Artificial Intelligence and the Restructuring of the Organizational Architecture

Jasmijn C. Bol

Tulane University

Dennis Campbell

Harvard University

Jake Krupa

Tulane University

Wenxin Wang

Harvard University

I. INTRODUCTION

The rapid diffusion of artificial intelligence (AI) is reshaping the nature of work in fundamental ways. While some tasks are becoming fully automated, many others are increasingly augmented through human–AI collaboration, producing outcomes that neither could achieve alone. These changes require organizations to reconsider not only how technology is deployed but also how organizational structures should adapt. In particular, technological advances are altering the calculus of organizational design by reducing knowledge and expertise barriers and facilitating access to centralized information. In this study, we use a field experiment to examine how reallocating decision rights, together with the implementation of AI, affects both decision quality and employee motivation. This question is critical because designing organizational architecture that both leverages new technology and motivates employees to collaborate effectively with AI is essential for long-term organizational effectiveness in AI-integrated environments.

We examine a home care organization that provides non-medical in-home services to help older adults live safely, comfortably, and independently. Caregivers assist with daily activities such as bathing, cooking, and errands, and the organization also offers specialized support for memory care, end-of-life care, and post-hospital recovery. A central challenge in this setting is scheduling, which goes beyond traditional concerns such as minimizing travel costs and ensuring availability. Matching caregivers with clients based on potential compatibility (i.e., personality traits, client and caregiver preferences, etc.) and maintaining continuity of care by keeping care teams small and consistent over time are also organizational priorities. To address this complexity, the organization implemented an AI-based scheduling tool that integrates these dimensions and guides schedulers in assigning caregivers to clients. Importantly, rather than being centralized at headquarters, the tool is placed in the hands of the care teams. This shift allows caregivers to use

AI support to design their own schedules, thereby reallocating decision-making authority from headquarters to frontline employees.

The organization implemented the intervention using a staggered rollout. In the first stage, scheduling authority was reallocated by granting decision-making rights to two-thirds of the caregiver teams (“self-scheduling”), while the remaining one-third continued to be scheduled by headquarters. This design allowed us to assess the motivational consequences of autonomy by comparing headquarters scheduling, representing centralized authority, with self-scheduling, representing decentralized authority. In the second stage of the staggered implementation, the organization introduced an AI-based scheduling tool to a subset of the self-scheduling teams. Half of these teams were provided with the AI tool, while the other half continued self-scheduling without AI support. As a result, the field experiment comprises three conditions: headquarters scheduling, self-scheduling without AI, and self-scheduling with AI. This design enables us to test not only the effects of autonomy but also whether these effects are further enhanced when teams collaborate with AI. Moreover, it allows us to examine the quality of scheduling decisions across four theoretically relevant conditions: with and without local knowledge, and with and without AI support. By intersecting these dimensions, we assess whether AI-assisted self-scheduling enables teams to make more effective use of their local knowledge, including insights into client relationships, staff availability, and evolving client needs.

This paper makes several contributions to the literature on organizational design, management control, and AI-enabled work. First, we extend the classic literature on organizational architecture (Jensen and Meckling 1976; Brickley, Smith, and Zimmerman 2016) by showing how AI reshapes the calculus of the “three-legged stool” of task allocation, performance measurement, and rewards. Specifically, we theorize and test how AI reduces expertise and information barriers, thereby making it feasible to reallocate decision rights closer to employees with local knowledge.

Second, we contribute to research on incentives and motivation (e.g., Deci et al. 1999; Bénabou and Tirole 2002; Bol and Loftus 2023) by demonstrating that autonomy over decision-making enhances motivation through self-cognitive activation. We provide evidence on whether motivation increases when employees are granted greater decision-making authority, and whether this effect is further amplified when such authority is paired with supportive AI technology.

Third, we advance the growing literature on human–AI collaboration by examining AI not only as a replacement technology but as a tool for enhanced employee autonomy. Whereas much existing research examines the effects of AI within fixed organizational structures (e.g., Dell'Acqua et al., 2025) or emphasizes the risks of diminished psychological ownership (e.g., Bol, Leung, and Sun, 2025) and overreliance on AI (e.g., Buçinca, Malaya, and Gajos, 2021), we focus on how AI support can strengthen employees' perceptions of competence and amplify the motivational benefits of autonomy.

Finally, by leveraging a natural field experiment in a caregiving organization, we provide rare causal evidence on how AI-enabled decision-support affects both decision quality and employee motivation in a real-world setting. This dual focus bridges organizational economics, psychology, and information systems, offering practical insights for managers seeking to design control systems that both leverage new technologies and provide employees with autonomy.

II. THEORY DEVELOPMENT

Organizational Architecture

Organizational architecture — the “three-legged stool” of task allocation, performance measurement, and rewards — is central to aligning employee incentives with organizational objectives and, ultimately, organizational success (Jensen and Meckling 1976). Research established that decision rights are best allocated to individuals who possess the relevant knowledge and skills, while accounting for the control costs of delegation and the need for effective performance evaluation (Jensen and Meckling 1976; Kaplan 1992; Gold et al. 2001). The economic literature thus emphasizes matching employees’ knowledge and skills with appropriate incentives, ensuring they are closely tied to the tasks for which employees are responsible (Raveendran et al. (2016), (2020)).

