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Algorithmic Management Resource Model and Crowdworking Outcomes: A Mixed Methods Approach to Computational and Configurational Analysis

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Abstract

The delegation of managerial functions such as job allocations, performance appraisals, and disciplining work behaviors to automated, intelligent algorithms has transformed various aspects of workplace dynamics. Despite the increasing prevalence of algorithmic management in today's workplaces, its implications for work outcomes remain underspecified. Given the contextual novelty of this research, we adopted a mixed methods approach to theorize an algorithmic management resource model and investigate its configural relationships with crowdworkers' engagement and burnout. This was achieved by analyzing online crowdworker community narratives and subsequently developing nuanced insights into the resources that algorithmic management offers or impedes. In Phase 1, drawing on conservation of resources (COR) theory tenets, we utilized computational text analysis to explore resource gains and losses associated with algorithmic management. Then, using configurational analysis over two studies (N = 322), we identified and empirically examined the interrelationships among resource passageways and work outcomes, specifically engagement and burnout. Our results support a theoretical understanding of the algorithmic management resource model and shed greater light on several configurations of algorithmic resource passageways, sufficiently explaining crowdworkers' engagement and burnout in distributed, dispatched work settings such as online labor platforms.

Keywords: Algorithmic Management; Crowdworkers; Engagement; Burnout; Computational Text Analysis; fsQCA; Resource Gains and Losses

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1 Introduction

The pervasive integration of algorithms into the workplace is radically reshaping the nature and structure of work. In today's work environments, algorithms are not only replacing human workers but also taking over managerial roles once exclusive to humans (Lee, 2018). Online labor platforms (OLPs) are particularly reliant on this novel form of management to orchestrate their day-to-day operations and manage their workforce efficiently (Möhlmann et al., 2021). Without algorithmic management, digital platforms such as Uber, Lyft, Deliveroo, and others would be unable to effectively manage their vast pool of crowdworkers and scale their operations. Recent estimates show that in the US and UK alone, over 64 million people work for OLPs (Statista, 2022).

Although automated self-learning algorithms in workforce management enhance efficiency, scalability, and reach, they also significantly transform work dynamics, such as job design, power structures, and work experiences (Cameron et al., 2023; Duggan et al., 2023; Gal et al., 2020). The detached, distributed nature of OLP environments creates new work dynamics in which automated algorithms not only mediate economic transactions but also play a central role in governing social exchanges. From the OLP perspective, algorithmic management aims to establish a highly transactional relationship with workers, compensating them for the quantity of work undertaken rather than focusing on developing mutual trust and commitment (Duggan et al., 2020). However, research suggests that many crowdworkers may perceive their work relationships with OLPs as extending beyond pure economic exchange (van Zoonen et al., 2024; Wood et al., 2019). Tensions over issues like supervision, work belonging, and dependency (Möhlmann et al., 2021) suggest that there is more to crowdworking arrangements than simply transactional exchanges (Ashford et al., 2018; Leicht-Deobald et al., 2022).

Extant research has investigated workers' positive and negative experiences with algorithmic workforce management (e.g., Benlian et al., 2022; Gal et al., 2020; Möhlmann et al., 2021). Findings indicate that while some crowdworkers report high levels of frustration and anxiety due to stressors such as pressure to follow app instructions, fear of negative ratings, penalties, and lack of transparency (Cram et al., 2022; Koivusalo et al., 2024), others express satisfaction or even preference for OLP work (Berger et al., 2019; Cropanzano et al., 2023). However, the reasons why some crowdworkers perceive this algorithmically managed work setting positively while others see it negatively remain ambiguous. This ambiguity is further complicated by the high attrition rates observed among OLP workers, estimated at 12.5% per month (MacDonald, 2019). Such mixed work outcomes underscore the need for a nuanced understanding of the complex dynamics at play in algorithmically managed work environments and the reasons that some workers find it challenging, while others perceive it as beneficial.

Scholars suggest that the variation in worker experiences might be attributed to the complicated challenge of balancing freedom and control in the crowdwork setting (Cameron & Rahman, 2022). Due to the special nature of crowdworking, OLPs must respect the autonomy of freelance workers while ensuring service quality and customer satisfaction. The multifaceted duality of crowdwork raises questions as to whether prior theories are sufficient to understand algorithmically managed work dynamics. In the absence of a conventional employer-employee relationship, the OLP work setting challenges the traditional understandings of governance (Gol et al., 2019), control (Wiener et al., 2023), and organizational support (Jabagi et al., 2019). For instance, rather than selecting workers based on cultural fit and providing socialization and training, OLPs simply require app downloads, registration, and basic background checks (Rosenblat, 2018). Additionally, algorithmic job allocation reimagines the work assignment process by both restricting and enabling crowdworker autonomy through selective information provision and work suggestions (Hajiheydari & Delgosha, 2024). Crowdworkers are also subject to constant surveillance, real-time control, and nudging (Cram et al., 2022). With its primary focus being collecting and processing huge amounts of work behavior data, algorithmic performance management introduces new configurations of evaluating, directing, and disciplining workers.

By offering or limiting resources such as information or monetary rewards, algorithmic management seeks to navigate the balance between freedom and control, which simultaneously enables and restricts crowdworkers. For instance, while OLP algorithms may provide a steady stream of work opportunities, they may also reduce crowdworkers' control over task selection and work pace. Similarly, algorithmic performance monitoring may offer clear feedback and opportunities for improvement, but it may also increase stress and reduce perceived autonomy. This intricate balance of enabling and restricting influences various aspects of crowdwork conditions and outcomes. We argue that the interplay of resource provision and restriction shapes crowdworkers' experiences and influences work outcomes such as *burnout* and *engagement*.

Burnout (a result of excessive resource losses) and low engagement (due to insufficient resource gains) are well-established precursors to attrition in the workplace (Bakker et al., 2023; Crawford et al., 2010). Research has demonstrated that burnout is a leading cause of employee turnover, as it undermines job satisfaction and organizational commitment (Bakker & Demerouti, 2017). Conversely, higher engagement levels have been associated with lower attrition rates, as engaged workers are more likely to remain committed to their work and organization (Schaufeli et al., 2006). Still, we have limited knowledge about the indicators behind burnout and engagement and little understanding of which constructs shape these two critical work outcomes in OLP contexts. Unpacking these outcomes is imperative for both theory (by developing a model that identifies new constructs and explains interdependencies and different pathways that shape burnout and engagement) and for practice (by informing strategies to reduce attrition, improve worker well-being, and enhance platform productivity).

Drawing on the conservation of resources (COR) theory (Halbesleben et al., 2014) and leveraging observational and survey data, we developed and tested a theoretical framework of an algorithmic management resource model. COR theory posits that environmental conditions, such as management practices affect resource gain and loss, with imbalances significantly impacting work outcomes. Stress arises from resource losses or the failure to gain resources. By conceptualizing algorithmic management practices as potential sources of resource gain and loss, we seek to investigate how these dynamics shape engagement and burnout.

Motivated by the theoretical and practical significance of the algorithmic management phenomenon, our first research question asks:

RQ1: What are crowdworkers' perceptions of resource gains and losses in the context of algorithmic management?

We address this question using an inductive computational approach (Nelson, 2020) grounded in firsthand crowdworker experiences (Study 1). We applied computational textual analysis techniques to unpack the thematic structure of conversations between users on uberpeople.net, an online community where crowdworkers share their work experiences, emotions, and opinions. Observational data offer the most natural way to study social phenomena, providing an aggregated picture of individuals' perceptions and experiences (Humphreys & Wang, 2018). By analyzing naturally occurring data (Müller et al., 2016), we aimed to identify representative topics of algorithmic management resource gains and losses and ensure the organic validity of our findings.

Rather than focusing on single, isolated variables, COR theory suggests that resources travel in packs or caravans (Hobfoll, 2011), which support, complement, or substitute for each other (Halbesleben et al., 2014). We thus adopted a deductive configurational approach to further reveal insights into how the constellations of algorithmic management resource gains and losses shape work outcomes. Studies 2 and 3 address our second research question:

RQ2: In what ways does the interplay of perceived algorithmic management resource gains and losses shape crowdworker burnout and engagement?

We used a configurational approach to examine the interrelationships among algorithmic management work conditions and their impacts on burnout and engagement. These studies suggest that crowdworkers perceive resource caravans of algorithmic management that cannot be fully explained by linear symmetrical models (Maier et al., 2021). Fuzzy-set qualitative comparative analysis (fsQCA), as a case-oriented comparative analytical approach (Fiss, 2011; Park et al., 2017; Ragin, 2009), was utilized across these two studies to uncover different configurational patterns.

This research contributes to the existing body of knowledge in two ways. First, it advances our understanding of the nuanced ways that algorithmic management can simultaneously enable and restrict crowdworkers, delineating its dual impact on resource provision and depletion. Leveraging a COR theoretical lens and computational methods, we provide granular, empirically grounded insights into crowdworkers' perceptions of algorithmic management, uncovering indicators of germane resource gain and loss constructs that affect burnout and engagement among OLP workers. Second, we adapted these constructs into a survey and examined their effects on burnout and engagement, developing a model of algorithmic management resources that explains the reasoning behind such effects. Our configurational analysis explores the complex interdependencies of resource gains and losses in algorithmically managed work settings. Shifting the focus from single resources to "resource caravans," our research sheds light on how the interplay of resource gains and losses shapes crowdworkers' engagement and burnout. This approach allows for more nuanced theorizing about the specific algorithmic management resource caravans that shape crowdworker outcomes and demonstrates the importance of resource constellations rather than single-resource analyses. Although "resource caravans" have received some attention in IS research (Giddens et al., 2023), more is needed to identify how resources combine or interact in digitally mediated environments.

2 Theoretical Background

2.1 Algorithmic Management and Crowdworkers

The essence of management is to efficiently and effectively coordinate, allocate, and control resources to achieve desired goals. As artificial intelligence advances and data infrastructures become more robust, organizations are increasingly delegating managerial tasks—such as resource allocation, performance management, or operational optimization—to automated self-learning algorithms. These intelligent agents are now capable of hiring staff, assigning tasks, measuring productivity, appraising performance, and even selecting workers for layoffs. This emergent type of management is reshaping conventional work settings (Duggan et al., 2020). On the positive side, assigning managerial functions to algorithms increases decision-making efficiency, optimizes resource distribution, and drives economic value (Brynjolfsson & McAfee, 2014; Kellogg et al., 2020; Lindebaum et al., 2020). Algorithms powered by computational big data analysis surpass human decision-making abilities, enhancing precision in actions, predictions, and resource allocation. However, recent research suggests that algorithmic decisions are sometimes perceived as inauthentic or even unethical (Jago, 2019), which can lead to resistance among workers (Dietvorst et al., 2018). With the growing use of algorithmic management, scholars are increasingly focused on examining its effects on workplace dynamics, including work relationships, job design, and employee well-being (Duggan et al., 2020; Kellogg et al., 2020; Parker & Grote, 2022). For instance, Curchod et al. (2020) argue that algorithms are far from neutral machines; They are designed primarily to serve the interests of business owners rather than empower workers.

Algorithmic management is particularly prevalent in digital platforms, where automated algorithms perform most managerial functions. This approach is crucial for OLPs due to the distributed nature of crowdworking (Jabagi et al., 2019), large amounts of market data (Möhlmann et al., 2021), and the need to effectively perform millions of supply and demand matches (Delgosha & Hajiheydari, 2020). Algorithms embedded within OLP applications match crowdworkers with consumers, assign jobs, monitor and evaluate performances, and regulate transactions. By leveraging algorithmic management, OLPs can scale their operations, coordinating activities of large, disaggregated crowdworkers and using big data to optimize operations and desired outcomes. However, employing automated algorithms for workforce management has reshaped various aspects of work arrangements, including rewards and recognition, job attitudes, and power structures. Although crowdworkers are increasingly attracted to OLPs for their flexibility and income potential (Fu et al., 2022; Rani et al., 2021), labor activists, worker unions, and academics have raised concerns regarding the consequences of algorithmic management. They caution that it may lead to unfair decisions (Fieseler et al., 2019), lack of support (Kuhn & Maleki, 2017), reduced interpersonal communication (Anicich, 2022; Goods et al., 2019), and power imbalances (Cutolo & Kenney, 2021).

Because algorithmic management is a relatively new phenomenon, the IS literature on the subject is limited but growing. As summarized in Appendix A, this limited research has discussed various algorithmic mechanisms and whether they are commercially effective or essential. Scholars have noted that platforms are required to implement some directives, which may lead to information and power asymmetry (e.g., Cheng & Foley, 2019; Jarrahi & Sutherland, 2019; Jarrahi et al., 2021), excessive governance and control mechanisms (e.g., Basukie et al., 2020; Gol et al., 2019; Huang, 2023; Möhlmann et al., 2021; Noponen et al., 2023), and mechanical interactions (e.g., Stark & Pais, 2020). Other studies have examined how workers make sense of and deal with algorithmic managerial functions (e.g., Gal et al., 2020; Möhlmann et al., 2023). Still others have studied the potential negative health impacts of algorithmic management on workers (e.g., Vignola et al., 2023).

While this research sheds light on different aspects of algorithms in the workplace, the primary reasons for the variation in crowdworkers' experiences under algorithmic management remain underexplored. Specifically, the factors influencing why some workers perceive algorithmic management positively—experiencing it as empowering—while others find it frustrating, stressful, or alienating have not been thoroughly examined. Our research seeks to address this gap by exploring how algorithmic management practices contribute to resource gains and losses and how those, in turn, shape burnout and engagement among crowdworkers. By applying COR theory, we aim to uncover the underlying mechanisms driving divergent work experiences in algorithmically managed work environments.

2.2 Conservation of Resources Theory

COR theory offers an overarching framework to explore the effects of algorithmic management on work outcomes such as engagement and burnout. This motivational theory suggests that individuals are driven to acquire and conserve resources that are essential for their well-being and goal attainment (Hobfoll et al., 2018). As per COR theory, individuals always seek to protect, obtain, foster, and retain resources. Halbesleben et al. (2014) define resources as objects, states, or conditions perceived as valuable for achieving one's goals. For example, workers may seek personal resources such as autonomy, social resources such as relationships, and material resources such as financial rewards. COR theory suggests that resource loss can lead to stress and burnout (Crawford et al., 2010; Menguc et al., 2013) and resource gain can enhance employees' well-being (Demerouti et al., 2017; Huettermann & Bruch, 2019). COR theory also posits that situational conditions, functioning as passageways, can either facilitate or hinder individuals' abilities to gain or conserve resources (Hobfoll et al., 2018).

IS researchers have used COR theory to analyze the effects of new workplace technologies, examining how they can accelerate the work pace (Chen et al., 2009), increase job demands (Ward & Steptoe-Warren, 2014), and lead to the risk of technology-induced overload (Harris et al., 2015). From the COR perspective, the benefit and cost functions of algorithmic management (i.e., those with positive and negative directionalities of influence on work outcomes) can be captured as resource gains and losses. Here, *resource gain* refers to the acquisition of resources through automated algorithms that can create value and help crowdworkers achieve their goals. Conversely, algorithmic management may also lead to *resource loss*, heightening cognitive load and depleting energy. For instance, crowdworkers managed by algorithms might experience resource gains (autonomy and financial rewards) or losses (unclear procedures or lack of power). Resource loss has primarily been studied in the form of burnout, which refers to "a syndrome of chronic exhaustion, a cynical, negative attitude regarding work, and reduced professional efficacy" (Bakker & Demerouti, 2017; p. 273).

Algorithmic management thus serves as an important passageway, either providing resources to meet job demands or depleting them and creating job strain. Our study uses a COR theoretical lens to capture both resource-gain and resource-loss passageways of algorithmic management. This framework allowed us to investigate crowdworkers' work outcomes under algorithmic management from both gain and loss perspectives. Rather than focusing narrowly on specific consequences of algorithmic management, our work takes a bottom-up approach by analyzing discussions within an online crowdworker community. This approach enabled us to capture a diverse range of opinions and concerns regarding this emerging form of management, thereby providing a comprehensive view of algorithmic management's impacts on crowdworkers' experiences.

3 Mixed Methods Design

Given the contextual novelty of our research, we adopted a mixed methods approach to explore the implications of algorithmic management and develop rich insights into its impacts on work outcomes. Although prior research has examined resource changes due to technology and their effects on users' well-being, the specific resources associated with algorithmic management and its gain and loss passageways remain insufficiently explored.

Our mixed methods approach comprised two primary strands, which were methodically designed to serve a *developmental* purpose. Initially, we employed computational analysis to develop an algorithmic management resource model, which was then subjected to further investigation through configurational analysis. From a timing standpoint, this research design follows an *exploratory sequential* mixed methods approach (Creswell & Clark, 2017), involving the collection of quantitative data to empirically examine and elaborate on the findings uncovered through our textual data analysis. In the first stage, an inductive computational exploration was performed on digital trace data obtained directly from crowdworkers to reveal resource gains and losses resulting from algorithmic management. The computational analysis strand relied on narratives sourced from uberpeople.net, an online community originally launched for Uber drivers to share their experiences, opinions, and feelings. With over 150,000 members, the forums contain contributions from Uber drivers, Lyft drivers, and delivery drivers working with services such as DoorDash, Uber Eats, and Amazon Flex. We analyzed this rich source of textual data, comprising more than 5 million posts, to identify resource gains and losses of algorithmic management based on crowdworkers' firsthand experience, perceptions, and discussions. In the next stage of our empirical analysis, we designed two studies using configurational analysis to explore and examine the interrelationships between the resource passageways of algorithmic management and crowdworkers' work outcomes, including burnout and engagement.

