	ENG	IS	MO	PJC	RC	RQ	RS	RW	SA	EXH	PRO
AG	0.830													
DS	0.011	0.813												
EN	0.021	0.055	0.884											
ENG	0.381	−0.015	0.048	0.846										
IS	0.055	−0.053	0.060	0.299	0.845									
MO	0.091	0.010	−0.042	−0.190	−0.049	0.838								
PJC	−0.136	0.029	−0.083	−0.333	−0.186	0.099	0.864							
RC	−0.023	−0.032	−0.021	0.254	0.070	−0.060	−0.179	0.859						
RQ	0.012	−0.031	−0.081	−0.202	0.042	0.006	0.183	0.006	0.846					
RS	−0.007	0.006	0.064	−0.110	0.032	−0.030	0.135	0.041	−0.040	0.866				
RW	−0.036	−0.007	−0.067	−0.205	0.001	0.025	0.223	−0.019	0.006	0.007	0.862			
SA	−0.001	0.109	0.022	−0.159	0.013	−0.044	0.161	0.075	−0.058	−0.036	−0.046	0.838		
EXH	−0.253	0.076	−0.063	−0.439	−0.247	0.192	0.566	−0.196	0.202	0.176	0.171	0.218	0.844	
PRO	0.330	0.006	0.026	0.661	0.298	−0.106	−0.267	0.265	−0.130	−0.087	−0.149	−0.102	−0.357	0.830

4.5. Validating Higher Order Constructs

This study integrated Algorithmic control and Algorithmic support as second-order formative constructs. These constructs were validated using a hierarchical component model within the PLS-SEM framework. A two-stage approach was employed to assess the reliability and validity of the higher-order constructs (Hair et al., 2019). In the first stage, the measurement quality of the lower-order constructs was examined by evaluating indicator reliability, internal consistency, and convergent validity. In the second stage, latent variable scores obtained from the lower-order constructs were used as indicators of the higher-order constructs (Diamantopoulos & Winklhofer, 2001). The outer weights of the second-order construct indicators were examined to assess their relative contribution, and their significance was evaluated using bootstrapped *p*-values. Significant outer weights indicate that the indicators meaningfully form the higher-order construct. In addition, variance inflation factor (VIF) values were assessed to examine potential collinearity among the indicators of the second-order construct. All VIF values were below the recommended threshold of 5.0, with Hair et al. (2017) suggesting that multicollinearity is not a concern. Overall, the results presented in Table 5 support the validity of the second-order construct.

Table 5. Higher-order formative constructs and their indicator collinearity.

Latent Constructs	Outer Weights	T Statistics	*p*-Value	VIF
ACON				
RW → ACON	0.519	5.991	0.000	1.003
RS → ACON	0.486	5.399	0.000	1.004
RQ → ACON	0.512	6.010	0.000	1.005
MO → ACON	0.528	3.820	0.000	1.003
SA → ACON	0.484	4.915	0.000	1.004
ASUP				
AG → ASUP	0.610	10.741	0.000	1.004
RC → ASUP	0.456	7.882	0.000	1.006
IS → ASUP	0.593	11.440	0.000	1.009

4.6. Analysis of Structural Model and Hypotheses Testing

The structural model was assessed to examine the hypothesized relationships among the constructs. Path coefficients and their statistical significance were evaluated using a bootstrapping procedure with 5000 resamples (Hair et al., 2019). Model adequacy and explanatory power were further examined using several fit and quality indicators, including the standardized root mean square residual (SRMR) = 0.044, chi-square = 2042.190, and normed fit index (NFI) = 0.907. These indices provide information about model fit;

explanatory and predictive performance should be evaluated separately using the relevant structural-model measures.

4.6.1. Main Effect

Table 6 presents the standardized path coefficients (β) and t-statistics for the structural model. Age, gender, education, tenure, job role, and working hours were included as control variables. None showed statistically significant associations with the endogenous constructs at the 0.05 level. The focal relationships were estimated while accounting for these characteristics; nonsignificant control coefficients do not establish that the relationships are invariant across demographic or occupational groups.

Table 6. Structural model results: Main effects.

Variables	Engagement		Promotion-Focused Crafting		Exhaustion		Prevention-Focused Job Crafting	
	β	t-Value	β	t-Value	β	t-Value	β	t-Value
Age	0.028	0.664	0.014	0.342	−0.022	0.491	0.025	0.622
Gender	0.022	0.298	0.090	1.291	−0.037	0.482	−0.026	0.355
Education	−0.010	0.268	0.000	0.010	0.013	0.342	−0.033	0.893
Tenure	−0.038	0.953	0.070	1.823	−0.020	0.475	0.018	0.452
Job Role	−0.064	1.708	−0.049	1.460	0.045	1.144	0.017	0.471
Hours	−0.045	1.273	0.019	0.552	−0.060	1.570	0.052	1.488
Algorithmic Support	0.468 ***	13.931	0.299 ***	7.641	−0.283 ***	6.939	−0.179 ***	4.929
Algorithmic Control	−0.297 ***	8.071	−0.154 ***	3.884	0.354 ***	9.563	0.255 ***	6.788
Work engagement	-	-	0.403 ***	11.045	-	-	-	-
Work exhaustion	-	-	-	-	-	-	0.433 ***	12.206
R square	0.300		0.398		0.213		0.363	

*** $p < 0.001$.

Algorithmic control was positively associated with prevention-focused job crafting (β = 0.255, t = 6.788), supporting H1. Algorithmic support was positively associated with promotion-focused job crafting (β = 0.299, t = 7.641), supporting H2. Additional direct relationships were also identified: algorithmic support was negatively associated with prevention-focused crafting (β = −0.179, t = 4.929), while algorithmic control was negatively associated with promotion-focused crafting (β = −0.154, t = 3.884).

Algorithmic support was positively associated with work engagement (β = 0.468, t = 13.931) and negatively associated with exhaustion (β = −0.283, t = 6.939), supporting H3. Algorithmic control was positively associated with exhaustion (β = 0.354, t = 9.563) and negatively associated with engagement (β = −0.297, t = 8.071), supporting H5. These findings are consistent with algorithmic support and control being relevant to both motivational and strain-related processes, rather than each being associated exclusively with one psychological state.

Work engagement was positively associated with promotion-focused job crafting (β = 0.403, t = 11.045), while exhaustion was positively associated with prevention-focused job crafting (β = 0.433, t = 12.206). These relationships provide components of the proposed indirect pathways, which are evaluated separately in the mediation analysis.