Building on these insights, managers recognize that designing organizational architecture involves balancing multiple, often competing considerations and is therefore a complex task. Although decision rights should ideally rest with those who possess the most relevant information and have incentives to use it effectively, achieving this alignment in practice is challenging. Lower-level employees often hold critical local knowledge about operations, customers, and technologies, while higher-level managers typically possess a broader, integrative understanding of the organization (Jensen and Meckling, 1992; Brickley, Smith, and Zimmerman, 2016). Because much of the knowledge required for effective decision making is tacit and context-specific, sharing it across hierarchical levels is both costly and imperfect (Dessein 2002; Bol et al., 2018). As a result, many organizations have historically concentrated decision-making authority at higher levels, where incentive alignment, although never perfect, is less costly. This centralization, however, comes at a significant informational cost, as it limits the organization’s ability to draw on valuable local knowledge.

The rise of new technologies, and AI in particular, is fundamentally reshaping the balance between centralization and decentralization in organizational decision making (Gibbs and Van der Stede, 2025). AI systems can aggregate, process, and analyze large, complex datasets in real time, thereby reducing the informational frictions that historically constrained the effective delegation of decision rights. By lowering the cost of acquiring, transmitting, and interpreting information, AI enables knowledge that was previously dispersed or tacit to be more systematically captured and utilized. Moreover, contemporary AI tools increasingly function as decision-support systems that embed specialized expertise once attainable only through extensive training and experience. For example, AI can extract patterns and generate insights from centralized databases, transforming raw information into actionable recommendations that frontline employees can readily interpret and apply (e.g., Brynjolfsson, Li and Raymond 2025).

We posit that these technological developments change the calculus of organizational design. Specifically, when AI reduces the knowledge and expertise barriers and facilitates access to centralized information, it becomes increasingly feasible to reallocate decision rights. Such restructuring allows organizations to better leverage employees' local knowledge while still ensuring that decisions are informed by firm-wide data and analytic capabilities.

This prediction, however, is not without tension. Empirical evidence shows that user expertise plays a critical role in the effectiveness of human–AI collaboration (e.g., Dell'Acqua 2025; Brynjolfsson, Li and Raymond 2025; Wang, Gao and Agarwal 2024). This suggests that employees lower in the hierarchy may not always be able to leverage AI-generated insights as effectively as higher-level experts, particularly when AI systems are opaque or misaligned with task demands. Additionally, recent work underscores that user expertise mediates how individuals interpret and apply AI advice. For example, a recent field experiment at Procter & Gamble found that while AI elevated individuals' performance to rival that of human teams and helped professionals bridge functional silos, its benefits depended on users' expertise to integrate AI outputs into their own judgment (Dell'Acqua et al. 2025).

Hence, although the role of expertise must be considered, when local knowledge is rich and AI tools are developed to be transparent, intuitive, and supportive of non-expert users, decision-making authority can be shifted downward without losing access to the analytical insights traditionally concentrated at higher organizational levels. In such settings, employees can combine their local knowledge with AI-generated analyses, enabling more informed and responsive decisions. Accordingly, reallocating decision rights to employees with local knowledge, when supported by well-designed AI decision-support tools, is expected to enhance both decision quality and organizational performance. This leads to the following formal hypothesis:

> *Hypothesis 1: Decision quality is higher in teams combining local knowledge with AI decision-support than in teams relying either solely on centralized authority or on local decision-making without AI.*

Incentive Alignment

As noted above, the design of organizational architecture depends not only on information and expertise but also on incentive alignment. Traditionally, organizations have relied on performance evaluation and reward systems to ensure that decision-making authority is coupled with appropriate incentives (Holmstrom 1979; Holmstrom and Milgrom 1994). However, incentive alignment is not limited to the explicit rewarding of outcomes or actions. Research has shown that other mechanisms can also motivate and direct effort. A growing body of work suggests that controls can also operate through non-extrinsic reward channels (Lerner and Tirole 2002; Osterloh and Frey 2000; Deci, Koestner, and Ryan 1999; Baumeister and Leary 1995).

In this study, following the framework of Bol and Loftus (2023), we focus on self-cognitive activation. By this, we mean the positive or negative self-evaluations employees experience in response to their work. These include positive states such as feelings of competence, pride, self-esteem, and self-efficacy, as well as negative states such as incompetence, inferiority, or diminished self-worth. Decades of psychological and economic research demonstrate that individuals are motivated to exert effort not only to secure extrinsic outcomes but also to achieve positive self-cognitive activation and to avoid negative self-cognitive activation (Akerlof and Kranton 2005; Bénabou and Tirole 2002; Ryan, Mims, and Koestner 1983; Deci, Connell, and Ryan 1989; Bandura 1997; Bandura and Locke 2003; Stajkovic and Luthans 1998; White 1959).

Management controls influence self-cognitive activation in several ways. For example, the frequency, quality, and tone of performance feedback directly shape employees' self-evaluations. Positive feedback can enhance self-efficacy and feelings of competence, while negative or overly critical feedback may diminish affect and motivation (Ilgen, Fisher, and Taylor 1979; Nease, Mudgett, and Quiñones 1999; Ilgen and Davis 2000; Hall 2008). Beyond feedback, the allocation of decision-making rights also plays a critical role in shaping self-cognition. Prior research demonstrates that expanding employees' decision-making authority, often conceptualized as empowerment, strengthens motivation by fostering feelings of autonomy, competence, and self-worth. Conversely, restrictive monitoring or surveillance practices can undermine these self-cognitive benefits and contribute to feelings of mistrust or diminished status (Sewell and Barker 2006; Gopinath and Becker 2000). Building on this line of work, we posit that motivation can be enhanced by restructuring organizations to provide employees with a greater sense of autonomy through expanded decision-making authority. This leads to the following hypothesis:

Hypothesis 2: Employees granted greater decision-making authority exhibit higher motivation than employees with limited decision-making authority.