Venkatesh et al. (2013, 2016) urged researchers to evaluate the *appropriateness* of mixed methods research design by considering the requirements of the research questions and the purpose and context of the study. Our current understanding of crowdworking settings and, more importantly, the implications of algorithmic management is still in its infancy (e.g., Möhlmann et al., 2021; Tarafdar et al., 2022). There is, therefore, a need to develop novel theoretical perspectives by integrating findings from qualitative and quantitative methods, triangulating data, and overcoming the limitations of each perspective (Creswell & Clark, 2017; Venkatesh et al., 2013). The employment of a mixed methods approach enriches our understanding of algorithmic management implications in the crowdworking context. This involves, first, exploring the firsthand experiences of workers predominantly managed by automatic algorithms and, second, examining the implications of this emerging management on work outcomes. Specifically, using opinion mining and topic modeling as computational text analysis techniques, this research uncovers resource-loss and resource-gain passageways tied to algorithmic management. Furthermore, utilizing fsQCA as a configurational analysis method, this research seeks to gain insights into how these resource passageways drive crowdworkers' work outcomes.

The configurational approach employed in Studies 2 and 3 enables us to formulate new theoretical propositions for explaining and analyzing nonlinear, bottom-up emergent relations. Considering recent research (which recognizes that work conditions have synergistic, not isolated, effects on worker outcomes; Parker et al., 2017), applying configurational models, rather than a linear approach, can better elucidate the mutual relations shaping crowdworker burnout and engagement. In keeping with Hobfoll et al.'s (2018, p. 107) position that "resources do not exist individually, but travel in packs, or caravans," we adopted a configurational approach to examine the interplay of algorithmic management-related resource gains and losses. This approach allowed us to thoroughly capture how specific configurations (i.e., caravans) of work conditions lead to crowdworkers' burnout or engagement. Figure 1 illustrates the research design of this study.

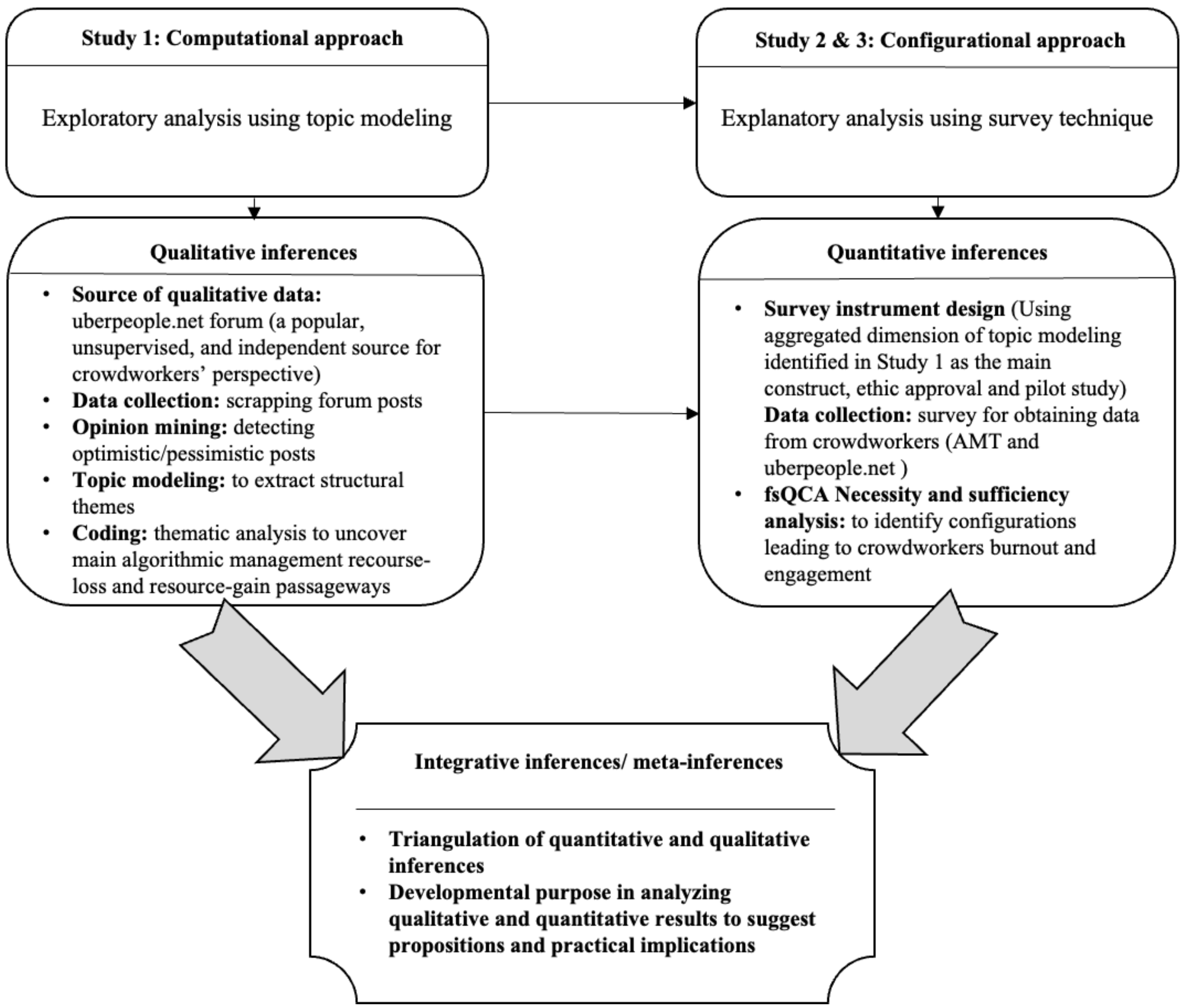


Figure 1. Mixed Methods Research Design

4 Study 1: Exploring the Algorithmic Management Resource Model From Crowdworkers' Narratives

4.1 Data Collection and Preprocessing

In the first stage, we based our computational analysis on textual narratives generated by crowdworkers participating in an online community. We used a combination of opinion mining and topic modeling to uncover the thematic structure of discussions. Our primary data source for the first study was uberpeople.net, a well-known independent online community for crowdworkers with more than 150,000 members. User-generated data scraped from online communities or forums are increasingly being used by scholars to examine various economic, social, and organizational phenomena (Berente et al., 2019). The availability of large-scale digital trace data in online forums provides an invaluable opportunity to access detailed behavioral insights with unprecedented scale and depth.

In our context, crowdworkers on uberpeople.net post content and interact with each other to seek and offer advice. Our textual dataset was built using a web crawler to extract 5.8 million forum posts from April 2014 (the beginning of uberpeople.net) to March 2020. Most of the posts were from Uber and Lyft drivers or delivery riders who worked for DoorDash, Uber Eats, or Amazon Flex. This dataset represents a broad spectrum of crowdworkers' perspectives, as these users frequently share experiences and seek advice within this community. The organic nature of these discussions makes it an ideal source for capturing the authentic firsthand experience of working under algorithmic management on OLPs. By analyzing these interactions, we gained valuable insights into the real-world impacts of algorithmic management on crowdworkers.

4.2 Data Analysis: Opinion Mining and Topic Modeling

We applied two machine learning methods—XLNet (Yang et al., 2019) and structural topic modeling (STM) (Roberts et al., 2019)—to analyze the crowdworkers' attitudes and opinions toward algorithmic management. The sentiment-based topic extraction process allowed us to explore resource gains and losses resulting from algorithmic management. This text-mining process tapped into the crowdworkers' conversations to understand their feelings and experiences, which were expressed in unstructured textual data associated with algorithmic management.

We first used XLNet, a deep learning technique, to capture crowdworkers' attitudes as expressed in their posts. XLNet is a contextualized language representation learning method founded on a generalized permutation language modeling objective. With self-attention mechanisms and bidirectional learning as its backbone model, XLNet produces more accurate representations and achieves improved prediction accuracy (Yang et al., 2019), which makes it an appropriate method for analyzing our textual data. Details on the implementation of XLNet are provided in Appendix B.

Given our large dataset, we then employed topic modeling to identify the thematic content in user posts and extract topics related to the resource passageways of algorithmic management. Topic modeling is an unsupervised computational technique that generates semantic categories based on meaning and commonalities among words in a large collection of textual data—a task otherwise impractical with large empirical datasets (Brown et al., 2020). We selected STM for its capability to incorporate metadata into textual analysis (Roberts et al., 2019), allowing us to extract topics grounded in crowdworkers' optimistic and pessimistic attitudes. Previous studies have demonstrated STM's superiority over the commonly employed latent Dirichlet allocation method in terms of both predictive performance and qualitative interpretation (Karanović et al., 2021; Roberts et al., 2019). Details on our topic modeling method and results are provided in Appendix C.

4.3 Coding and Interpretation of Topics

To interpret the empirical themes of each topic, we identified the top words associated with each topic using two weighting algorithms: *highest probability* (which weighs words using raw per-topic probabilities) and *FREX* (which calculates word frequency and exclusivity). Two authors and a research assistant independently reviewed the top 10 words from both weighting methods, along with the top 20 posts most closely associated with each topic, to assign descriptive labels representing the resource gains and losses of algorithmic management. Labels were assigned to each topic with a name that both summarized and accounted for that topic (Charmaz, 2014). The labels were primarily based on the top probability terms in each topic and, secondarily, on the top related corpora/texts that represent that topic.

The labels applied during this initial coding phase encompassed various aspects of crowdworkers' jobs, such as "unclear routines," "automated messaging," "false accusation," and "traffic information," all of which directly relate to algorithmic management. Whenever possible, we used comparative methods, more specifically within-source comparisons (Charmaz, 2014) comparing data (posts) from one part of a forum category and thread with another one. Consolidating and comparing the individual results indicated that there was generally high similarity in the labels assigned to each topic, with an intercoder agreement of 75%. Conflicts in labeling between researchers were managed by discussing discrepancies to reach a consensus on topic labels. Topics that none of the researchers identified as relevant to the research question (such as "tipping," "car conditions," and "insurance") were marked as not meaningful and excluded from the results. Appendix C provides a detailed overview of extracted topics, including examples of posts related to each topic, highly associated words, topic labels, and their Rank-1 metric.

In the second step, we used an iterative process to interpret the extracted topics by extensively examining the original data. Our interpretation focused on identifying an algorithmic management resource model. We used a grounded theory coding scheme (Corbin & Strauss, 2014) and clustered first-order codes (topics) into axial second-order themes that were then further abstracted via selective coding (aggregated dimensions). After identifying relevant topics, we performed axial coding to develop theoretical themes by combining common topics and abstracting them into subcategories. During this step, we iterated a process to evaluate the data and existing theory, combining topics into themes (Charmaz, 2014; Gioia et al., 2013). We compared our emerging computational codes (topics) with the extant literature, noting similarities and distinctions between topics informed by research on COR theory and algorithmic management. For example, we found that the topics of "unpredictable fares" and "unstable commission fees" had connections, and clustered them as *reward uncertainty.* Similarly, "intrusive rating system," "scrutinizing cancellation rates," and "nitpicking boss" were grouped as *invasive supervising*. Finally, we conducted selective coding by further abstracting second-order themes into aggregated theoretical dimensions.

Table 1. Thematic Structure of Algorithmic Management Resource Model

First-order codes (topics)	Second-order themes	Aggregated dimensions	+/-
Unclear routines Unforeseen app changes	Procedural inconsistency	Algorithmic ambiguity	Resource loss passageway
Unpredictable fare Unstable commission fees	Reward uncertainty		
Unfair surge pricing Unacceptable fare	Unfair compensation	Algorithmic unfairness	
False accusation Account deactivation/suspension	Unfair punishment		
Long waiting time Job misallocation	Unfair workload		
Automated messaging Ineffective communication Insufficient explanation	Detached relationship	Algorithmic miscommunication	
Neglecting drivers' concerns Unresponsiveness	Lack of voice		
App monitoring Overcontrolling Privacy concern	Ongoing surveillance	Algorithmic constant monitoring	
Intrusive rating system Scrutinizing cancellation rate Nitpicking boss	Invasive supervising		
Time flexibility Location flexibility	Work flexibility	Algorithmic assignment	Resource gain passageway
Job availability Task allocation	Providing gigs		
Traffic information Navigation advice Performance feedback	Information provision	Algorithmic support	
Extra pay Income	Reward provision		

Drawing on a COR theoretical lens, we clustered our themes to develop algorithmic management passageways that generate resources for crowdworkers (i.e., algorithmic job allocation and support) or deplete them (i.e., algorithmic ambiguity, unfairness, constant monitoring, and mechanistic communication). Following Gioia et al.'s (2013) template, Table 1 presents the results of our coding process, including first-order codes (topics), second-order themes, and aggregated dimensions. For more details, please refer to Appendix D.

4.4 Results

The topic modeling analysis indicated that 42.7% of crowdworkers' posts primarily addressed issues related to resource loss (labeled as pessimistic posts), while 23.7% focused on resource gain (labeled as optimistic posts). Our analysis identified six key thematic clusters that encapsulate these topics. These six aggregate dimensions effectively grouped topics at a broader level, with four dimensions representing resource losses and two representing resource gains resulting from algorithmic management (see Appendix D).

4.4.1 Resource Loss Passageway

Algorithmic ambiguity: Topics referring to algorithmic ambiguity contained two second-order themes—"procedural inconstancy" and "reward uncertainty." These accounted for 8.6% of online community posts, covering four out of 30 relevant topics in our analysis. In their narratives, crowdworkers expressed concerns about unclear routines, emphasizing the uncertainty and opacity of the algorithmic system. They expressed sentiments such as, "There probably is a whole lot that goes into the algorithm. But there's no way for us to know for sure exactly what goes into it and what's currently being used." Additionally, they highlighted dissatisfaction with sudden, unexpected, and unnecessary changes in the application, stating, for example, "My app was working just fine until the latest update. Why do those tech geeks at Uber insist on fixing something that ain't broken?" This theme suggests that the procedures or routines dictated by the algorithmic system are not stable or predictable. Workers may feel that the algorithmic processes and the application guiding their tasks are subject to frequent changes, making it challenging to understand or anticipate the specific steps or rules governing their work.

In addition to process inconsistency, crowdworkers expressed discontent with changes in payment structure and fares, citing concerns about the transparency and predictability of the algorithmic reward system. For example, one asked, "Since Uber seems to adjust fares without notification to the driver, how does everyone monitor their statements?" This lack of transparency and clarity in the reward system can lead to confusion and frustration among workers, as they may find it challenging to predict the outcomes of their efforts or understand the factors influencing their compensation. According to the role theory (Kahn et al., 1964), experiencing ambiguity in responsibilities and procedures leads to confusion, stress, and job dissatisfaction. When workers are uncertain about procedures and what is expected of them, they may consume more cognitive and emotional resources (Lee & Ashforth, 1996). This increased effort can result in resource depletion, leaving workers with fewer resources to cope with other work-related challenges or personal demands (e.g., O'Driscoll & Beehr, 1994; Schmidt et al., 2014). In the context of algorithmic management, we therefore suggest that uncertainty or a lack of clarity about how income is calculated or how the system works is a significant stressor with negative implications for crowdworkers' cognitive resources.

Algorithmic unfairness: Topics related to algorithmic unfairness, comprising three second-order themes and six topics, emerged as the predominant focus within the entire corpus, representing 16% of community posts. We clustered discussions on unfair surge pricing and low earnings into the second-order theme of "unfair compensation." Conversations on false accusations and account deactivation/ suspension were grouped into the theme of "unfair punishment," and topics addressing long waiting times and job misallocation were labeled under the theme of "unfair workload." Given that algorithms widely govern compensation and other work conditions, crowdworkers continuously "hold [a] magnifying glass up to justice issues" (Colquitt & Zipay, 2015, p. 82) to assess the fairness of algorithmic decision-making.

Unfair compensation was the topic of 8.3% of crowdworkers' discussions in the online forum. Unfair compensation is a crucial concern as it directly impacts the financial well-being of crowdworkers, potentially leading to dissatisfaction and a sense of exploitation. They complained, "Why does Uber make so much more than we do on these rides? Not at all fair paymen[t] practice on Uber's part!" A portion of community posts (4.9%) also argued that, in some cases, the algorithm punished them unfairly or falsely accused them. For example, they shared bitter experiences of being punished, such as, "I was permanently deactivated from Uber, apparently some customer complained to them that I tried to ask for sexual favors when I was dropping them. (Before anyone asks no I didn't do any such thing)." Finally, under the same category of unfairness, 2.8% of posts were related to unfair workload, with complaints about long wait times or being sent to the wrong job or pick up point. For example, "As I write this it's been well over 3 hours and have yet to get a ping … I think Lyft does not like me." Others complained about the algorithm's allocation: "Long pick up, no PAX no fee: Saturday night I accept a long pick up. 22 min and about 16 miles. I get to the location, timer starts the countdown."