The model accounted for 30.0% of the variance in engagement, 39.8% in promotion-focused crafting, 21.3% in exhaustion, and 36.3% in prevention-focused crafting. These R^2 values describe the model's explanatory performance within the sample; they do not establish causal relationships or out-of-sample predictive accuracy. Figure 2 illustrates the baseline structural-model results reported in Table 6, whereas Appendix C presents the baseline structural model with standardized path coefficients, bootstrap t-values and

p-values, together with the outer weights and significance statistics for the higher-order formative dimensions.

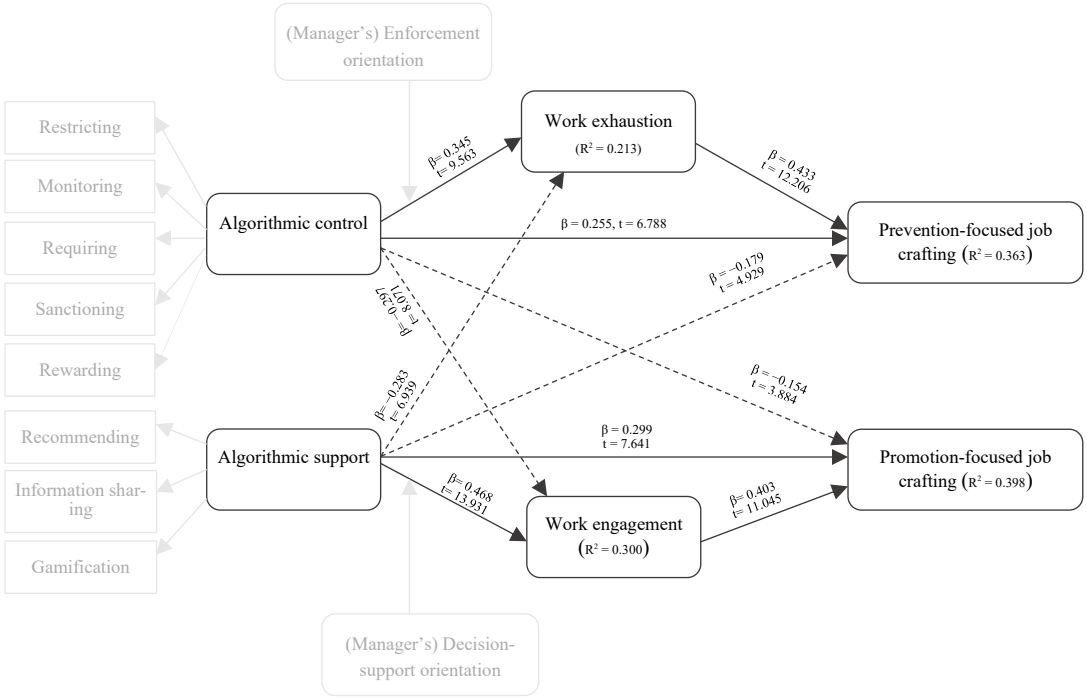


Figure 2. Baseline structural model with standardized path coefficients.

4.6.2. Mediating Effects

The proposed indirect pathways were evaluated using bootstrapping with 95% confidence intervals. As reported in Table 7, the indirect association between algorithmic support and promotion-focused job crafting through work engagement was positive and statistically significant (β = 0.189, 95% CI [0.150, 0.235]). This finding supports H4 and is consistent with engagement as a proposed mechanism linking algorithmic support to growth-oriented crafting.

Table 7. Mediation effects.

Indirect Path	Indirect Effect (β)	Boot SE	t-Value	*p*-Value	95% CI
ASUP → ENG → PRO	0.189	0.021	8.829	0.000	[0.150, 0.235]
ACON → EXH → PJC	0.153	0.019	7.884	0.000	[0.118, 0.193]
ASUP → EXH → PRE	−0.123	0.023	5.316	0.000	[−0.173, −0.081]
ACON → ENG → PRO	−0.120	0.020	5.936	0.000	[−0.164, −0.084]

The indirect association between algorithmic control and prevention-focused job crafting through exhaustion was also positive and statistically significant (β = 0.153, 95% CI [0.118, 0.193]), supporting H6. The direction is consistent with algorithmic control being associated with greater exhaustion and exhaustion being associated with more efforts to reduce hindering job demands.

Two additional cross-path indirect associations were identified. Algorithmic support was negatively associated with prevention-focused crafting through exhaustion (β = −0.123, 95% CI [−0.173, −0.081]). This pattern is consistent with the negative support–exhaustion relationship and the positive exhaustion–prevention-crafting relationship. Algorithmic control was negatively associated with promotion-focused crafting through engagement

(β = −0.120, 95% CI [−0.164, −0.084]), consistent with the negative control–engagement relationship and the positive engagement–promotion-crafting relationship.

All four reported confidence intervals excluded zero. Together, the findings indicate that the indirect associations of algorithmic support and control extend across both psychological pathways. They do not imply that lower prevention-focused crafting is necessarily preferable, because reducing hindering demands may serve a protective function. Moreover, the time-lagged observational design does not establish causal mediation; the results are interpreted as associations consistent with the proposed mechanisms.

4.6.3. Moderation Analysis

Table 8 presents the moderating relationships involving employees' perceptions of managers' decision-support orientation (DS) and enforcement orientation (EN). The analysis identified three statistically significant interaction terms.

Table 8. Results of the moderation effect analysis.

Variables	Engagement		Exhaustion	
	β	t	β	t
Control variables				
Age	0.025	0.449	−0.020	0.499
Gender	0.022	0.294	−0.037	0.492
Education	−0.003	0.079	0.016	0.429
Tenure	−0.037	0.910	−0.016	0.376
Job Role	−0.062	1.648	0.033	0.849
Hours	−0.038	1.085	−0.070	1.849
Independent variables				
Algorithmic Support (ASUP)	0.460 ***	13.424	−0.288 ***	7.131
Algorithmic Control (ACON)	−0.283 ***	7.587	0.353 ***	9.530
Moderators				
Decision support orientation (DS)	−0.047	0.906	0.025	0.416
Enforcement orientation (EN)	0.015	0.496	0.085	1.878
Interaction terms				
ASUP × DS	0.174 ***	3.908	−0.104 *	2.421
ASUP × EN	0.015	0.650	−0.005	0.261
ACON × DS	−0.054	1.332	−0.001	0.028
ACON × EN	−0.068	1.777	0.147 ***	3.543
R^2	0.335		0.240	

* $p < 0.05$; *** $p < 0.001$.