Human-AI Collaboration

As discussed above, embedding AI-based tools into daily work enables organizations to reallocate decision-making authority without necessarily requiring extensive domain-specific training. Drawing on self-determination theory (Deci and Ryan, 1985), we argue that pairing enhanced decision-making authority with AI-enabled decision-support tools increases employee motivation by strengthening employees' perceived competence, a core psychological need identified in self-determination theory. Without AI support, employees may be reluctant to assume new decision-making responsibilities if they perceive these tasks as overly complex or traditionally reserved for higher-level managers (Karim, Lee and Hoehn-Weiss, 2023). By providing real-time feedback and analytical guidance, AI reduces perceived uncertainty and cognitive load, enabling employees to approach tasks with greater confidence. This strengthened sense of competence, together with increased autonomy, fosters positive self-cognitive activation and, consequently, motivation.

This prediction, however, is not without tension. Some prior studies have also shown that heavy reliance on algorithmic systems may reduce employees' sense of psychological ownership and engagement with their work (Bol, Leung, and Sun 2025). Under such conditions, collaboration with AI may paradoxically undermine rather than enhance feelings of competence and self-worth, reducing motivation. This tension suggests that the motivational consequences of advanced technology tools are not uniform but contingent on how the technology is embedded.

Nevertheless, emerging evidence suggests that large language models (LLMs) differ from earlier generations of artificial intelligence because they function less as impersonal tools and more as cybernetic teammates, fostering richer, more interactive, and socially grounded forms of collaboration (Dell'Acqua et al., 2025; Boussioux et al., 2024). These developments make it increasingly plausible that AI support will amplify, rather than diminish, the motivational benefits of enhanced autonomy through expanded decision-making rights. Based on this reasoning, we propose the following directional hypothesis:

Hypothesis 3: Employees granted greater decision-making authority exhibit higher motivation when supported by AI-enabled decision-support systems, relative to employees with equivalent authority but without AI support.

III. RESEARCH SETTING AND EXPERIMENTAL DESIGN

Research Method

To test our hypotheses, we employ a mixed-method approach consisting of interviews, a field experiment, two surveys, and archival data of a home care organization. We began with semi-structured interviews to gain insight into the organization's strategy, priorities, and culture. Semi-structured interviews were chosen for their ability to elicit rich, contextualized information. We interviewed the founder/CEO, a board member, and the two head-office schedulers. Insights from these interviews informed the design of the experimental interventions and measurement strategy.

A central theme emerging from the interviews was the CEO's longstanding interest in increasing caregiver agency. She emphasized that caregivers possess a strong sense of responsibility toward clients and hold valuable knowledge on client needs. She also noted that overly centralized decision rights risk suppressing this initiative. As a result, caregivers are afforded the agency to decide how to structure their day with clients, respond to what is actually happening rather than follow rigid protocols, and bring difficult situations to the team to jointly develop solutions. She further expressed a desire to move beyond agency toward what she defines as autonomy or self-governance, where caregivers self-schedule within cooperative groups, collectively determine policies and practices, teams hold budget authority and decision-making power, and the organization is guided by those who carry out the work. At the same time, she voiced concern about how to transition toward autonomy without overwhelming caregivers with new responsibilities that may require skills they do not yet possess. Consequently, the research team assisted her in developing a user-friendly AI decision-support tool designed to bridge the skill gap, reduce informational frictions in scheduling, and facilitate the reallocation of decision-making authority. The organization implemented the AI tool through a two-stage field experiment that first reallocated scheduling authority and subsequently introduced AI support. This design produced three regimes — centralized scheduling, self-scheduling without AI, and self-scheduling with AI — enabling tests of our hypotheses regarding decision quality and employee motivation (see Experimental Design for details on stages and group assignments).

To capture key outcomes from the field experiment, we developed two questionnaires in close collaboration with the organization to ensure contextual relevance and validity. The caregiver survey (administered pre-intervention, after Stage 1, and after Stage 2) measures employee perceptions such as motivation, satisfaction (generally and with scheduling assignments specifically), and intended retention, as well as process variables such as self-cognition, along with controls including demographics and experience (see Appendix 1 for the full questionnaire). The client survey assessed client satisfaction and perceived client–caregiver connection; when clients were unable to participate, a close proxy respondent completed the instrument (see Appendix 2 for the full questionnaire). Finally, the organization provided administrative records, including hours worked, reported incidents, caregiver records of each client appointment, retention and turnover, and scheduling adjustments.

In sum, the interview evidence motivated the interventions and clarified managerial objectives; the field experiment identified the causal effects of the reallocation of decision rights and the introduction of the AI; the surveys captured attitudinal and process-level mechanisms; and the archival data provided behavioral and performance-based outcomes. Taken together, the triangulation of these components enabled rigorous testing of our hypotheses regarding decision quality, employee motivation, and the moderating role of AI-enabled decision support.

Research Setting

We examine a U.S.-based home care organization that provides non-medical in-home services to help older adults live safely, comfortably, and independently. Caregivers assist clients with daily activities such as bathing, cooking, and errands, and the organization also offers specialized services in memory care, end-of-life support, and post-hospital recovery. The organization operates as a non-profit, relying on private pay and charging premium rates in exchange for its commitment to high-quality, personalized care.