From a social exchange perspective (Wayne et al., 1997), researchers maintain that fair procedures and distribution signal that employees are valued, while unfairness communicates devaluation, which can be devastating for individuals (Howard & Cordes, 2010). In this context, employees may internalize blame or perceive themselves as less worthy of their job. Coping with perceived unfairness demands cognitive and emotional resources, leading to a gradual depletion of energy for employees (Dishon-Berkovits, 2018). Similarly, in OLPs, crowdworkers seeing no clear and fair relationship between their effort and the allocation of rewards may initially invest time, effort, and resources to alleviate the situation. However, if unfairness persists, a substantial amount of mental energy may be devoted to processing and responding to perceived injustice, resulting in reduced feelings of personal accomplishment, exhaustion, and energy depletion.

Algorithmic miscommunication: Conversations about algorithmic miscommunication constituted 8.9% of community posts. We grouped five topics into two second-order themes: "detached relationship" and "lack of voice." Through topic modeling, we uncovered that automated messaging, ineffective communication, insufficient explanations, neglecting drivers' concerns, and unsupportiveness were communication issues that crowdworkers experienced in working with algorithms. In platform work settings, crowdworkers typically lack the opportunity to build a personal relationship with a supervisor. They may not have colleagues to socialize with or a team to be a part of. In addition, unlike conventional work settings—where open communication exists between workers and their supervisors, as well as among co-workers—OLPs primarily rely on algorithmic determinations to optimize efficiency, resulting in predetermined interactions (Walsh, 2020).

Preprogrammed and algorithm-generated messages lack personalization, a human touch, or nuanced responses. This is frustrating for crowdworkers. In their narratives, crowdworkers criticized how the algorithm contributes to a sense of disconnection between the workers and the platform, saying, "I didn't even receive their usual 'request received' robomail. I then sent a test email, and I instantly got a robo response. Sent original once more, then nothing." Similarly, one worker noted that "The only complaint I actually do have is that it is very frustrating that you can only communicate with Uber via email."

Moreover, companies overlooking or not adequately addressing the issues and feedback raised by crowdworkers—in other words, lack of assistance or encouragement from the platform—was a significant topic of crowdworker discussion. As one crowdworker shared: "So twice now I have asked that a supervisor/manager contact me to discuss this trip. And twice now I have received an email from a first-level support person asking me to call the Helpline to discuss the problem(s). ARGH!!!" The perception of being undervalued can lead to heightened stress or frustration, leading in turn to decreased morale and job satisfaction.

Algorithmic constant monitoring: Six topics comprising 9.2% of the community posts were related to algorithmic constant monitoring. We categorized app monitoring, overcontrolling, and privacy concerns under the theme of "ongoing surveillance," and grouped the topics of the intrusive rating system, the scrutinization of cancellation rates, and nitpicking bosses into the "invasive supervising" second-order theme. These topics highlight the frustrations expressed by crowdworkers in their posts, particularly regarding how the algorithm constantly monitors them and their behavior: "They threatened to deactivate me if my cancellation rate rises. The funny part is that I always keep it below 15% over 2 years of driving. They want me to keep it below 2%, which is absolute bullcrap!!" Similarly, they shared experiences on how tightly the app monitors the rating scores; for example, one user mentioned that "Anyone [else] notice the newest bullshit about rider feedback issues. ALMOST every day I drive now I get some kind of rider feedback issue ... Latest was 'late arrival missed eta.'" The fact that the platform has access to their information also raises privacy concerns, as exemplified in this example: "Where is the privacy for the drivers, pax can know literally everything there is to know about us as uber give them all the tools to do so."

Unlike traditional close supervision, OLP algorithms largely monitor crowdworkers continuously, intrusively, and without warning. By collecting real-time data on workers' performances, algorithms seek to control work behaviors. This can be interpreted as an electronic panopticon (Prassl, 2018) used by platforms to invasively monitor crowdworkers, creating work conditions akin to a permanent probation period (Gramano, 2020). Such invasive supervision and monitoring undermine employees' autonomy and control over their work, depleting their psychological resources and contributing to stress (George, 1996). Algorithmic constant monitoring also raises the possibility of resource loss related to feelings of uncertainty and fear about being punished for not meeting expectations.

4.4.2 Resource Gain Passageway

Algorithmic assignment: Four of the 30 relevant topics in our analysis referred to algorithmic assignment, accounting for 9.2% of online community posts. We grouped time flexibility and location flexibility topics into the second-order theme of "work flexibility." Job availability and task allocation were clustered under the "providing gigs" label. One of the key advantages of algorithmic management in contemporary work settings, such as OLPs, is the ability to afford crowdworkers a high degree of flexibility in choosing where and when to work. For example, a sample post points to the time flexibility that the algorithm grants drivers: "Today is supposed to be my day off, but the app is open and if I get a good ride I'll hop on it. Love the flexibility, love how I can decide to make $50 or so today to take the pressure off of tomorrow as I'll be up watching football tonight." Posters also appreciated the availability of jobs and task allocation by the algorithm: "Ever since my rating gone up to 4.73, I been getting lots of lux ride for my pool. Today I just got off a new Lexus NX on pool." By dynamically assigning jobs based on real-time demand and worker availability, OLPs' algorithms allow workers to adjust their work hours and availability based on their preferences or changing circumstances. Workers can choose to work more during busy periods or reduce their workload during low-demand periods, providing flexibility in terms of time and location.

Algorithmic support: Making up 14.5% of the community narratives, five topics referred to algorithmic support. The second-order theme "information provision" consisted of traffic information, navigation advice, and performance feedback. Extra pay and income topics were grouped into the "reward provision" theme, accounting for 7.4% of the posts. The algorithms offer real-time data on task availability, demand patterns, and performance metrics that support crowdworkers in effectively managing their work endeavors. Posters appreciated receiving live information, saying, for example, "I finally created Excel worksheets with the info that Uber provides." More frequently, workers talked about their payment, reimbursement, and reward provision from the platforms in various posts: "It's real. Caught a few 1.5x and a couple 1.2x. With Lyft's earnings, I walked away after about 5-6 hours with $140." "I got a 1.8 with Uber today but when I checked the passenger pays 12 I got $21 Uber paid the difference." "I'm happy with my earnings this week, but even happier I got my $235 for 55 rides! Best bonus yet." Automated algorithms manage rewards and incentives based on workers' performances. By rewarding crowdworkers, OLPs incentivize desirable behaviors, motivating workers to excel and increasing their engagement.

4.5 Discussion

Study 1 explores how crowdworkers perceive the resource dynamics of algorithmic management. By analyzing crowdworkers' firsthand experiences, as shared in an online community, we reveal how algorithmic management both enables and constrains crowdworkers by providing or limiting resources. On the one hand, by employing automated algorithms, OLPs offer resource gains such as flexibility, informational and reward support, and efficient task allocation. On the other hand, resource losses—including procedural ambiguity, unfairness, miscommunication, and constant monitoring—are prominent challenges. These findings uncover the underlying work conditions in OLP work settings. The insights from this study inform the development of the algorithmic management resource model and provide a foundation for exploring how these resource dynamics shape key work outcomes like burnout and engagement.

5 Study 2: Configurations of Crowdworker Burnout

Study 2 addresses RQ2 by specifically focusing on how algorithmic management-related resource gains and losses collectively affect crowdworkers' experiences of burnout. Research grounded in COR theory has demonstrated that resource loss and lack of resource gain both directly contribute to worker burnout (Crawford et al., 2010). When workers face significant resource losses—such as job insecurity, financial setbacks, or lack of support—they experience increased job strain. These resource losses deplete their overall resource pool and create a deficit, making it challenging to meet job demands (Halbesleben et al., 2014). The imbalance between resource gains and losses can lead to chronic exhaustion and eventual burnout (Hobfoll et al., 2018). In examining how these algorithmic management passageways contribute to burnout, we adopted a configurational approach (Misangyi et al., 2017; Park et al., 2017), employing fsQCA (Ragin, 2009).

5.1 Participants and Procedure

We chose a parallel sampling approach, in which "samples for the quantitative and qualitative components of the study are different but drawn from the same underlying population" (Venkatesh et al., 2016, p. 446). For Study 2, the primary research population consisted of crowdworkers from various OLPs. Using Amazon's Mechanical Turk (MTurk), we recruited participants working for Uber, Deliveroo, Lyft, Uber Eats, Just Eat, or any other ride-hailing or delivery platform. MTurk has been recognized for its ability to produce high-quality survey data through the use of attention checks (Berinsky et al., 2012) and reputation scores (Peer et al., 2014). To ensure data quality, we limited participation to individuals with an approval rating above 95% and excluded those who failed an attention check ("Please select the '*Disagree*' button if you believe your answers are correct"; 12 cases) or did not work on an OLP (5 cases), resulting in a final sample size of 185 (M_{age} = 38.6, SD_{age}=12.7; 59.4% male).

5.2 Survey Instrument and Measures

We identified and adapted appropriate scales from previous studies to develop our survey instrument, which was designed to evaluate algorithmic management resource passageways. Appendix E lists the final survey items. To further contextualize and validate our instrument, we consulted five experts in job design (three academics and two industry professionals) and conducted a pretest with 17 crowdworkers. Feedback from both the experts and pretest respondents led to minor adjustments in terminology and item sequencing to improve clarity.

To measure algorithmic job allocation, we used the results from the topic modeling and subsequent qualitative analysis (first- and second-order coding) in Study 1, considering the perceived autonomy associated with managing work through algorithms. We adopted the four-item perceived autonomy scale from Morgeson and Humphrey (2006) and modified it based on the context of this study. Our topic modeling identified two primary themes for algorithmic support: information provision and reward provision. For information provision, we used information sharing scales by Mohr and Spekman (1994); to measure reward provision, we used the financial benefit scale from Bock et al. (2005). To measure algorithmic ambiguity, we used the procedural justice construct (Colquitt, 2001) and reversed its related five items. Algorithmic unfairness was measured based on a distributive justice scale (Colquitt, 2001). The concept of perceived availability of social support in the workplace (Fernet et al., 2013) was reversed and used to measure algorithmic miscommunication. A five-item scale by Jensen and Raver (2012) on perceived surveillance was used to measure algorithmic constant monitoring. Finally, to measure burnout, we applied a 4-item scale from Little et al. (2007) on a 7-point scale (*never* = 1, *always* = 7).

Our assessment of the measurement model after testing content, convergent, and discriminant validity indicates that the measures are reliable and valid (see Appendix F). To mitigate the potential for common method bias (CMB), we followed the recommendations outlined by Podsakoff et al. (2003) to apply certain procedural remedies, and explicitly tested for the presence of CMB, as detailed in Appendix G.

5.3 Configurational Analysis

fsQCA, a case-oriented method based on set theory, allowed us to analyze within-case relationships and explore complex interdependencies and asymmetric relationships between conditions and outcomes. Using a configurational perspective, we aimed to identify equifinal and asymmetric links among algorithmic management-elated resource losses and gains (which served as our conditional variables) and work outcomes. Configurations are equifinal because alternative combinations of resource passageways may produce the same outcome, and links are asymmetric because the presence of resource losses and gains, as well as their absence, may create different configurations resulting in the same outcome (Furnari et al., 2021; Misangyi et al., 2017). In Study 2, the conditions included resource-loss and resource-gain passageways, with burnout as the outcome of interest.

When conducting fsQCA, we initially calibrated all interval scale values into fuzzy-set membership scores. The fsQCA calibration process involves choosing threshold levels where the respondent's score is judged to be "fully in" membership or "fully out" of membership of the set (Soltani Delgosha et al., 2024). We calibrated the data by using a common rule for all conditions, setting the fully-in and fully-out cutoff points at +/- one standard deviation from the median, with the point of maximum ambiguity set at the median value of each variable (Douglas et al., 2020). Following this process, the resulting fuzzy membership score is between 0 and 1, where 0 shows a fully-out membership, 1 shows fully-in membership, and 0.5 represents the most ambiguous situation (neither fully in nor fully out).

fsQCA analyzes the necessary and sufficient conditions to identify which configurations of conditions lead to an outcome. The necessity analysis revealed that algorithmic unfairness is essential for burnout, as its raw consistency score exceeded the 0.90 threshold (Greckhamer et al., 2018). In addition, to avoid trivial necessary conditions (type 1 error), we ensured that the coverage score (0.82) and the relevance of necessity score (0.73) of the necessity condition were higher than 0.60. Next, sufficiency analysis was conducted using the fsQCA Quine-McClusky truth table as a Boolean chart to detect all logically possible combinations of conditions found in the dataset. Following the recommendations of Greckhamer et al. (2018), we set the raw consistency cutoff at 0.80, the frequency cutoff at 2 (to retain more than 80% of the cases), and the proportional reduction in inconsistency (PRI) at 0.60.

5.4 Results

The configurations driving crowdworker burnout are shown in Table 2. The fsQCA results yielded five configurations associated with high burnout and one configuration for low burnout.

High burnout: The overall solution coverage of 0.78 and solution consistency of 0.93 reflect high empirical relevance and consistency among the five high-burnout configurations. Each configuration characterizes a class of crowdworkers experiencing significant exhaustion. Among the configurations, HB5 holds the highest empirical relevance, with a raw coverage of 0.38. This configuration depicts crowdworkers as perceiving algorithmic management as straining, characterized by the OLP behaving unfairly, interacting mechanistically, constantly monitoring, and enforcing ambiguous procedures. Crowdworkers in HB5 would experience burnout regardless of resource gains.

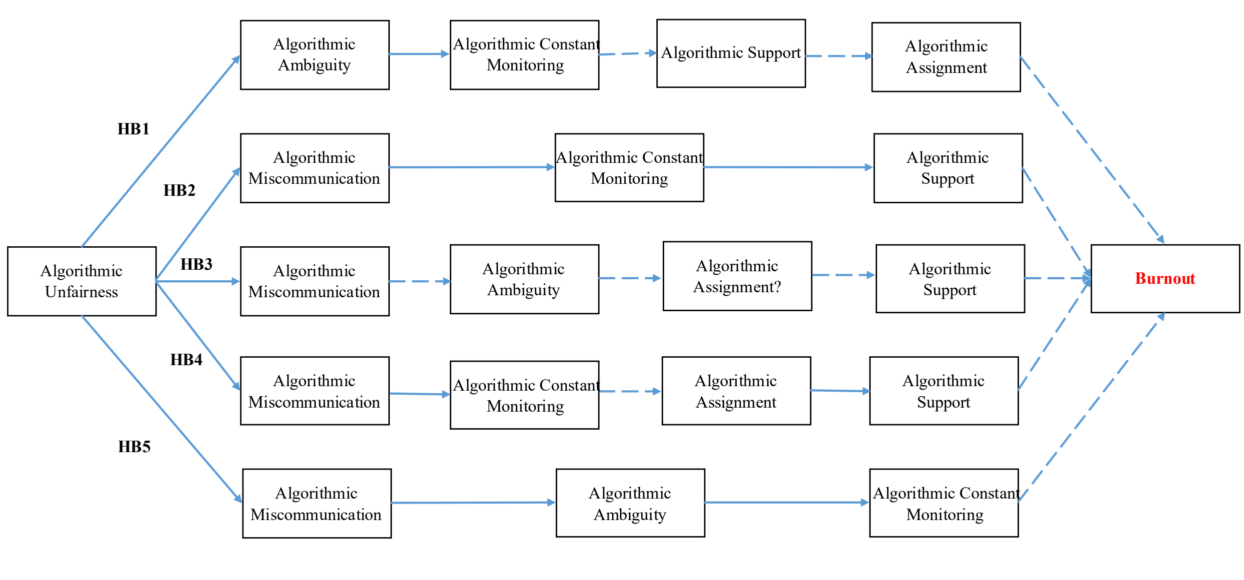
HB1 represents crowdworkers facing challenges of algorithmic ambiguity and unfairness, expressing dissatisfaction with job allocation and support provided by algorithmic management. The HB2 configuration denotes crowdworkers facing relational challenges; although they perceive a high level of autonomy, the lack of support within a mechanistic and unfair relationship structure contributes to their burnout. Crowdworkers in the HB3 configuration feel exhausted, primarily due to algorithmic unfairness. These workers believe that the algorithmic assignment and support fail to meet their expectations, and also feel that compensation, workloads, or penalties determined by algorithms are not fair. Configuration HB4 is largely similar to HB2, reemphasizing that when algorithmic management does not provide adequate support, mechanistic and unfair relationships can lead crowdworkers to burnout.

Low burnout: The fsQCA results indicate only one configuration associated with low burnout, suggesting an asymmetric relationship between algorithmic management-related resource passageways and work outcomes. This finding implies that the adverse effects of resource loss outweigh the benefits of resource gains within algorithmic management. Configuration LB1 demonstrates that when algorithmic management is not ambiguous, effective algorithmic job allocation can mitigate the negative impacts of algorithmic miscommunication and constant monitoring, ultimately reducing job strain. In other words, appropriate job assignment helps crowdworkers cope with the demands of overmonitoring and miscommunication, thereby reducing the likelihood of burnout.

