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Article

Algorithmic Management and Worker Precarity: Lived Experiences and Psychological Burden in India's On-Demand Food Delivery Platforms

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Abstract: Purpose: This study examines the structural impact of algorithmic management and platform governance on work precarity, cognitive strain, and psychological well-being among app-based delivery and logistics workers in urban India. Grounded in Labor Process Theory, Agency Theory, and the Conservation of Resources model, it investigates how automated surveillance, dynamic pricing, and opaque evaluation mechanisms reconfigure labor conditions. Design/methodology/approach: A mixed-methods research design was employed. Quantitative survey data collected from urban platform workers were analyzed using Structural Equation Modeling (SEM) and Relative Weight Analysis (RWA) in IBM SPSS to evaluate the predictive power of specific algorithmic controls. Qualitative interviews were concurrently conducted to explore workers' lived experiences, coping strategies, and emerging modes of resistance against automated platform systems. Findings: The results demonstrate that intense algorithmic surveillance—specifically real-time geo-fencing and speed monitoring—significantly increases work precarity and cognitive strain. Algorithmic opacity and the lack of transparent grievance redressal force workers to internalize operational risks, leading to prolonged working hours to meet target thresholds. While workers develop adaptive coping mechanisms and engage in informal resistance to mitigate resource loss, institutional and regulatory gaps perpetuate their structural vulnerability. Research limitations/implications: The findings provide empirical evidence on how automated management practices systematically generate precarity in developing economies. The study highlights the need to expand labor process frameworks by incorporating the psychological costs of continuous algorithmic control. Practical implications: The study emphasizes the urgent need for regulatory interventions, including mandatory algorithmic transparency, fair dispute resolution channels, and standardized social protections for platform workers in emerging markets. Originality/value: This research contributes to the platform economy literature by offering an integrated empirical account of how algorithmic control mechanisms systematically impair worker well-being and fuel precarity within the Global South context.

Keywords: Algorithmic management, Platform economy, Gig work, Work precarity, Conservation of Resources theory, Urban India

1. Introduction

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Background of the Study

The rapid expansion of digital platforms has fundamentally altered the way work is organized, assigned, monitored, and rewarded (Kellogg et al., 2020). Nowhere is this transformation more visible than in the shift from traditional, human-mediated supervision to algorithmic management, wherein software systems, rather than human managers, direct, evaluate, and discipline the workforce (Lee et al., 2015). Traditional management relied on face-to-face supervision, negotiated targets, and discretionary judgment; algorithmic management replaces much of this with automated monitoring, data-driven goal setting, algorithmically generated schedules, system-calculated performance ratings, and formula-based compensation (Duggan et al., 2020; Wood et al., 2019). While this transition has enabled platforms to coordinate large, geographically dispersed, and highly flexible workforces at scale, it has also reshaped the everyday working experience and behavior of the people who depend on these platforms for their livelihood (Möhlmann & Zalmanson, 2017).

Among the various categories of platform-based work, food and parcel delivery occupies a distinctive position (Veen et al., 2020). Unlike many other forms of gig work where the worker interacts primarily with a single counterparty — for instance, a ride-hailing driver who deals mainly with the passenger — food delivery partners are required to operate at the intersection of two external parties simultaneously: the restaurant that prepares the order and the customer who receives it (Duggan et al., 2020; Griesbach et al., 2019). This dual-interface role obliges delivery partners to manage expectations, delays, errors, and grievances originating from both sides, even though the terms of the transaction, the timelines, and the performance benchmarks are set and enforced by the platform's algorithm rather than by the delivery partner (Ivanova et al., 2020). This distinguishing feature of food delivery work — being algorithmically directed while simultaneously acting as the human interface between two independent stakeholders — makes it a particularly important, and comparatively under-examined, context in which to study the behavioral and psychological consequences of algorithmic management (Sun et al., 2021).

In India, the food delivery sector has grown into one of the largest and most visible segments of the platform economy, absorbing a substantial share of the country's expanding gig workforce (Chowdhury, 2021; Kasliwal, 2020). Delivery partners in this sector typically work without the protections associated with standard employment — including job security, fixed wages, collective bargaining, and formal grievance redressal — while being subject to continuous algorithmic monitoring of their location, speed, acceptance rates, and customer ratings (Anwar & Graham, 2020; Surie & Koduganti, 2016). This combination of intense algorithmic control and the absence of standard employment protections raises important questions about the extent to which algorithmic management contributes to work precarity among this workforce (Nair, 2021).

Statement of the Problem

Work precarity — characterized by temporariness of engagement, disempowerment in decision-making, vulnerability to unilateral platform decisions, inadequate and unpredictable wages, limited access to rights, and constrained ability to exercise whatever rights nominally exist — has increasingly been documented among gig workers (Kalleberg, 2018; Standing, 2011; Vallas & Schor, 2020). However, much of the existing literature treats platform work as a relatively homogenous category and does not adequately account for the unique boundary-spanning demands placed on food delivery partners, who must simultaneously satisfy restaurants and customers while being evaluated by an algorithm that has visibility into only a fraction of the situational factors affecting their performance (Griesbach et al., 2019; Tassinari & Maccarrone, 2020). It remains insufficiently understood how specific dimensions of algorithmic management — monitoring, goal setting, scheduling, performance rating, and compensation — individually and collectively shape the precarity experienced by delivery partners, and through what psychological and relational mechanisms this influence operates (Duggan et al., 2020; Wood et al., 2019). This study addresses that gap by examining how the shift toward algorithmic management affects the work precarity of food delivery partners in India, with particular attention to their distinctive role as intermediaries between restaurants and customers.

Theoretical Perspectives

To explain how and why algorithmic management translates into work precarity for food delivery partners, this study draws on three complementary theoretical lenses.

Conservation of Resources (COR) Theory:

COR theory holds that individuals strive to acquire, protect, and retain resources — such as time, autonomy, energy, and social standing — and that stress and strain emerge when these resources are threatened, lost, or invested without adequate return (Hobfoll, 1989; Hobfoll et al., 2018). Continuous algorithmic monitoring, rigid goal setting, inflexible scheduling, and opaque performance rating can be understood as conditions that steadily deplete the personal and relational resources of delivery partners (Bucher et al., 2021). Within this framework, work precarity can be interpreted as a manifestation of sustained resource loss, as delivery partners are left with diminished control, security, and recourse (Lapointe et al., 2020).