The organization's strategy is rooted in a philosophy of respect, both for clients and for employees. While client well-being is the foremost priority, the leadership also emphasizes treating caregivers with dignity and fairness. This stance represents a deliberate departure from industry norms: the home care sector has historically undervalued caregivers, often exploiting their limited employment opportunities. In contrast, the company's founder sought to radically transform this dynamic by creating an environment where caregivers are respected as professionals and supported in their work.

Scheduling

Scheduling represents a central operational challenge for many organizations, but it is particularly complex in home care settings. Two industry-specific factors contribute to this complexity. First, demand can fluctuate dramatically and unpredictably; for instance, in end-of-life care, client deaths may occur suddenly, leading to an immediate reduction in service needs. Second, caregivers are employed on an hourly contract basis. When their hours are reduced, they often need to seek additional income by taking on private clients or other jobs, which in turn decreases their availability and further destabilizes scheduling.

Moreover, the organization's emphasis on connection and respect introduces additional layers of complexity. Scheduling decisions are not driven solely by the need to ensure coverage but are instead shaped by a broader commitment to high standards of care. A central consideration is the match between caregivers and clients, with attention paid to aligning personalities and preferences. For example, avoiding pairing a quiet client with a particularly talkative caregiver. Continuity of care is also viewed as essential, as clients find it disruptive to interact with a constant rotation of caregivers. To foster familiarity and trust, the organization therefore seeks to maintain consistency in client–caregiver relationships. Finally, the organization extends its philosophy of respect to employees by granting grievance days when a client passes away, acknowledging the emotional toll such events can take on caregivers. Prior to the interventions described below, scheduling was handled at the head office by two schedulers who communicated directly with individual caregivers.

Organizational Structure

Employees are compensated with a fixed hourly wage, which is structured as an efficiency wage, set above the industry average. The organization does not offer bonuses and does not operate a formal performance measurement system. However, substantiated client or peer complaints , although rare, can result in dismissal. In terms of responsibilities, the organization deliberately deviates from sector norms. Consistent with its philosophy of treating employees with respect, it emphasizes recognition of caregivers' skills and their internal motivation to act in the best interest of clients. Rather than micromanaging, the organization extends greater responsibilities to caregivers, operating on the belief that employees will rise to the challenge when given agency and trust.

AI-based Scheduling Tool

The schedulers at the head office do not use a sophisticated scheduling system. Instead, they constructed schedules manually, relying heavily on tacit knowledge and personal relationships with both clients and caregivers. A significant amount of their time was devoted to contacting caregivers to manage frequent scheduling changes. While the organization believed this approach worked reasonably well, it proved difficult to scale. The challenge became even more pronounced as the organization expanded into new cities, where greater information asymmetry existed between caregivers and the head office schedulers.

To address these challenges, the organization, in collaboration with the research team, developed an AI-based scheduling tool. The AI-scheduling tool was built using LettaAI, a large language model (LLM) wrapper that enables the creation of AI agents with long-term memory, advanced reasoning, and the ability to use custom tools. LettaAI is model agnostic, meaning it can be developed with LLMs from AI companies such as OpenAI, Anthropic and Google, of which we chose to run the AI agent on Gemini 2.5 Flash.

LettaAI allows the development of memory blocks in order to give agents a long-term memory, even as different users interact with it. We construct four key memory blocks, two that are static (unchanging) and two that are mutable (modifiable) by the LLM. The first static memory block is the agent's persona memory block. This aligns the LLMs conversational tone and style to align with the organization's cultural principles around connection, respect, and trust between caregivers and clients.

The second static memory block controls the factors considered when the LLM is asked to assist the user in scheduling a caregiver with a client. In order to provide useful information for this memory block, the head office schedulers provided historical client-caregiver match scores (1 to 5, where 5 was an ideal match between client and caregiver) based on their own recall. The research team used a ridge regression to extract factors that contributed to higher match scores, based on client and caregiver characteristics such as age, gender, client risk profile, caregiver experience at the company, and location. The second static memory block includes the relative importance of each factor that contributes to high match scores in order to mimic the knowledge and expertise that the head office schedulers developed in matching clients and caregivers. This memory block also contains general information on the scheduling task and priorities of the organization, such as considering the workload of caregivers, the distance between client and caregiver, and other instructions that all schedulers receive, to make sure the AI agent operates with the same information set and heuristics that head office schedulers have. This memory block also controls how the AI agent reads the future organizational schedule to prevent double-scheduling caregivers.

The third memory block enables the AI agent to record and update caregiver availability over time. Many caregivers hold second jobs or have personal commitments that limit when they can accept new scheduling assignments. Although no formal records of this availability are maintained, head-office schedulers gradually develop informal knowledge about each caregiver's schedule. With the introduction of the AI tool, this knowledge becomes systematized. As self-schedulers contact caregivers to confirm their availability and report this information to the AI agent, the system continuously updates the caregiver availability memory block. Over time, the AI agent learns to incorporate increasingly granular availability data, allowing it to generate more accurate and efficient scheduling recommendations.[1]

The fourth memory block allows updates from the AI agent to record specific information about each self-scheduler (i.e., user). As the self-scheduler uses the tool more, the AI agent updates the user memory block with information it learns about the self-scheduler. Primarily the AI agent will record preferences for communication style, including objective factors such as communicating in English or Spanish as well as subjective factors such as a preference for more