Table 2. fsQCA Configurations for Study 2

Conditions\configurations	Burnout					Low burnout
	HB1	HB2	HB3	HB4	HB5	LB1
Algorithmic ambiguity	●		⊗		●	⊗
Algorithmic unfairness	●	●	●	●	●	
Algorithmic miscommunication		●	⊗	●	●	●
Algorithmic constant monitoring	⊗	●		⊗	●	●
Algorithmic assignment	⊗		⊗	●		●
Algorithmic support	⊗	⊗	⊗	⊗		
Consistency	0.86	0.90	0.92	0.88	0.89	0.91
Raw coverage	0.34	0.18	0.25	0.22	0.38	0.36
Unique coverage	0.14	0.11	0.07	0.09	0.21	0.36
Overall solution consistency	0.93					0.91
Overall solution coverage	0.78					0.36

Note: Black circles (●) indicate the presence of a causal condition, and (⊗) circles represent the absence of a causal condition; Blank spaces indicate "don't care."



Note: representing the condition presence in the configuration; indicating the condition absence in the configuration.

Figure 2. Configural Algorithmic Resource Model to Crowdworkers' Burnout

5.5 Discussion

The findings from Study 2 deepen our understanding of how algorithmic management resource caravans drive burnout among crowdworkers. Using fsQCA, we identified five distinct configurations of resource losses and gains that lead to burnout. Notably, algorithmic unfairness emerged as a core condition present in all burnout pathways, underscoring its salience as a stressor in OLP environments. This finding indicates that many crowdworkers perceive algorithmic management as unfair and as a tool to make them subservient to the platforms. The analysis also reveals that the absence of algorithmic support amplifies the negative effects of resource losses, indicating that support mechanisms can buffer against some resource losses. However, the asymmetric nature of the relationships highlights that not all resource gains can compensate for resource losses, particularly when unfairness, miscommunication, and invasive supervision are perceived. The pathways illustrated in Figure 2 correspond to distinct algorithmic management resource gain and loss caravans that lead to crowdworker burnout.

6 Study 3: Pathways to Crowdworker Engagement

Organizational and psychological studies show that when work environments provide valuable resources, they can motivate workers to dedicate their efforts to accomplish tasks and achieve work goals (Bakker & Demerouti, 2017). When jobs provide resources that satisfy basic needs or support goal achievement, workers have a positive work-related mindset that drives engagement. Lin et al. (2019) suggest that work engagement is the function of resource gains and losses. Gains such as recognition, rewards, or accomplishment enhance workers' resource pool, giving them a sense of progress and growth. Engaging in activities that lead to resource gains can be highly motivating, as they can contribute to the expansion and improvement of an individual's resource reservoir. Engaged workers will thus proactively attempt to meet their job requirements and take initiatives that go beyond what is expected or required of them. In contrast, resource loss leads to a sense of helplessness, disappointment, and reduced control over one's circumstances, which in turn can undermine motivation and engagement.

Recent research has recognized that engagement and burnout are not simply opposing outcomes (e.g., Demerouti et al., 2017; Maslach & Leiter, 2008). For instance, Ong and Johnson (2023) found that configurations of job conditions shaping engagement and burnout are asymmetrical. That is, the conditions that promote engagement are distinct from those that contribute to the lack of burnout. Study 3 aimed to investigate how algorithmic management-related resource gains and losses affect crowdworker engagement. In addressing this query, we used fsQCA to identify configurations of resource passageways that produce engagement.

6.1 Participants and Procedure

For Study 3, we approached the community of uberpeople.net contributors. As noted above, most members of this community work with the Uber, Lyft, DoorDash, Uber Eats, and Amazon Flex platforms. In February 2021, we posted a temporary announcement under the community category and stories threads. In this post, we provided information about our research and explained that we would analyze anonymized personal descriptions of participants' work conditions from their own perspectives. We further clarified that their participation in this study was voluntary, that results would be used only for research purposes, and that our study was not related to any business and was not organized by any platform firm. To motivate participation, we committed to providing a £5 electronic gift card to those who answered the questionnaire completely and accurately. After three weeks and three reannouncements of the post, we collected 175 questionnaires. We excluded respondents who did not work for a platform (6 cases). We also removed responses that indicated inappropriate response behavior, including unreasonable time for completion, i.e., handling time of less than 5 minutes (11 cases) or failing at least one attention-trap question (21 cases). Thus, for the third study, we were left with 137 appropriately completed responses for our configurational analysis. The final sample group ranged from 18 to 68 years of age (M_{age} = 41.7, SD_{age} = 13.2) and was approximately 62% male.

6.2 Survey Instrument and Measures

All resource-gain and resource-loss passageway conditions were measured using the same scales as Study 2. To measure engagement, we used the nine-item scale from Schaufeli et al. (2006). Similar to Study 2, we tested the measurement model and the convergent and discriminant validity of constructs. Table F3 in Appendix F presents the measurement test results.

6.3 Results

High engagement: The fsQCA analysis revealed three configurations associated with high engagement among crowdworkers (see Table 3). Configuration HE1, which has the highest coverage (0.29), represents the most prevalent group of engaged crowdworkers. They display vigor, absorption, and dedication when all resource loss conditions are absent and resource gains are at high levels. In HE2, crowdworkers are satisfied with the algorithmic support and perceive algorithmic management as neither unfair nor overly mechanistic. While they may express discontent with constant monitoring and overcontrolling, the support provided by the platform enhances their engagement. In the third configuration (HE3), despite opaque procedures and miscommunication from the OLP, crowdworkers do not view algorithmic management as unfair. They benefit from algorithmic job assignment and support, resulting in an enhanced sense of engagement.

All three of the configurations leading to crowdworker engagement demonstrated consistency scores above the threshold of 0.8, ensuring that each identified path reliably resulted in our outcome of interest. The overall solution consistency (0.91) guarantees that these three configurations are consistently linked to engagement. However, the overall solution coverage for engagement configurations (0.42) was notably lower than that for burnout (0.78), corroborating our findings from Study 1. This implies that crowdworkers perceive algorithmic management as more straining than engaging. Furthermore, the presence of algorithmic support across all engagement-promoting configurations underlines its salient role in fostering crowdworker engagement.

Low engagement: fsQCA identifies two configurations associated with low engagement. Both configurations show high satisfaction with the flexibility and autonomy offered by algorithmic management. However, in Configuration LE1, miscommunication poses a barrier to engagement, limiting the effectiveness and frequency of workers' interactions with the OLP. Configuration LE2 indicates that a lack of adequate support—despite the flexibility provided by algorithmic management—diminishes crowdworkers' engagement.

Table 3. fsQCA Configurations for Study 3

Conditions \ configurations	Engagement			Low engagement	
	HE1	HE2	HE3	LE1	LE2
Algorithmic ambiguity	⊗		●	⊗	
Algorithmic unfairness	⊗	⊗	⊗		
Algorithmic miscommunication	⊗	⊗	●	●	⊗
Algorithmic constant monitoring	⊗	●		⊗	⊗
Algorithmic assignment	●		●	●	●
Algorithmic support	●	●	●		⊗
Consistency	0.91	0.89	0.89	0.91	0.84
Raw coverage	0.29	0.16	0.14	0.43	0.36
Unique coverage	0.11	0.08	0.06	0.14	0.09
Overall solution consistency	0.91			0.85	
Overall solution coverage	0.42			0.49	

Note: Black circles (●) indicate the presence of a causal condition, and (⊗) circles represent the absence of a causal condition; Blank spaces indicate "don't care."

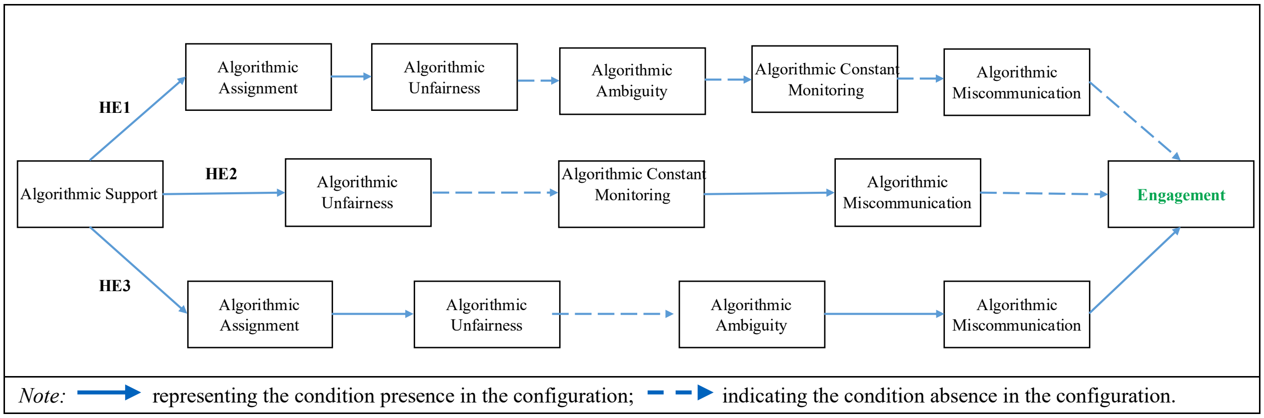


Figure 3. Configural Algorithmic Resource Model of Crowdworkers' Engagement

6.4 Discussion

Study 3 extends our exploration of how algorithmic management resource gains and losses shape crowdworker engagement. Figure 3 shows three algorithmic management resource caravans that enhance engagement, with high levels of algorithmic support and fair management practices emerging as pivotal enablers. These findings indicate the importance of providing reward resources and information, making fair decisions, and offering flexible and efficient job allocation in order to foster engagement. Interestingly, even in the presence of resource losses like constant monitoring, ambiguous procedures, or miscommunication, engagement can be sustained when resource gains, especially algorithmic support, are present. This study highlights the dynamic interdependencies of resource gains and losses in promoting engagement and suggests that platform firms should prioritize supportive and fair practices to promote positive worker experiences. Together with the findings from Study 2, this study illuminates the various pathways through which algorithmic management influences burnout and engagement.

7 General Discussion and Post Hoc Analysis of Findings

7.1 Discussion

We used the findings from Studies 1-3 to draw inferences, which were then integrated into the development of meta-inferences for the algorithmic management resource model (see Table 4 for a summary of inferences and meta-inferences). Based on these meta-inferences, we conclude with six propositions to explain and predict the impacts of algorithmic management on work outcomes.

In OLPs, algorithms function as the primary decision makers, playing a pivotal role millions of times a day by determining job assignments, pay rates, penalties, and more. Conceivably, crowdworkers constantly assess the fairness of these algorithmic decision-making practices, particularly concerning outcomes that directly impact them. An analysis of crowdworkers' narratives revealed that 16% of community posts noted perceived injustices in compensation (e.g., low fares and surge pricing issues), penalty enforcement (e.g., false accusations and account deactivation/suspension), and workload allocation (e.g., long waiting times and job misallocations). Mounting evidence suggests that perceived unfairness is a significant job stressor and a potential driver of job strain. As per the relational model of authority, individuals care deeply about how authorities treat them and continuously assess the neutrality, integrity, and trustworthiness of those authorities' decisions (Blader & Tyler, 2015). When organizational procedures and interpersonal treatment are perceived as unjust, employees are more likely to experience frustration and stress. For crowdworkers, unfair decisions also amplify uncertainty about future earnings and job security. Due to their inability to appeal or influence these decisions (Choudary, 2018), crowdworkers often feel constrained by algorithmic directives (Deng et al., 2016), which could undermine their sense of dignity and professional identity (Jabagi et al., 2024). Fieseler et al. (2019) argue that the lack of bargaining power and low social standing contribute to inadequate application of *justice principles* in algorithmic decisions. This perception of unfairness can lead to decreased job satisfaction and increased attrition rates. Our fsQCA results further underscore the critical role of algorithmic unfairness, which is present in all burnout configurations but absent in those leading to engagement. We therefore suggest the following:

Proposition 1: Perceived unfairness of algorithmic management practices regarding the compensation system, punishment mechanisms, and workload allocation is a salient work condition contributing to burnout.

Table 4. Inferences from Studies 1-3 and Development of Meta-inferences

Study 1 inferences	Study 2 inferences	Study 3 inferences	Meta-inferences
Unclear routines + Unforeseen app changes + Unpredictable fees + Unstable commission fees = Resource losses, perceived as "**algorithmic ambiguity**"	Present in burnout (HB1, HB5), but not in lack of burnout	Absent in HE1, present in HE3 for engagement, but "don't care" in lack of engagement	*Algorithmic ambiguity* is a salient resource-loss condition for burnout outcome. Algorithmic support and assignment can jointly mitigate the negative impact of *algorithmic ambiguity* on crowdwork engagement.
Unfair surge pricing + Unacceptable fares + False accusations + Unreasonable account deactivations + Long waiting times + Job misallocations = Resource losses, perceived as **"algorithmic unfairness"**	A necessary condition for burnout (HB1-HB5), but "don't care" in lack of burnout	Absent in engagement (HE1-HE3) but "don't care" in lack of engagement.	*Algorithmic unfairness* is an essential resource-loss condition for burnout and absent in all configurations for engagement. Findings indicate critical importance of ensuring fairness in compensation, workload distribution, and penalty assessment
Automated messaging + ineffective communication + insufficient explanations + neglecting workers' concerns + unresponsiveness = Resource losses, perceived as **"algorithmic miscommunication"**	Present in burnout (HB2, HB4, HB5) and present in the lack of burnout	Absent in engagement (HE1, HE2) and present in lack of engagement (LE1, LE2)	*Algorithmic miscommunication* has asymmetrical relationship with burnout, functions as a supplementary condition, and its impact contingent on the other conditions. Both algorithmic assignment and support are required for crowdwork engagement when *algorithmic miscommunication* is present.
App monitoring + Overcontrolling + Privacy concerns + Intrusive rating system Scrutinizing cancellation rates + Nitpicking = Resource losses, perceived as **"algorithmic constant monitoring"**	Present in burnout (HB2, HB5) and absent in lack of burnout	Absent in engagement (HE1) and present lack of engagement (LE2)	*Algorithmic constant monitoring* has asymmetrical relationship with burnout, functions as a supplementary condition, and its impact contingent on the other conditions. Algorithmic support may facilitate coping with *algorithmic constant monitoring* and promote engagement.
Time flexibility + Location flexibility + Job availability + Task allocation = Resource gains, perceived as **"algorithmic assignment"**	Absent in (HB1, HB3), present in (HB2, HB4), and don't care condition in HB5 for burnout, present in lack of burnout	Present in engagement (HE1, HE3) and present in lack of engagement (LE1, LE2)	*Algorithmic assignment* may mitigate the expected associations between burnout and algorithmic constant monitoring as well as algorithmic miscommunication. Findings reveal that *algorithmic assignment* is not sufficient condition for engagement.
Traffic information + Navigation advice + Performance feedback + Extra pay + Income = Resource gains, perceived as **"algorithmic support"**	Absent in burnout (HB1-HB4) and 'don't care' in lack of burnout	Present in engagement (HE1-HE3) and 'don't care' for lack of engagement	*Algorithmic support's* presence is a critical condition for engagement, and its absence can largely contribute to burnout. *Algorithmic support* alone can mitigate the adverse effects of algorithmic constant monitoring.

Note: "Don't care" conditions refer to situations where certain conditions in a configuration are considered irrelevant to the outcome.

Consistent with the "coping hypothesis" (Van Woerkom et al., 2016), we found that specific resource gains promote coping with resource depletion. Our findings reveal that algorithmic support and positively perceived algorithmic job assignment can help offset the negative impacts of ambiguity and miscommunication. Specifically, when algorithms support crowdworkers by providing rewards, information, and flexible job allocations, crowdworkers may better cope with ambiguous or inconsistent procedures, helping them stay engaged. This occurs because algorithmic support can act as one of the compensatory resources that help workers navigate uncertainty and maintain their sense of control. When algorithms provide rewards and information, they create predictable pathways for success, reducing the cognitive load and anxiety associated with ambiguous procedures (Gonzalez-Mulé et al., 2021). Further, flexible job allocations give workers agency in managing their work, which research shows can buffer against stress from procedural uncertainty (Maslach & Leiter, 2008). Job autonomy is primarily a cognitive resource, providing discretion to individuals to process and apply information in their work (de Jonge & Dormann, 2006). As a job resource, autonomy allows workers to prioritize tasks and align their responsibilities with their skills and preferences, fostering a sense of control and reducing job strain. Likewise, our findings reveal that high levels of perceived autonomy and support allow crowdworkers to tolerate the detached relationships and lack of voice. We thus propose the following:

Proposition 2: Algorithmic support and assignment facilitate coping with algorithmic ambiguity and miscommunications, thereby enhancing crowdworker engagement.