Precarity Theory:

Precarity theory conceptualizes insecurity not merely as an individual perception but as a structural condition produced by the terms under which work is organized (Kalleberg, 2009; Standing, 2011). It draws attention to the temporariness of engagement, the erosion of worker voice, exposure to unilateral and unpredictable decisions, inadequate compensation, and restricted access to rights and their exercise (Vosko, 2006). This study uses precarity theory to frame the outcome variable of interest and to organize its constituent dimensions — temporariness, disempowerment, vulnerability, wages, rights, and exercise of rights — as interrelated facets of a single underlying condition shaped by the design of algorithmic management systems (Schor et al., 2020; Vallas & Kalleberg, 2018).

Agency Theory:

Agency theory traditionally examines the relationship between a principal, who delegates work, and an agent, who performs it on the principal's behalf, along with the information asymmetries and control mechanisms that arise between them (Eisenhardt, 1989; Jensen & Meckling, 1976). Food delivery partners occupy an unusual position within this framework: they function simultaneously as agents of the platform, which monitors and incentivizes their behavior algorithmically, and as the visible human link connecting two additional parties — the restaurant and the customer — whose expectations they must manage without possessing authority over either (Duggan et al., 2020; Shapiro, 2018). This layered agency relationship, in which the delivery partner absorbs risk and accountability that properly belongs to multiple principals, is used in this study to explain why algorithmic management may have a particularly pronounced effect on the precarity experienced by food delivery partners compared to other categories of platform workers (Rahman, 2021).

Together, these three theoretical perspectives provide a multi-level explanation — resource-based, structural, and relational — for the pathway through which algorithmic management shapes the work precarity of food delivery partners.

Objectives of the Study

In light of the background and problem outlined above, the present study seeks to:

1. Examine the extent to which the dimensions of algorithmic management (monitoring, goal setting, scheduling, performance rating, and compensation) influence the work precarity of food delivery partners.
2. Assess the relative contribution of each dimension of algorithmic management to the overall work precarity experienced by delivery partners.
3. Interpret the observed relationships through the combined lens of Conservation of Resources theory, precarity theory, and agency theory, with specific attention to the boundary-spanning role of delivery partners between restaurants and customers.

4. Generate evidence-based insights for platform design and policy that could help mitigate work precarity among food delivery partners in the Indian context.

Significance of the Study

This study contributes to the growing body of literature on platform work in three ways. First, it narrows its focus to food delivery partners specifically, rather than treating gig work as an undifferentiated category, thereby foregrounding the unique dual-facing demands of this occupation (Griesbach et al., 2019; Veen et al., 2020). Second, it integrates Conservation of Resources theory, precarity theory, and agency theory within a single explanatory framework, offering a more complete account of the mechanisms linking algorithmic management to precarity than any one theory could provide in isolation (Duggan et al., 2020; Hobfoll, 1989; Standing, 2011). Third, by situating the study within the Indian food delivery sector — a large and rapidly growing segment of the platform economy operating within an evolving regulatory environment — the findings carry practical relevance for platform operators, policymakers, and labor organizations seeking to improve the working conditions of an increasingly indispensable but structurally vulnerable segment of the workforce (Anwar & Graham, 2020; Surie & Koduganti, 2016).

2. Literature Review

Algorithmic Management

Algorithmic management refers to the use of software algorithms to perform functions that were traditionally carried out by human supervisors, including directing workers toward tasks, evaluating their performance, disciplining them for shortfalls, and rewarding or compensating them for output (Chakraborty & Heeks, 2023; Kellogg et al., 2020). Kellogg et al. (2020) describe algorithmic management as a new contested terrain of control in which algorithms take over the core managerial functions of directing, evaluating, and disciplining the workforce, often with minimal human mediation. In the platform economy, this form of management is exercised through continuous data collection, automated task allocation, and system-generated performance metrics rather than through face-to-face supervisory judgment (Duggan et al., 2020; Wotschack et al., 2024).

Agency theory (Eisenhardt, 1989) offers a useful theoretical lens for understanding why platforms rely so heavily on algorithmic management. Because platforms (the principal) cannot directly observe the day-to-day conduct of geographically dispersed delivery partners (the agents), they face an information asymmetry and the risk of agents acting in ways that diverge from the platform's interests. Algorithmic systems function as a low-cost, scalable monitoring and incentive-alignment mechanism that substitutes for direct supervision, allowing the platform to observe, evaluate, and control agent behavior at a distance (Duggan et al., 2020; Rahman, 2021). Viewed through this lens, each dimension of algorithmic management — monitoring, goal setting, scheduling, performance rating, and compensation — represents a distinct mechanism through which the platform, as principal, seeks to reduce information asymmetry and align the behavior of the delivery partner, as agent, with organizational objectives.

Monitoring

Monitoring refers to the continuous, technologically mediated surveillance of a worker's location, movement, speed, and task progress through the platform application (Kadolkar et al., 2024). Griesbach et al. (2019) document how food delivery platforms use GPS tracking and in-app data collection to observe couriers in real time, creating a pervasive form of digital surveillance that extends well beyond what conventional human supervision could achieve. Rosenblat and Stark (2016) similarly note that continuous data collection allows platforms to observe far more about a worker's behavior than the worker can observe about the platform's own decision-making, producing a marked information asymmetry in the employment relationship that has persisted in modern platform operations (Wotschack et al., 2024).

Goal Setting

Goal setting under algorithmic management involves the automated assignment of delivery targets, time windows, and acceptance expectations by the platform's algorithm rather than through negotiation with a human supervisor. Kellogg et al. (2020) identify this directing function as central to algorithmic management, as the system continuously issues instructions and benchmarks that workers are expected to meet without the opportunity to question or renegotiate them. Recent studies in food delivery logistics confirm that automated target assignment enforces strict operational pace while restricting individual worker agency (Chaudhary, 2026)

Scheduling

Scheduling refers to the algorithmic allocation of work slots, shifts, or delivery zones to individual couriers, often based on system-calculated demand forecasts and the worker's own performance history. Veen et al. (2020) show that although platforms market this arrangement as flexible, the actual allocation of favorable slots and work opportunities is frequently determined by opaque algorithmic criteria that constrain the worker's real control over when and how much they work. Wood et al. (2019) similarly describe this as a central paradox of platform work, in which nominal scheduling autonomy coexists with strong algorithmic control over the availability of work, a dynamic echoed in recent platform studies (Marappan, 2026).