[1] As an illustrative example, suppose that Self-scheduler A uses the AI agent to assign a caregiver to a new client who needs assistance on Monday nights. The AI agent first recommends Caregiver B based on general schedule availability. Self-scheduler A converses with Caregiver B and learns that Caregiver B has an outside obligation that prevents them from working on Monday nights. Self-scheduler A reports back to the AI agent that Caregiver B is unavailable on Monday nights (and they can include if that is temporarily – for example, for a child's sports league – or if that unavailability is for the foreseeable future). The AI agent will suggest the next best caregiver and update the caregiver availability memory block to note that Caregiver B is not available on Monday nights. In future scheduling tasks, the AI agent will know to deprioritize Caregiver B if the assignment requires working on Monday night. Also, if Caregiver B is one of the few caregivers available for a new client in the future, the AI agent can prompt Self-scheduler A to check with Caregiver B to see if their outside obligation on Monday night still exists after some time.

direct tasks (“text this person”) or more gentle nudges (e.g., “have you considered this person?”). All AI agent communication will primarily consider the persona memory block first, but then allow slight modifications based on the user memory block. This memory block mimics the collegiality developed between head office schedulers and caregivers under their current organizational structure.

Overall, the AI scheduling tool functions as an on-demand expert assistant for local self-schedulers, directly addressing the CEO's concern about how to expand caregiver autonomy without overwhelming them with responsibilities that require unfamiliar skills. Self-schedulers remain responsible for contacting caregivers and entering final schedules into the system, but the tool bridges the skill gap in two key ways: (1) it narrows down the pool of potential caregivers by analyzing availability data and optimizing client-caregiver matches, and (2) it provides real-time guidance through scheduling challenges. For example, when a self-scheduler faces a last-minute change and needs step-by-step help navigating the rescheduling process. In essence, the tool reduces the information frictions and skill barriers that might otherwise inhibit caregivers successfully taking on self-scheduling responsibilities, making the transition toward self-governance more feasible.

Experimental Design

In line with its philosophy of respecting and trusting caregivers, the organization sought to enhance caregiver autonomy. Management chose to begin with scheduling, recognizing that caregivers possess valuable local knowledge that informs these decisions. Caregivers not only have a clearer understanding of their team’s availability and preferences but also a deeper awareness of clients’ needs than the schedulers based at the head office.

First Intervention: Employee Autonomy

In the first stage of the field experiment, the company created a treatment group of 27 caregivers and a control group of 16 caregivers (see Figure 1). Caregivers in the control group continued with the status quo, with all scheduling handled by the head office. By contrast, caregivers in the treatment group were organized into client-based teams and collectively assumed responsibility for the scheduling of their clients' hours. To initiate this process, management first held "huddles" in which team members met to discuss client needs. Afterward, scheduling responsibilities were formally delegated to the teams. Within each team, one caregiver took on the administrative task of entering and maintaining the schedule, but the team as a whole received decision-making authority and worked independently. Head office schedulers remained available for support if assistance was required.

Second Intervention: AI Deployment

In the second stage, half of the caregivers in the treatment group were randomly assigned to be given access to the AI scheduling tool to support their scheduling tasks. The other half continued to operate in team-based groups with collective responsibility for scheduling, effectively serving as a second control group. The original control group, meanwhile, remained under the traditional arrangement, with all scheduling handled by the head office schedulers (see Figure 1).

Variable Measurement

Decision Quality

We proxy decision quality through three complementary measures. First, we assess the quality of client-caregiver connection using client survey responses that capture overall satisfaction and relational dimensions such as curiosity, compassion, collaboration, consistency, and courage in caregiving interactions (see Appendix 2). Second, we examine caregiver-reported match quality through post-visit notes where caregivers rate their connectivity and satisfaction with each client assignment. Third, we evaluate caregiver satisfaction with the scheduling process itself, using survey responses that address fairness, timeliness, alignment with availability and preferences, and willingness to take on additional responsibilities (see Appendix 1). We also assess continuity of care by comparing the degree of caregiver reassignments and consistency in care provision across control and treatment groups, given the organization's emphasis on minimizing disruptive caregiver rotation.

Employee Motivation

We measure employee motivation using survey responses to the item: "I feel strongly motivated to give my best effort at work every day." Participants were asked to indicate their level of agreement on a seven-point Likert scale (1 = Strongly disagree, 7 = Strongly agree). Caregivers completed the survey (see Appendix 1) at three points in time: the pre-period, Stage 1, and Stage 2 of the field experiment. This design allows us to compare motivation levels not only across experimental conditions but also over time.

IV. RESULTS

Planned Tests of the Hypotheses

Hypothesis 1: Decision Quality

To examine whether reallocating decision rights to caregivers improves decision quality, we compare outcomes across three scheduling regimes using a difference-in-differences approach that controls for pre-period baselines: (a) centralized scheduling by head office (control group), (b) decentralized scheduling by caregiver teams without AI support, and (c) decentralized scheduling with AI support. We assess decision quality through multiple measures—client-reported satisfaction and relational quality, caregiver-reported match quality, and caregiver scheduling satisfaction—and test whether Treatment B (self-scheduling with AI) in Stage 2 outperforms both the centralized control and Treatment A (self-scheduling without AI). We plan to employ ANOVA to compare outcomes across the three conditions, as well as targeted regressions that control for relevant caregiver and client characteristics to isolate the effect of AI-supported decentralization on each decision quality indicator.

Hypothesis 2: Motivation from Autonomy

To assess the motivational consequences of reallocating decision rights, we use repeated survey measures of employee motivation collected in the pre-period, after Stage 1, and after Stage 2. Using ANOVA and a difference-in-differences framework, we compare changes in self-reported motivation between the treatment groups (A and B combined in Stage 1) and the control group. This staggered design allows us to examine both cross-sectional differences between conditions and within-subject changes over time, controlling for pre-period baseline levels.