Approximately 9.2% of community posts included crowdworkers venting about being micromanaged by algorithms. They expressed feeling pressured by the constant, real-time tracking of their performance and behavior. Crowdworkers shared stories of dealing with ongoing surveillance, including app tracking, overcontrolling, and invasions of their privacy. Many criticized this invasive supervision style, describing algorithms as nitpicking bosses that scrutinize even minor actions and impose strict penalties for low rating scores and high cancellation rates. Such feelings of being under constant monitoring diminish engagement, lower morale, and damage trust (Carlson et al., 2017; Holland et al., 2015). The demanding nature of algorithmic control restricts crowdworkers' autonomy and increases work intensity through a combination of behavioral nudges and constant surveillance (Duggan et al., 2020; Wood et al., 2019). Further, 8.9% of forum posts highlighted crowdworkers' frustrations with ineffective and unsupportive communication from the OLP. Many reported that their concerns were overlooked and that they had little opportunity to voice their opinions or receive meaningful responses. This lack of responsiveness may create a sense of disconnection between workers and the platform, reinforcing the perception that they are merely managed by impersonal algorithms rather than being recognized as valued contributors. Ultimately, this absence of meaningful communication can heighten stress and exacerbate job strain. However, our configurational analysis revealed that the relationships between algorithmic constant monitoring, algorithmic miscommunication and burnout is not symmetrical; the effects of overmonitoring and miscommunication on burnout depend on interactions with other conditions. Specifically, algorithmic constant monitoring, when coupled with algorithmic unfairness and miscommunication, will produce crowdworker burnout. Similarly, algorithmic miscommunication, in conjunction with perceived unfairness, may also lead to burnout. These findings suggest that the impacts of these two conditions are contingent upon the broader resource environment in which crowdworkers operate. Therefore, we propose the following:

Proposition 3: The impacts of algorithmic constant monitoring and miscommunication on crowdwork burnout are asymmetrical, with burnout emerging not from overmonitoring or miscommunication alone but from their interaction with other conditions.

In line with the "buffering hypothesis," our results suggest that by providing flexibility and autonomy, algorithmic assignment can alleviate the impact of some resource losses on exhaustion (Bakker et al., 2005). Prior research has demonstrated that the associations between resource depletion and burnout are less pronounced when resource gains function as buffers against resource losses (Bakker & Demerouti, 2017). As a job resource, perceived autonomy promotes a sense of control over work conditions and fosters intrinsic motivation (Deci & Ryan, 2004). Providing employees with control is an important job resource that can buffer against the adverse effects of some limitations, such as workload (Bakker et al., 2005; Brauchli et al., 2014). In the context of OLPs, crowdworkers can better tolerate close supervision and interactions with non-human agents when the algorithm provides work flexibility and guarantees the availability of jobs. Based on the fsQCA results and established psychological theories, we propose that algorithmic assignment can serve as a buffer. This perspective offers a practical understanding of how positive aspects of algorithmic management can mitigate potential negative effects. Therefore, we suggest the following:

Proposition 4: Algorithmic assignment can buffer the impacts of algorithmic constant monitoring and algorithmic miscommunication, thereby reducing crowdworker burnout.

Our findings further reveal that although algorithmic micromanagement can increase job strain, providing informational support (e.g., performance feedback) and reward support (e.g., income) can facilitate coping with the negativity associated with micromanagement. Prior research has found that excessive monitoring signals to workers that managers want to restrict their autonomy (Long & Sitkin, 2018). They perceive supervisor monitoring as something that limits their flexibility and ability to act on their own decisions (George & Zhou, 2001). Excessive and invasive monitoring can be seen as a manifestation of micromanagement that takes away autonomy from workers (Alvesson & Sveningsson, 2003), which has been shown to be associated with increased stress levels because workers may feel pressured to always meet their manager's expectations. Nevertheless, a number of studies have demonstrated that organizational support facilitates coping with job stressors (e.g., Ganster et al., 1986; Demerouti et al., 2001). Organizational support, by offering tangible and cognitive resources such as information or financial rewards, can help employees address specific stressors. As per organizational support theory (Kurtessis et al., 2017), workers with high perceived organizational support engage in increased job-related effort, resulting in enhanced in-role job performance. Accordingly, we suggest the following:

Proposition 5: When algorithmic management constantly monitors crowdworkers, algorithmic support may facilitate coping with this resource loss and enhance engagement.

There has been an expectation in past research that resource gains might buffer against resource losses (Bakker & Demerouti, 2017). Conversely, our findings suggest that when crowdworkers experience unfair treatment in terms of reimbursement, job allocation, or punishment, along with a lack of voice (i.e., OLPs neglecting their concerns) and a detached relationship (characterized by automated messaging, ineffective communication, and insufficient explanations), work flexibility alone is not enough to prevent frustration. Analyzing the fsQCA paths to burnout indicates that the autonomy resulting from algorithmic job assignment does not shield crowdworkers from the negative impacts of unfairness and mechanistic interactions. While algorithmic assignment creates a sense of flexibility, it cannot compensate for deeper relational and procedural injustices. This occurs because crowdworkers' psychological needs for fairness, respect, and meaningful communication supersede instrumental flexibility. When algorithmic management fails to address these fundamental needs, workers may experience high levels of stress and frustration that flexibility cannot mitigate. Our results indicate that supportive mechanisms (information and reward provision) are essential to preventing crowdworker exhaustion. We thus propose the following:

Proposition 6: When algorithmic management is unfair and unsupportive and communication is mechanistic, crowdworkers are likely to experience burnout, despite the flexibility provided by such algorithms.

7.2 Conclusion, Implications, and Limitations

Across three studies, we extended our understanding of algorithmic management implications and offered insights into the realities of OLP work settings. Utilizing a COR theoretical lens and employing computational and configurational analysis, our findings unearth both which resource gains and losses emerge from algorithmic management and how they jointly influence work outcomes.

Our work responds to scholarly calls for further empirical investigation into the conditions under which algorithmic management becomes either more enabling or more restraining (Meijerink & Bondarouk, 2023). Taking a bottom-up computational approach, we gained fine-grained insights into crowdworkers' opinions and perceptions of algorithmic management and its associated resource gains and losses. While prior research has noted the complex balance of freedom and control in OLPs (Cameron & Rahman, 2022)—where algorithmic management simultaneously enables and restrains crowdworkers—our research takes a step toward a better understanding of how this dual complexity of algorithmic management reshapes work conditions and outcomes. Leveraging a COR theoretical lens, this work theorizes and operationalizes an algorithmic management resource model to explore the resource dynamics emerging from this form of management.

One contribution of this model is to explain why some crowdworkers have more positive work experiences and continued engagement, compared to others who experience high levels of stress and frustration. Specifically, Study 1 offers valuable insights into how algorithmic management influences work conditions by uncovering the resource gains and losses that result from this emerging form of management. Our findings indicate that algorithmic management can cause frustration by generating various recourse losses, including procedural inconsistencies; reward uncertainties; unfair compensation, workload, and punishment; detached relationships; lack of voice; ongoing surveillance; and invasive supervising. At the same time, it can enable crowdworkers by providing resource gains such as flexible work schedules and locations, efficient gig allocations, and informational and reward support.

In Studies 2 and 3, we adapted identified resource gain and loss constructs and examined their mutual impacts on key work outcomes, including engagement and burnout. Utilizing a configurational approach, we explored the algorithmic management resource caravans that shape crowdworkers' engagement and burnout in OLP work settings. Shifting attention from linear, net-effect variables to configurations of variables, we contribute to algorithmic management scholarship by theorizing and empirically examining complex relationships between algorithmic management and work outcomes. Our fsQCA analysis revealed five distinct configurations that explain/predict how resource gains and losses contribute to crowdworkers' burnout—and three configurations that lead to their engagement. The extracted configurations resemble resource caravans: patterns of interdependencies between resource losses and gains in terms of contingencies, complementarities, and substitutions. These findings contribute to COR theory by demonstrating how algorithmic management creates resource caravans where gains and losses are interlinked. Our findings show that, unlike traditional work environments, where resource caravans develop primarily through human interactions, algorithmic management can simultaneously trigger multiple resource gains or losses by providing or restricting resources. This advances our understanding of how resource caravans form and propagate in algorithmically managed work environments.

Third, our results confirm "the primacy of resource loss" principle of COR theory in the OLP work setting. We found that the presence of all four resource losses increases crowdworker burnout regardless of resource gains. This conclusion is supported by the high raw coverage of burnout configurations, indicating that high levels of algorithmic management resource losses lead to burnout. Additionally, in line with organizational justice theory (Colquitt & Zipay, 2015), our work shows that perceiving algorithmic decisions as unfair might lead to crowdworker burnout. However, this mechanism is contingent on the level of support offered by algorithmic management. The fsQCA results indicate a notable absence of algorithmic support within burnout configurations, suggesting that algorithmic support may facilitate coping with unfairness. Additionally, by comparing configurations that lead to burnout or lack of burnout, we found that the flexibility and autonomy offered by algorithmic job allocation is an effective buffer against the adverse effects of algorithmic micromanagement and miscommunication, thereby inhibiting exhaustion. Nonetheless, it is interesting to note that when crowdworkers perceive algorithmic management as unfair, especially in conjunction with miscommunication or overmonitoring, the resource gains derived from algorithmic job assignment may not sufficiently alleviate the resulting psychological costs, leading crowdworkers to experience burnout. These findings are important because while prior research in conventional work settings suggests that job autonomy can buffer the adverse effects of resource loss and mitigate job strain (Bakker et al., 2005; Brauchli et al., 2014), our results indicate that in algorithmic management, autonomy and flexibility alone appear insufficient to cope with resource losses.

The fsQCA analysis further shows that a high level of algorithmic support, coupled with fair management, is a salient condition for enhancing crowdworkers' engagement. Importantly, this finding once again underscores the interdependence between algorithmic management support and unfairness conditions in shaping work outcomes. We also found that even in the face of micromanagement and invasive supervision, crowdworkers can still experience engagement when algorithmic management provides a high level of support. However, the presence of both resource gains, i.e., algorithmic assignment and support, is imperative to effectively address the challenges associated with the ambiguity of algorithmic procedures and miscommunication. Further, our findings establish complex asymmetrical relationships between algorithmic management resource passageways and work outcomes by showing that some conditions are present in one configuration and absent in another. Notably, we observed an asymmetrical relationship between constant algorithmic monitoring and burnout; this resource loss may be present in one configuration driving crowdworker burnout but absent in another. Our fsQCA results confirm that burnout and engagement are not opposite outcomes (Ong & Johnson, 2023). More importantly, they reveal that algorithmic management resource loss passageways hold greater significance than resource gain passageways because the path to crowdworker burnout is wider. Several different configurations can shape exhaustion similarly; its overall solution coverage is far greater than engagement, 0.78 vs. 0.42, respectively.

From a practical perspective, our findings highlight key implications pertaining to algorithmic management that platform firms should take into account. Transitioning from human managers to algorithmic bosses entails particular types of resource provision and depletion that impact the crowdworking experience. Our findings indicate that optimizing the balance between resource gains and losses plays a fundamental role in determining important work outcomes, including burnout or engagement. Because crowdworkers are particularly susceptible to frustration, platforms should strive to recognize when crowdworkers are feeling exhausted and develop strategies to alleviate such perceptions, potentially by reinforcing algorithmic management resource gain passageways. By ensuring that algorithmic decision-making processes and criteria for job allocation, performance monitoring, and remuneration are clearly communicated to crowdworkers, OLPs can promote transparency and prevent confusion. Human-in-the-loop design, especially when dealing with high-stakes scenarios such as suspending or deactivating crowdworkers, can be effective in mitigating workers' perceptions that the algorithm might err or lack consideration (Burton et al., 2020). It would also be beneficial to establish human-centered interactions with crowdworkers in order to address their sense of isolation. Furthermore, platform firms can establish open and transparent lines of communication, encouraging two-way interactions, active listening, and feedback mechanisms to ensure that crowdworkers' concerns and ideas are heard and addressed appropriately. They can also facilitate access to counseling services or coaching programs (e.g., professional guidance on how to resolve issues with job allocation, compensation, performance appraisal, and more). By doing so, managers can create a more supportive and effective work environment, ultimately benefiting both the crowdworkers and the platform itself.

Finally, some limitations of our research warrant consideration. First, while our analysis draws on both naturally occurring data from an online community and study survey responses, these sources may not capture the full diversity of crowdworker experiences across different platforms or regions, potentially limiting the generalizability of our findings. Second, the mixed outcomes observed in crowdworking suggest the potential presence of individual idiosyncrasies and/or contextual moderators that shape the relationship between algorithmic management and worker experiences. Further research should examine the person-centered and contextual factors contributing to crowdworker exhaustion and the potential interventions or safeguards for algorithmic management challenges. Third, the focus in the current study on specific work outcomes, such as burnout and engagement, may overlook other important variables, such as job satisfaction or turnover intentions, which could provide additional insights into the nuanced impacts of algorithmic management. Lastly, although our configurational approach offers a deeper understanding of the interplay between resource gains and losses, it may not fully capture the temporal dynamics or long-term impacts of algorithmic management practices, as our data were cross-sectional rather than longitudinal. Future research could benefit from longitudinal studies and cross-platform analyses to further validate and expand our findings.

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Appendix A: Review of Algorithmic Management Literature

Authors	Context	Research design	Major findings
Cheng & Foley (2019)	Airbnb hosts	Thematic analyses of online community forum posts	• The asymmetry of algorithmic information can enhance Airbnb's influence and control over hosts' practices. • This information asymmetry can substantially impede hosts' sense of control.
Gol et al. (2019)	Crowdworking platforms	Theoretical review strategy	• For effective crowdwork platform governance, control and coordination mechanisms are crucial. • Governance, particularly control, plays a more significant role in centralized platforms, while coordination is vital for decentralized ones. • The emphasis on effective governance is particularly pronounced in non-routine creative crowdwork.
Jarrahi & Sutherland (2019)	Digital labor platforms, the case of Upwork users	Qualitative study based on interviews with Upwork workers	• Workers are not passive recipients of algorithmic management and control but they develop "algorithmic competencies" as a source of personal competitive advantage in platform work. • Workers may decide to circumvent or manipulate the algorithms to their advantage. • The gig workers on Upwork often lack a complete understanding of the inner workings of many algorithms, creating information asymmetry that can impede their ability to exert control over their work.
Basukie et al. (2020)	Go-Jek, an Indonesian ride-sharing platform	Qualitative research design, case study	• Legal and ethical concerns are the main challenges of Go-Jek in emerging markets. • Go-Jek is appreciated in this emerging economy since it offers job opportunities and income generation.
Duggan et al. (2020)	Employment relations and HRM for App-work	Conceptual paper	• App workers perceive their work relationship with the platform beyond merely economic or transactional exchanges. • The work relationship in app work raises concerns around power imbalances, fairness, and worker well-being. • Algorithms mainly undertake roles in work assignment and performance management that were traditionally the preserve of HR professionals.
Gal et al. (2020)	General people analytics applications of Algorithmic Management	Conceptual paper	• Three ethical consequences of people analytics are discussed: opacity, datafication of the workplace, and nudging. • The adverse effects of these challenges on members' ability to cultivate their virtues are examined. • Three mitigation strategies are suggested including: reframing PA, adopting new roles, and applying alternative design principles.
Galiere (2020)	Food-delivery platform (Deliveroo)	Qualitative case study	• Algorithmic rational control, though fallible, is strengthened by subjectification techniques. • Various platform features, including pay-per-delivery and shift picker systems, actively mobilize workers.

Stark & Pais (2020)	Platform economy	Conceptual paper	• Unlike traditional markets, hierarchies, and networks, platforms draw upon external assets, resources, and activities. • Platforms manage value creation activities on their platforms without traditional managerial authority, reshaping the managerial class in the 21st century. • Users' and providers' actions are translated into rankings and calculations through complex feedback loops, leading to a unique form of cybernetic control where accountability can be elusive.
Bucher et al. (2021)	Upwork workers	Systematic content analysis of comments from Reddit	• Workers employ anticipatory compliance practices to pacify algorithms and avoid scrutiny or punishment. • These practices involve direct and indirect strategies, such as avoiding triggering words or undervaluing work for better ratings.
Jarrahi et al. (2021)	Standard and non-standard work settings	Conceptual paper	• Algorithmic management influences power dynamics at work by increasing the power of managers over workers and simultaneously decreasing managerial authority. • Algorithmic management shapes organizational roles through algorithm aversion and cognitive complacency. • Algorithmic management impacts knowledge and information exchange within an organization.
Möhlmann et al. (2021)	Online labor platforms: The case of Uber	Case study and grounded theory	• OLPs play dual roles of matching and control: using algorithms, they optimize matching and accommodate the market, while simultaneously, monitoring and controlling platform work. • Platform workers experience autonomy, uncertainty and self-identity tensions relating to work execution, compensation, and belonging. • In managing the experienced tension, workers present market-like (bypassing & switching) or organization-like (striking & embracing) responses.
Wood (2021)	Examples of platform works and conventional employment settings	Conceptual paper	• Algorithmic management expedites the growth of precarious, fragmented employment arrangements (such as outsourcing, franchising, temporary employment agencies, labor intermediaries, and digital labor platforms). • Algorithmic management exacerbates work conditions by increasing standardization and reducing opportunities for using discretion and intrinsic skills. • Evidence from platform work and logistics highlights the danger of algorithmic management intensifying work effort, creating new sources of algorithmic insecurity and provoking workplace resistance.