First, the interaction between algorithmic support and decision-support orientation was positively associated with work engagement (β = 0.174, t = 3.908, $p < 0.001$), supporting H7. This indicates that the positive relationship between algorithmic support and engagement was stronger among employees who perceived their managers as using algorithmic outputs for contextual judgment, guidance, and developmental support. Figure 3 depicts positive slopes at both high and low decision-support orientation, with a steeper slope at the high level. The figure therefore illustrates a stronger positive association rather than a reversal in its direction.

Second, the interaction between algorithmic control and enforcement orientation was positively associated with exhaustion (β = 0.147, t = 3.543, $p < 0.001$), supporting H8. The positive control–exhaustion relationship was stronger among employees who perceived their managers as treating algorithmic outputs as authoritative prescriptions for compliance and action. Figure 4 depicts this pattern, showing a steeper positive slope under high enforcement orientation than under low enforcement orientation. This finding concerns

enforcement orientation specifically and does not imply that employees perceiving high enforcement necessarily perceived low decision-support orientation.

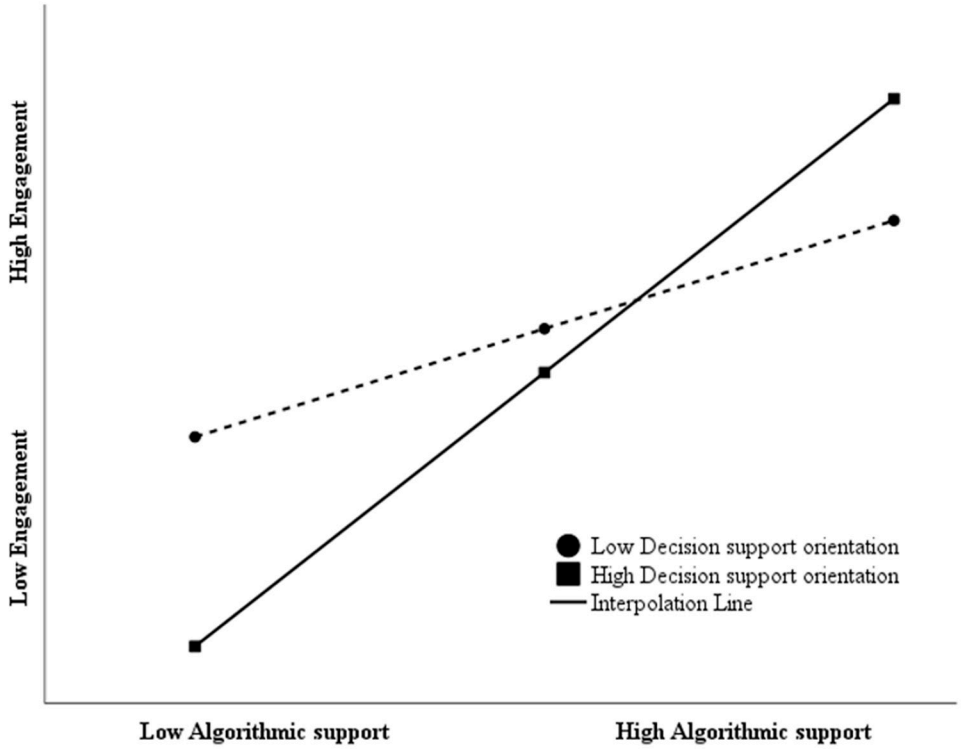


Figure 3. Conditional relationship between algorithmic support and work engagement at low and high levels of managers' decision-support orientation.

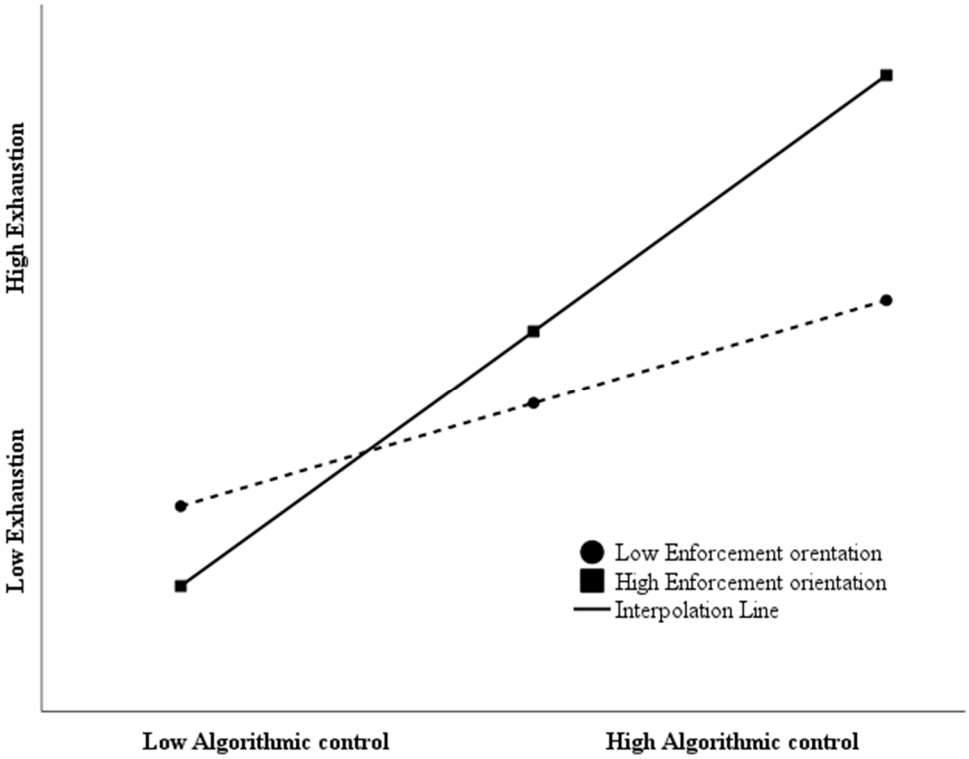


Figure 4. Conditional relationship between algorithmic control and exhaustion at low and high levels of managers' enforcement orientation.

Third, the interaction between algorithmic support and decision-support orientation was negatively associated with exhaustion ($\beta = -0.104$, t = 2.421, $p < 0.05$). This additional finding indicates that the negative relationship between algorithmic support and exhaustion became stronger as perceived decision-support orientation increased. It is consistent with developmental managerial enactment strengthening the potential resource value of algorithmic support across both engagement and exhaustion. Because this interaction was not separately hypothesized, it is interpreted as an additional finding requiring replication.

The remaining interaction terms were not statistically significant at the 0.05 level. Accordingly, the results do not support claims that every managerial orientation moderated every psychological pathway. These interaction findings also do not, by themselves, establish moderated mediation, which requires separate evaluation of differences in indirect effects. Because statistical power for these tests was not established, the nonsignificant findings do not demonstrate the absence of the corresponding relationships.