Hypothesis 3: Incremental Effects of AI on Motivation

To test whether AI strengthens the motivational benefits of autonomy, we exploit the second-stage randomization within the decentralized condition. Half of the self-scheduling teams were provided with AI support (Treatment B), while the other half continued scheduling without technological assistance (Treatment A). Using ANOVA and difference-in-differences regressions that control for Stage 1 levels, we compare motivation outcomes between these two groups to isolate the incremental effect of AI support, holding autonomy constant.

Process Analyses

We plan to further explore the mechanisms underlying our main findings. Specifically, we plan to conduct mediation analyses to examine whether the observed effects on motivation operate through feelings of empowerment and self-cognitive activation. This allows us to test whether increases in autonomy and AI support enhance motivation by strengthening employees' sense of competence, self-worth, and control over their work. In doing so, we seek to provide evidence on the psychological processes through which structural changes in decision-making authority and technological support translate into motivational outcomes. By distinguishing between direct effects (arising from increased autonomy or improved information access) and indirect effects (arising from enhanced self-perceptions of competence and feelings of empowerment), these analyses help clarify whether AI-assisted autonomy motivates employees primarily through informational improvements, psychological mechanisms, or a combination of both. This approach thus offers a more nuanced understanding of how organizational design and technological interventions jointly shape motivation and performance in frontline work settings.

Additional Analyses.

Beyond our primary hypotheses, we examine caregiver retention as an additional outcome. We assess retention through both survey measures of retention intentions (likelihood to stay with the company) and archival data tracking actual turnover rates across experimental conditions. Using similar difference-in-differences approaches, we test whether reallocating decision rights and providing AI support affect caregiver retention, comparing outcomes across the control and treatment groups in both stages of the experiment.

V. CONCLUSION

This study aims to advance understanding of how AI reshapes organizational architecture by examining how AI-enabled decision support and delegated authority jointly influence decision quality and employee motivation. Through a field experiment in a home care organization, we aim to provide evidence on whether reallocating decision rights to employees with local knowledge can improve decision quality, particularly when supported by AI systems that reduce informational frictions. At the same time, we expect that granting greater autonomy will enhance employees' motivation, especially when AI strengthens their sense of competence and control. Together, these analyses seek to illuminate how AI can serve as a catalyst for more decentralized and autonomous forms of organizational design. Rather than replacing human judgment, AI implemented in a supportive and transparent manner has the potential to enable frontline employees to make more informed and motivated decisions, aligning technological innovation with human autonomy and organizational effectiveness. Future research can build on this work to identify the conditions under which AI most effectively complements human decision making across different organizational contexts.

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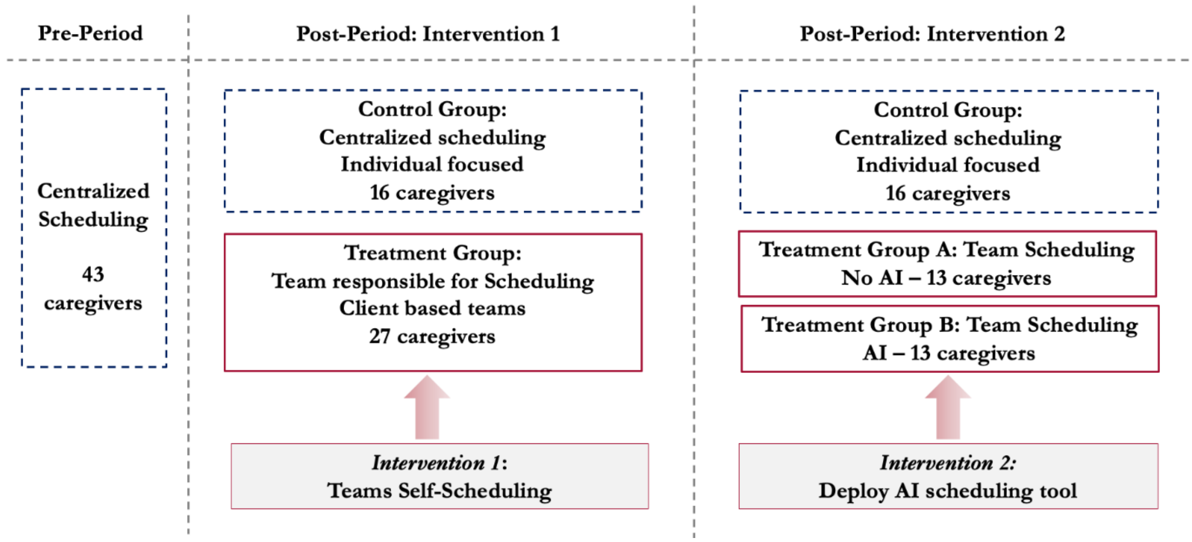
Figure 1 Research Design

This figure visualizes our interventions and the composition of treatment and control group in this field experiment. This figure illustrates the two-stage field experiment. The resulting design yields three experimental conditions: (1) centralized scheduling by head office, (2) decentralized self-scheduling without AI support, and (3) decentralized self-scheduling with AI support.



Appendix 1 Employee Questionnaire

Section 0 - Demographical Information

What is your gender?

- Female
- Male
- Non-binary / third gender
- Prefer not to say

What is your level of education?

- Less than a high school degree
- A high school degree
- Some college
- A college degree
- Higher than a college degree

What is your race?