Anicich (2022)	App-based, food delivery platform	Qualitative, autoethnography	• Due to independent contracting, technological constraints, and having no coworkers, app work results in high depersonalization and low interpersonal accountability for workers. • To overcome this, app workers rely on narrative structuring, fantasizing, rationalizing, and connecting through storytelling in online forums.
Bujold et al. (2022)	Truck drivers in Eastern Canada	Questionnaire-based survey from truck drivers	• Algorithmic surveillance transparency is linked to procedural justice, and algorithmic performance management transparency is tied to distributive justice. • Procedural justice mediates the negative link between algorithmic surveillance transparency and intention to quit.
Gagné et al. (2022)	Conceptual effects of algorithmic management on work motivation	Literature review based on self-determination theory (SDT).	• Algorithmic management has predominantly negative impacts, frustrating key psychological needs such as competence, autonomy, and relatedness. • Some features of algorithmic management systems such as transparency, reliability, fairness of the system, and level of human influence can moderate these effects.
Kinowska & Sienkiewicz (2022)	Workplace well-being in case of using data analytics for some organizational functions	Analyzing the 2019 ECS data (European human resource managers and employees)	• The results affirm a moderate, direct impact of algorithmic management practices on workplace well-being. • There is an indirect influence, primarily through a negative impact on job autonomy and total rewards practices. • The level of influence varies significantly, particularly in larger organizations, where the impacts of algorithmic management on well-being and job autonomy decrease.
Parent-Rocheleau & Parker (2022)	Conceptual work design and HRM	Review/conceptual paper	• Algorithms are currently able to perform six managerial functions including: monitoring, goal setting, performance management, scheduling, compensation, and job termination. • Algorithmic management can affect job resources (e.g., job autonomy, job complexity) and job demands (e.g., workload, physical demands). • Transparency, fairness and human influence can moderate the link between algorithmic management on work design.
Tomprou & Lee (2022)	The impact of organizational agent type—algorithmic versus human—on psychological contract	Online experiments	• The agent type (either human or algorithm) has no impact on psychological contracts regarding transactional inducements but does for relational inducements, particularly in recruiting and low-inducement delivery scenarios. • Algorithmic agents signal reduced employer commitment to relational inducements during recruiting, while the use of human agents results in greater perceived breaches when the delivery of relational inducements is low.

Felix et al. (2023)	Brazilian gig-workers	Grounded theory based on interviews	• Workers and gig work organizations prefer relationships with more autonomy or security. • Wellbeing increases when preferences align, but divergent preferences lead to violations and reduced well-being. • Not everything is a matter of fit: when both individuals and organizations have the same preference (for example, for more autonomy and less security), worker well-being may be vulnerable to abuse such as in the case of unsustainable workloads.
Huang (2023)	food-delivery platform in China	Ethnographic study	• There are two primary mechanisms for organizing labor under algorithmic management: virtual organization of labor and algorithm-driven labor process control. • Initially, platform drivers are restructured into an outsourced labor force, operating within an application-based virtual-networked production framework • Additionally, food-delivery platforms employ four algorithm-driven control techniques—smart machinery control, information monopoly, management by multi-stakeholders, and "carrots and sticks,"
Meijerink & Bondarouk (2023)	Human resource management (HRM) algorithms	Conceptual paper	• Algorithmic management exhibits a dual nature: while it restricts job autonomy and value in some aspects, it simultaneously enhances job autonomy and value for workers. • Algorithmic management is both influenced by and influential in terms of job autonomy and value for workers.
Möhlmannn et al. (2023)	Uber platform	Empirical case study	• It builds upon Weick's enactment theory to conceptualize how platform workers make sense of the algorithms managing them. • Algorithm sensemaking is a sophisticated, strategic, multistep process enabling platform workers to systematically comprehend and follow algorithmic activity. • Algorithm sensemaking serves as a mediating process, connecting workers' perceptions of tensions in their work environment (antecedents) to their behavioral responses (consequences).
Noponen et al. (2023)	Reviewing algorithmic systems in management literature	Systematic literature review	• Organizations are using algorithms to manage workers in four different ways: Algorithm as a manager, mentor, controller, and servant. • Despite the potential for enabling workers, companies predominantly utilize algorithmic systems for control, neglecting their organizing and enabling potentials.
Vignola et al. (2023)	Workers' health in platform-based food and grocery delivery companies	Review	• Algorithmic management's impact on job quality likely extends to worker health and well-being. • The design and implementation of algorithms can be balanced to meet both organizational and worker needs. • Policy changes in labor and social welfare laws are potential intervention points, contingent on a better understanding of algorithmic management's effects on workers' health.

Appendix B: Opinion Mining using XLNet

XLNet was architected as a multilayer bidirectional transformer encoder pretrained on a large corpus, including the Toronto Book Corpus and English Wikipedia. To adapt XLNet to a specific text mining task, a proper fine-tuning procedure is needed. Fine-tuning involves adding an extra output layer on top of the pretrained XLNet structure to align with a specific task. This is a method of transfer learning, where the knowledge acquired by the large neural network on a vast corpus, such as Wikipedia, is applied to a specific task, such as opinion mining (Dong et al., 2019). As a result, fine-tuning XLNet requires comparatively smaller training data to achieve satisfactory results, making it an advantageous technique for organizational and management studies, where obtaining labels for text data, like valence, can be expensive and time-consuming. To fine-tune XLNet, we used an optimism/pessimism labeled dataset that was made available by Ruan et al. (2016). The dataset contains textual data that was manually annotated by human raters as either optimistic or pessimistic, which aligns perfectly with the classification tasks in our study. We followed the approach proposed by Alshahrani et al. (2020) and considered (1/-1) threshold; that is, posts with an average score of 1 or greater were labeled as optimistic, whereas those with an average score of -1 or lower were labeled as pessimistic.

We partitioned the dataset into an 80% training set and a 20% testing set. To train the model, XLNet's tokenizer was first used to convert the input sequence into tokens that corresponded to XLNet's vocabulary. These tokens were then fed into the model. The architecture of the XLNet base model used for training consisted of 12 layers, 768 hidden neurons, 12 heads, and a total of 110 million parameters. Our XLNet model was topped with an untrained classifier layer, which was fine-tuned in addition to tuning the transformers. We set a conservative base learning rate of 2e-4 and batch size of 16 for 10 epochs (Fyffe et al., 2023).

As presented in Table B1, our fine-tuned XLNet model has achieved an outstanding overall accuracy of 93%, surpassing the Linguistic Inquiry and Word Count (LIWC)-based SVM by 14% and the LIWC-based logistic regression by 19% as base models. This higher performance may be attributed to XLNet's special capability to not only understand the relations between words but also to compute contextualized representations of textual data.

Table B1. Model accuracy comparison with benchmark models on the hold-out test dataset

Opinions	Fine-tuned XLNet	Baseline 1: SVM based on LIWC features	Baseline 2: Logistic regression based on LIWC features
Optimism	90	73	68
Pessimism	96	85	80
Overall accuracy	93	79	74

Appendix C: Topic Modeling Method and Results

C1. Identification of Topics

The topic modeling algorithms, such as STM, leverage statistical generative procedures to uncover topics representing the latent, underlying structure in the text. Simply put, topic modeling imitates the process of generating a document by decomposing the documents into two matrices: words per topic, and topics per document. Topic modeling assumes that each document has its own topic distribution, and each topic has its own word distribution. The algorithm outputs a list of the highest weighted words per topic, suggesting the content of the topics, as well as the words' probabilistic relation with each topic. In addition, each document can be annotated by a distribution over topics, which enables the detection of thematic patterns across the documents. As a result, this computational approach makes inductive content analysis more efficient, valid, transparent, and reproducible, enabling us to thematically classify and discover hidden patterns in massive amounts of user-generated data.

To prepare the corpus for topic modeling analysis, we followed Hickman et al.'s (2022) recommendations and performed several preprocessing steps to clean and parse the textual data. All forum posts were converted to lowercase, and nonalphabetic characters, including punctuation, symbols, numbers, and white spaces, were removed from the final textual corpus. The cleaned corpus was converted into a sparse token count matrix with documents (i.e., posts) in rows, tokens in columns, and cell values showing the number of times each token appeared in each post. To mitigate the likelihood of extracting uninformative topics and increase model convergence, words with fewer than three letters or words that repeated fewer than five times (usually typos or proper nouns) or appeared in fewer than 500 posts were removed. Any forum posts that no longer contained any tokens were also eliminated from the corpus. We used the stm package (Roberts et al., 2019) in the programming language R to estimate topic models. As recommended by Roberts et al. (2019), the topic model was estimated using the Spectral algorithm, as it outperforms other methods for modeling a large corpus. In addition, we followed Schmiedel et al.'s (2019) guidelines to algorithmically find the right number of topics. We fitted a structural topic model to investigate different topics discussed among crowdworkers' posts within pessimistic and optimistic posts. The final model identified 40 topics in total that were both semantically coherent and highly exclusive (see Table C.1 for details of topic modeling and list of extracted topics).

To determine which topic model was best for our corpus, we were required to specify the number of topics to be discovered from the document collection. Following Schmiedel et al. (2019), we iteratively ran different topic models and analyzed the results to find the appropriate number of topics that were not overloaded and overlapping. We used semantic coherence and exclusivity metrics to find an appropriate number of topics in our corpus. Semantic coherence is a measure of the internal coherence of topics and is maximized when the most probable words in a given topic frequently co-occur together (Roberts et al., 2019). Exclusivity is gauged by assessing the distinctiveness of topics through the comparison of word distributions associated with each topic (Schmiedel et al., 2019).

Given the size of our corpus, we ran different topic models ranging from 10 to 100 topics and assessed the average semantic coherence and exclusivity for each topic model. Figure C1 shows the scores for exclusivity at the top plot and scores for semantic coherence at the bottom plot. Results indicate that a model consisting of 40 topics has better semantic coherence and exclusivity values.

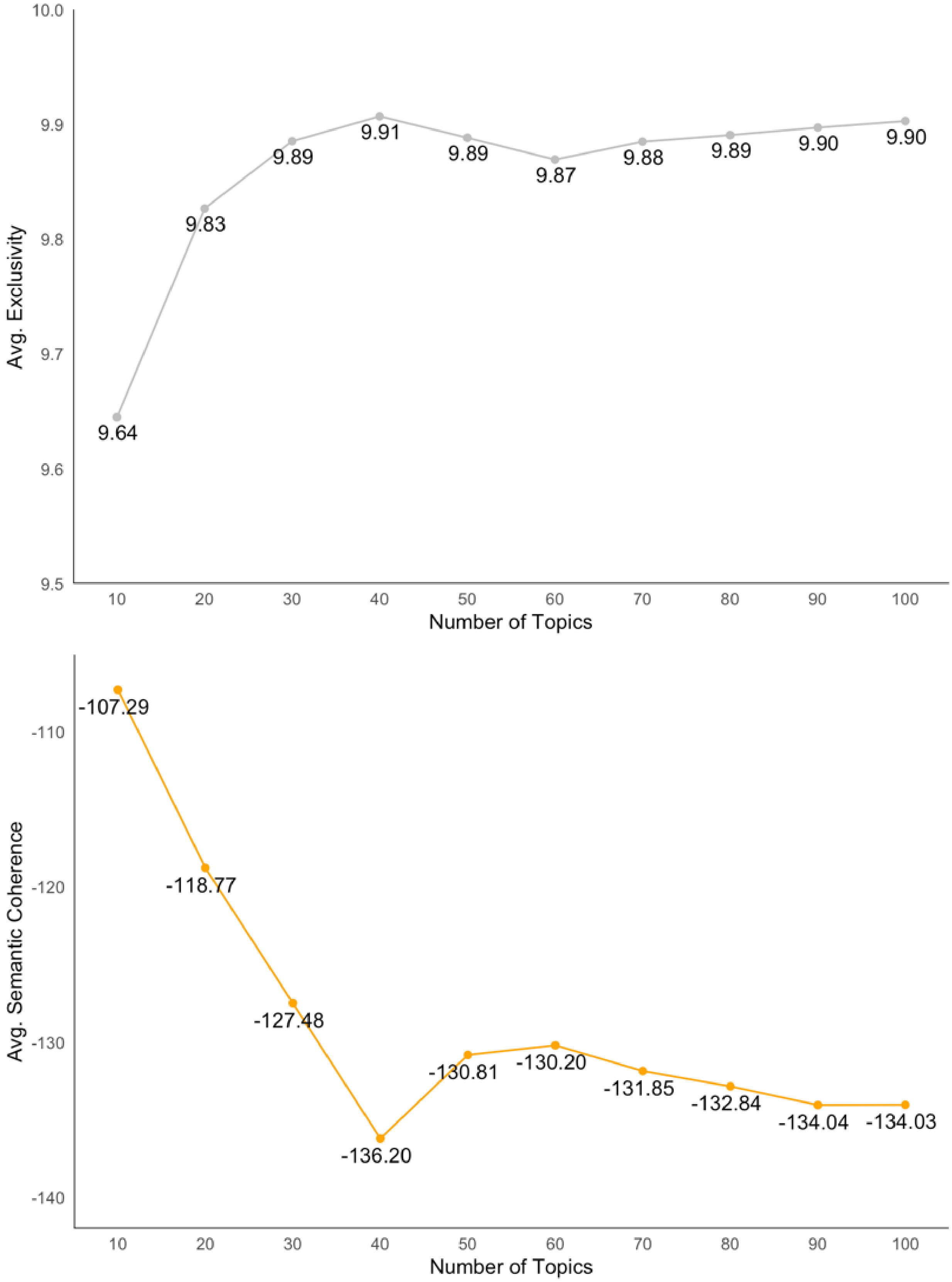


Figure C1. Exclusivity and Semantic Coherence Scores of Topic Models

C2. Topic Modeling Results

To complement the quantitative analysis and select the relevant topics, we qualitatively examined the interpretability of the different models. Our analysis led to the exclusion of 10 topics due to irrelevance (discussions included general feelings, questions, and different issues that were not specifically related to our research question). As a result, the final model used for the analysis consisted of 30 topics and we excluded topics 1 (general feelings), 10 (tipping), 11 (riders' behaviors), 19 (general forum posts), 20 (tenure), 29 (interactions with riders), 33 (car condition), 35 (types of riders), 37 (general questions), and 39 (insurance).

Topic ID	Top probability words	Exemplary forum posts	Topic label	Rank1
1	good, thing, point, idea, best, sound, bad, pretty, luck, damn	Good luck to everyone. Im not giving any rides untill Monday. My stress levels csnt handle that traffic. Keep safe everyone.	General feelings	300,875
2	rate, low, acceptance, increase, count, current, high, result, bad, gave	My acceptance rate was nearly perfect then Uber started sending me requests that were 8-18 miles away. Has anyone else experienced this? No way I'm doing a pick up so far away when I live in a resort area (Virginia Beach) that's busy.	Job misallocation	73,014
3	fee, cancel, show, far, charge, take, pickup, get, return, location	Why are they playing games with the cancellation rate? So I've noticed this over the last few months and I think the cancellation rate is being manipulated. Take for example last night... When I started the night, I was at a 7% cancellation rate, then I got it down to 5%. …	Scrutinizing cancellation rate	83,326
4	time, long, waste, wait, happen worse, reject, gas, period, spend	Is waiting on the lot a complete waste nowadays? I waited almost 1 hour and half for a 15 dollar ride... I would have made at least 30 by just driving and not waiting on the lot. Anyone has any tips. I drive xl and for both Uber and Lyft 4.9 rating.	Long waiting time	80,806
5	job, meet, work, gig, benefit, drive, make, living, regular, enjoy	If you can run twenty pools in a day where you get two/shuffle two, you are getting more money at the end of the day than would a cab driver who ran his meter on each of those same trips. The thing is that they come fast and furious enough that you could knock out those twenty is six hours on a good day where almost everything fell just right, with a little room for an aberrant trip, or two. Only on the very best of days could a cab driver run twenty trips in six hours, and EVERYTHING would have to come and fall JUST EXACTLY RIGHT, with no room for anything aberrant.	Task allocation	103,633
6	mile, cent, true, cost, gas, maintenance, value, profit, drive, math	Apparently Uber is experimenting with the rate structure. Raising the per-minute rate and lowering the per-mile rate. Rolling out in Dallas, Houston, Sacramento, Salt Lake City and Minneapolis. They claim that driver earnings will stay the same (So why bother?). They are raising the per-minute rate by 50-82% and reducing the per-mile rate by 10-19% They recently raised overall rates in Chicago by a paltry amount which didn't come close to covering gas increases.	Unpredictable fare	176,337
7	service, feedback, provide, income, complaint, notice, order, act, terms, correct	Been driving for only four months, got this email: "I'm following up on feedback about your behavior during a recent ride. The feedback alleged that you asked your Passenger personal questions or requested contact information. As a reminder, Lyft is an inclusive community…	Nitpicking boss	56,732
8	check, state, case, video, safety, record, seek, know, privacy, data	When downloading the app it obviously asks to allow access to other content and areas of your phone. Is this just like Facebook in a sense, having all of your data in the palm of their hands? Is this moral or an invasion of privacy, especially if information gathered is abused?	Privacy	88,646