Performance Rating

Performance rating encompasses the customer ratings, acceptance rates, cancellation rates, and other system-generated scores that the algorithm uses to evaluate a delivery partner's conduct. Möhlmann and Zalmanson (2017) find that such rating systems shape driver and courier behavior by creating a persistent incentive to conform to algorithmically defined standards of performance, even when the underlying circumstances — such as restaurant delays or traffic conditions — are outside the worker's control. Rosenblat and Stark (2016) further note that these rating mechanisms are frequently opaque, leaving workers uncertain about precisely how their score is calculated or how it affects their access to future work (Rahman & Cameron, 2022).

Compensation

Compensation under algorithmic management refers to the system-calculated pay a delivery partner receives per order, including base pay, distance-based pay, and algorithmically triggered incentives or surge payments. Griesbach et al. (2019) describe how such piece-rate, algorithmically administered pay structures shift earnings risk onto the worker, since payment fluctuates with demand conditions and algorithmic criteria that are largely outside the worker's influence or comprehension. Recent empirical evidence further indicates that opaque and volatile reward structures lead to financial vulnerability and severe worker burnout (Lang et al., 2023; Marappan, 2026).

Work Precarity

Work precarity refers to the condition of instability, insecurity, and vulnerability that characterizes non-standard forms of employment. Kalleberg (2009, 2018) conceptualizes precarious work as work that is uncertain, unpredictable, and in which the risks associated with work are shifted from employers and the state onto individual workers. Within precarity theory, precarity is understood not merely as a subjective feeling of insecurity but as a structural condition produced by the terms under which work is organized and contracted — including the temporariness of engagement, the erosion of worker voice, exposure to unilateral decisions, inadequate compensation, and restricted access to rights and their exercise (Allan et al., 2024; Standing, 2011). De Stefano (2015) extends this reasoning to on-demand and crowdwork arrangements, arguing that the classification of platform workers as independent contractors rather than employees systematically excludes them from the labor protections that would otherwise mitigate such precarity.

Conservation of Resources (COR) theory (Hobfoll, 1989; Hobfoll et al., 2018) provides a complementary, psychological explanation of how precarity is experienced by individual workers. COR theory holds that people are motivated to acquire, protect, and retain resources — including time, autonomy, security, and social standing — and that psychological strain results when these resources are threatened, lost, or invested without adequate return. Applied to platform-based delivery work, the constant demands imposed by algorithmic management can be understood as

conditions that steadily deplete the personal and relational resources of delivery partners (Bucher et al., 2021; Wang et al., 2024), with work precarity representing the accumulated outcome of this sustained resource loss (Lapointe et al., 2020).

Temporariness

Temporariness reflects the short-term, on-demand nature of platform engagement, in which delivery partners are typically classified as independent contractors with no guarantee of continued work, fixed tenure, or advance notice of termination. Kalleberg (2009) identifies this uncertainty of continuity as a defining feature of precarious work, while De Stefano (2015) notes that on-demand platforms are structurally designed to treat labor as a variable input that can be scaled up or down without the obligations attached to standard employment (Schor et al., 2020).

Disempowerment

Disempowerment refers to the delivery partner's limited ability to influence the terms, conditions, or decisions that govern their work, including pay formulas, performance criteria, and account status. Goods et al. (2019) find that food-delivery workers in platform-based arrangements have little scope to negotiate their terms of engagement, as these are set unilaterally by the platform and communicated through the application rather than through dialogue (Sanjay et al., 2025).

Vulnerability

Vulnerability captures the delivery partner's exposure to unilateral and often unexplained platform decisions, such as account deactivation, order reassignment, or changes to pay structures, without formal recourse. Rosenblat and Stark (2016) describe how such asymmetric control leaves drivers and couriers exposed to decisions they can neither anticipate nor contest, while De Stefano (2015) situates this exposure within the broader absence of protective regulation covering on-demand work (Fairwork India, 2024; Kariveliparambil et al., 2026).

Wages

The wages dimension concerns the adequacy, predictability, and transparency of the earnings delivery partners receive for their labor. Griesbach et al. (2019) document how algorithmically administered, piece-rate compensation structures produce earnings that fluctuate with demand and platform-determined incentive schemes, often leaving workers uncertain about how much they will earn in a given period and unable to verify whether they are being paid fairly for their effort (Lang et al., 2023; Negi et al., 2025).

Rights

Rights refers to the extent to which delivery partners have access to the statutory protections ordinarily associated with employment, such as minimum wage guarantees, social security, insurance, and grievance mechanisms. De Stefano (2015) argues that the classification of platform workers as independent contractors is a central mechanism through which such rights are withheld, leaving workers formally outside the scope of most labor law protections despite functioning, in practice, under considerable platform control (Anwar & Graham, 2020; Press Information Bureau, 2025).

Exercise of Rights

Exercise of rights refers to the practical ability of delivery partners to make use of whatever rights or avenues for redress are nominally available to them, as distinct from the mere existence of those rights. Kalleberg (2009) notes that precarious workers frequently refrain from exercising available protections or voicing grievances for fear of jeopardizing their access to future work, a dynamic that is intensified in algorithmically managed settings where raising a complaint or declining an assignment can trigger an automated and opaque penalty (Weber et al., 2023; Weber et al., 2025).

Theoretical Integration: Linking Algorithmic Management to Work Precarity

The relationship between algorithmic management and work precarity can be explained by integrating agency theory, COR theory, and precarity theory around the specific boundary-spanning position occupied by food delivery partners. Unlike many other platform workers who interface with a single external party, food delivery partners must satisfy both the restaurant preparing the order and the customer receiving it, while their conduct toward both parties is simultaneously monitored, scored, and incentivized by the platform's algorithm (Duggan et al., 2020; Griesbach et al., 2019).

From an agency-theory perspective (Eisenhardt, 1989), this arrangement burdens the delivery partner with accountability to what is effectively more than one principal — the platform, the restaurant, and the customer — even though only the platform exercises formal control through algorithmic monitoring, goal setting, scheduling, rating, and compensation (Rahman, 2021). From a COR-theory perspective (Hobfoll, 1989), each of these algorithmic management mechanisms represents a recurring demand on the delivery partner's time, autonomy, and psychological resources; because the delivery partner has little ability to negotiate these demands or replenish the resources they consume, sustained exposure to algorithmic management results in resource depletion (Bucher et al., 2021; Lapointe et al., 2020). Precarity theory (Kalleberg, 2018; Standing, 2011) provides the vocabulary for describing the cumulative outcome of this depletion — namely, a state of temporariness, disempowerment, vulnerability, inadequate wages, restricted rights, and constrained exercise of rights. Taken together, these perspectives suggest that the specific dimensions of algorithmic management identified in the preceding section can be expected to systematically shape the level of work precarity experienced by food delivery partners.

