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Gig Workers and Side Hustlers: Advancing Organizational Behavior Research for a Modernized Employee Population

To Be (Safe), or Not to Be (Safe)? A Daily Exploration of Why and When Gig Workers Stay Safe Under Customer Demands

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ABSTRACT

Gig workers in the food delivery industry constantly face life-threatening occupational safety risks. However, little scholarly attention has been paid to the hazards of this work that entail potential dangers in traffic situations. Drawing on paradox theory, we theorize a typical tension in the daily experiences of food delivery workers, the finance–safety paradox. We examine how this dilemma can be triggered by customer demands that could influence delivery workers' safety (i.e., safety behavior and driving speed) through altering their finance and safety concerns. Using the experience sampling method, we conducted a 14-day diary study with 117 food delivery workers (1430 observations) in China. The results indicate that daily customer demands increased workers' daily safety concern when workers perceived stronger algorithmic supervision and fewer algorithmic errors on the focal day. Higher daily safety concern resulted in increased daily safety behavior and lower daily driving speed, while higher daily finance concern enhanced daily driving speed. Our research identifies a key driver of safety risks for gig workers in the food delivery industry, elucidates the role of algorithms in their safety compliance, and broadens our knowledge of how they navigate the salient tension between financial precarity and safety risks.

1 | Introduction

> *"Delivering food is like racing against death, pitting yourself against traffic cops, and making friends with red lights."*
>
> A delivery worker (Lai 2020)

The convenience of ordering takeout has driven a rapid expansion in food delivery companies within the gig industry, including Deliveroo, Just Eat, Uber Eats, Meituan, and Eleme (Waring 2021). While the surge of gig work has created great opportunities for economic growth by transforming traditional job structures (Ashford et al. 2018), it has also introduced potential challenges and costs for gig workers (Bajwa et al. 2018; Caza et al. 2022; Wu and Huang 2024). One hidden cost lies in the safety risks faced by gig workers (Lim and

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Ong 2022). Food delivery riders, in particular, frequently encounter traffic accidents and injuries while delivering orders (Sanusi and Emmelin 2015). For instance, data from Singapore indicates that one-third of food delivery riders were involved in accidents that required medical treatment (Kok 2022). This risk of driving accidents poses a significant threat to riders' safety, thereby meriting more scholarly attention.

Despite the profound salience of unsafe working conditions, unfortunately, research on the causes of safety risks in the food delivery process and how riders manage safety compliance remains very limited. Previous studies have either briefly mentioned safety issues without in-depth exploration (e.g., Cameron 2022; Myhill et al. 2021; Veen et al. 2020) or focused on individual differences in safety risk-taking (e.g., Papakostopoulos and Nathanael 2021; Zhang et al. 2020). In particular, the literature has largely overlooked a salient situation in which riders' safety awareness is mainly influenced by certain external factors (e.g., customers and algorithms; Newlands 2021) that occur frequently in their day-to-day work rather than by internal factors (e.g., personality and demographics). Studies on riders' personal profiles fail to fully address the inherent risks this population faces during delivery work. Therefore, this oversight hinders our understanding of the working dynamics affecting gig workers' safety, as their actions are heavily influenced by customers, algorithmic management, and other contextual cues (Rahman 2021).

The present study addresses this underexplored issue by focusing on how external factors influence food delivery workers' safety. We draw on paradox theory (Berti and Cunha 2023; Putnam et al. 2016; Schad et al. 2016; Smith and Lewis 2011) to theorize that food delivery riders face a unique form of paradox: finance–safety paradox. Paradox refers to "contradictory yet interrelated elements that exist simultaneously and persist over time" (Smith and Lewis 2011, 382). We argue that the finance–safety paradox arises from the persistent tension between the financial precarity of gig workers and the safety risks inherent in delivery driving (Christie and Ward 2018; Gerber 2022). Ideally, riders should be able to adopt a "both–and" approach, simultaneously avoiding potential safety risks while completing as many deliveries as possible to achieve higher income (Waring 2021). However, the tension between financial security and physical safety may escalate into a significant dilemma (i.e., forced competing choices with advantages and disadvantages on each side) in which riders are forced to make "either–or" choices by sacrificing one aspect for the other. Although the concepts of paradox and dilemma incorporate tensions, they differ conceptually (Berti and Cunha 2023). A paradox emphasizes interrelated elements that entail temporal persistence and may be synergistic within a larger system, whereas a dilemma highlights the temporary tradeoff between the pros and cons of competing choices (Smith and Lewis 2011).

We identify a typical tension intensifier that may cause riders to violate safety rules, namely, customer demands (i.e., the extra workload demanded by customers), which motivate riders to pursue high earnings or tips by completing order deliveries more quickly (Popan 2021). When customers demand more from the rider, the extra pressure could fuel the dilemma between safety goals and financial gains. Consequently, food delivery workers may shift their focus from safety compliance (e.g., following traffic rules) to the pursuit of efficiency for maximizing income (e.g., completing orders quickly). This shift is particularly salient given that most delivery workers rely on this job to make a living (Papakostopoulos and Nathanael 2021). We propose a dual mechanism to capture the finance–safety paradox, incorporating two motivation constructs: finance concern (i.e., motivation to pursue finance-related goals) and safety concern (i.e., motivation to achieve safety-related goals) (Elliott et al. 2003; Meuris and Leana 2018).

Furthermore, we examine the moderating roles of algorithms in the delivery process, which may significantly influence how delivery workers navigate the finance–safety dilemma in response to customer demands. Paradox theory suggests that severe tensions (e.g., dilemma) can be mitigated by context features (e.g., organizational arrangements) (Berti and Cunha 2023). In the absence of traditional work elements like organizational structures or managers, the algorithms used by food-ordering platforms play a dominant role in guiding riders' actions (Kellogg et al. 2020). In terms of positive aspects, algorithms direct and supervise work by guiding riders along optimal routes and monitoring safety compliance (Dong et al. 2021; Wang et al. 2021a). However, algorithms may also provide wrong guidance due to inaccurate and biased data (Kellogg et al. 2020; Meijerink and Bondarouk 2021; Rahman 2021), thereby potentially undermining riders' awareness of safety risks.

In summary, we propose algorithm-based boundary conditions that alter riders' focus on resolving the finance–safety paradox while meeting customer demands. Specifically, we identify perceived algorithmic supervision as a safety-enhancing moderator and algorithmic errors as a safety-undermining moderator. We theorize that in response to higher customer demands, food delivery riders are more likely to disobey safety norms and exhibit less safety-aware behavior when they perceive weaker supervision and more errors in the algorithms. We conducted a diary study among full-time food delivery riders in China to test our model (see Figure 1).

Our work makes several significant contributions. First, we advance the gig work literature by introducing a theoretical perspective on food delivery riders' safety issues. Our research adopts a paradox lens to specify two key external antecedents (i.e., customers and algorithms) and elucidates why and when gig workers prioritize safety compliance. Second, we contribute to the gig work literature by identifying the finance–safety paradox. We conceptualize this unique paradox in food delivery riders' daily work and offer insights into its daily dynamics. Third, we contribute to the workplace safety literature by shifting the focus from traditional work arrangements to gig work. Our research refines the job characteristics (i.e., customer demands, algorithm supervision, and algorithmic errors) associated with this new form of work and integrates them with safety behaviors in delivery workers' daily work.

2 | Theory and Hypothesis

2.1 | The Finance–Safety Paradox in Food Delivery Work: A Paradox Perspective

Individuals may encounter various types of paradoxes at work, such as the paradox of exploration and exploitation (Greco et al. 2019). Paradox theory seeks to address such paradoxes

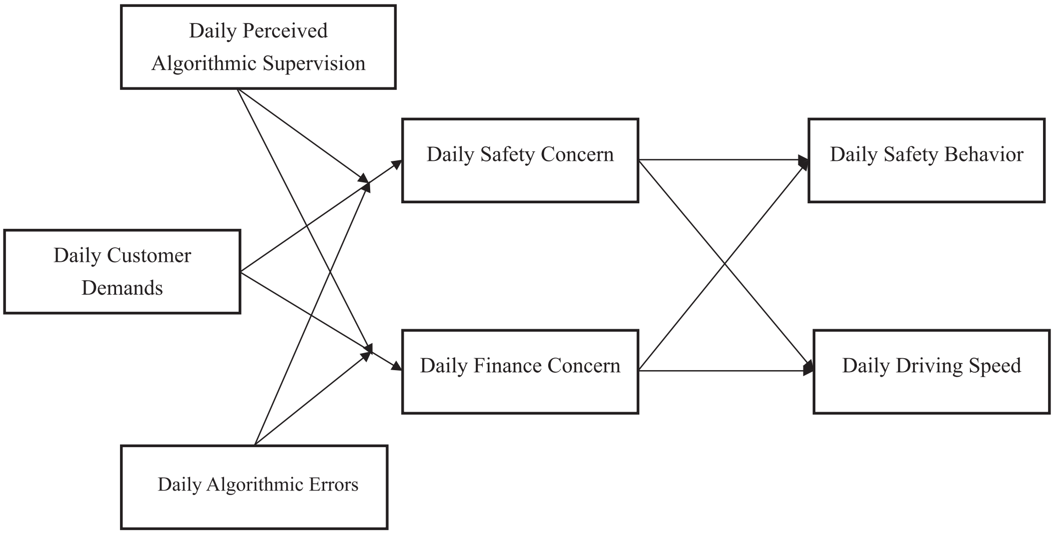

FIGURE 1 | Conceptual model.

effectively by arguing that individuals may adopt “either–or” or “both–and” approaches to cope with paradoxical tensions (Putnam et al. 2016). An either–or approach treats the contradictory sides of a tension as distinct and independent components, whereas a both–and approach seeks to treat the opposites as interdependent and compatible (Putnam et al. 2016). In this paper, we define the finance–safety paradox as the persistent contradiction between food delivery workers' financial precarity and safety risks.