The reported interaction tests use employee-level standard errors without adjustment for outlet or supervisor clustering. Their statistical significance should therefore be interpreted cautiously, because within-group dependence could affect the estimated uncertainty. Power for detecting interaction associations was also not established.

4.6.4. Moderated Mediation Effects

Table 9 presents the bootstrapped conditional indirect associations between algorithmic management and job crafting through exhaustion and engagement at selected levels of perceived managerial decision-support orientation (DS) and enforcement orientation (EN). High and low moderator values represent +1 SD and −1 SD, respectively. Table 10 reports the bootstrapped indices assessing variation in each indirect association with one moderator, holding the other moderator constant. All confidence intervals derive from employee-level bootstrapping without adjustment for outlet or supervisor clustering; statistical significance is therefore interpreted provisionally.

Table 9. Moderated mediation results.

Paths	Indirect Effect	BootSE	Lower	Upper
Algorithmic Control → Exhaustion → Prevention-focused crafting				
High DS, high EN	0.216	0.031	0.157	0.278
High DS, low EN	0.089	0.033	0.028	0.160
Low DS, high EN	0.217	0.036	0.143	0.284
Low DS, low EN	0.090	0.028	0.039	0.147
Algorithmic Control → Engagement → Promotion-focused crafting				
High DS, high EN	−0.163	0.030	−0.220	−0.103
High DS, Low EN	−0.109	0.029	−0.166	−0.053
Low DS, high EN	−0.120	0.034	−0.188	−0.055
Low DS, low EN	−0.065	0.028	−0.127	−0.014
Algorithmic Support → Exhaustion → Prevention-focused crafting				
High DS, high EN	−0.172	0.037	−0.241	−0.096
High DS, low EN	−0.168	0.034	−0.235	−0.099
Low DS, high EN	−0.082	0.034	−0.150	−0.016
Low DS, low EN	−0.078	0.031	−0.143	−0.019
Algorithmic Support → Engagement → Promotion-focused crafting				
High DS, high EN	0.262	0.032	0.195	0.321
High DS, low EN	0.249	0.036	0.176	0.316
Low DS, high EN	0.122	0.031	0.069	0.191
Low DS, low EN	0.109	0.030	0.055	0.174

Table 10. Bootstrapped indices of moderated mediation.

Indirect Pathway	Moderator	Index	Bootstrap SE	t	*p*	95% Bootstrap CI	Supported
ACON → exhaustion → prevention-focused job crafting	EN	0.064	0.018	3.465	0.001	[0.026, 0.098]	Yes
ACON → exhaustion → prevention-focused job crafting	DS	−0.001	0.018	0.028	0.978	[−0.035, 0.037]	No
ASUP → engagement → promotion-focused job crafting	DS	0.070	0.019	3.649	<0.001	[0.026, 0.102]	Yes
ASUP → engagement → promotion-focused job crafting	EN	0.006	0.014	0.430	0.667	[−0.021, 0.036]	No
ASUP → exhaustion → prevention-focused job crafting	DS	−0.045	0.019	2.360	0.018	[−0.079, −0.005]	Yes
ASUP → exhaustion → prevention-focused job crafting	EN	−0.002	0.017	0.120	0.905	[−0.035, 0.033]	No
ACON → engagement → promotion-focused job crafting	DS	−0.022	0.016	1.330	0.184	[−0.053, 0.012]	No
ACON → engagement → promotion-focused job crafting	EN	−0.027	0.016	1.738	0.082	[−0.057, 0.005]	No

Note. ACON = algorithmic control; ASUP = algorithmic support; DS = decision-support orientation; EN = enforcement orientation; SE = standard error; CI = confidence interval. For the specified linear model with moderation of the predictor-to-mediator paths, each index is the product of the corresponding interaction coefficient and the mediator-to-outcome coefficient. An index represents variation in the indirect association per one-unit increase in the moderator, holding the other moderator constant. Moderated mediation is supported when the 95% bootstrap confidence interval excludes zero. Estimates and intervals are reproduced from the supplied SmartPLS output.

The conditional indirect association between algorithmic control and prevention-focused job crafting through exhaustion was positive across all reported conditions, with 95% confidence intervals excluding zero. Estimates were larger under high EN (0.216 and 0.217) than under low EN (0.089 and 0.090). Consistent with the positive ACON × EN interaction on exhaustion in Table 8, the EN index was positive and its confidence interval excluded zero (index = 0.064, 95% CI [0.026, 0.098]). This provides provisional support for H9a specifically for enforcement orientation under the employee-level analysis. The corresponding DS index was not statistically supported (index = −0.001, 95% CI [−0.035, 0.037]).

The conditional indirect association between algorithmic control and promotion-focused job crafting through engagement was negative across all reported conditions, ranging from −0.163 to −0.065, with confidence intervals excluding zero. However, neither the DS index (−0.022, 95% CI [−0.053, 0.012]) nor the EN index (−0.027, 95% CI [−0.057, 0.005]) excluded zero. Thus, the numerical differences between conditional estimates did not establish statistically supported moderation of this indirect pathway.

For algorithmic support, the conditional indirect association with prevention-focused job crafting through exhaustion was negative across all reported conditions, ranging from −0.172 to −0.078, with confidence intervals excluding zero. Under low DS and low EN, the estimate was −0.078 (95% CI [−0.143, −0.019]). These negative associations are consistent with algorithmic support being associated with lower exhaustion and, through exhaustion, lower prevention-focused crafting. The DS index was negative and its confidence interval excluded zero (index = −0.045, 95% CI [−0.079, −0.005]), consistent with a stronger negative indirect association at higher DS. This additional finding corresponds to the negative ASUP × DS interaction on exhaustion in Table 8, although its robustness to clustering remains untested. The EN index was not statistically supported (index = −0.002, 95% CI [−0.035, 0.033]).

The conditional indirect association between algorithmic support and promotion-focused job crafting through engagement was positive across all reported conditions, with confidence intervals excluding zero. Estimates were larger at high DS (0.262 and 0.249) than at low DS (0.122 and 0.109). The positive DS index had a confidence interval excluding zero (index = 0.070, 95% CI [0.026, 0.102]), providing provisional support for H9b specifically for decision-support orientation under the employee-level analysis. This result is consistent with the positive ASUP × DS interaction on engagement in Table 8. The EN index was not statistically supported (index = 0.006, 95% CI [−0.021, 0.036]).