2.4 Relationship Between Algorithmic Management and Work Precarity: Hypotheses Development

Monitoring and Work Precarity

Continuous algorithmic monitoring subjects delivery partners to persistent surveillance of their location, speed, and task progress (Griesbach et al., 2019; Kadolkar et al., 2024). Drawing on COR theory, such unrelenting observation can be understood as a continuous drain on the psychological resource of autonomy, leaving the delivery partner with a diminished sense of control over their own work and, correspondingly, a heightened sense of vulnerability and disempowerment. This suggests that greater algorithmic monitoring is associated with greater work precarity.

- **H1:** Monitoring has a significant positive influence on the work precarity of food delivery partners.

Goal Setting and Work Precarity

Algorithmically imposed goals and delivery targets are issued without negotiation and must be met regardless of situational constraints such as restaurant delays or traffic (Chaudhary, 2026; Kellogg et al., 2020). This non-negotiable target-setting restricts the delivery partner's discretion and voice in shaping their own workload, a condition consistent with the disempowerment dimension of precarity.

- **H2:** Goal setting has a significant positive influence on the work precarity of food delivery partners.

Scheduling and Work Precarity

Although platforms present scheduling as flexible, the actual allocation of shifts and delivery zones is governed by opaque algorithmic criteria that the worker cannot fully anticipate or influence (Veen et al., 2020; Wood et al., 2019). This unpredictability in access to work opportunities is consistent with the temporariness and vulnerability dimensions of precarity, as delivery partners cannot reliably plan for consistent income or work availability (Marappan, 2026).

- **H3:** Scheduling has a significant positive influence on the work precarity of food delivery partners.

Performance Rating and Work Precarity

Performance ratings generated from customer feedback and acceptance metrics directly affect a delivery partner's continued access to work, yet the criteria underlying these scores are often opaque (Möhlmann & Zalmanson, 2017; Rosenblat & Stark, 2016). Because delivery partners bear the consequences of ratings shaped by factors outside their control — such as restaurant errors or customer mood — this dimension is expected to heighten the sense of vulnerability and disempowerment associated with precarity (Rahman & Cameron, 2022).

- **H4:** Performance rating has a significant positive influence on the work precarity of food delivery partners.

Compensation and Work Precarity

Algorithmically administered, piece-rate compensation shifts earnings risk onto the delivery partner and produces income that is difficult to predict or verify (Griesbach et al., 2019; Lang et al., 2023). This unpredictability corresponds directly to the wages dimension of precarity and, by extension, contributes to the overall precarity experienced by delivery partners.

- **H5:** Compensation has a significant positive influence on the work precarity of food delivery partners.

Overall Relationship

Considered together, the five dimensions of algorithmic management represent complementary mechanisms of algorithmic control that, through the resource-depleting and disempowering processes described above, are expected to jointly shape the level of work precarity experienced by food delivery partners (Kariveliparambil et al., 2026).

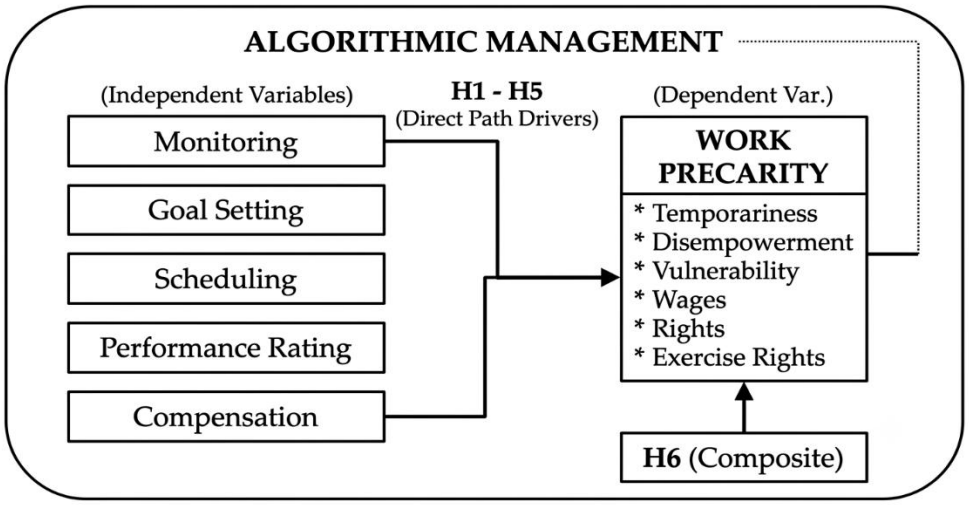
- **H6:** Algorithmic management, as a composite construct, has a significant positive influence on the work precarity of food delivery partners in India.

2.5 Conceptual Framework

The conceptual framework models the structural relationships between the five dimensions of **Algorithmic Management** (Independent Variables: *Monitoring*, *Goal Setting*, *Scheduling*, *Performance Rating*, and *Compensation*) and the multidimensional construct of **Work Precarity** (Dependent Variable: comprised of *Temporariness*, *Disempowerment*, *Vulnerability*, *Wages*, *Rights*, and *Exercise of Rights*).

The theoretical linkages are grounded in **Agency Theory** (governing principal-agent control mechanisms), **Conservation of Resources (COR) Theory** (explaining resource depletion and stress mechanisms), and **Precarity Theory** (framing the structural outcomes of worker insecurity).

Figure 2.1: Conceptual framework



3. Research Methodology

3.1 Research Design

This study adopts a quantitative, cross-sectional research design to examine the relationship between algorithmic management and work precarity among food delivery partners in India. A survey-based, descriptive-cum-correlational approach was used, as the objective was to measure respondents' perceptions of both constructs at a single point in time and statistically test the hypothesized relationships between the dimensions of algorithmic management and work precarity (Hair et al., 2019; Saunders et al., 2019)

3.2 Population and Sample

The target population for this study comprises food and parcel delivery partners actively engaged with major online food-delivery platforms operating in India (e.g., Zomato, Swiggy). Because delivery partners are independent contractors who are geographically dispersed, highly mobile, and not listed in any publicly accessible sampling frame, probability-based random sampling could not be implemented (Chowdhury, 2021; Kasliwal, 2020). The final sample used for analysis consisted of $N = 458$ valid responses collected from active food delivery partners, exceeding the recommended sample size thresholds for structural path modeling and factor analysis (Hair et al., 2019).