Paradox theory argues that paradoxical tensions emerge from three sources: plurality, change, and scarcity (Smith and Lewis 2011). We argue that in food delivery work, the finance–safety paradox stems from the following sources: First, delivering food effectively requires meeting the multiple demands and needs of various stakeholders (e.g., riders themselves, restaurants, platforms, traffic police, and customers) (Duggan et al. 2020; Lai 2020). Second, each delivery involves unique interactions because delivery orders may differ in location, time, customers, and other relevant features, which constitute the dynamics of this form of work (Heiland 2021). Third, riders not only face financial scarcity due to their socioeconomic status but also endure persistent uncertainty and insecurity regarding their income (Caza et al. 2022; Watson et al. 2021).

The finance–safety paradox incorporates two sides in its latent tension. Riders are required to work to satisfy their financial needs because their financial conditions are often precarious (Cameron 2022; Watson et al. 2021). Most food delivery riders earn their basic income from this job because it is probably one of the few options available to them, especially when they are in financially vulnerable periods (e.g., COVID-19 pandemic) (Apouey et al. 2020; Figueroa et al. 2023; Koustas 2019). Their general profiles typically offer few alternative means of livelihood, even though this work may require sacrificing their health and risking safety (Bajwa et al. 2018; Christie and Ward 2018; Keith et al. 2020). Therefore, completing more orders while receiving good ratings or tips is exactly what food delivery riders desire from gig work to satisfy financial needs (Katz and Krueger 2017).

Additionally, riders constantly face safety risks while making food deliveries (Nguyen-Phuoc et al. 2022). The inherent safety risks emerge from several sources. First, platform algorithms may induce risks to maximize benefits, implicitly encouraging riders to take risks (Oviedo-Trespalacios et al. 2022). Second, riders face an unavoidable risk of traffic accidents. Many investigations have indicated that occupations involving driving are related to higher accident rates (Wang et al. 2021b; Zhang et al. 2020). Third, unsafe consequences are usually caused by a high workload (Nguyen-Phuoc et al. 2022). Recent studies have found that most delivery riders are engaged in work for more than 9 h per day and rarely have days off (Figueroa et al. 2023; Zheng et al. 2019). Overtime work leads to higher levels of fatigue and stress, and reduced alertness, which increases safety risks (Aidman et al. 2015).

Although finance and safety are vital aspects for riders' survival, the tension between these aspects may result in contradictions. When riders prioritize safety by fully complying with traffic rules, they may take financial risks, as taking extra precautions could delay their deliveries (Melián-González 2022). Remaining safe typically requires riders to drive more cautiously, adhering to speed limits and traffic regulations (Christie and Ward 2018). A lower speed probably leads to fewer deliveries and more delayed orders, resulting in reduced income. Especially, customers may leave negative ratings when they experience hunger while waiting for delayed orders (Cameron 2022). Negative ratings from customers undermine riders' profile assessments and decrease future orders assigned by algorithms to those workers (Jabagi et al. 2019). However, if delivery workers prioritize financial goals, they risk involvement in traffic accidents (Figueroa et al. 2023; Oviedo-Trespalacios et al. 2022). Riders must complete all the orders they are assigned as quickly as possible to maximize their potential income, thereby increasing their exposure to traffic risks (Lai 2020). Therefore, the simultaneous pursuit of finance and safety constitutes an inherent paradox for food delivery riders.

2.2 | From Paradox to Dilemma: Customer Demands as a Tension Intensifier

Paradox theory argues that paradoxes can escalate to dilemmas when tensions are intensified and become optimization problems or tradeoffs (Berti and Cunha 2023; Putnam et al. 2016). We posit that a typical and common extra demand for riders that intensifies the tension is raised by customers. In the food delivery context, *customer demands* refer to the extra workload required to meet customers' additional needs beyond the basic requirements (i.e., the timely delivery of food based on orders) (Goods et al. 2019). On many delivery platforms (e.g., Meituan and Uber Eats), customers can interact with riders directly to indicate personal needs or to promise tips or good ratings in exchange for riders' commitment and efforts. For example, customers may ask riders to buy something (e.g., water, snacks, a lighter, or a condom) from a nearby corner shop or to deliver oral messages (e.g., holiday wishes) to someone else. Customer demands may motivate riders to work harder to earn more tips and higher ratings, which serve as incentives (Cameron 2022). However, the role of algorithms complicates this matter, thereby altering the reciprocity between riders and customers with extra demands.

Platform algorithms calculate the estimated delivery time based mainly on geographic conditions (e.g., distance) without considering customer demands, which often require more time than anticipated by the system (Kellogg et al. 2020; Veen et al. 2020). Ideally, riders are expected to achieve financial and safety goals when the estimated delivery time does not account for extra demands (Cameron 2022; Christie and Ward 2018). However, when customer demands emerge and transform the latent tension of the paradox into a dilemma, both–and approach no longer works effectively as riders are forced to make a rational choice with a clear cost–benefit justification (Berti and Cunha 2023). This is because the salient tension largely reduces the possibility for riders of achieving maximum benefit by addressing each aspect simultaneously (Berti and Cunha 2023). When customers make extra requests, it becomes difficult for riders to comply with the estimated time set by algorithms to satisfy the safety goal (i.e., safe delivery) and the financial goal (i.e., on-time delivery). The limited time set by the algorithms forces riders to calculate how to maximize their use of time to satisfy competing goals. Customer demands require riders to spend more (e.g., attention, energy, and time) to meet these requirements in addition to accomplishing their basic tasks (i.e., delivering food) (Goods et al. 2019). Therefore, riders are forced to choose to satisfy one side or the other to reach the relative maximized benefit; attempts to satisfy both sides are unlikely to yield the expected benefits (Berti and Cunha 2023).

We present two parallel constructs to capture food delivery riders' motivations to satisfy the two sides of the finance–safety paradox: finance concern and safety concern. The former term refers to riders' state motivation to complete finance-related goals; the latter term refers to their state motivation to achieve safety-related goals. During the delivery process, gig workers must regulate both motivations dynamically to accomplish their safety and financial goals and reach relative equilibrium. Nevertheless, the cost of addressing both goals increases when they must also meet customer demands. In this case, they must assess the relative benefits and costs of the two goals strategically and appropriately.

2.3 | The Role of Algorithms in Determining Riders' Either–or Choice in the Finance–Safety Dilemma

Paradox theory offers insights into what directs riders to choose either side (Berti and Cunha 2023; Putnam et al. 2016). When a dilemma emerges, appropriate organizational arrangements may help mitigate pressure by influencing actors' strategic tradeoff choices, thereby making either–or choices sustainable (Berti and Cunha 2023). When customer demands create a finance–safety dilemma, riders are forced to decide which aspect is more beneficial and cost-effective in resolving contradictory problems. In this situation, riders tend to make the rational either–or choice that best suits the algorithmic conditions. For riders who work in the gig industry, platform algorithms (i.e., "computer-programmed procedures that transform input data into desired outputs"; Kellogg et al. 2020, 366) represent an organizational practice that provides guidance and supervision. Platform algorithms are designed to help riders navigate safety compliance by directing and guiding them to drive safely on roads by establishing relevant regulations and offering specific notifications (Kellogg et al. 2020).

Algorithms play determining roles in the basic aspects of riders' daily delivery work (Curchod et al. 2020; Rahman 2021). Algorithmic systems exert technical control over riders' actions by real-time tracking surveillance and provide managerial instructions for expected actions in certain circumstances (Kellogg et al. 2020; Newlands 2021). Platform algorithms can assign orders based on the availability of nearby riders, suggest optimal routes that link riders' current locations with delivery destinations, establish temporal goals based on the estimated time required for expected delivery, and track riders' real-time road conditions (Kellogg et al. 2020; Newlands 2021; Veen et al. 2020). Platforms aim to use algorithmic supervision to ensure adequate safety regulations during riders' daily delivery work (e.g., safety reminders and notifications) (Oviedo-Trespalacios et al. 2022). However, algorithms neither detect nor take into account any extra demands for the estimated time of expected delivery. Therefore, aspects of algorithms may interact with customer demands, thereby affecting a rider's motivation and subsequent behavior.

2.3.1 | The Role of Daily Perceived Algorithmic Supervision

Despite the stabilized features of algorithms, riders' perceptions of algorithmic supervision may vary across workdays because the salience of algorithmic actions may change due to contextual dynamics (Duggan et al. 2020; Kellogg et al. 2020). We focus on *daily perceived algorithmic supervision*, which refers to the extent to which riders perceive daily algorithmic direction, management, and guidance.