9	sure, doesnt, sense, feel, wonder, know, difference, change, clear, sound	someone knows how the ping system works? I am still trying to figure out this system. Receiving trips surcharge for trips on uber. No idea how it works. You guys have more information about it ?	Unclear routines	50,512
10	tip, sign, expect, cheap, delivery, cash, dollar, add, nice, option	I do real good with the tips. I'm pretty sure the signs help. I get a lot of people asking about the included tip. I explain to them that not only is a tip not included, but they take 25% of every single fare, and that they provide nothing but passengers. I provide the car, insurance, maintenance, tires plus everything in the car like Wi-Fi and Satellite Radio just to make your ride more enjoyable.	Tipping	119,189
11	seat, back, front, door, left, put, passenger, open, behind, window	I purposely kept my "stuff" on the front seat so people wouldn't sit there. I don't know why, but most of the riders I pick up want to sit in the front seat. After reading post on this thread, I would prefer them riding in the back as well. I pick up a pax today who opened the front door …	Riders' behaviors	106,517
12	night, day, home, morning, late, weekend, stay, early slow, free	I think I'm doing alright as a part-time driver. I've been driving for three months and I put in about 20 hours a week, mostly on Fridays and Saturdays. I have a full-time job with benefits and a solid income. Thus Uber, gives me flexibility to take on some additional projects with my home. Also, I itemize my taxes; so, I believe the IRS business deductions help to make Uber more profitable. I guess I'll know after I've been doing it for awhile. Does anyone know how long the average Uber partner remains a partner?	Time flexibility	105,444
13	make, agree, fact, reason, understand, follow, ask, talk, unfortunately, response	I get this message from Lyft support. The problem is, I don't pull those tricks to get out of a short run like some drivers do. Apparently the Lyft nanny bots are sniffing out what they THINK are tell-tale signs of me doing that. After an experience the other morning I found out what's really happening, and why. … I called Lyft to ask if the customer had cancelled or was it a Lyft bot. He said a Lyft bot did it, since I wasn't making fast enough progress to the pickup and another driver with a shorter ETA became available, so the ride got switched to the other driver. … The worst part? Unless you get on the phone and beg, like I did, you don't even get a cancellation fee in that case, since they consider YOU to be the problem.	Insufficient explanation	69,320
14	account, email, support, info, send, message, late, help, call, contact	Uber (and Lyft) Driver "Support" is outsourced. Most of the e-Mail "support" is handled in Bangalore and Pondicherry. Most of the telephone support is handled in Quezon City. The average employee has a command of the English Language that approaches that of a third grader. You send an e-Mail to "support". The employee opens it. The computer program highlights certain words and phrases, then suggests several replies, in order of what the program interprets as "relevant". The employee than picks one and the program either sends that templated e-Mail or, it takes the cookie cutter phrases and composes an e-Mail. This is often why the response that you receive has less than nothing to do with your problem. If you are going to deal with Driver "Support", you must be prepared to send several e-Mails and make the tone of each one more and more obnoxious	Ineffective communicatio n	120,713
15	cant, believe, find, anymore, wont, without, able, speak, stand, trust	No one listens when I complain. I pour my heart out in an Uber and get secretly recorded and I'm the bad guy? …	Neglecting drivers' concerns	120,334

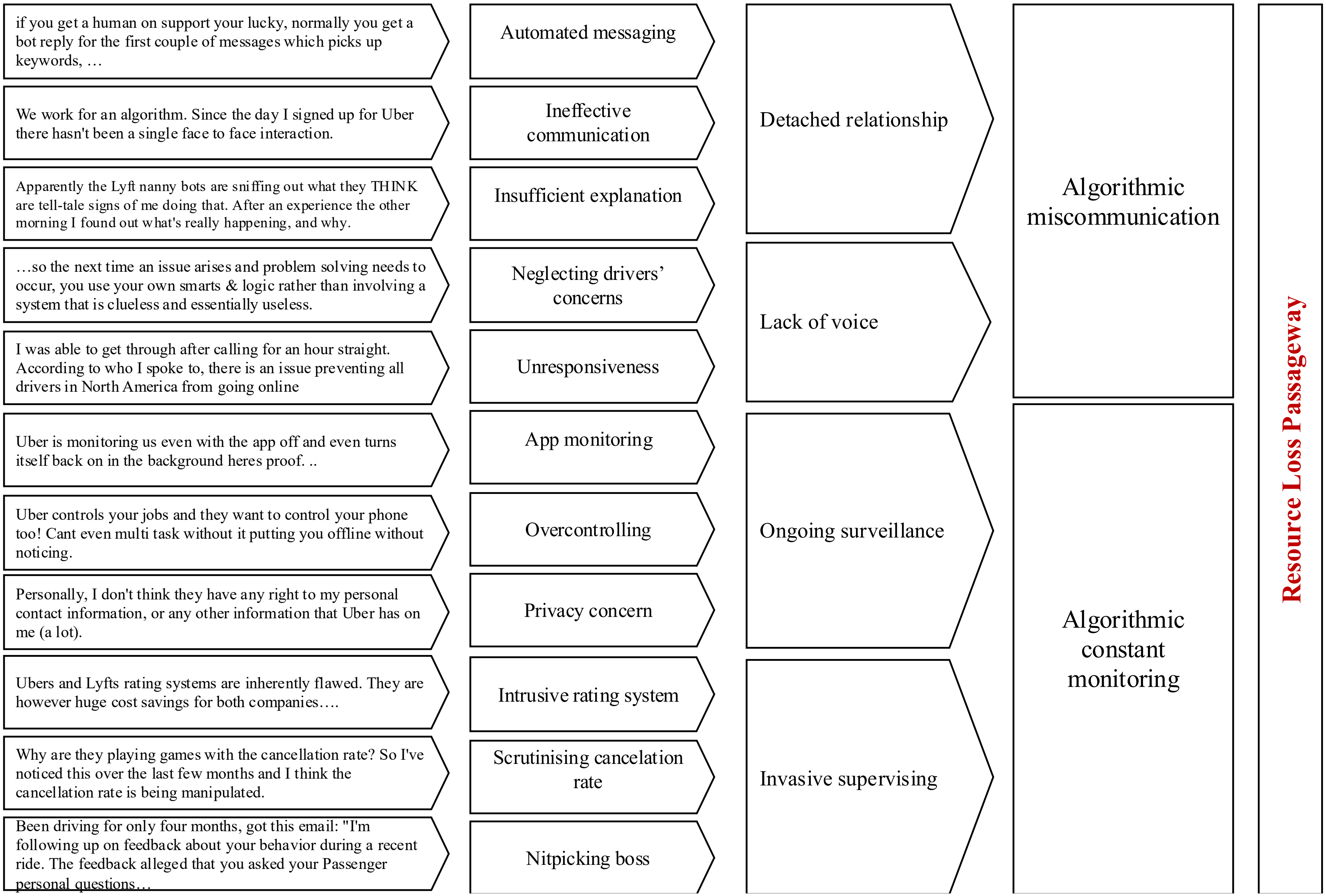
16	airport, lot, around, traffic, street, town, city, area, road, avoid	Drivers now have their own personal navigator to help steer them to their destination using the best available, least congested route. A new mobile phone app called ACT Traffic provides audio alerts and other information about congestion on the road network in real time.	Traffic information	175,025
17	rating, star, ridder, system, give, worry, driver, change, attitude, five	I believe the rating system is ridiculous. It starts at 5 and has no where to go but down. Psychologically a terrible plan! Constantly worrying and fighting to maintain a perfect record. No wonder the 6th star plan shows behavior by drivers that is impossible to sustain and benefits only the company's bottom line. Forcing Uber drivers to try to live up to an impossible standard, with failure resulting in termination, is truly a stupid idea. Incredible how this rating concept even started….	Intrusive rating system	172,269
18	surge, driver, demand, market, price, many, huge, change, fare, available	I haven't seen surge pricing or any promotions in the Harrisburg area in over a month. Anyone know why? I am getting frequent requests for over 16 miles away for 3-5 min trips so obviously no Uber's in area, isn't this definition of supply and demand? Uber support had no answers (as usual)	Unfair surge pricing	154,823
19	post, youre, read, forum, thread, reading, saying, right, talking, welcome	I guess there are more people participating in this Forum.....ants or not, UP is growing....welcome everybody... ask for the Billboard	General forum posts	145,754
20	year, age, old, month, started, day, new, couple, week, past	I started driving Uber in the IE over 3 years ago. Since then I moved to LBC then Vegas and now I'm back In the IE. I was here when Uber opened shop in the IE and Lyft was just making a name for themselves in LA only. When I came out to drive in the early mornings on the weekend there would be an average of 3-5 cars max online from San Berdo to Pomona. …	Tenure	220,112
21	stop, report, police, rule, state, law, suck, mistake, charge, claim	it is inevitable. After a certain amount of time especially in Philly you will get a false report, and you will get falsely deactivated. I have sent dash cam footage to Uber to no avail. Uber is always going to protect themselves before anything. I will never send them dahs cam footage again, as it did not effect my outcome of what i wanted done.	False accusation	100,963
22	help, info, great, well, advice, receive, got, thought, set, message	I finally created excel worksheets with the info that Uber provides. I searched on how are the promotions that we sign up for paid and it says that it will be either a Miscellaneous or Other payment.	Performance feedback	147,905
23	ever, time, question, heard, wait, happen, since, notice, late, take	Tried contacting other driver's insurance company, and miraculously, it looks like they are taking responsibility and will arrange repairs! Keeping my fingers crossed! BTW, still have not had any response from Uber.	Unresponsive ness	131,942
24	app, free, know, try, use, plan, time, control, work, watch	Uber controls your jobs and they want to control your phone too! Cant even multi task without it putting you offline without noticing. I know uber constantly pings the app and put you offline and then online if the app is open.	Overcontrolli ng	39,317
25	trip, fare, minimum, distance, long, take, base, short, change, add	Since Uber seems to adjust fares without notification to the driver , how does everyone monitor their statements ? Seems for a driver that does any more than a few trips a week it would be too hard to remember trips.	Unstable commission fees	105,367
26	contract, rule, driver, deactivate, public, legal, account, wait, talk, ban	I worked for Flex for 5 months at their West Drayton London depot. I was unemployed so I thought ok, it's reasonable money. … I recvd their email last week saying I'm being deactivated cos I dont pick up all the parcels on my route. That is 200% wrong...I have NEVER refused to pick up parcels at all.	Account deactivation/s uspension	172,409

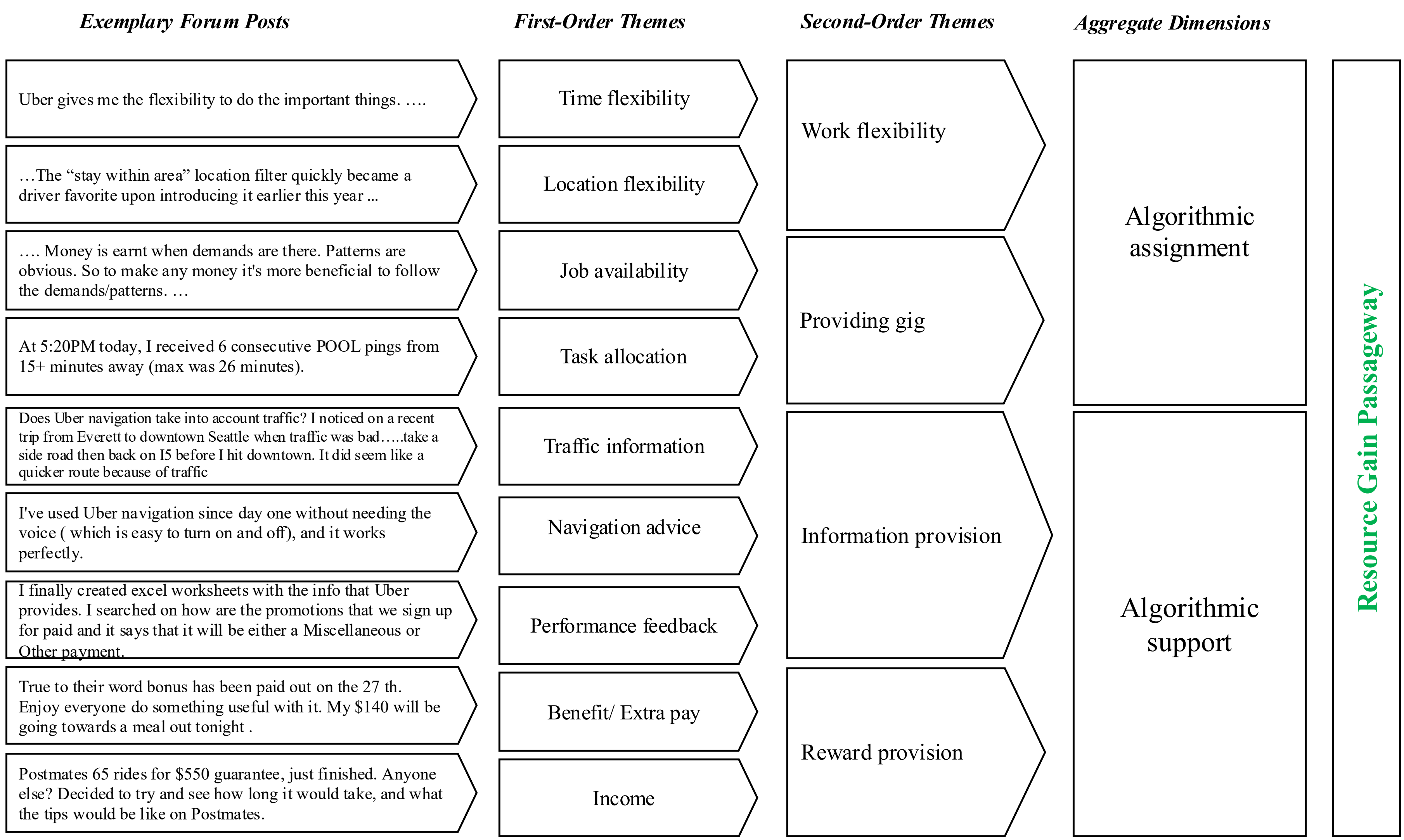
27	pay, statement, amount, daily, bill, get, enough, attention, agree, app	On Thursday, the company announced Uber Pro, a driver loyalty program that offers perks ranging from extra pay and free online education to dent repair and gas discounts. The program may help retain drivers, who often quit within a few months, research shows. Uber's drivers are independent contractors so they do not receive benefits such as health care or tuition reimbursement.	Extra pay	91,970
28	ride, accept, pool, request, pick, ping, destination, select, area, around	New-and-improved driver experience includes upgrades to upfront pay, plus features offering drivers even more control, choice and transparency … The "stay within area" location filter quickly became a driver favorite upon introducing it earlier this year, enabling drivers to stay closer to home with shorter rides, avoid traffic, combine with streak zones to maximize earnings …	Location flexibility	185,839
29	Pax, water, talk, music, want, play, hear, prefer, game, conversation	So I have this couple on a select ride,. They were talking to each other and when they got out the woman says "be safe tonight, stay hydrated, I brought this bottle of water for you!" That was a first for me. …	Interactions with riders	100,368
30	app, phone, address, screen, google, show, gps, location, update, route	I use the in app Uber and Lyft navigation along with my knowledge of the area I am driving. My Uber Navigation has a map and voice directions as well. Wish Uber would add a quick touch mute button like Lyft has. For now if I want to silence the Uber voice directions I just turn on one of my Bluetooth ear buds to redirect the sound to there.	Navigation advice	67,987
31	money, make, lose, save, decent, fare, profit, need, spend, care	Both Uber & Lyft have increased numbers of riders, especially in our markets. However, they do not pay drivers fare or decent wages. The costs of driving rideshare is hidden in our depreciating and deteriorating cars. … I have been driving less and less...its just not worth the gas, wear and tear, and risk at these measly earnings.	Unacceptable fare	301,699
32	different, thing, app, try, exactly, mind, didnt, turn, issue, stop	my app version suddenly changed on me: -my profile is gone -option to share location is gone -rider complements are gone -gps voice is changed -connection to gobank gone etc etc did anyone experience this problem before? do you know how to change back to previous version? I had this happen..	Unforeseen App changes	143,319
33	car, clean, wear, eat, smell, leave, inside, food, put, keep	Dear Paxholes: My car is not an eating place ... Please!!! No food, no drinks, no smoking, no hairspray. Cleaning up spills and working to get rid of food, smoke, odors, and dirty windows, costs me time and lost income. Please eat, drink, and apply your makeup somewhere else …	Car condition	95,472
34	income, earning, hour, guarantee, gross, number, dollar, total, profit, average	Postmates 65 rides for $550 guarantee, just finished. Anyone else? Decided to try and see how long it would take, and what the tips would be like on Postmates. They do not give you a bonus, they guarantee your income after completing 65 trips and maintaining above a 4.5 star rating. It took me 6 days to hit the required number of rides. I found that tips are better and you do stay busy. At the end I had $480, so they will wait for 3 days to see about tips coming in, then cash me out at $550	Income	311,769
35	people, black, man, kid, woman, life, family, world, school, white	This afternoon I had a ride with a nice young family. 2 young kids and one on the way. It was a minimum fare to Walmart and they were getting a few things for the baby. …	Types of riders	310,475
36	wait, minute, start, ready, soon, get, ride, ping, within, quick	I'm new to Uber after delivering for Postmates for a few months. I run both platforms, but in my opinion, Uber does a better job assigning jobs for bicycle deliveries. For example, Postmates will ping for a delivery from Market Square to the other side of Oakland. This cuts down on the amount of	Job availability	110,669

		deliveries I can make because of the distance traveled. Uber, on the other hand, seems to assign shorter deliveries, which is great when delivering by bicycle. For example, I get a ping for a delivery from Market Square to Smallman Street. I can take more deliveries per evening, than I can with Postmates.		
37	something, anything, someone, know, else, anyone, say, need, somewhere, maybe	Anyone know any car auction places near the city of Boston that is open to the public to bid on? Any advice for a first timer going? If you could, provide a link or website so I can check it out. Thanks!	General questions	410,780
38	ask, tell, question, answer, call, explain, straight, let, need, bot	if you get a human on support your lucky, normally you get a bot reply for the first couple of messages which picks up keywords, … After four attempts, Uber still hasn't answered this email (below). I didn't even receive their usual "request received" robomail. I then sen a test email, and I instantly got a robo response. Sent original once more, then nothing.	Automated messaging	42,768
39	insurance, personal, accident, policy, risk, cover, rideshare, vehicle, claim, fault	I received the notice that my insurance policy was expiring in <30 days, and to upload my new information. No problem, I do that, and that's when everything went weird. They rejected it, saying that the policy has not reached it's start date! …	Insurance	52,502
40	see, mile, check, speed, think, monitor, far, know, system, course	Uber is monitoring us even with the app off and even turns itself back on in the background heres proof. I shut the app off and put it to sleep the battery monitor shows when I start moving my phone around and then the red shows when I start driving …	App monitoring	70,011