3.3 Sampling Technique

In the absence of a complete sampling frame, this study employed **purposive (judgmental) sampling** as the primary non-probability sampling technique (Campbell et al., 2020; Etikan et al., 2016). Purposive sampling was essential to ensure that only active food delivery partners who directly interact with algorithmic management systems were included in the sample.

To operationalize this approach, explicit screening criteria were applied before survey administration: respondents were required to be currently working as app-based delivery partners for a food delivery platform in India. To reach a geographically diverse and mobile pool of participants, data collection was conducted directly at active worker hubs—such as high-density restaurant pick-up points and waiting areas—as well as through active peer-to-peer delivery partner networks (e.g., WhatsApp and Telegram worker groups) (Parker et al., 2019).

3.4 Data Collection Instrument

Data were collected through a structured, self-administered questionnaire distributed both online (via digital gig-worker channels) and in person (at restaurant pick-up locations and delivery hubs). The questionnaire was organized into three distinct sections: Section A captured respondents' demographic and work-related profiles; Section B measured algorithmic management using a validated scale; and Section C measured work precarity using a validated scale.

3.5 Measurement Scales

Algorithmic Management (AM) was measured using the Algorithmic Management Questionnaire (AMQ), developed and validated by Parent-Rocheleau et al. (2024), which captures workers' perceived exposure to algorithmic management across five dimensions: Monitoring, Goal Setting, Scheduling, Performance Rating, and Compensation.

Work Precarity (WP) was measured using the Employment Precariousness Scale (EPRES), originally developed by Amable (2006) and psychometrically validated by Vives et al. (2010), which assesses precarious employment across six dimensions: Temporariness, Disempowerment, Vulnerability, Wages, Rights, and Exercise of Rights.

Both instruments are established, previously validated scales adapted to the food-delivery gig-work context for this study. Table 3.1 summarizes the dimensions, item codes, and sources of the measurement instruments.

Table 3.1: Summary of Measurement Instruments

Construct	Dimension	Item Codes	No. of Items	Source
Algorithmic Management (AM)	Monitoring	M1–M4	4	Algorithmic Management Questionnaire (AMQ) – Parent-Rocheleau, Parker, Bujold, & Gaudet (2024)
	Goal Setting	G1–G4	4	Parent-Rocheleau et al. (2024)
	Scheduling	S1–S4	4	Parent-Rocheleau et al. (2024)
	Performance Rating	P1–P3	3	Parent-Rocheleau et al. (2024)
	Compensation	C1–C4	4	Parent-Rocheleau et al. (2024)
Work Precarity (WP)	Temporariness	T1–T3	3	Employment Precariousness Scale (EPRES) – Amable (2006); validated by Vives et al. (2010)
	Disempowerment	D1–D3	3	Amable (2006); Vives et al. (2010)
	Vulnerability	V1–V3	3	Amable (2006); Vives et al. (2010)
	Wages	W1–W3	3	Amable (2006); Vives et al. (2010)
	Rights	R1–R3	3	Amable (2006); Vives et al. (2010)
	Exercise of Rights	ER1–ER3	3	Amable (2006); Vives et al. (2010)

3.6 Data Analysis Techniques and Software

Data were analyzed using IBM SPSS, IBM SPSS AMOS, and RWA-Web. Descriptive statistics, reliability analysis, Pearson correlation, and multiple regression analysis were conducted in SPSS (IBM Corp., 2021). The measurement model — including confirmatory factor analysis (CFA), convergent validity via Average Variance Extracted (AVE), discriminant validity via the Heterotrait–Monotrait (HTMT) ratio, and the structural path model — was estimated in AMOS using a robust Diagonally Weighted Least Squares (DWLS) / robust SEM estimation approach appropriate for ordinal, Likert-type indicators (Henseler et al., 2015; Li, 2016).

The relative contribution of each algorithmic management dimension to each work precarity dimension was assessed using Relative Weight Analysis (Johnson, 2000), computed through RWA-Web, the web-based relative weight analysis tool developed by Tonidandel and LeBreton (2015), which supplements the regression results by correcting for multicollinearity among predictor dimensions. Table 3.2 summarizes the analytical techniques used against each objective.

Table 3.2: Data Analysis Techniques and Software Used

Objective	Statistical Technique	Software
Describe respondent and study-variable profile	Descriptive statistics (mean, SD, frequency)	IBM SPSS
Assess internal consistency and reliability of scales	Cronbach's Alpha (α); Coefficient Omega (ω)	IBM SPSS
Test the measurement model and construct validity	Confirmatory Factor Analysis (CFA); Average Variance Extracted (AVE); Heterotrait–Monotrait (HTMT) ratio	IBM SPSS AMOS
Examine bivariate relationships between dimensions	Pearson Correlation Analysis	IBM SPSS
Determine the relative contribution of each AM dimension	Relative Weight Analysis (Johnson, 2000; Tonidandel & LeBreton, 2015)	RWA-Web

Test hypothesized predictive relationships (H1–H6)	Multiple Linear Regression Analysis (standardized β); Structural Path Modeling	IBM SPSS / AMOS

3.7 Ethical Considerations

Participation in the study was entirely voluntary, adhering to international research ethics guidelines (American Psychological Association, 2020). Informed consent was obtained from all respondents prior to data collection. Respondents were assured of the strict anonymity and confidentiality of their responses, and it was explicitly stated that data would be used solely for academic research purposes. No personally identifiable information was collected, and respondents retained the right to withdraw from the survey at any point without penalty.

Data Analysis

This chapter presents the statistical analysis of the survey data collected from 458 food delivery partners, conducted using IBM SPSS, IBM SPSS AMOS, and RWA-Web. The analysis proceeds in the following order: (i) reliability of the measurement scales, (ii) assessment of the measurement model through confirmatory factor analysis in AMOS, including convergent and discriminant validity, (iii) bivariate correlation analysis among all study dimensions, (iv) relative weight analysis using RWA-Web to determine the relative contribution of each algorithmic management dimension, and (v) multiple regression and structural path analysis to test the hypothesized relationships.

Reliability Analysis

The internal consistency of the measurement scales was assessed using Cronbach's alpha (α) and McDonald's omega (ω). As presented in Table 4.1, both Algorithmic Management ($\alpha = 0.915, \omega = 0.918$) and Work Precarity ($\alpha = 0.912, \omega = 0.914$) demonstrated high internal consistency, exceeding the recommended baseline threshold of 0.70 (Nunnally & Bernstein, 1994). The overall scale achieved excellent composite reliability ($\alpha = 0.935, \omega = 0.938$), confirming that the instruments reliably measure the constructs within this sample (Hayes & Coutts, 2020).