Current algorithms are designed to factor in workers' safety to avoid potential legal and public relations problems related to employment (Tan et al. 2021; Vallas and Schor 2020). To promote riders' welfare in their highly risky work, algorithms are responsible for ensuring their safety. For instance, algorithms can allocate orders that are assumed to be feasible for riders in terms of the time required to complete them (Huang 2023). Before delivery commences, riders can check the optimal and safe routes generated by algorithms (Christie and Ward 2018). Algorithms also collect real-time traffic information from digital maps and adjust routes to avoid potential safety risks. Moreover, when supervising riders' safety compliance, algorithms require riders to perform some safety actions. During the delivery process, algorithms remind riders to wear helmets, stay within the speed limit, and drive in the correct direction (Huang 2023; Oviedo-Trespalacios et al. 2022). Consequently, algorithms offer safety-relevant signals that prioritize the achievement of safety goals, reducing the need for riders themselves to assess safety factors (Kellogg et al. 2020). When riders perceive and process these signals, the subjective weight of safety is prioritized in the focal goals.

According to the paradox theory, tension triggers and organizational arrangements interact to influence the rational either–or choice of a dilemma (Berti and Cunha 2023; Putnam et al. 2016). We argue that perceived algorithmic supervision signals the benefit and reduces the cost of safety goals (vs. financial goals) under customer demands. When algorithmic supervision provides safety-relevant cues to remind and guide riders to focus on safety, it seems to riders that meeting safety requirements is more important than achieving financial goals (Nahrgang et al. 2011). Previous research has indicated that external safety-relevant prompts can facilitate safety compliance when individuals are coping with contradictory demands (Li et al. 2013). Riders' perceived algorithmic supervision urges them to prioritize their safety and inhibits their potential traffic-violating behaviors in response to extra requests (Hansez and Chmiel 2010). Accordingly, customer demands strengthen riders' motivation to achieve safety goals when algorithmic support and guidance reduce attentional costs on safety.

Correspondingly, when riders face customer demands and perceive stronger algorithmic supervision, the relatively lower additional benefits lead them to deprioritize financial goals. The algorithm itself does not take into account customer demands in offering delivery guidance; riders' perceived algorithmic supervision signals little financial benefit because algorithms mainly calculate in-system incentives rather than extra incentive by customers (Kadolkar et al. 2024). Specifically, since algorithms do not reward riders for fulfilling customers' extra wishes, they are less motivated to focus on financial goals. Meanwhile, by offering stable guidance on routes, delivery times, and safety, algorithms help create a more predictable work environment, which may lessen the pressure on riders to maximize financial gains at the cost of safety. Therefore, we propose that customer demands reduce riders' finance concern under salient algorithmic control because they fail to highlight potential financial gains. In this case, riders are encouraged by perceived algorithmic supervision to be concerned more with safety and less with finance when attempting to meet customer demands. Thus, we propose the following:

Hypothesis 1a. *Customer demands and perceived algorithmic supervision interact to influence food delivery riders' safety concern, such that the relationship between customer demands and safety concern is more negative when they perceive less algorithmic supervision.*

Hypothesis 1b. *Customer demands and perceived algorithmic supervision interact to influence food delivery riders' finance concern, such that the relationship between customer demands and finance concern is more positive when they perceive less algorithmic supervision.*

2.3.2 | The Role of Daily Algorithmic Errors

In most cases, algorithms are presumed to provide instructions that are correct and to always make optimal decisions (Lee 2018). Accordingly, riders are expected to trust the automatically computed results generated by algorithms and obey the regulations and commands (Duggan et al. 2020). However, algorithms may sometimes give instructions that are not aligned with the actual situations faced by riders. In this paper, we define *daily algorithmic errors* as daily instances where algorithmic actions direct workers in unexpected ways, offering misleading guidance that fails to account for actual conditions. Sudden incidents, adverse weather, outdated information, and incorrect route suggestions all constitute potential sources of algorithmic errors (Chen 2024; Heiland 2021). For instance, when a regular delivery route is temporarily shut down, algorithms may not detect this unexpected traffic situation immediately, thereby failing to modify the estimated delivery times on time. The expected delivery time could be more difficult to meet under customer demands when algorithmic errors occur (Heiland 2021).

When customer demands intensify the tension between finance and safety, algorithmic errors may signal higher costs and lower benefits for achieving safety goals compared to financial ones. Algorithmic mistakes, such as incorrect routes or inaccurate time estimates, require riders to independently identify and correct errors, which increases the effort and cost of maintaining safety (Homsma et al. 2009). For instance, riders may need to verify road conditions, especially when the suggested routes are blocked, or if they are unfamiliar with the area (Dong et al. 2021; Duggan et al. 2020). In such cases, maintaining safety requires additional time and resources, particularly when riders must decide how to travel efficiently without relying on algorithmic corrections. This is further complicated by the fact that, when forced to resolve issues caused by algorithmic mistakes, riders face limited time to wait for corrections, which may lead them to prioritize financial goals instead of safety, as doing so does not incur extra costs. Moreover, riders experience stress and negative emotions when their goal progress is impeded. The pressure from hungry customers and the possibility of receiving negative ratings for delayed deliveries exacerbate these feelings, which may reduce their perceived income and affect their profile assessments (Christie and Ward 2018; Grandey et al. 2004). Stress often leads to risky driving behaviors, as evidence suggests that riders tend to take more risks under stress (Bowen et al. 2020). As suggested by paradox theory

(Berti and Cunha 2023), these combined factors push riders to focus less on safety when dealing with algorithmic errors under customer demands. In this finance-safety dilemma, prioritizing safety becomes more costly, leading riders to take safety risks in an attempt to perform better and meet customer demands.

However, algorithmic errors may strengthen the salience of potential finance consequences under customer demands. Riders have to spend extra time dealing with errors, identifying mistakes quickly, and switching to correct routes. These errors typically make it more difficult to deliver food on time, increasing the likelihood of delays (Lai 2020). This risk amplifies riders' sensitivity to financial loss, driving them to focus more on financial gains to counteract potential losses (Meuris and Leana 2018). The precarious situations resulting from their financial vulnerability and job insecurity jointly urge the riders to accomplish their financial goals, especially when the pursuit of safety goals is impeded by algorithmic errors (Apouey et al. 2020; Watson et al. 2021). Therefore, errors often highlight the immediate and tangible benefits of focusing on financial goals, such as meeting delivery deadlines to avoid negative ratings or maximize income. Customers may also become aware of the errors shown on platform applications. This could make riders expect that customers would likely tip the riders generously to reward them for satisfactory delivery under the conditions of extra demands and platform errors. As a result, algorithmic errors shift riders' attention away from the value of safety and toward the perceived advantages of financial goals. Thus, we propose the following:

Hypothesis 2a. *Customer demands and algorithmic errors interact to influence food delivery riders' safety concern, such that the relationship between customer demands and safety concern is more negative when the riders experience more algorithmic errors.*

Hypothesis 2b. *Customer demands and algorithmic errors interact to influence food delivery riders' finance concern, such that the relationship between customer demands and finance concern is more positive when the riders experience more algorithmic errors.*

2.4 | The Influences on Safety Behavior and Driving Speed

Paradox theory posits that specific approaches to paradoxes can determine individuals' behavioral reactions (Putnam et al. 2016; Smith and Lewis 2011). We used the following two indicators to indicate food delivery workers' safety in terms of subjective and objective criteria: safety behavior and driving speed. Safety behavior captures riders' behavioral compliance with and adherence to safety-related regulations, rules, and laws (Beus et al. 2015; Neal and Griffin 2006). Driving speed is a major road safety indicator and is closely related to the frequency and severity of traffic accidents (Elliott et al. 2003). Riders' safety compliance and driving speed largely depend on their safety motivation (Neal and Griffin 2006).

When riders are motivated to pursue safety goals, they are more likely to comply with safety standards. Their safety concern encourages them to follow traffic rules and safety regulations to mitigate risks. Empirical studies have revealed that workers' safety motivation increases their safety compliance (Neal and Griffin 2006). Safety standards require riders to behave according to traffic regulations (Zhang et al. 2020). For instance, riders should follow the safer routes recommended directly by algorithms, even if these routes do not include shortcuts (Oviedo-Trespalacios et al. 2022). Furthermore, when riders are sensitive to risk perceptions, they tend to ensure safe driving by driving at a lower speed. Higher safety concern causes them to be aware of potential risks on the road and to be attentive and vigilant to safety-related stimuli (e.g., traffic signs, traffic lights, and road conditions).