Overall, the employee-level bootstrap indices provided provisional support for the two hypothesized orientation-specific pathways and an additional DS-moderated support–exhaustion–prevention-crafting association. These interpretations rely on the indices rather than the significance of individual conditional associations. However, whether the confidence intervals would continue to exclude zero after accounting for outlet or supervisor dependence is unknown. Power for moderated-mediation tests was also not established; consequently, nonsignificant indices do not demonstrate the absence of the corresponding relationships. These findings remain associational, and enforcement orientation reflects perceived enforcement practices that may capture organizational constraints alongside managerial tendencies.

Table 10 presents the bootstrapped indices of moderated mediation. Enforcement orientation moderated the indirect association between algorithmic control and prevention-focused job crafting through exhaustion (index = 0.064, 95% CI [0.026, 0.098]), supporting H9a specifically for enforcement orientation. Decision-support orientation moderated the indirect association between algorithmic support and promotion-focused job crafting through engagement (index = 0.070, 95% CI [0.026, 0.102]), supporting H9b specifically for decision-support orientation. An additional significant index indicated that the negative indirect association between algorithmic support and prevention-focused job crafting through exhaustion became stronger as decision-support orientation increased (index = −0.045, 95% CI [−0.079, −0.005]). The remaining indices had confidence intervals including zero and did not support moderated mediation

5. Discussion

5.1. Summary of Results

This study examined the associations of algorithmic control and algorithmic support with promotion-focused and prevention-focused job crafting among frontline fast-food employees, with engagement and exhaustion as proposed mediating mechanisms. Building on prior recognition of algorithmic management's enabling and constraining functions, the study examined these functions simultaneously and considered employees' perceptions of managerial orientation as boundary conditions.

The results were consistent with the corresponding motivational and health-impairment pathways proposed by JD–R theory. Algorithmic support was positively associated with engagement, which was positively associated with promotion-focused job crafting. Algorithmic control was positively associated with exhaustion, which was positively associated with prevention-focused job crafting. The indirect associations were consistent with engagement and exhaustion as proposed mechanisms linking algorithmic functions to different forms of employee adaptation. These findings do not establish causal mediation, because temporal separation cannot rule out reverse relationships or unmeasured confounding.

The findings also extended beyond these corresponding pathways. Algorithmic support was negatively associated with exhaustion and indirectly associated with lower prevention-focused crafting through exhaustion. Algorithmic control was negatively associated with engagement and indirectly associated with lower promotion-focused crafting

through engagement. These cross-path findings suggest that support and control are relevant to both motivational involvement and strain. They do not demonstrate that engagement and exhaustion interact, but indicate that algorithmic functions are not associated exclusively with one psychological pathway. Lower prevention-focused crafting is not necessarily a superior outcome, because reducing hindering demands may represent an appropriate protective adjustment.

The moderation results identified a stronger positive support–engagement relationship at higher perceived decision-support orientation and a stronger positive control–exhaustion relationship at higher perceived enforcement orientation. Decision-support orientation also strengthened the negative support–exhaustion relationship. These findings are consistent with managerial enactment as a boundary condition: system functions concern what algorithmic tools provide or regulate, whereas managerial orientation concerns how employees perceive managers interpreting and acting on system outputs. The orientations were assessed separately, so supportive managerial use does not necessarily exclude enforcement-oriented use. Moreover, enforcement-related responses may reflect organizational requirements alongside managerial tendencies; they cannot be interpreted exclusively as managers' freely chosen preferences.

The bootstrapped indices in Table 10 supported orientation-specific moderated mediation. Enforcement orientation strengthened the positive indirect association between algorithmic control and prevention-focused crafting through exhaustion (index = 0.064, 95% CI [0.026, 0.098]), supporting H9a specifically for EN. Decision-support orientation strengthened the positive indirect association between algorithmic support and promotion-focused crafting through engagement (index = 0.070, 95% CI [0.026, 0.102]), supporting H9b specifically for DS. An additional significant index indicated that the negative support–exhaustion–prevention-crafting association became stronger as DS increased (index = −0.045, 95% CI [−0.079, −0.005]). The remaining indices were not statistically supported. Accordingly, numerical variation in conditional estimates is not interpreted as evidence of moderation where the corresponding index includes zero.

Overall, the findings support examining algorithmic system functions alongside perceived managerial enactment when explaining engagement, exhaustion, and job crafting. The conclusions concern associations in the present sample rather than demonstrated causal effects. Interpretation remains qualified by unestablished power for interaction and moderated-mediation tests and the inability to assess or adjust for outlet or supervisor clustering.

5.2. Theoretical Implications

First, this study builds on the established recognition that algorithmic management can enable and constrain employees (Jarrahi et al., 2021; Meijerink & Bondarouk, 2023). Its contribution is to examine control and support simultaneously as distinct configurations of system functions in frontline service work. This distinction makes it possible to assess their different associations with employee psychological states and crafting behaviors without assuming that an overall algorithmic-management measure adequately represents both. The findings are consistent with the value of distinguishing functions that regulate work through requirements and consequences from functions that provide recommendations, information, and performance cues. Algorithmic support is understood here as a specific configuration of potential job resources, rather than a newly discovered category of resources.

Second, the findings provide a broader application of JD–R reasoning to algorithmic management than a model limited to corresponding demand–exhaustion and resource–engagement pathways. Algorithmic support was positively associated with engagement

and negatively associated with exhaustion, whereas algorithmic control was positively associated with exhaustion and negatively associated with engagement. These cross-path relationships suggest that algorithmic functions may be relevant to both motivational and health-impairment processes. Support may assist task accomplishment while also making demands more manageable, whereas control may be associated with strain alongside reduced motivational involvement. These findings do not establish that engagement and exhaustion interact, nor do they overturn the JD–R framework. Rather, they illustrate the relevance of its broader demand- and resource-related mechanisms in algorithmically managed work.

Third, the study links these psychological relationships to different forms of job crafting. Alongside the positive indirect association of support with promotion-focused crafting through engagement and the positive indirect association of control with prevention-focused crafting through exhaustion, the reported results identify negative cross-path indirect associations. Control was indirectly associated with lower promotion-focused crafting through engagement, while support was indirectly associated with lower prevention-focused crafting through exhaustion. This pattern suggests that algorithmic management may be associated with both employees' motivation to pursue developmental changes and their perceived need to make protective adjustments. The distinction concerns the direction and psychological basis of crafting rather than a simple classification of promotion-focused crafting as beneficial and prevention-focused crafting as undesirable. Because the study relies on time-separated employee reports, these indirect relationships are interpreted as consistent with the proposed mechanisms rather than as evidence establishing causal mediation.