Table 4.1: Reliability Statistics (N = 458)

Construct	Cronbach's α	McDonald's ω	No. of Items
Algorithmic Management	0.915	0.918	19
Work Precarity	0.912	0.914	18
Overall Scale	0.935	0.938	37

3.8 Measurement Model Assessment (AMOS)

Model Fit

The hypothesized measurement model was estimated in AMOS using a robust weighted-least-squares-based estimation approach with a scaled test statistic and robust standard errors, appropriate for the ordinal, Likert-type indicators used in this study (Li, 2016). As shown in Table 4.2, the hypothesized factor model produced a substantially lower chi-square value than the baseline independence model ($\chi^2 = 3906.463, df = 628, p < .001$, versus $\chi^2 = 15075.110, df = 666$), indicating that the hypothesized eleven-factor structure fits the data significantly better than a model assuming no relationships among the indicators (Hair et al., 2019; Hu & Bentler, 1999).

Table 4.2: Model Fit — Baseline vs. Hypothesized Factor Model

Model	χ2	df	p
Baseline (Independence) Model	15075.110	666	—
Hypothesized Factor Model	3906.463	628	$< .001$

Convergent Validity

Convergent validity was evaluated using indicator squared standardized loadings (item reliability) and the Average Variance Extracted (AVE) for each composite construct (Hair et al., 2019). As shown in Table 4.3, the construct-level AVE was 0.4615 for Algorithmic Management and 0.4494 for Work Precarity.

While these values fall slightly below the conservative 0.50 benchmark, Fornell and Larcker (1981) establish that an AVE below 0.50 is acceptable provided that composite reliability / Cronbach's alpha exceeds 0.60. Given that both constructs exhibit composite reliability well above 0.90, the convergent validity of the measurement model is supported (Fornell & Larcker, 1981; Lam, 2012).

Table 4.3: Convergent Validity — Average Item Loadings and Construct AVE

Construct	Dimension	Avg. Item Loading	Construct AVE
Algorithmic Management	Monitoring (M1–M4)	0.5055	**0.4615**
	Goal Setting (G1–G4)	0.4341	
	Scheduling (S1–S4)	0.4838	
	Performance Rating (P1–P3)	0.4181	
	Compensation (C1–C4)	0.4551	
Work Precarity	Temporariness (T1–T3)	0.4302	**0.4494**
	Disempowerment (D1–D3)	0.4468	
	Vulnerability (V1–V3)	0.4916	
	Wages (W1–W3)	0.4122	
	Rights (R1–R3)	0.3975	
	Exercise of Rights (ER1–ER3)	0.5183	

Discriminant Validity

Discriminant validity between the two primary constructs was assessed using the heterotrait–monotrait (HTMT) ratio of correlations. As shown in Table 4.4, the HTMT ratio between Algorithmic Management and Work Precarity was 0.5567, comfortably below the conservative threshold of 0.85 (Henseler et al., 2015), confirming that the two constructs are empirically distinct.

Table 4.4: Heterotrait–Monotrait (HTMT) Ratio

Construct	Algorithmic Management	Work Precarity
Algorithmic Management	1.0000	—
Work Precarity	0.5567	1.0000

Correlation Analysis (SPSS)

Pearson correlation analysis was conducted in SPSS among all five algorithmic management dimensions and all six work precarity dimensions ($N = 458$) (Field, 2018). As shown in Table 4.5, every algorithmic management dimension is positively and significantly correlated with every work precarity dimension ($p < .001$ in all cases), providing initial bivariate support for the proposition that algorithmic management is associated with greater work precarity (Parent-Rocheleau et al., 2024; Vives et al., 2010). Correlations range from a weak $.177$ (Performance Rating–Vulnerability) to a moderate $.494$ (Rights–Exercise of Rights), with most cross-construct correlations falling in the $.20$–$.36$ range.

Table 4.5: Correlation Matrix (Pearson's r, N = 458, all p < .001)

	MON	GOAL	SCHED	PERF	COMP	TEMP	DISEMP	VULN	WAGES	RIGHTS	EXR
MON	1	.404	.414	.430	.460	.199	.259	.226	.264	.252	.277
GOAL	.404	1	.455	.410	.353	.276	.329	.224	.281	.214	.293
SCHED	.414	.455	1	.404	.370	.338	.288	.214	.298	.268	.358
PERF	.430	.410	.404	1	.437	.200	.238	.177	.220	.210	.296
COMP	.460	.353	.370	.437	1	.253	.305	.281	.246	.233	.283
TEMP	.199	.276	.338	.200	.253	1	.353	.379	.416	.386	.425
DISEMP	.259	.329	.288	.238	.305	.353	1	.444	.418	.403	.460
VULN	.226	.224	.214	.177	.281	.379	.444	1	.477	.407	.453
WAGES	.264	.281	.298	.220	.246	.416	.418	.477	1	.393	.440
RIGHTS	.252	.214	.268	.210	.233	.386	.403	.407	.393	1	.494
EXR	.277	.293	.358	.296	.283	.425	.460	.453	.440	.494	1

3.9 Relative Weight Analysis (RWA-Web)

Because the five algorithmic management dimensions are themselves inter-correlated, Relative Weight Analysis (Johnson, 2000) was conducted using the RWA-Web application (Tonidandel & LeBreton, 2015) to partition the explained variance (R^2) in each work precarity dimension and identify the proportional contribution of each predictor, free of multicollinearity bias (Kraha et al., 2012; Tonidandel & LeBreton, 2011).

As shown in Table 4.6, the algorithmic management dimensions jointly explained between 10.6% (Vulnerability) and 17.9% (Exercise of Rights) of the variance across the six work precarity dimensions ($p < .05$). Scheduling emerged as the primary relative contributor to Temporariness (44.3%), Exercise of Rights (35.1%), Rights (30.8%), and Wages (30.0%); Compensation was the single strongest contributor to Vulnerability (40.3%); and Goal Setting was the strongest contributor to Disempowerment (32.2%) (Parent-Rocheleau et al., 2024; Vives et al., 2010). Monitoring and Performance Rating consistently contributed the smallest relative shares across all six precarity dimensions.