However, when delivery riders emphasize their financial goals, they tend to engage in more risky driving behaviors (e.g., driving as quickly as possible), even though these behaviors may put them in danger. As Meuris and Leana (2015, 148) indicated, "the attentional demands of economic scarcity can also have consequences for worker safety and compliance with safety standards, especially in jobs where vigilance to safety is crucial to employee …." Some riders tend to use mobile phones to take upcoming orders while driving even before the current order is delivered, causing them to be less attentive to traffic stimuli (Christie and Ward 2018; Oviedo-Trespalacios et al. 2022; Papakostopoulos and Nathanael 2021). Riders who are more concerned with financial goals tend to complete as many orders as quickly as possible, regardless of safety conditions. To pursue efficiency goals, riders tend to drive faster, driven by financial incentives established by algorithms without regard for their safety (Cameron 2022). Thus, we propose the following:

Hypothesis 3(a-b).. *Safety concern mediates the effect of the interaction between customer demands and perceived algorithmic supervision on (a) safety behavior and (b) driving speed.*

Hypothesis 3(c-d).. *Finance concern mediates the effect of the interaction between customer demands and perceived algorithmic supervision on (c) safety behavior and (d) driving speed.*

Hypothesis 4(a-b).. *Safety concern mediates the effect of the interaction between customer demands and algorithmic errors on (a) safety behavior and (b) driving speed.*

Hypothesis 4(c-d).. *Finance concern mediates the effect of the interaction between customer demands and algorithmic errors on (c) safety behavior and (d) driving speed.*

3 | Method

3.1 | Sample and Procedure

The field advertising approach was used to recruit participants in China. We invited food delivery workers to participate by distributing advertising cards to their work sites, pickup points, and on the streets. We also posted online advertisements to the rider community on WeChat, an instant messaging application widely used in China. Participants were provided with consent information regarding confidentiality, timeline, and incentives. We verified our target sample by implementing a strict identity verification process for food delivery riders. This involved the requirement of submitting their previous work records and current daily delivery records. Once their professional identity was confirmed, the participants were formally invited to take part in our study. Initially, 124 participants were invited to complete the entry survey, which included a consent form and questions about their demographic information.

Food delivery work, unlike typical jobs, has a unique and flexible work cycle. Food delivery riders typically work all day, with their busiest periods aligning with lunch, dinner, and late-night snack times. They can be given half-day or full-day breaks depending on their personal preferences and performance assessments. During a 14-day period, the participants in this study received two online surveys each day via WeChat. The first survey opened at 13:30 and closed at 18:00, providing a break between lunch and dinner time. The second survey opened at 20:30 and closed at 1:00 the following day, targeting the remaining or late-night snack period. The afternoon survey asked participants to rate customer demands, perceived algorithmic supervision, and algorithmic errors, whereas the night survey required them to report their safety concern, finance concern, safety behavior, and driving speed. All participants received a 5 RMB reward for each survey completed and 10 RMB for completing both surveys every day. They were eligible for a bonus of 50 RMB if they completed most of the daily surveys, with a tolerance of three missed surveys. In total, participants could receive up to 190 RMB, equivalent to approximately 26.50 USD.

There were 1736 potential reporting data in total (124 riders × 14 days); 117 participants responded for an average of 13.22 days (ranging from 5 to 14 days, $SD = 2.06$) and submitted a total of 1547 matched daily observations[1] (a compliance rate of 89.11%). We generated riders' current-day safety concern (t), finance concern (t), safety behavior (t), and driving speed (t) and created lag variables for these endogenous constructs by using prior-day safety concern ($t-1$), finance concern ($t-1$), safety behavior ($t-1$), and driving speed ($t-1$) as control variables. The final number of daily observations was 1430 (the total number of daily observations minus all participants' first-day observations, i.e., 1547–117). The final sample was predominantly male (94.02%), with an average age of 26.15 years ($SD = 4.70$). Among all riders surveyed, the majority (75.21%) worked via the Meituan platform, while 15.38% relied on Eleme, with the remainder utilizing other platforms, such as Dada and Fengniao. On average, their tenure in the food delivery industry was 1.96 years ($SD = 1.19$). Most participants did not have a college degree (83.76%), and 76.92% had an income ranging from 3000 RMB to 9000 RMB per month. They were distributed across all types of cities in China, with 33.33% situated in large cities, 44.44% in middle-sized cities, and the remaining individuals in small cities and towns.

3.2 | Measures

We presented the survey items in Chinese following Brislin's (1986) translation/back-translation procedures to ensure the proper use of all scales. The online supplementary materials (https://osf.io/u94c2/?view_only=352b471a378b4a74ad0ce36451dae4bc) show comprehensively the development and validation of the tools used.

3.2.1 | Daily Customer Demands

Daily customer demands were assessed with four items adapted from Karasek (1979). Participants were asked to indicate the degree to which customers imposed demands on them during food delivery (1 = *not at all*, 7 = *always*) (average $\alpha = 0.91$, ranging from 0.88 to 0.94). A sample item is “Today, customers required me to deliver faster.”

3.2.2 | Daily Perceived Algorithmic Supervision

Three items were adapted from Norlander et al. (2021) to measure daily perceived algorithmic supervision. Participants were asked to reflect on their perception of algorithmic supervision (1 = *strongly disagree*, 7 = *strongly agree*) (average $\alpha = 0.91$, ranging from 0.82 to 0.95). A sample item is “Today, I felt that the algorithms were monitoring my delivery work (e.g., rule following, interaction with customers).”

3.2.3 | Daily Algorithmic Errors

We developed a scale to measure daily algorithmic errors (see online materials). Participants reported the frequency of algorithm errors via six items (1 = *not at all*, 7 = *always*) (average $\alpha = 0.96$, ranging from 0.92 to 0.97). A sample item is “Today, the algorithm miscalculated my estimated delivery time.”

3.2.4 | Daily Safety Concern and Daily Finance Concern

We assessed the extent to which riders were concerned about their safety and financial problems using four items for each concern. We adapted the items from Meuris and Leana's (2018) financial concern scale and Meyer et al.'s (1990) Penn State Worry Questionnaire. Responders rated these concerns on two scales, ranging from 1 (*strongly disagree*) to 7 (*strongly agree*) (safety concern: average $\alpha = 0.87$, ranging from 0.82 to 0.93; finance concern: average $\alpha = 0.92$, ranging from 0.88 to 0.94). A sample item for safety concern is “Today, I was very concerned about safety issues during the delivery process.” A sample item for finance concern is “Today, how much money the order brings is very important to me.”

3.2.5 | Daily Safety Behavior

Daily safety behavior was measured using three items adapted from the Neal and Griffin's (2006) safety compliance scale. Participants were asked to rate the degree of their engagement in safety behaviors (1 = *strongly disagree*, 7 = *strongly agree*) (average $\alpha = 0.83$, ranging from 0.78 to 0.88). A sample item is “Today, I followed the correct traffic rules for carrying out my job.”

3.2.6 | Daily Driving Speed

Participants were asked to report their daily average driving speed in kilometers per hour. The average driving speed generally characterizes the pursuit of efficiency in the food delivery process; a higher driving speed might pose potential safety risks.

3.2.7 | Control Variables

Based on theory and prior research, we controlled for several variables at the between-person and within-person levels. First, we aimed to exclude the effects of individual differences by controlling for riders' gender, education, age, food delivery work experience, and income. This is because previous studies have emphasized the influence of these demographic factors on riders' behavior during food delivery work (Papakostopoulos and Nathanael 2021). Second, we included platform factors as control variables because different delivery platforms may embody distinct management cultures, methods, and policies that can profoundly shape the work attitudes and behaviors of their riders (Veen et al. 2020). Third, the literature has inferred that local traffic patterns, road conditions, and food delivery service development might systematically influence riders' driving behavior (Cameron 2022; Papakostopoulos and Nathanael 2021; Wang et al. 2021a). We addressed this by constructing a control variable reflecting the local economic level of the cities where food deliveries occurred.

We employed two approaches to address potential confounds at the within-person level. We included positive affect (average $\alpha = 0.92$, ranging from 0.90 to 0.95) and negative affect (average $\alpha = 0.92$, ranging from 0.84 to 0.92) in our analyses using 10 items from Mackinnon et al. (1999) because daily moods can affect perceptions of safety and finance concerns (Meuris and Leana 2018; Monteiro et al. 2022; Wilson et al. 2020). In line with prior experience sampling method (ESM) work (e.g., Bartels et al. 2023; Lennard et al. 2019; Liao et al. 2021) and best-practice recommendations (Gabriel et al. 2019), we also controlled the prior-day variables for endogenous constructs to address the potential influence of serial dependence. The pattern of our results remained consistent, regardless of the control variables.

3.3 | Multilevel Confirmatory Factor Analyses

We conducted a series of multilevel confirmatory factor analyses (MCFAs) in Mplus 8.3 (Muthén and Muthén 2017) to establish the distinctiveness of all measured variables. The 8-factor measurement model demonstrated a superior goodness of fit to the data ($\chi^2 = 2999.70$, $df = 998$, CFI = 0.90, TLI = 0.89, RMSEA = 0.04, $\text{SRMR}_{\text{within}} = 0.03$, $\text{SRMR}_{\text{between}} = 0.08$) compared to any alternative model, supporting construct distinctiveness (see online materials).

3.4 | Analytical Strategy

We tested the hypothesized relationships using multilevel path analysis (Preacher et al. 2010) because of the nested within-person nature of the data. In alignment with best practice for ESM (Gabriel et al. 2019), we applied group mean centering to within-person predictors at Level 1 and grand mean centering to between-person predictors at Level 2. We estimated all hypothesized paths at the within-person level. Therefore, the resulting coefficients reflect pure within-person relationships at Level 1, allowing us to test our within-person hypotheses while examining and controlling for potential between-person confounding (Dimotakis et al. 2013). We conducted a multilevel path analysis in Mplus 8.3 to run the analyses. We further ran the Monte Carlo simulation procedures with 20 000 replications using the unstandardized effects to estimate 95% bootstrapped confidence intervals in the open-source software R (Preacher et al. 2010). In addition, we calculated pseudo-R^2 for the effect sizes in predicting our outcome variables (Gabriel et al. 2019; LaHuis et al. 2014; Snijders and Bosker 1999).