Finally, the study brings managerial enactment into the explanation of employees' responses to algorithmic management. Its contribution lies in distinguishing the functions employees experience from algorithmic systems from their perceptions of how managers interpret and implement those functions. Algorithmic support provides recommendations, information, and performance cues, whereas decision-support orientation concerns managerial practices that help employees interpret and use those outputs. Algorithmic control regulates work through requirements, monitoring, and consequences, whereas enforcement orientation concerns the managerial treatment of those outputs as authoritative prescriptions. The reported interactions are consistent with stronger support–engagement associations under decision-support orientation and stronger control–exhaustion associations under enforcement orientation.

These findings provide an empirical application of the sociotechnical argument that technological arrangements and their social enactment should be examined together (Leonardi, 2011; Orlikowski, 2000; Trist & Bamforth, 1951). They suggest that identifying system functions alone may be insufficient to explain differences in employee experience. However, the study measures both system functions and managerial orientation through employee perceptions. The findings therefore concern perceived managerial enactment and do not directly establish managers' intentions, objective implementation practices, or causal changes in employee outcomes.

5.3. Practical Implications

The findings suggest that fast-food chains should consider both the functions of algorithmic management systems and how managers use their outputs. Algorithmic support was associated with greater engagement and lower exhaustion, whereas algorithmic control showed the opposite pattern. These associations encourage attention to whether digital tools provide usable information and guidance alongside operational requirements. For example, dashboards could communicate changing priorities, explain performance indicators,

and provide recommendations that employees can apply during busy periods. Gamified features should also be evaluated carefully: progress indicators may offer useful feedback, while competitive rankings or demanding targets may add pressure. The study does not establish that any particular redesign will improve employee outcomes, so proposed changes should be piloted and evaluated.

The moderation findings also suggest that managerial enactment deserves attention alongside system design. The support–engagement association was stronger when employees perceived higher decision-support orientation, while the control–exhaustion association was stronger under higher enforcement orientation. Organizations could therefore train managers to interpret algorithmic information in context, explain its meaning, and discuss feasible responses with employees. When a performance alert occurs, managers might first examine workload, staffing, equipment problems, or training needs before deciding on an appropriate action. Such practices are consistent with developmental uses of performance information and the importance of human judgment in technology-enabled work (Boswell & Boudreau, 2000; Parker & Grote, 2022). Their effectiveness should nevertheless be assessed rather than assumed from the present associations.

These recommendations do not imply abandoning operational standards or treating every enforcement action as inappropriate. Fast-food outlets require consistent procedures, particularly where service quality and safety are concerned. A practical distinction is between necessary requirements and discretionary responses to system-generated evaluations. Franchise policies could specify when contextual review is appropriate, what discretion managers have, and how employees can clarify or question an output. Clear explanations of evaluation criteria and consequences may also help employees understand the requirements they face. This approach recognizes the importance of aligning technical arrangements with managerial practices and local work conditions (Orlikowski, 2000; Trist & Bamforth, 1951).

The job-crafting findings further suggest that managers should attend to both developmental and protective forms of employee adaptation. Promotion-focused crafting may involve seeking feedback, developing skills, or undertaking additional challenges. Managers could support these activities by providing learning opportunities and ensuring that additional responsibilities are feasible within existing workloads. Prevention-focused crafting, such as reducing emotionally taxing interactions or making work mentally less intense, should not automatically be interpreted as disengagement or poor performance. It may indicate that employees are trying to manage demands and conserve resources. Managers should examine the conditions behind such adjustments and discuss whether staffing, task allocation, pacing, or access to support requires attention.

Finally, organizations should evaluate changes using more than efficiency indicators alone. Employee feedback, engagement and exhaustion measures, service quality, and workload information could be considered together when assessing system functions and managerial practices. Comparisons across outlets or phased implementation could help identify whether proposed changes improve employee experience without compromising operational requirements. Because the study uses observational employee reports, its practical implications identify promising areas for evaluation rather than interventions with demonstrated causal effectiveness.

5.4. Limitations and Future Research

Several limitations should be considered when interpreting the findings. First, the study focuses on frontline employees in fast-food franchise outlets in northern China. This setting is relevant because standardized service work frequently involves digital scheduling, task coordination, and performance monitoring. However, the relationships observed may

depend on the operational demands, employment arrangements, and managerial practices of these outlets. Algorithmic management may function differently in professional or knowledge-intensive work, where discretion, expertise, and task ambiguity are greater. Replication across sectors, countries, and employment settings would help establish the scope of the findings. Comparisons between conventional organizations and digital labor platforms would be particularly useful for examining how access to human managers shapes employees' experiences of algorithmic management.

Second, although the final analytical sample comprised 547 employees, sample size alone does not demonstrate adequate power for these tests. Consequently, nonsignificant interactions and moderated-mediation indices are interpreted as a lack of statistical support in the present sample rather than evidence that the corresponding associations are absent. These results may reflect small or absent associations or insufficient precision to detect them. Their confidence intervals should therefore be considered when evaluating the range of associations compatible with the data. Future studies should undertake a prospective simulation-based power assessment reflecting the measurement structure, multiple pathways, moderation, and any dependence among employees within outlets or supervisors. Furthermore, as outlet and supervisor identifiers were not retained, this prevented assessment or adjustment for clustering. Employees sharing workplaces or managers may provide correlated responses, potentially understating uncertainty in the reported estimates. Moderation and moderated-mediation findings should therefore be interpreted cautiously. Future studies should retain confidential grouping identifiers and account for clustering in the analysis.

Third, the three-wave design provides temporal separation among predictors, mediators, and outcomes but does not establish causality. Because each focal construct was measured at one designated wave, the study does not assess within-person changes or adequately test reciprocal relationships. Engaged employees may evaluate algorithmic systems more favorably, while exhausted employees may perceive stronger control. Job crafting may also subsequently influence engagement and exhaustion. Unmeasured factors, including workload, leadership practices, and organizational climate, may contribute to the observed associations. Future research should measure the focal constructs repeatedly and examine reciprocal relationships and changes over time. Field experiments or carefully designed quasi-experimental studies of changes in system functions or managerial practices could provide stronger evidence concerning causal mechanisms.

Fourth, all focal constructs were assessed through employee self-reports. These perceptions are relevant to understanding employees' experiences, but shared reporting sources may introduce common method variance, evaluative biases, or consistency effects. Temporal separation reduces some sources of method bias without eliminating them, and reliability or discriminant-validity statistics cannot establish their absence. Future studies could combine employee surveys with manager reports, observations, and system-generated records. These sources would help distinguish the functions actually provided by algorithmic systems from employees' interpretations of those functions and managers' enacted practices.