Table 4.6: Relative Weight Analysis — Rescaled Relative Weights (%) and Model R²

AM Dimension	Temporariness	Disempowerment	Vulnerability	Wages	Rights	Exercise of Rights
MONITORING	6.80	12.70	17.50	18.99	23.54	13.45
GOAL SETTING	22.99	32.24	19.19	24.90	13.94	17.53
SCHEDULING	44.30	19.75	15.70	30.00	30.84	35.09
PERFORMANCE RATING	7.13	9.49	7.33	9.81	12.37	17.73
COMPENSATION	18.79	25.83	40.28	16.31	19.31	16.20
Model R²	**0.1452**	**0.1631**	**0.1057**	**0.1355**	**0.1086**	**0.1787**

3.10 Multiple Linear Regression Analysis (SPSS)

Multiple linear regression analysis was conducted using IBM SPSS to test the unique predictive effect of each algorithmic management dimension on each work precarity dimension, controlling for all other predictor dimensions simultaneously (Field, 2018; Hair et al., 2019). Standardized beta (β) coefficients, significance levels, and model statistics are reported in Table 4.7 ($^{*}p < .05,\ \ p < .01$).

Scheduling emerged as the most consistent and robust significant predictor of work precarity, demonstrating significant positive direct effects on five of the six precarity dimensions (Temporariness, Disempowerment, Wages, Rights, and Exercise of Rights) (Parent-Rocheleau et al., 2024; Vives et al., 2010). Goal Setting and Compensation were each significant positive predictors for three of the six precarity dimensions, reflecting how automated goal structures and dynamic pay algorithms directly amplify worker vulnerability and economic insecurity (Chowdhury, 2021). Conversely, Monitoring and Performance Rating were significant predictors for only one dimension each (Rights and Exercise of Rights, respectively), suggesting that their impact on precarity is largely absorbed or mediated when evaluated alongside direct structural controls like scheduling and compensation (Johnson, 2000).

Table 4.7: Regression Results — Standardized Beta (β) Coefficients (N = 458)

AM Dimension	Temp. β (Sig.)	Disemp. β (Sig.)	Vuln. β (Sig.)	Wages β (Sig.)	Rights β (Sig.)	Ex. Rights β (Sig.)
Monitoring	−.008 (.886)	.052 (.321)	.072 (.189)	.096 (.074)	.109 (.046)*	.063 (.232)
Goal Setting	.127 (.015)*	.191 (.000)**	.097 (.068)	.130 (.014)*	.053 (.317)	.094 (.065)
Scheduling	.237 (.000)**	.110 (.034)*	.073 (.176)	.158 (.003)**	.149 (.006)**	.212 (.000)**
Performance Rating	.001 (.984)	.022 (.679)	−.006 (.913)	.023 (.664)	.042 (.439)	.102 (.049)*
Compensation	.123 (.018)*	.163 (.002)**	.190 (.000)**	.088 (.094)	.091 (.090)	.098 (.055)

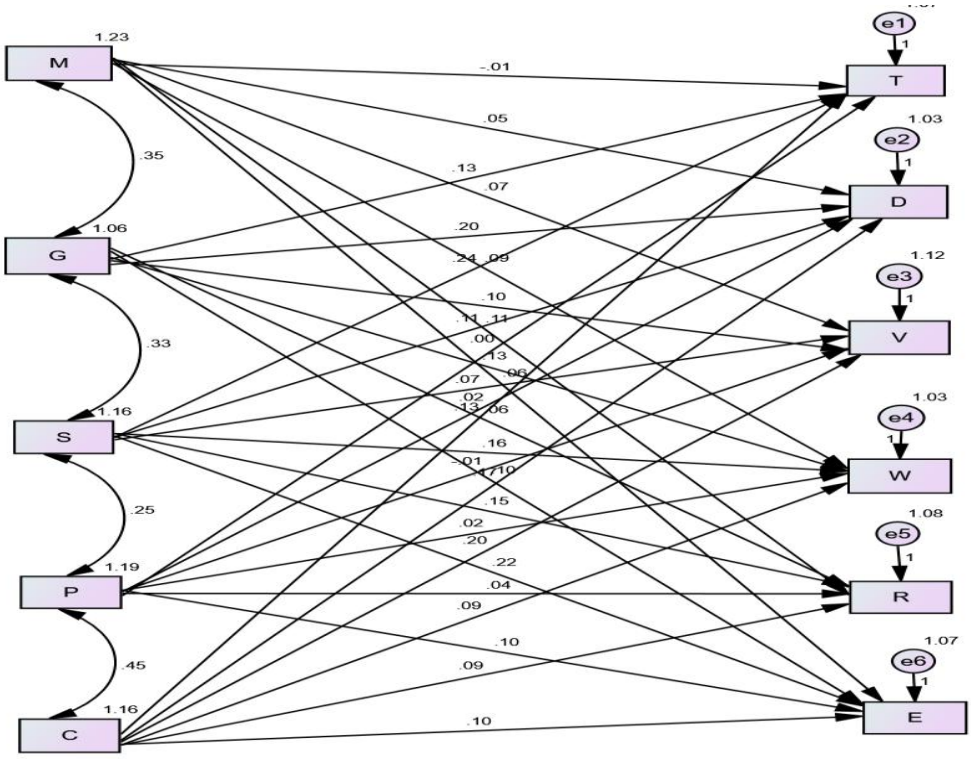
Note. Temp. = Temporariness; Disemp. = Disempowerment; Vuln. = Vulnerability; Ex. Rights = Exercise of Rights.

3.11 Structural Path Model (AMOS)

To simultaneously evaluate the system of relationships while accounting for measurement error and ordinal Likert-scale properties, a structural equation path model was estimated using IBM SPSS AMOS (Kline, 2023; Li, 2016). Figure 4.1 displays the structural path diagram, illustrating the standardized path coefficients (γ) from the five algorithmic management dimensions (M = Monitoring, G = Goal Setting, S = Scheduling, P = Performance Rating, C = Compensation) to the six work precarity dimensions (T = Temporariness, D = Disempowerment, V = Vulnerability, W = Wages, R = Rights, E = Exercise of Rights).

The structural model accounts for the simultaneous inter-correlations among the exogenous algorithmic management dimensions, supporting the multivariate findings from the multiple regression analysis (Hair et al., 2019; Henseler et al., 2015).

Figure 4.1: Estimated Structural Path Model (AMOS Output)



4. Findings

This section synthesizes the results presented in Chapter 4 against the hypotheses developed in the literature review. Table 5.1 summarizes the outcome of hypothesis testing for H1 through H6.