4 | Results

4.1 | Variance Components

Before testing our hypotheses, we examined the proportion of variance at the within-person level for our daily constructs to ensure that our within-person modeling approach was appropriate. The results indicated that daily variables using a continuous scale exhibited statistically significant within-person variance (27.09% in daily customer demands, 31.95% in daily perceived algorithmic supervision, 19.22% in daily algorithmic errors, 27.87% in daily safety concern, 22.28% in daily finance concern, and 27.08% in daily safety behaviors), all of which fell within the 11%–99% range from Podsakoff et al.'s (2019, 732) review. Approximately 11% of the variance in daily driving speed can be attributed to within-person variability, partly because of contextual constraints (e.g., speed limit). The intraclass correlations (ICCs) for all variables were also significant (all $ps < 0.001$), indicating sufficient variance at the within-person level, thereby justifying the use of multilevel modeling.

4.2 | Hypothesis Testing

Table 1 shows the descriptive statistics, within-person and between-person correlations, and average reliability. Table 2 reports the multilevel path analysis results, and Figure 2 summarizes the path coefficients. The overall structural model demonstrated an adequate fit to the data ($\chi^2 = 16.56$, $df = 13$, CFI = 0.99, TLI = 0.94, RMSEA = 0.01, $\text{SRMR}_{\text{within}} = 0.02$, $\text{SRMR}_{\text{between}} = 0.00$). Hypothesis 1a predicted that daily customer demands and daily perceived algorithmic supervision would have an interactive effect on food delivery riders' daily safety concern. As Table 2 shows, the interaction effect between customer demands and perceived algorithmic supervision on safety concern was significant after including all controls ($\gamma = 0.05$, $SE = 0.02$, $p < 0.01$). We investigated the interaction effects by plotting the interaction at the higher (+1SD) and lower (−1SD) levels of perceived algorithmic supervision (see Figure 3). Simple slope test results revealed that customer demands were negatively related to safety concern when perceived algorithmic supervision was lower ($\gamma = -0.12$, $SE = 0.04$, $p < 0.01$) while the relationship between customer demands and safety concern

TABLE 1 | Descriptive statistics, reliabilities, and correlations among variables.

Variable	*M*	SD	1	2	3	4	5	6	7	8	9
1. Positive affect	4.15	1.75	*(0.92)*	−0.08	0.13	−0.15	−0.09	0.21*	0.11	0.28**	−0.30**
2. Negative affect	1.89	1.14	0.02	*(0.89)*	0.60***	0.08	0.54***	−0.39***	−0.22*	−0.47***	0.14
3. Customer demands	1.69	1.13	0.02	0.13***	*(0.91)*	−0.09	0.60***	−0.35***	−0.20*	−0.37***	0.24**
4. Perceived algorithmic supervision	5.12	1.61	0.05†	0.02	0.14***	*(0.92)*	0.13	0.39***	0.42***	0.23*	0.05
5. Algorithmic errors	2.27	1.56	0.03	0.09**	0.16***	0.07**	*(0.96)*	−0.20*	−0.05	−0.41***	0.38***
6. Safety concern	6.23	1.00	0.06**	−0.07**	−0.06*	0.04	−0.08**	*(0.86)*	0.66***	0.83***	−0.07
7. Finance concern	6.13	1.21	0.03	0.00	−0.04	0.04	0.06*	0.07**	*(0.92)*	0.56***	−0.02
8. Safety behavior	6.19	1.08	0.02	−0.03	−0.06*	0.03	−0.06*	0.22***	0.05*	*(0.83)*	−0.13
9. Driving speed	38.54	13.65	0.00	0.01	−0.03	−0.05*	0.00	−0.08**	0.05†	0.02	—

Note: $N = 1430$ observations; $N = 117$ participants. Within-individual correlations are below the diagonal, and between-individual correlations are above. Averaged Cronbach's αs across daily measurements are reported in italics along the diagonal.
†$p < 0.10$.
*$p < 0.05$.
**$p < 0.01$.
***$p < 0.001$.

was nonsignificant when perceived algorithmic supervision was higher ($\gamma = 0.05$, $SE = 0.04$, $p = 0.23$). The slope difference was also significant (*Estimate* $= 0.17$, $SE = 0.06$, $p < 0.01$). Therefore, Hypothesis 1a was supported. Hypothesis 1b predicted that daily customer demands and daily perceived algorithmic supervision would interact to influence daily finance concern. However, we did not find a significant interaction effect of customer demands and perceived algorithmic supervision on finance concern ($\gamma = 0.02$, $SE = 0.02$, $p = 0.43$). Therefore, Hypothesis 1b was not supported.

Hypothesis 2a predicted that customer demands and algorithmic errors would have an interactive effect on food delivery riders' safety concern on a daily basis. As hypothesized, we found that the interaction of customer demands and algorithmic errors was negatively related to safety concern after including all controls ($\gamma = -0.06$, $SE = 0.02$, $p < 0.01$); the relationship between customer demands and safety concern was negative at higher levels of algorithmic errors ($\gamma = -0.12$, $SE = 0.04$, $p < 0.01$; see Figure 4), but was not significant at lower levels of algorithmic errors ($\gamma = 0.06$, $SE = 0.04$, $p = 0.16$). The difference between the slopes at high and low levels of algorithmic errors was also significant (*Estimate* $= -0.18$, $SE = 0.06$, $p < 0.01$). Therefore, Hypothesis 2a was supported. Hypothesis 2b predicted that daily customer demands and daily algorithmic errors would have an interactive effect on food delivery riders' daily finance concern. We did not find a significant interaction effect of customer demands and algorithmic errors on finance concern ($\gamma = -0.04$, $SE = 0.02$, $p = 0.08$). Therefore, Hypothesis 2b was not supported.

We examined Hypotheses 3a and 3b, which predicted that the indirect effects were conditional on the level of daily perceived algorithmic supervision. As Table 2 shows, on a daily basis, safety concern had a significant positive relationship with safety behaviors ($\gamma = 0.21$, $SE = 0.03$, $p < 0.001$) and a significant negative relationship with driving speed ($\gamma = -0.63$, $SE = 0.22$, $p < 0.01$). A 20000-repetition Monte Carlo simulation showed us that the indirect effect of customer demands on safety behavior via safety concern was negative at lower levels of perceived algorithmic supervision (*Indirect Effect* $= -0.024$, $SE = 0.009$, 95% CI [−0.041, −0.008]; see Table 3), whereas it was not significant at higher levels (*Indirect Effect* $= 0.011$, $SE = 0.009$, 95% CI [−0.006, 0.029]). The difference between the two indirect effects was also significant (*Estimate* $= 0.035$, $SE = 0.014$, 95% CI [0.009, 0.062]). As Table 3 shows, the difference test results for driving speed (*Estimate* $= -0.104$, $SE = 0.053$, 95% CI [−0.222, −0.016]) were significant. Specifically, the indirect effect of customer demands on driving speed via safety concern was positive at lower levels of perceived algorithmic supervision (*Indirect Effect* $= 0.073$, $SE = 0.035$, 95% CI [0.013, 0.148]), whereas it was not significant at higher levels (*Indirect Effect* $= -0.032$, $SE = 0.028$, 95% CI [−0.098, 0.019]), thereby supporting Hypotheses 3a and 3b.

Hypotheses 3c and 3d predicted that daily finance concern mediated the effect of the interaction between daily customer

TABLE 2 | Multilevel path analysis results.