- White/ Caucasian
- Black
- Latino
- Asian
- Other
- I prefer not to answer

What is your age?

Do you consider yourself to be part of the LGBTQ+ Community?

- Yes
- No
- I prefer not to answer.

How many years have you been working for Biscochito?

How many years have you been working as a caregiver (paid/unpaid)?

Section 1 – Drivers of Effort

Indicate the extent to which you agree with each of the statements below. All questions will have the following scale: 1 = Strongly disagree, 2 = Disagree, 3 = Somewhat disagree, 4 = Neither agree nor disagree, 5 = Somewhat agree, 6 = Agree, 7 = Strongly agree.

Explicit rewards

- I am very well compensated for the work I perform.
- I receive a lot of recognition for the work I perform.
- I feel appreciated for my contributions at work.
- Receiving rewards is very motivating to me.
- Receiving recognition is very motivating to me.

Self-cognition

- My job gives me a strong sense of self-worth.
- I feel empowered to do my job.
- My interactions with management make me feel incompetent.
- Feeling good about myself is very motivating to me.
- Feelings of empowerment are very motivating to me.

Status

- There is public recognition for high performers in our organization.
- There are large differences in status between employees at our organization.
- Status is very motivating to me.
- Public recognition is very motivating to me.

Prosocial behavior

- I often go beyond my responsibilities to help the clients I care for.
- I often go beyond my responsibilities to help my colleagues.
- Helping others is very motivating to me.

Affiliation

- When someone criticizes my organization, it feels like a personal insult.
- When I talk about my organization, I usually say “we” rather than “they”.
- My organization’s successes are my successes.
- My direct colleagues feel like a community to me
- Being part of a community is very motivating to me.

Intrinsic motivation

- In my job, there are lots of tasks I genuinely like to perform.
- Performing tasks I enjoy is very motivating to me

Section 2 – Directing Effort

Indicate the extent to which you agree with each of the statements below. All questions will have the following scale: 1 = Strongly disagree, 2 = Disagree, 3 = Somewhat disagree, 4 = Neither agree nor disagree, 5 = Somewhat agree, 6 = Agree, 7 = Strongly agree.

Understanding

- I understand the mission of the organization.
- I understand the tasks the organization wants me to perform.
- I understand which of my tasks to prioritize.

Capabilities

- I have the skills to excel in my job.
- I have the tools to perform my job effectively.
- I have the training to succeed in my job.
- I have sufficient time to excel in my job.

Preference

- My personal preferences for which tasks to prioritize match the priorities of the organization.

Section 3

Indicate the extent to which you agree with each of the statements below. All questions will have the following scale: 1 = Strongly disagree, 2 = Disagree, 3 = Somewhat disagree, 4 = Neither agree nor disagree, 5 = Somewhat agree, 6 = Agree, 7 = Strongly agree.

- I feel strongly motivated to give my best effort at work every day.
- I trust my company to act in my best interests.
- I am satisfied with my current job.
- I am treated respectfully at this organization.
- I am treated fairly at this organization.
- I am frequently provided with relevant feedback.
- I feel micromanaged in my role.
- I have a say in how I complete my work tasks.
- How much longer are you anticipate staying with this company?
    a. Less than 1 more year
    b. 1 to 3 more years
    c. 3 to 8 more years
    d. 8 to 15 more years
    e. More than 15 years

Section 4

Indicate the extent to which you agree with each of the statements below. All questions will have the following scale: 1 = Strongly disagree, 2 = Disagree, 3 = Somewhat disagree, 4 = Neither agree nor disagree, 5 = Somewhat agree, 6 = Agree, 7 = Strongly agree.

- The scheduling process is extremely fair
- The scheduling process does not take my personal circumstances into account.
- Not considering emergencies, the scheduling process is timely.
- It is easy for me to communicate when I am not available
- I am never scheduled for shifts when I am not available.
- I am consistently scheduled for shifts that align with my preferences.
- I am extremely willing to take on tasks beyond client caregiving.

Section 5 Resistance to change

Indicate the extent to which you agree with each of the statements below. All questions will have the following scale: 1 = Strongly disagree, 2 = Disagree, 3 = Somewhat disagree, 4 = Neither agree nor disagree, 5 = Somewhat agree, 6 = Agree, 7 = Strongly agree.

This is adapted from the Resistance to Change Scale by Shaul Oreg – Journal of Applied Psychology (2003).

Routine Seeking

- Generally, change is good

Emotional Reaction

- If I were to be informed that there's going to be a significant change regarding the way things are done at work, I would probably feel stressed.

Short-Term Focus

- Changing plans seems like a real hassle to me.

Cognitive Rigidity

- I don't change my mind easily.

Psychological Safety - Edmondson (1999) Psychological Safety Scale (7 items)

- If you make a mistake on this team, it is often held against you. *(Reverse-coded)*
- Members of this team are able to bring up problems and tough issues.
- People on this team sometimes reject others for being different. *(Reverse-coded)*
- It is safe to take a risk on this team.
- It is difficult to ask other members of this team for help. *(Reverse-coded)*
- No one on this team would deliberately act in a way that undermines my efforts.
- Working with members of this team, my unique skills and talents are valued and utilized.

Adaptability

- I am encouraged to develop new skills in my role.
- I feel supported in adapting to changes at work.

Section 6 Open-ended questions

- What feedback would you like to provide leadership?
- Are there any ideas to improve the organization you would like to share?

Appendix II Client Satisfaction Survey

Client Survey: Evaluating Your Caregiver Team

Overall Satisfaction

How satisfied are you with COMPANY’s services?