Appendix D: Thematic Structure of Algorithmic Management Resource Loss and Gain Passageways

Sample Forum Posts	*First-Order Themes*	*Second-Order Themes*	*Aggregate Dimensions*	
someone knows how the ping system works? I am still trying to figure out this system.	Unclear routines	Procedural inconsistency	Algorithmic ambiguity	**Resource Loss Passageway**
my app version suddenly changed on me: -my profile is gone -option to share location is gone -rider complements are gone -gps voice is changed …	Unforeseen App changes			
Apparently Uber is experimenting with the rate structure. Raising the per-minute rate and lowering the per-mile rate. …	Unpredictable fare	Reward uncertainty		
Today I noticed my commission is no longer 20% but 22%. I only noticed because of cancel fee. Normally I get $8 today only $7.80 More rate cut.	Unstable commission fees			
I haven't seen surge pricing or any promotions in the Harrisburg area in over a month. Anyone know why?	Unfair surge pricing	Unfair compensation	Algorithmic unfairness	
Both Uber & Lyft have increased numbers of riders, especially in our markets. However, they do not pay drivers fare or decent wages. The costs of driving rideshare is hidden in our depreciating and deteriorating cars…	Unacceptable fare			
…apparently some customer complained to them that I tried to ask for sexual favors when I was dropping them. (Before anyone asks no I didn't do any such thing) they asked me to tell them what happened on that day and I was clear nothing happened with any customer.	False accusation	Unfair punishment		
Last week I found out uber deactivated me for no reason and without giving me a warning. Or anything in the email.	Account deactivation/suspension			
Is waiting on the lot a complete waste nowadays? I waited almost 1 hour and half for a 15 dollar ride... I would have made at least 30 by just driving and not waiting on the lot.	Long waiting time	Unfair workload		
My acceptance rate was nearly perfect then Uber started sending me requests that were 8-18 miles away. Has anyone else experienced this?	Job misallocation			


if you get a human on support your lucky, normally you get a bot reply for the first couple of messages which picks up keywords, …
We work for an algorithm. Since the day I signed up for Uber there hasn't been a single face to face interaction.
Apparently the Lyft nanny bots are sniffing out what they THINK are tell-tale signs of me doing that. After an experience the other morning I found out what's really happening, and why.
…so the next time an issue arises and problem solving needs to occur, you use your own smarts & logic rather than involving a system that is clueless and essentially useless.
I was able to get through after calling for an hour straight. According to who I spoke to, there is an issue preventing all drivers in North America from going online
Uber is monitoring us even with the app off and even turns itself back on in the background heres proof. ..
Uber controls your jobs and they want to control your phone too! Cant even multi task without it putting you offline without noticing.
Personally, I don't think they have any right to my personal contact information, or any other information that Uber has on me (a lot).
Ubers and Lyfts rating systems are inherently flawed. They are however huge cost savings for both companies….
Why are they playing games with the cancellation rate? So I've noticed this over the last few months and I think the cancellation rate is being manipulated.
Been driving for only four months, got this email: "I'm following up on feedback about your behavior during a recent ride. The feedback alleged that you asked your Passenger personal questions…
Automated messaging
Ineffective communication
Insufficient explanation
Neglecting drivers' concerns
Unresponsiveness
App monitoring
Overcontrolling
Privacy concern
Intrusive rating system
Scrutinising cancelation rate
Nitpicking boss
Detached relationship
Lack of voice
Ongoing surveillance
Invasive supervising
Algorithmic miscommunication
Algorithmic constant monitoring
Resource Loss Passageway


Exemplary Forum Posts
First-Order Themes
Second-Order Themes
Aggregate Dimensions
Uber gives me the flexibility to do the important things. ….
…The “stay within area” location filter quickly became a driver favorite upon introducing it earlier this year ...
…. Money is earnt when demands are there. Patterns are obvious. So to make any money it's more beneficial to follow the demands/patterns. …
At 5:20PM today, I received 6 consecutive POOL pings from 15+ minutes away (max was 26 minutes).
Does Uber navigation take into account traffic? I noticed on a recent trip from Everett to downtown Seattle when traffic was bad…..take a side road then back on I5 before I hit downtown. It did seem like a quicker route because of traffic
I've used Uber navigation since day one without needing the voice (which is easy to turn on and off), and it works perfectly.
I finally created excel worksheets with the info that Uber provides. I searched on how are the promotions that we sign up for paid and it says that it will be either a Miscellaneous or Other payment.
True to their word bonus has been paid out on the 27 th. Enjoy everyone do something useful with it. My $140 will be going towards a meal out tonight .
Postmates 65 rides for $550 guarantee, just finished. Anyone else? Decided to try and see how long it would take, and what the tips would be like on Postmates.
Time flexibility
Location flexibility
Job availability
Task allocation
Traffic information
Navigation advice
Performance feedback
Benefit/ Extra pay
Income
Work flexibility
Providing gig
Information provision
Reward provision
Algorithmic assignment
Algorithmic support
Resource Gain Passageway

Appendix E: Survey Instrument

Construct		Items
Algorithmic assignment		[Platform] allows me to make my own decisions about how to schedule my work. [Platform] gives me a considerable opportunity for independence and freedom in how I do the work.
		[Platform] allows me to plan how I do my work. [Platform] gives me the opportunity to select my tasks.
Algorithmic support	*Information provision*	[Platform] shares information about my performance with me. I am informed in advance of changing needs of clients. In [platform], any information which might help me will be provided. The platform keeps me informed about the events or changes that may affect my job.
	Reward provision	I earn money when I work in [platform]. Working in [platform] benefits me financially. Working in [platform] can improve my economic situation.
algorithmic ambiguity		[Platform] procedures in assigning my tasks are not consistent. [Platform] procedures in evaluating my tasks are not clear. The task assignment and evaluation procedures of [platform] are biased. [Platform] task assignment and evaluation procedures are based on accurate information ® I cannot understand how [platform] assigns jobs to me.
Algorithmic unfairness		The reward I get from [platform] does not reflect the effort I have put into my work. Usually, the reward I get from [platform] is not appropriate for the work I have completed. The jobs that [platform] assigns to me are not fair. Considering my performance, the reward [platform] gives me is unfair.
Algorithmic miscommunication		[Platform] cannot help me understand and resolve my problems. I cannot count on [platform] if I need advice to make a decision or to cope with a problem. I cannot ask [platform] for advice, because it does not understand me.
Algorithmic constant monitoring		[Platform] watches me carefully to control my task completion. [Platform] closely monitors me while I'm trying to do my work. [Platform] inspects my work closely to see that it measures up to applicable standards. I feel that I am constantly being watched to see that I obey all rules of [platform]. [Platform] ensures that our behaviors are being closely monitored at all times
Burnout		I feel emotionally drained from working for [platform]. I feel used up at the end of the day. I dread getting up in the morning and having to face another day of working for [platform]. I feel I'm working too hard on my job at [platform]. My work really puts a lot of stress on me.
Engagement	*Vigor*	At my work in [platform], I feel bursting with energy. At my job in [platform], I feel strong and vigorous. When I get up in the morning, I feel like going to work for [platform]
	Dedication	I am enthusiastic about my job in [platform]. My job inspires me. I am proud of the work that I do at [platform]
	Absorption	I am immersed in my work. I get carried away when I'm working. I feel happy when I am working intensely.

Appendix F: Measurement Model

We assessed the measurement model by testing content, convergent, and discriminant validity. Content validity was examined by ensuring alignment between the measurement items and the established literature. This evaluation was conducted during the questionnaire design phase. We asked the experts to provide feedback on whether the items were relevant and representative of the constructs (Kerlinger & Lee, 2000). We assessed the convergent validity to ensure that the measures of the same construct were more correlated with each other than with the measures of another construct (Petter et al., 2007; Schwab, 2005). As presented in Table F1, our factor analysis confirmed convergent validity. Factor loading values (shaded) show that there is a strong correlation between each of the items and their corresponding construct. We further verified the convergent validity using four criteria: internal consistency of constructs (>0.7), composite reliability (CR >0.7), Cronbach's alpha (CA >0.7), and average variance extracted (AVE >0.5). Table F2 presents the mean, standard deviation, and CA, CR, AVE for the constructs, whose values confirm the satisfaction of convergent validity.

As recommended by Fornell and Larcker (1981), we assessed the discriminant validity by evaluating the cross-loadings in factor analysis and examining the square root values of the AVEs. The cross-loadings of the items on other constructs (Table F1) exhibit low values, thereby confirming discriminant validity. Additionally, the values of the square root of the AVE, as presented on the diagonal in Table F2, surpass the interconstruct correlations (off-diagonal entries in Table F2), underscoring the satisfactory discriminant validity of the measurement model.

Table F1. Factor Analysis

Factors	AAs	AS-IP	AS-RP	APA	AU	AM	ACM	BUR
AAs1	0.77	0.05	0.13	0.07	0.05	0.02	-0.13	0.06
AAs2	0.78	0.07	0.06	0.05	-0.09	0	-0.01	0.12
AAs3	0.80	-0.04	0.09	0.03	-0.02	-0.03	0.07	0.01
AAs4	0.85	0.15	0.11	-0.06	-0.03	0.05	-0.04	-0.07
IP1	-0.02	0.83	0.03	0.03	-0.13	-0.01	-0.01	-0.01
IP2	0.11	0.84	0.17	0.12	-0.02	0	0.03	0.09
IP3	0.12	0.91	0.15	0.09	-0.06	0.03	0,05	0,02
IP4	0.08	0.87	0.03	0.04	-0.03	0.12	0.17	-0.03
RP1	-0.01	-0.06	0.92	0.05	0.08	0.05	0.1	-0.01
RP2	0.15	0.05	0.90	0.05	0.01	0.05	0.01	0.04
RP3	0.18	0.21	0.88	0.16	0.05	-0.08	-0.03	0.06
AA1	0.11	0.16	-0.03	0.78	0.08	0.05	0.04	0.13
AA2	-0.03	0.06	0.05	0.88	0.06	0.03	0.09	0.05
AA3	0.01	0.09	0.09	0.75	0.02	0.05	0.11	0.08
AA4	0	-0.03	0.06	0.77	0.03	0.01	0	-0.09
AA5	-0.05	0.05	0.03	0.83	0.17	0.04	0.07	0.06
AU1	0.14	0.13	0.08	0.01	0.92	0.15	-0.03	0.03
AU2	0.09	0.07	-0.03	0.11	0.85	0.04	0.01	0
AU3	-0.03	0.18	0.06	-0.06	0.90	0.09	0.03	-0.06
AU4	0.07	0.05	-0.09	0.05	0.86	0.01	0.13	0.02
AM1	0.04	0.09	0.17	0.01	0.09	0.75	0	-0.01
AM2	-0.05	0	0.04	-0.05	0.06	0.80	0.03	0.11
AM3	0.09	-0.03	0.08	0.02	0.03	0.77	0.01	0
AO1	0.17	0.02	-0.14	-0.05	0.02	0.04	0.74	-0.04
AO2	0.02	0.06	0.08	0.03	-0.05	0.15	0.81	0.14
AO3	0.03	0.09	-0.06	0.07	0.12	0.06	0.76	0.07
AO4	0.06	0.05	0.02	-0.02	-0.02	-0.02	0.83	0
AO5	-0.06	-0.01	0.12	-0.01	-0.05	0.05	0.82	0.02
BUR1	0.04	0.13	-0.01	0.17	0.04	0.01	-0.04	0.85
BUR2	-0.07	-0.11	-0.11	-0.03	0.07	0.01	-0.01	0.93
BUR3	0.05	0.01	-0.02	0.06	0.02	0.21	0.09	0.92
BUR4	0.09	-0.05	0.07	-0.02	0.14	0.03	0.12	0.88
BUR5	0.1	0.02	-0.02	0	0.06	-0.07	0.16	0.87

Note: AAs = algorithmic assignment, AS-IP = algorithmic support-information provision, AS-RP = algorithmic aupport-reward provision, AA = algorithmic ambiguity, AU = algorithmic unfairness, AM = algorithmic miscommunication, ACM = algorithmic constant monitoring, BUR = burnout

Table F2. Descriptive Statistics, Validity, and Reliability Results in Study 2

Factors	Mean	SD	CA	CR	AVE	1	2	3	4	5	6	7
Algorithmic ambiguity	5.14	1.53	0.78	0.9	0.78	**0.88**						
Algorithmic unfairness	5.38	1.14	0.75	0.88	0.83	0.26	**0.92**					
Algorithmic miscommunication	5.07	1.22	0.82	0.85	0.81	0.35	0.13	**0.93**				
Algorithmic constant monitoring	5.52	1.08	0.76	0.83	0.78	0.21	0.27	0.25	**0.9**			
Algorithmic assignment	3.47	1.37	0.85	0.78	0.82	-0.11	-0.09	-0.07	-0.15	**0.88**		
Algorithmic support	3.25	1.45	0.8	0.83	0.78	-0.16	-0.25	-0.18	-0.19	0.23	**0.86**	
Burnout	5.23	1.25	0.77	0.85	0.82	0.21	0.17	0.32	0.25	-0.12	-0.25	**0.85**

Table F3. Descriptive Statistics, Validity, and Reliability Results in Study 3

Factors	Mean	SD	CA	CR	AVE	1	2	3	4	5	6	7
Algorithmic ambiguity	5.07	1.32	0.82	0.88	0.79	**0.85**						
Algorithmic unfairness	5.18	1.17	0.81	0.85	0.82	0.16	**0.83**					
Algorithmic miscommunication	5.23	1.85	0.75	0.84	0.81	0.25	0.24	**0.95**				
Algorithmic constant monitoring	4.47	1.53	0.92	0.95	0.93	0.31	0.22	0.15	**0.88**			
Algorithmic assignment	4.02	1.13	0.93	0.92	0.85	-0.14	0.05	0.27	-0.03	**0.92**		
Algorithmic support	3.45	1.28	0.88	0.93	0.89	-0.07	-0.15	-0.28	-0.17	0.18	**0.87**	
Engagement	4.13	1.24	0.81	0.85	0.83	-0.22	-0.34	-0.13	-0.18	0.24	0.32	**0.93**

Appendix G: Results of Assessing Common Method Bias

As mentioned above, we followed the guidelines of Podsakoff et al. (2003) in applying some procedural remedies for decreasing potential CMB. For instance, on the questionnaire's cover page, we emphasized that data would remain confidential, with the results of this survey only being used only for academic purposes and the respondents' information kept anonymous. We further designed the questionnaire using some reverse-coded items and diversity in item anchors.

In order to assess CMB, we used Harman's one-factor test (Podsakoff et al., 2003) and the marker-variable technique (Lindell & Whitney, 2001). This test assesses the threat of CMB by examining whether a single latent factor emerged from the factor analysis or whether one general factor accounted for the majority of the covariance in the independent and dependent variables. For our sample, unrotated factor analysis indicated that the first factor accounted for 28.4% of the total variance. Because a single factor did not emerge and one general factor did not account for most of the variance, we gained preliminary evidence that the measurement model was robust to CMB (Podsakoff et al., 2003). Due to possible limitations of Harman's one-factor test, we additionally employed Lindell and Whitney's (2001) marker variable assessment technique. The low correlation between the main constructs and the marker variable confirms that the CMB was not an issue. Collectively, across these criteria, we can conclude that CMB does not present a significant threat to the study.

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