	Daily safety concern		Daily finance concern		Daily safety behavior		Daily driving speed	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Intercept	6.18***	0.07	6.09***	0.09	6.14***	0.08	38.39***	1.11
Daily customer demands (CD)	−0.03	0.03	−0.05†	0.03	−0.04	0.03	−0.18	0.20
Daily perceived algorithmic supervision (PAS)	0.03†	0.02	0.03	0.02	0.02	0.02	−0.23†	0.13
Daily algorithmic errors (AE)	−0.06**	0.02	0.05*	0.02	−0.03	0.02	0.00	0.17
Moderator								
Daily CD × Daily PAS	0.05**	0.02	0.02	0.02	0.04*	0.02	−0.06	0.15
Daily CD × Daily AE	−0.06**	0.02	−0.04†	0.02	−0.02	0.02	0.01	0.15
Mediator								
Daily safety concern					0.21***	0.03	−0.63**	0.22
Daily finance concern					0.03	0.03	0.43*	0.20
Control								
Prior-day safety concern	0.01	0.03						
Prior-day finance concern			0.10***	0.03				
Prior-day safety behavior					0.03	0.03		
Prior-day driving speed							0.09**	0.03
Daily positive affect	0.04*	0.02	0.02	0.02	0.00	0.02	0.01	0.14
Daily negative affect	−0.05*	0.02	0.00	0.03	−0.01	0.02	0.09	0.19
Gender	−0.70*	0.32	−0.68†	0.41	−0.71*	0.35	0.91	4.83
Education	0.06	0.09	−0.02	0.11	−0.02	0.10	−2.27†	1.31
Age	0.00	0.02	0.02	0.02	−0.03†	0.02	−0.26	0.26
Food delivery work experience	−0.24***	0.07	−0.27**	0.08	−0.17*	0.07	−0.93	0.99
Platform 1	0.12	0.27	−0.05	0.34	0.12	0.29	2.19	4.02
Platform 2	0.30	0.33	0.19	0.41	−0.01	0.36	1.32	4.89
Local economic level	0.00	0.05	−0.02	0.06	−0.02	0.05	1.58*	0.73
Income level	−0.11†	0.06	−0.06	0.08	−0.06	0.07	1.49	0.92
R^2	14.86%		10.45%		12.49%		10.33%	

Note: $N = 1430$ observations; $N = 117$ participants. Gender (1 = female; 2 = male); Platform 1 (1 = Meituan; 0 = not Meituan), Platform 2 (1 = ELeme; 0 = not ELeme). All Level 1 predictors were group-mean centered, and all Level 2 predictors were grand-mean centered. Unstandardized effects were reported and SE = standard error.
†$p < 0.10$.
*$p < 0.05$.
**$p < 0.01$.
***$p < 0.001$.

demands and daily perceived algorithmic supervision on daily safety behavior (3c) and daily driving speed (3d). Finance concern was positively related to driving speed ($\gamma = 0.43$, $SE = 0.20$, $p < 0.05$) but not significantly related to safety behavior ($\gamma = 0.03$, $SE = 0.03$, $p = 0.20$). As Table 3 shows, the indirect moderating effect of perceived algorithmic supervision on the relationship between customer demands and (3c) safety behavior, and (3d) driving speed via finance concern was 0.002 ($SE = 0.003$, 95% CI = [−0.003, 0.010]) and 0.022 ($SE = 0.030$, 95% CI = [−0.028, 0.106]), respectively. Hypotheses 3c and 3d were not supported.

Hypotheses 4a and 4b predicted that the indirect effects of daily safety concern relied on daily algorithmic errors. As expected, the results showed that the indirect effect on safety behavior via safety concern was negative at higher levels of algorithmic errors (*Indirect Effect* = −0.026, $SE = 0.008$, 95% CI [−0.044, −0.011]) and not significant at lower levels (*Indirect Effect* = 0.012, $SE = 0.009$, 95% CI [−0.003, 0.031]). The difference between the two indirect effects was also significant (*Estimate* = −0.038, $SE = 0.013$, 95% CI [−0.067, −0.015]). For driving speed, the difference test results (*Estimate* = 0.113, $SE = 0.053$, 95% CI [0.027, 0.241]) were significant. Specifically, the indirect effect

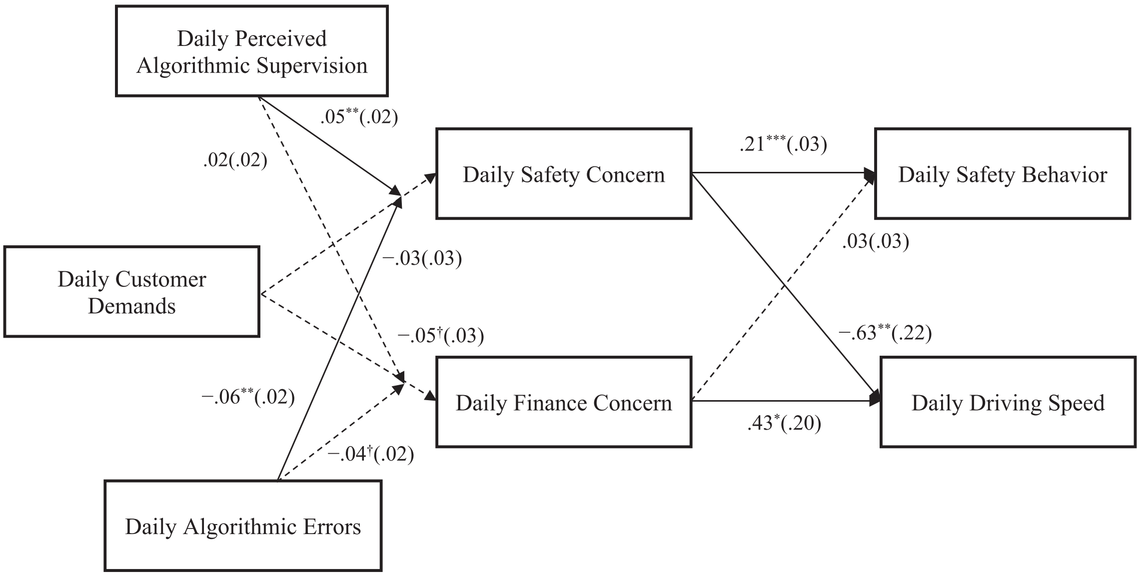

FIGURE 2 | Path model results. *Note:* $N = 1430$ observations; $N = 117$ participants. All variables were set at the within-person level. Unstandardized effects were reported. The dashed lines indicate nonsignificant relationships. Standard errors are presented in brackets. $^{\dagger}p < 0.10$. $^{*}p < 0.05$. $^{**}p < 0.01$. $^{***}p < 0.001$.

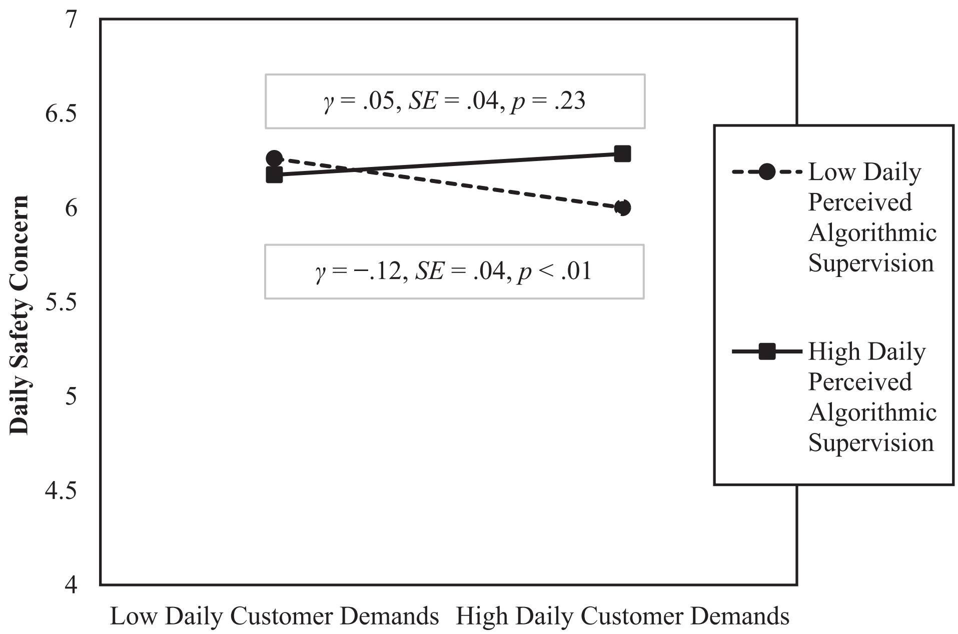

FIGURE 3 | The interaction effect of daily customer demands and daily perceived algorithmic supervision on daily safety concern.

on driving speed via safety concern was positive at higher levels of algorithmic errors (*Indirect Effect* = 0.077, *SE* = 0.035, 95% CI [0.018, 0.157]), whereas it was not significant at lower levels (*Indirect Effect* = −0.036, *SE* = 0.028, 95% CI [−0.110, 0.009]). Thus, Hypotheses 4a and 4b were supported.

Hypotheses 4c and 4d predicted that daily finance concern mediated the effect of the interaction between daily customer demands and daily algorithmic errors on daily safety behavior (4c) and daily driving speed (4d). Table 3 shows that the indirect moderating effect of algorithmic errors on the relationship between customer demands and safety behavior (4c) and driving speed (4d) via finance concern was −0.004 (*SE* = 0.004, 95% CI = [−0.013, 0.003]) and −0.046 (*SE* = 0.034, 95% CI = [−0.143, 0.003]). Thus, Hypotheses 4c and 4d were not supported.