□ Very satisfied □ Satisfied □ Neutral □ Dissatisfied □ Very dissatisfied

How likely are you to recommend COMPANY's caregiving services to others?

□ Very likely □ Somewhat likely □ Neutral □ Somewhat unlikely □ Very unlikely

Evaluating the 5 C’s of Connection

Please rate how your caregivers demonstrate each of the 5 C's of Connection. For each quality, rate:

1. The caregiver who shows this quality the most
2. The caregiver who shows this quality the least

Curiosity

Curiosity means showing genuine interest in you as a person - what brings you joy and comfort. It's about wanting to know you, not just completing tasks.

For the caregiver who shows the most curiosity, how would you rate their level?

□ High □ Moderate □ Low

For the caregiver who shows the least curiosity, how would you rate their level?

□ High □ Moderate □ Low

Comments about Curiosity: (optional)
____

Compassion

Compassion means truly caring about your feelings and needs. It's responding with kindness and understanding when you need support, rather than rushing or dismissing your concerns.

For the caregiver who shows the most compassion, how would you rate their level?

□ High □ Moderate □ Low

For the caregiver who shows the least compassion, how would you rate their level?

□ High □ Moderate □ Low

Comments about Compassion: (optional)

____

Collaboration

Collaboration means working together as true partners. It's about valuing your input, preferences, and decisions rather than telling you what to do or just doing it for/to you.

For the caregiver who collaborates with you the most, how would you rate their level?

□ High □ Moderate □ Low

For the caregiver who collaborates with you the least, how would you rate their level?

□ High □ Moderate □ Low

Comments about Collaboration: (optional)

____

Consistency

Consistency means you can depend on your caregiver. It's about following through on promises and creating a sense of security, not leaving you wondering or anxious about your care.

For the caregiver who is the most consistent, how would you rate their level?

□ High □ Moderate □ Low

For the caregiver who is the least consistent, how would you rate their level?

□ High □ Moderate □ Low

Comments about Consistency: (optional)

Courage

Courage means speaking up for you and trying new approaches. It's about advocating for your needs and being honest, even when difficult, rather than taking the easy way out.

For the caregiver who shows the most courage, how would you rate their level?

□ High □ Moderate □ Low

For the caregiver who shows the least courage, how would you rate their level?

□ High □ Moderate □ Low

Comments about Courage: (optional)

Additional Feedback

What helps you feel connected with your caregivers? (optional)

What could help you connect better with your caregivers? (optional)

Is there anything else you would like to share about your experience with your caregiver team? (optional)

Thank you for taking the time to complete this survey. Your feedback helps us provide the best possible care.

Family Survey: Evaluating Your Loved One’s Caregiver Team

Overall Satisfaction

How satisfied are you overall with COMPANY's services?

□ Very satisfied □ Satisfied □ Neutral □ Dissatisfied □ Very dissatisfied

How likely are you to recommend COMPANY's caregiving services to other families?

□ Very likely □ Somewhat likely □ Neutral □ Somewhat unlikely □ Very unlikely

Evaluating the 5 C's of Connection

Please rate how the caregivers demonstrate each of the 5 C's of Connection with your loved one. For each quality, rate:

1. The caregiver who shows this quality the most
2. The caregiver who shows this quality the least

Curiosity

Curiosity means showing genuine interest in your loved one as a person - what brings them joy and comfort. It's about wanting to know them, not just complete tasks.

For the caregiver who shows the most curiosity, how would you rate their level?

□ High □ Moderate □ Low

For the caregiver who shows the least curiosity, how would you rate their level?

□ High □ Moderate □ Low

Comments about Curiosity: (optional)

____

Compassion

Compassion means truly caring about your loved one's feelings and needs. It's responding with kindness and understanding when they need support, rather than rushing or dismissing their concerns.

For the caregiver who shows the most compassion, how would you rate their level?

□ High □ Moderate □ Low

For the caregiver who shows the least compassion, how would you rate their level?

□ High □ Moderate □ Low

Comments about Compassion: (optional)

___

Collaboration

Collaboration means working together with your loved one as true partners. It's about valuing their input, preferences, and decisions rather than telling them what to do or just doing it for/to them.

For the caregiver who collaborates with your loved one the most, how would you rate their level?

□ High □ Moderate □ Low

For the caregiver who collaborates with your loved one the least, how would you rate their level?

□ High □ Moderate □ Low

Comments about Collaboration: (optional)

___

Consistency

Consistency means your loved one can depend on their caregiver. It's about following through on promises and creating a sense of security, not leaving them wondering or anxious about their care.

For the caregiver who is the most consistent, how would you rate their level?

□ High □ Moderate □ Low

For the caregiver who is the least consistent, how would you rate their level?

□ High □ Moderate □ Low

Comments about Consistency: (optional)

___

Courage

Courage means speaking up for your loved one and trying new approaches. It's about advocating for their needs and being honest, even when difficult, rather than taking the easy way out.

For the caregiver who shows the most courage, how would you rate their level?

□ High □ Moderate □ Low

For the caregiver who shows the least courage, how would you rate their level?

□ High □ Moderate □ Low

Comments about Courage: (optional)

____

Additional Feedback

What helps you feel confident about your loved one's care? (optional)

What could the caregivers do to improve your loved one's experience? (optional)

Is there anything else you would like to share about your loved one's experience with the caregiver team? (optional)

Thank you for taking the time to complete this survey. Your feedback helps us provide the best possible care for your loved one.