Fifth, the decision-support and enforcement orientation scales were newly developed for this study. The measurement evidence provides initial support within the present sample, but independent validation remains necessary. Future research should examine the scales' dimensional structure, content coverage, stability, and measurement equivalence across occupations and cultural contexts. Particular attention should be given to distinguishing managerial enactment from system functions and broader leadership behaviors. Some enforcement items may also reflect organizational constraints on managerial discretion rather than a manager's preferred approach. Subsequent studies should investi-

gate whether enforcement-oriented behavior arises from managerial preferences, formal organizational requirements, or their combination.

Sixth, managerial orientation was measured at the first wave and interpreted as a contextual characteristic. The study therefore does not establish its stability over time or capture variation across situations. Managers may use algorithmic information developmentally in some circumstances and authoritatively in others. Repeated assessments and event-based studies could examine whether orientations change with performance pressure, staffing shortages, system errors, or employee needs. Research incorporating employees nested within managers and outlets could also distinguish shared managerial practices from individual differences in their perception.

Seventh, the higher-order measures summarize several algorithmic functions whose implications may differ. Recommendations, information sharing, and gamified cues may not offer equivalent resources, just as monitoring, restrictions, sanctions, and rewards may create different demands. The composite-level relationships should therefore not be interpreted as demonstrating uniform effects of every component. Future studies could examine individual functions, their combinations, and the conditions under which they are experienced as useful or pressuring. In particular, gamified rankings may provide feedback while intensifying comparison, and performance-contingent rewards may communicate recognition while increasing evaluation pressure.

Eighth, the interpretation of conditional indirect effects requires caution. Significant indirect effects at selected moderator levels do not by themselves demonstrate that those effects differ significantly across conditions. Conclusions about moderated mediation should rely on appropriate bootstrapped indices or contrasts and remain specific to the pathways supported by those tests.

Finally, future research could investigate how managerial enactment interacts with algorithmic system design and organizational governance. Explainable outputs, opportunities to question automated evaluations, and discretion to adapt recommendations may influence how managers use algorithmic information. Organizational policies and performance-accountability arrangements may likewise encourage developmental or enforcement-oriented practices. Examining these conditions would help explain why employees experience different managerial uses of similar technologies. Such research should also assess the consequences of both forms of job crafting over time, recognizing that prevention-focused adjustments may protect employees under demanding conditions, while promotion-focused changes may involve additional effort whose sustainability depends on available resources.

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Institutional Review Board Statement: According to China's Measures for Ethical Review of Life Science and Medical Research Involving Human Beings, the study employs anonymized questionnaire data, poses no harm to participants, involves no sensitive information or commercial interests, and therefore qualifies for exemption from ethical review.

Informed Consent Statement: Informed consent for participation was obtained from all subjects involved in the study.

Data Availability Statement: The data supporting the findings of this study are available from the corresponding author upon reasonable request. The data are not publicly available due to privacy and confidentiality considerations associated with participant-level survey responses.

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Appendix A

Table A1. Algorithmic Control.

Construct	Questions
Algorithmic Restricting	When interacting with algorithmic tools (ATs) during work, I feel like I am not provided with the whole picture.
	At work, I feel like ATs restrict access to information.
	I feel like ATs at my workplace are used to interactively restrict my behavior.
Algorithmic Requiring	During my workday, I am required to follow the instructions provided by ATs.
	ATs provide explicit work instructions on which tasks I must fulfill.
	On my job, I am required to adhere to the exact instructions I receive via ATs
	During my work, I receive tasks or objectives from ATs that are mandatory for me to complete
Algorithmic Monitoring	ABTs collect extensive data on my daily work routine.
	During my workday, I am constantly tracked by ATs.
	I feel like my work performance is under constant surveillance by ATs
	I feel observed through the ATs at my workplace.
Algorithmic Sanctioning	If I get sanctioned at work, it is likely to be automated by ATs rather than by a human supervisor.
	Disciplinary actions in my organization are automated through ATs
	If I do not reach certain work targets, I will be sanctioned for this by ATs.
	At work, I receive penalties through ATs.
Algorithmic Rewarding	Rewards for my work are allocated through ATs.
	My organization utilizes ATs to pay workers based on their performance.
	ATs reward me for good work performance.

Table A2. Algorithmic Support.

Construct	Questions
Algorithmic Recommendations	I receive recommendations on what I should work on via Algorithmic tools (ATs).
	ATs send me recommendations on how I should behave at work
	ATs send me recommendations on what I should do during my work
	ATs provide me with hints on how I could improve my performance.
Algorithmic Information Sharing	In this tool, information about my performance is shared with me.
	I am informed in advance of changing needs of clients.
	In this tool, any information that might help me is provided.
	The algorithmic tool keeps me informed about events or changes that may affect my job.
Algorithmic Gamification	My work performance is translated into points, scores, or levels by algorithmic systems.
	Algorithmic systems use rankings or leaderboards to compare my performance with others.
	I receive real-time feedback on my work progress through algorithm-generated indicators (e.g., scores, progress bars).
	Game-like features embedded in algorithmic systems are used to motivate me to improve my performance.
	Algorithmic systems frame work tasks as challenges, targets, or missions to be achieved.

Table A3. Work engagement.

Construct	Questions
Work Engagement	At my work, I feel bursting with energy.
	At my job, I feel strong and vigorous.
	Time flies when I am working.
	When I am working, I forget everything else around me
	I feel happy when I am working intensely.
	My job inspires me.
	I am enthusiastic about my job.
	I find the work that I do full of meaning and purpose.
	When I get up in the morning, I feel like going to work.

Table A4. Work Exhaustion.

Construct	Questions
Work Exhaustion	I feel emotionally drained from my work.
	I have felt irritable or short-tempered because of work pressures
	I have felt muscle tension or back pain related to my job.
	I have had trouble sleeping due to work demands.
	I have felt tired or physically exhausted after working.

Table A4. *Cont.*

Construct	Questions
Work Exhaustion	I have experienced headaches because of my work.
	I feel burned out from my work.
	Working all day is really a strain for me.
	I feel tired when I get up in the morning and have to face another day on the job.
	I feel used up at the end of the workday.

Table A5. Prevention-Focused Jon Crafting.

Construct	Measuring Item
Prevention-focused job crafting	I make sure that my work is mentally less intense.
	I try to ensure that my work is emotionally less intense.
	I manage my work so that I minimize contact with people whose problems affect me emotionally.
	I organize my work to minimize contact with people whose expectations are unrealistic.
	I try to ensure that I do not have to make many difficult decisions at work.
	I organize my work so that I do not have to concentrate for too long at one time.