5 | Discussion

Food delivery riders constantly face finance–safety tensions, especially when working to meet customer demands. In the present study, we explored delivery riders' daily experiences with the finance–safety paradox and how they regulate their safety motivation and behaviors while interacting with customers and algorithms. We drew on paradox theory (Berti and Cunha 2023)

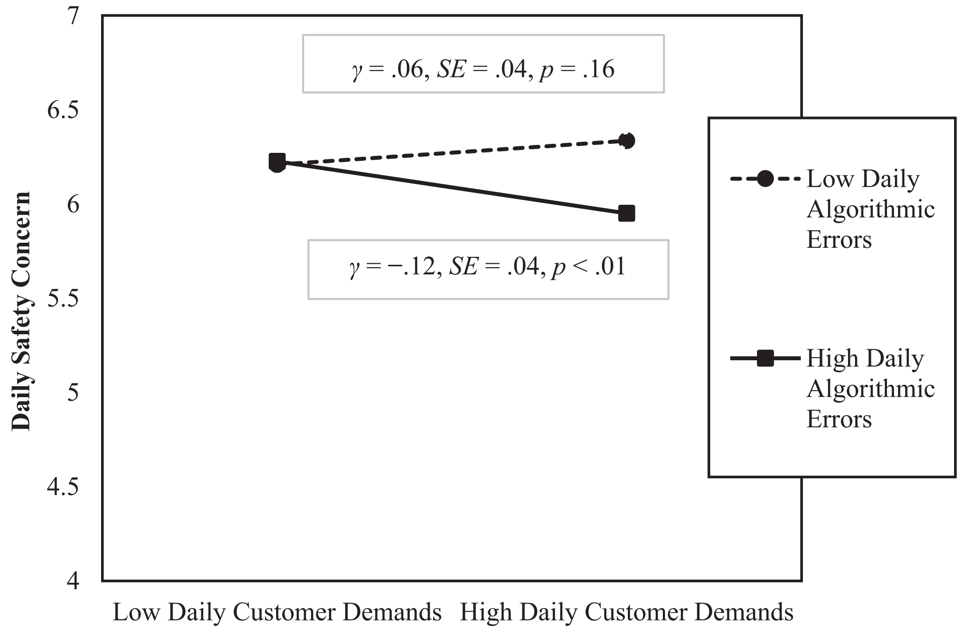

FIGURE 4 | The interaction effect of daily customer demands and daily algorithmic errors on daily safety concern.

to investigate how algorithmic supervision and errors shape the ways in which these workers cope with customer demands and influence their safety compliance. Through a 14-day diary study, we found support for our general hypothesis that algorithms affect riders' choice to resolve finance–safety tension when facing conditions of extra stress. Specifically, we found that customer demands increased riders' motivation to achieve safety goals when the algorithms provided more supervision and fewer errors. These workers were motivated to comply with the relevant safety standards and drive at a limited speed. Moreover, our approach to measuring safety and finance concerns led to shared variances, which may reduce the manifestation of the finance–safety paradox. Nevertheless, we found that this paradox had a more pronounced effect on outcomes, particularly when finance concern increased while safety concern decreased, leading to higher driving speeds. In addition to hypothesis testing, we explicitly examined whether finance–safety paradox existed in our data. We found that this paradox was intensified by customer demands (see online materials).

Unfortunately, we did not find significant effects on finance concern, likely because delivery riders' financial conditions remain relatively stable and are generally perceived as a constant burden (Ashford et al. 2018; Caza et al. 2022). Given their chronic economic stress, riders' finance concern may be less sensitive to daily fluctuations in customer demands and algorithmic features, making such effects difficult to detect in daily contexts. In contrast, within the finance-safety paradox, safety concern may be more susceptible to daily external influences (e.g., customers, algorithms, and traffic condition), as these factors directly shape riders' immediate driving decisions. Thus, finance concern may exhibit less variability than safety concern in response to external conditions.

5.1 | Theoretical Contributions

Our work makes several theoretical contributions. First, our primary contribution is to systematically address the safety issues faced by food delivery workers in the gig economy. Although gig work has been extensively explored in recent years (Cropanzano et al. 2022), the safety risks faced by gig workers remain largely overlooked—despite being a prominent and frequently discussed issue in the media, especially following tragic accidents (Kok 2022; Lai 2020; Lim and Ong 2022; Waring 2021). Relatively fewer studies have often explored a variety of personal factors, but did not clarify the underlying mechanisms of safety threats that account for the predicament faced by these workers (Oviedo-Trespalacios et al. 2022; Zhang et al. 2020). We add a necessary focus to the literature on gig workers' safety issues by theorizing and examining how food delivery riders navigate their safety behavior when meeting customer demands and interacting with algorithms. Based on paradox theory (Berti and Cunha 2023), our study suggests that customer demands undermine riders' safety when algorithms show more supervision and fewer errors. When algorithms exhibit appropriate monitoring and a lower level of inappropriate guidance, customer demands are shown to strengthen workers' safety concern, thereby increasing their safety compliance. Ultimately, when a finance–safety dilemma arises, algorithms can prioritize the importance of safety by providing supervision, but can also minimize the utility of temporary safety by making unexpected mistakes.

Second, we identify the finance–safety paradox faced by food delivery riders and the conditions under which the tension intensifies the dilemma. Existing literature emphasizes riders' financial vulnerability as a major challenge to gig workers (Caza et al. 2022). Concurrently, an increasing body of research characterizes delivery riding as a high-risk occupation where basic safety concerns are often overlooked (Papakostopoulos and Nathanael 2021; Zhang et al. 2020). While these studies separately examine how riders improve their financial situations or address safety issues, they largely overlook the persistent, conflicting paradox between the two factors, which can escalate into a dilemma in certain circumstances. Our study theorizes and investigates the tension between financial and safety goals for food delivery workers. Rather than being isolated, these

TABLE 3 | Conditional (indirect) effects.

	Daily safety behavior				Daily driving speed			
	Estimate	**SE**	**LLCI**	**ULCI**	**Estimate**	**SE**	**LLCI**	**ULCI**
(*a*) Mediator: Daily safety concern								
(*1*) Moderator:								
Daily perceived algorithmic supervision								
High level	0.011	0.009	−0.006	0.029	−0.032	0.028	−0.098	0.019
Low level	**−0.024**	**0.009**	**−0.041**	**−0.008**	**0.073**	**0.035**	**0.013**	**0.148**
Difference test	**0.035**	**0.014**	**0.009**	**0.062**	**−0.104**	**0.053**	**−0.222**	**−0.016**
(*2*) Moderator:								
Daily algorithmic errors								
High level	**−0.026**	**0.008**	**−0.044**	**−0.011**	**0.077**	**0.035**	**0.018**	**0.157**
Low level	0.012	0.009	−0.003	0.031	−0.036	0.028	−0.110	0.009
Difference test	**−0.038**	**0.013**	**−0.067**	**−0.015**	**0.113**	**0.053**	**0.027**	**0.241**
(*b*) Mediator: Daily finance concern								
(*1*) Moderator:								
Daily perceived algorithmic supervision								
High level	−0.001	0.002	−0.005	0.003	−0.010	0.020	−0.055	0.035
Low level	−0.003	0.002	−0.009	0.002	−0.032	0.023	−0.095	0.002
Difference test	0.002	0.003	−0.003	0.010	0.022	0.030	−0.028	0.106
(*2*) Moderator:								
Daily algorithmic errors								
High level	−0.004	0.003	−0.011	0.002	**−0.044**	**0.027**	**−0.116**	**−0.002**
Low level	0.000	0.001	−0.003	0.005	0.002	0.019	−0.035	0.052
Difference test	−0.004	0.004	−0.013	0.003	−0.046	0.034	−0.143	0.003

Note: Bias-corrected indirect effect confidence intervals are based on a Monte Carlo bootstrap simulation with 20000 replications in *R*. SE = standard error. LLCI = 95% confidence interval lower limit; ULLCI = 95% confidence interval upper limit. Bold values are significant.

goals form a dynamic tension that can, over time, even mutually reinforce each other (Pagell et al. 2015, 2020). We find that customer demands exacerbate this tension, transforming the two into competing trade-offs, where pursuing one requires sacrificing the other (Christie and Ward 2018; Lai 2020). This dilemma, faced by gig workers, is significant as it inevitably heightens their safety risks, underscoring a persistent paradox they must navigate in their everyday work.

Third, our findings advance the workplace safety literature by focusing on a new form of job (i.e., gig work). Mainstream research on safety is primarily within the scope of the “organization,” which involves standard employment relationships and formal work arrangements (Beus et al. 2010; Zohar 1980; Zohar and Luria 2005). However, as a typical nonstandard and flexible form of work, gig work is substantively distinct from traditional jobs (Ashford et al. 2018; Spreitzer et al. 2017). Therefore, existing safety research may not be directly relevant to gig work. One of the most notable features of gig work is algorithmic management, and it plays a critical supervisory role in guiding gig workers (Cropanzano et al. 2022; Wu and Huang 2024). Our research implies that different characteristics of algorithms may cause contradictory effects (i.e., benefits and risks) on workers' safety behavior, suggesting a complicated, multifaceted role of algorithms in managing safety. In particular, we found that maintaining an appropriate level of algorithmic supervision and minimizing algorithmic errors could encourage delivery riders to prioritize safety goals more effectively. In this regard, our study contributes to the literature by exploring how food delivery workers navigate their safety dynamics outside the organizational setting.

Furthermore, we expand the focus of workplace safety research from internal factors to external stakeholders. While previous studies have concentrated on internal elements like safety practices, climate, and leadership to improve employee safety compliance (Hofmann et al. 2017; Lyubykh et al. 2022; Probst 2015; Zacharatos et al. 2005), our study explores how external stakeholders, particularly customers, influence worker safety. Stakeholders can shape the achievement of the organization's goals and, in turn, constrain or direct employee behavior (Freeman 1984). For example, in foodservice, customers may require waiters to wear masks, improving personal protection during crises. In healthcare, patients' demands for faster treatment may pressure medical professionals to overlook safety protocols. In the gig economy, we found that customer demands could influence riders' safe driving. However, it is important to recognize that workplace safety should not be solely shifted to consumers; organizational practices, such as algorithms, play a key role in shaping how employees respond to customer demands. Our study provides a novel perspective on how external stakeholders influence workers' safety compliance and risky behaviors, offering deeper insights into workplace safety.

5.2 | Practical Implications

Our research has several practical implications for food delivery platforms, gig workers, and policymakers. First, platforms should be aware of the previously ignored effects of customer demands on regular algorithms. Algorithms are designed to provide guidance based on well-known situations and may ignore unusual requests made to riders (Kellogg et al. 2020). When customers have unique needs that require riders to engage in additional work, this extra workload can intensify the finance–safety paradox and cause algorithms to underestimate the time of delivery. Therefore, it is worth considering whether platform algorithms could automatically increase the estimated time for expected delivery to minimize the tension and job stress of riders. A focus on the role of customer demands could help riders regulate their safety more effectively, thereby allowing riders to have a safe trip during the delivery process.

Second, algorithm designers and programmers could avoid errors by constantly improving and optimizing the accuracy and reasonableness of the guidance provided by algorithms (Jarrahi et al. 2021). Algorithmic estimation is not always consistent with the actual situations that food delivery riders encounter. External factors (e.g., bad weather, temporary traffic controls, blocked roads, and traffic accidents) can impede the normal process of delivery, especially in the context of intensely used crossroads in large cities, where traffic conditions can be rather complicated (Christie and Ward 2018). Thus, the real-time detection of such changes is important in enabling platform algorithms to provide appropriate guidance for routes and estimated times. Another practical suggestion is that algorithms could be used to offer increased payments in unusual situations that hinder delivery and decrease efficiency. A responsible approach to business sustainability, especially for food delivery companies in oligopolistic markets, would be to bear the risks of environmental uncertainties in riders' daily work and to invest in corresponding insurance to ensure their protection in the event of an accident. Specifically, for these firms, unique corporate social responsibility actions could be enacted to increase riders' benefits.

Third, there is a need to address legal protection for riders' safety rights and risks to enhance their quality of life. Food delivery, a job that lacks fixed employment contracts, is associated with visible uncertainties and job insecurity with respect to riders' long-term welfare (Watson et al. 2021). Especially during the COVID-19 pandemic, gig workers faced far more severe physical and economic risks (Cameron et al. 2021). The nonstandard drawbacks of this job make gig workers more vulnerable to such risks, while their lower socioeconomic status reinforces these challenges. Their basic benefits should be protected in a manner similar to that of factory workers; relevant institutions could enact laws to ensure the welfare of delivery riders. Putting food delivery riders in a weak and risky position is not a responsible strategy, even if this approach can offer them financial benefits (Bajwa et al. 2018; Duggan et al. 2020).

5.3 | Limitations

There are several limitations to this study. First, we used only the ESM to explore the short-term dynamics of our theoretical framework, whereas the long-term effect of customer demands and algorithms remains underexplored. The degree of within-person variance was relatively small, although it was still sufficiently significant to justify our methodological rigor (Podsakoff et al. 2019). Even if some riders prefer to drive as fast as possible, they usually attempt to keep their speed within the legal speed limit (e.g., max 60 km/h). Experienced riders become accustomed to a stable range of speeds that are relevant to their regular delivery areas. Future research could use a broader variety of methodological approaches (e.g., longitudinal surveys, field experiments, and in-depth interviews) to explore the safety risks faced by gig workers.

Second, we focus on only one typical demand faced by food delivery riders; other types of job demands are not addressed in this context. In a recent review, Watson et al. (2021) identified several main job demands (e.g., alienation, emotional labor, working hours, and overqualification) based on the work of Keith et al. (2020). Different demands may have distinct underlying mechanisms and lead to different outcomes for gig workers. More importantly, the type of gig work in question may also influence the frequency and salience of regular demands. For example, crowdsourced workers on online platforms (e.g., Prolific, Amazon MTurk) are less likely to encounter the safety risks addressed in the present paper because they are not required to leave their homes. Therefore, the task of identifying and examining the job demands associated with various types of gig work is theoretically vital to the improvement of gig workers' well-being and performance.

Third, our research findings may lack some degree of generalizability because the principles of platforms, traffic and market environments, and peoples' needs for food delivery vary across different cultures, nations, and regions. On some delivery platform apps (e.g., Just Eat), it is not possible for customers to contact riders to indicate any extra demands. Therefore, our findings cannot be applied to such platforms. In addition, people in different times and places have different lifestyles and dietary habits. Over time, there has been a noticeable shift toward increased preference for online food ordering, a trend that has intensified during the COVID-19 pandemic (Waring 2021). Geographically, people in developed countries may order food more frequently than those in underdeveloped countries. Therefore, given these market differences, gig work research should be encouraged to develop more generalizable theories.

Fourth, our measurement approach was limited in capturing the full pattern of the dilemma because the two issues were positively related.[2] This could be attributed to the fact that both concerns were measured in a similar way (i.e., same source, same time, and same item formulation) (Gabriel et al. 2019). In this case, it may not be optimal to measure the two sides of a paradox using traditional scales. Future paradox research could address this issue by adopting a forced-choice measure in dilemma contexts (Wetzel et al. 2020) or a double-barreled measure in paradoxical contexts (Menold 2020). With appropriate measurement, the paradoxical tension pattern could manifest clearly in the data rather than relying mainly on theoretical assumptions.

5.4 | Future Research Directions

Our research, focusing on novel issues relating to gig work, aims to inspire further explorations in this area. First, we call for more studies to examine the paradoxes embedded in gig work, beyond the finance–safety paradox. Gig worker face conditions of plurality, change, and scarcity, which can trigger various tensions in their work (Smith and Lewis 2011). For instance, while they enjoy flexibility in their working hours and location, they are also tightly controlled by platform algorithms, particularly regarding delivery time and service quality (Shapiro 2018; Wood et al. 2019). Paradox theory offers a framework that can help us understand four key paradoxes inherent in gig work: learning (e.g., stability vs. change), organizing (e.g., control vs. flexibility), belonging (e.g., individual vs. collective), and performing (e.g., internal vs. external) (Lewis 2000; Smith and Lewis 2011). Building on recent studies (Cameron 2022, 2024) that highlight how gig workers interact with algorithmic management in varied ways—ranging from engagement to deviance—we suggest that a paradox lens offers a valuable framework for examining these dynamics. By applying this perspective, future research can uncover how gig workers manage the tensions inherent in competing demands and better understand their strategies for navigating the complexities of gig work.

Second, we advocate for deeper investigations into how gig workers interact with algorithmic errors. While prior research has extensively examined algorithmic management, particularly its role in enhancing performance (Kellogg et al. 2020; Zhang et al. 2024), relatively little attention has been given to the consequences of algorithmic errors. These errors may arise from algorithms' inability to account for specific contextual factors in delivery work (Chen 2024; Heiland 2021), but they can also be driven by systemic issues, offering fertile ground for further exploration. Platforms aim to enhance rider efficiency through algorithms that rely on continuous data generated during deliveries. This data, such as shorter delivery times (e.g., below the algorithm's time standard) or the use of shortcuts (e.g., traveling against traffic), can inadvertently reinforce algorithmic biases in subsequent estimations. Given the loosely connected nature of gig workers, who often lack collective resistance to algorithmic oversight (Wu et al. 2019), individuals failing to meet increasingly stringent standards may face exclusion. Over time, these algorithmic errors risk becoming normalized. This dynamic highlights two critical avenues for future research: first, the ethical implications of algorithmic biases, including how these biases evolve as the gig economy expands and how they are perceived and addressed by governments, platforms, and individuals; and second, the disproportionate effects of these biases on specific groups, potentially exacerbating stress, safety risks, or inequities among workers.

Third, we look forward to more research on the safety issues of delivery workers, a major group of gig workers. The working conditions of these workers differ from those of gig workers in other industries (e.g., ride-hailing) and of delivery workers in standard employment with formal contracts. It has been shown that gig delivery workers are more vulnerable to safety risks (Kok 2022; Lai 2020; Lim and Ong 2022; Sanusi and Emmelin 2015). While we identified customer demands as a potential antecedent, this may not be sufficient to explain such salient phenomena. Customers may not always make additional requests, yet the platforms (with a focus on algorithms in our research) play a critical role in shaping the relationship between customer demands and gig worker safety compliance. It is essential to recognize that platforms have a decisive role in ensuring gig worker safety, rather than merely acting as arbitrators or intermediaries (Cameron and Rahman 2022). Thus, we hope that scholars can further provide a more systemic investigation of how platforms can reduce the safety risks faced by delivery riders.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

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

Endnotes

[1]We ran a MANOVA test to check whether the loss of participants caused any response or self-selection bias in our sample. We found no significant differences in the demographic variables between the final sample and the lost sample (Wilk's Lamba = 0.94, $p = 0.56$), suggesting that participant attrition is not a concern.

[2]To examine whether a paradox really existed, we conducted additional analysis to identify the finance–safety paradox. More details are shown in online supplementary materials. Overall, we found that customer demands intensified the inherent tension.

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