Table A6. Promotion-focused Job crafting.

Construct	Questions
Increasing structural job resources	I try to develop my capabilities.
	I try to develop myself professionally.
	I try to learn new things at work.
	I make sure that I use my capacities to the fullest.
	I decide on my own how I do things.
Increasing social job resources	I ask my supervisor to coach me.
	I ask whether my supervisor is satisfied with my work.
	I look to my supervisor for inspiration.
	I ask others for feedback on my job performance.
	I ask colleagues for advice.
Increasing challenging job demands	When an interesting project comes along, I offer myself proactively as project co-worker.
	If there are new developments, I am one of the first to learn about them and try them out.
	When there is not much to do at work, I see it as a chance to start new projects.
	I regularly take on extra tasks even though I do not receive extra salary for them.

Table A7. (Managers') Decision Support Orientation.

Construct	Questions
Decision Support Orientation	When algorithmic dashboards indicate performance changes, my manager uses the information to start a supportive discussion.
	My manager treats algorithmic alerts as signals to understand underlying issues rather than as final judgments.

Table A7. *Cont.*

Construct	Questions
Decision Support Orientation	If performance issues are flagged by the system, my manager collaborates with employees to find solutions.
	Algorithmic data helps my manager identify development needs and growth opportunities.
	When algorithmic systems highlight risks, my manager focuses on coaching rather than punishment.
	My manager considers individual circumstances before acting on algorithmic performance indicators.
	Algorithmic information is used by my manager to help employees learn and improve.
	My manager applies personal judgment when interpreting algorithmic performance data.

Table A8. (Managers') Enforcement Orientation.

Construct	Questions
Enforcement Orientation	When algorithmic systems flag underperformance, my manager must initiate formal actions regardless of context.
	Algorithmic alerts largely determine how my manager responds to performance issues.
	Algorithmic data is used to justify penalties or negative consequences.
	Algorithmic systems make my manager act as an enforcer of organizational rules rather than a supportive leader.
	My manager focuses more on meeting algorithm-defined metrics than on employee development.
	Once the system identifies a problem, managerial discretion is limited.
	Algorithmic performance indicators are used mainly to enforce compliance with targets.
	My manager has little flexibility to deviate from algorithmic performance rules.

Appendix B

Table A9. Pilot reliability reporting.

Construct	Pilot N	Items	Cronbach's α	Corrected Item–Total Correlation Range	Decision
Decision-support orientation	60	8	0.89	0.52–0.76	Retain eight items; clarify wording based on participant feedback
Enforcement orientation	60	8	0.91	0.58–0.79	Retain eight items; clarify wording based on participant feedback

Table A10. Distribution of the final sample across participating fast-food chains and outlets.

Chain	Participating Outlets	Final Respondents	Shared-Supervisor Information
KFC	32	180	Multiple respondents shared supervisors
Wallace	25	135	Multiple respondents shared supervisors
Subway	18	64	Multiple respondents shared supervisors
McDonald's	39	168	Multiple respondents shared supervisors
Total	114	547	Supervisor identifiers not retained

Appendix C

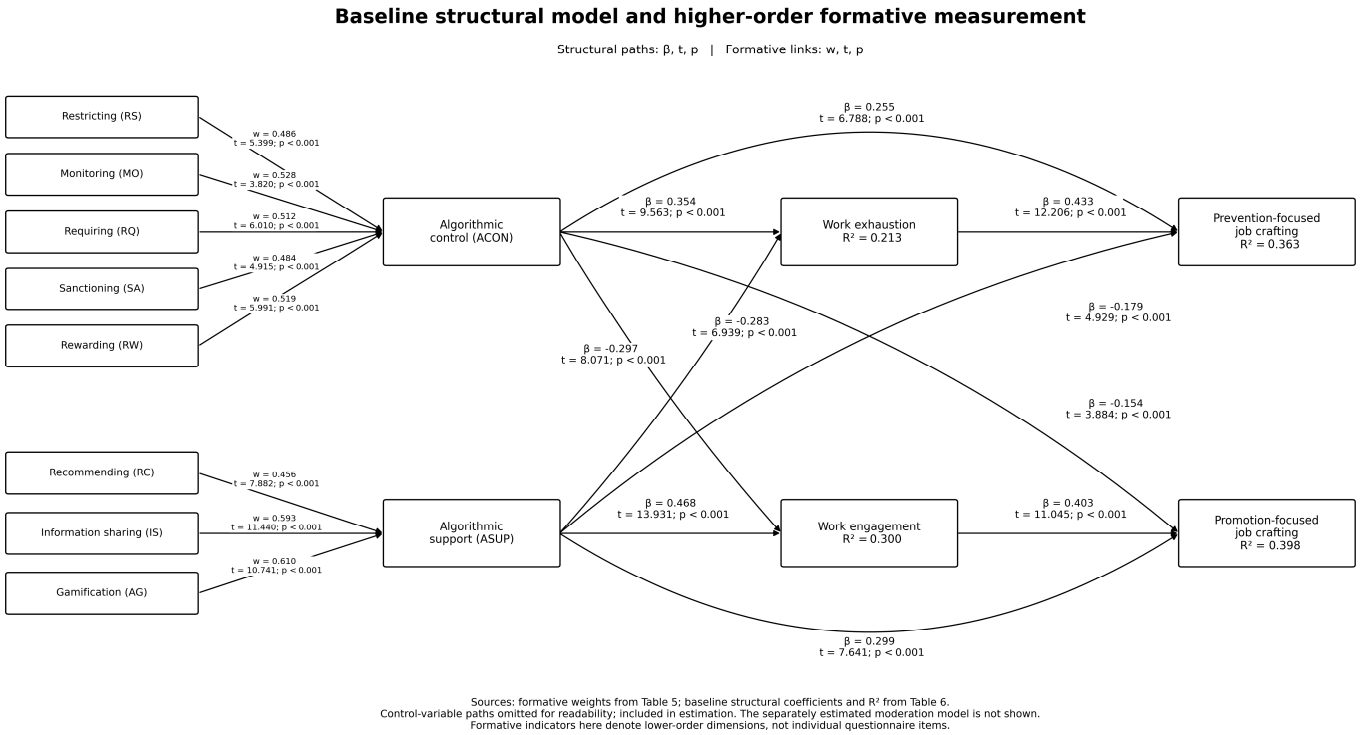


Figure A1. Baseline structural model and higher-order formative measurement.

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