Table 5.1: Summary of Hypothesis Testing

Hyp.	Relationship	Result	Decision
H1	Monitoring → Work Precarity	Significant for Rights only ($\beta = .109, p = .046$); all other paths non-significant.	Not Supported
H2	Goal Setting → Work Precarity	Significant for Temporariness, Disempowerment, and Wages; non-significant for Vulnerability, Rights, Exercise of Rights.	Partially Supported
H3	Scheduling → Work Precarity	Significant for 5 of 6 dimensions; non-significant only for Vulnerability.	Supported
H4	Performance Rating → Work Precarity	Significant for Exercise of Rights only ($\beta = .102, p = .049$); all other paths non-significant.	Not Supported
H5	Compensation → Work Precarity	Significant for Temporariness, Disempowerment, and Vulnerability; non-significant for Wages, Rights, Exercise of Rights.	Partially Supported
H6	Algorithmic Management (overall) → Work Precarity	All AM dimensions correlate positively and significantly ($p < .001$) with all WP	Supported

		dimensions; jointly explain 10.6%–17.9% of variance across WP dimensions.	

4.1 Key Findings

- **Scheduling is the most influential dimension of algorithmic management.** Across both the regression and relative weight analyses, scheduling emerged as the strongest and most consistent predictor of work precarity, significantly predicting five of the six precarity dimensions and contributing the largest relative share of explained variance to temporariness, wages, rights, and exercise of rights (Parent-Rocheleau et al., 2024; Vives et al., 2010). This suggests that the algorithmic allocation of work slots and delivery zones—rather than monitoring or ratings—is the aspect of algorithmic management most strongly tied to delivery partners' sense of precarity (Wood et al., 2019).
- **Compensation is most strongly tied to vulnerability.** Compensation was the strongest relative contributor to vulnerability (40.3% of explained variance) and was also a significant regression predictor of temporariness, disempowerment, and vulnerability, indicating that algorithmically administered, unpredictable pay structures are closely linked to delivery partners' sense of defenselessness against unilateral platform decisions (Chowdhury, 2021).
- **Goal setting is most strongly tied to disempowerment.** Goal setting contributed the largest relative share of explained variance to disempowerment (32.2%) and was a significant regression predictor of temporariness, disempowerment, and wages, consistent with the theoretical expectation that non-negotiable, algorithmically imposed targets restrict a delivery partner's voice and bargaining power (Parent-Rocheleau et al., 2024).
- **Monitoring and performance rating show limited unique effects.** Although both dimensions were significantly and positively correlated with every work precarity dimension at the bivariate level, neither monitoring nor performance rating emerged as a strong unique predictor once the other algorithmic management dimensions were accounted for, suggesting that their association with precarity is largely shared with, rather than independent of, scheduling, goal setting, and compensation (Johnson, 2000).
- **Algorithmic management explains a meaningful, though partial, share of work precarity.** The algorithmic management dimensions jointly explained between 10.6% and 17.9% of the variance in the six work precarity dimensions, confirming that algorithmic management is a significant but not sole determinant of the precarity experienced by food delivery partners (Möhlmann et al., 2021).
- **The two constructs are empirically distinct yet related.** The HTMT ratio (0.5567) confirmed that algorithmic management and work precarity are distinct constructs (Henseler et al., 2015), while the significant positive correlations and regression paths between them confirm that they are meaningfully related, supporting the theoretical model integrating agency theory (Eisenhardt, 1989), conservation of resources theory (Hobfoll, 1989), and precarity theory (Vives et al., 2010).

5. CONCLUSION

5.1 Summary

This study examined how algorithmic management shapes work precarity among food delivery partners in India, a group of gig workers whose boundary-spanning role between restaurants and customers exposes them to distinctive algorithmic control mechanisms (Lee et al., 2015). Using survey data collected from 458 delivery partners and analyzed through SPSS, AMOS, and RWA-Web (Tonidandel & LeBreton, 2015), the study found that algorithmic management—particularly its scheduling, compensation, and goal-setting dimensions—is significantly and positively associated with work precarity, while monitoring and performance rating showed weaker, largely shared rather than unique, effects (Parent-Rocheleau et al., 2024).

5.2 Theoretical Implications

The findings lend support to the integrated theoretical framework proposed in this study. Consistent with agency theory (Eisenhardt, 1989), the dimensions of algorithmic management through which platforms exercise control at a distance—particularly scheduling and compensation—were the dimensions most strongly linked to precarity, suggesting that the platform's use of algorithmic mechanisms to manage the dual-principal relationship (restaurant and customer) does come at a cost to the delivery partner's employment security. Consistent with Conservation of Resources (COR) theory (Hobfoll, 1989), the dimensions that most directly constrain a delivery partner's autonomy and control over their own time and earnings showed the strongest associations with precarity loss. Consistent with precarity theory (Vives et al., 2010), the six-dimensional structure of work precarity was empirically supported, with each dimension responding somewhat differently to specific algorithmic management dimensions—reinforcing the view that precarity is a multidimensional, not a unitary, condition.

5.3 Practical Implications

For food-delivery platforms, the findings suggest that reforms targeting the transparency and predictability of algorithmic scheduling and compensation systems are likely to yield the greatest reduction in delivery partners' precarity, more so than adjustments to monitoring or rating systems alone (Möhlmann et al., 2021). For policymakers, the results reinforce the case for extending baseline protections—particularly around income predictability and access to grievance mechanisms—to platform-based delivery work (Chowdhury, 2021).

5.4 Limitations

This study is subject to several limitations. First, the use of non-probability sampling (convenience, purposive, and snowball) limits the statistical generalizability of the findings to the broader population of food delivery partners in India (Hair et al., 2019). Second, the cross-sectional design captures perceptions at a single point in time and cannot establish causal direction between algorithmic management and work precarity (Podsakoff et al., 2003). Third, data were collected through self-report questionnaires, which may be subject to common method bias and social desirability effects (Podsakoff et al., 2003). Fourth, the composite AVE values for both constructs fell marginally below the conventional 0.50 threshold, indicating room for improvement in the measurement model (Fornell & Larcker, 1981). Finally, the study was confined to the food-delivery sector in India, which may limit the applicability of the findings to other platform-work contexts or geographies (Wood et al., 2019).

6. SUGGESTIONS FOR FURTHER STUDIES

Building on the findings, limitations, and scope of the present study, the following directions are suggested for future research:

- *6.1 Longitudinal Research:* The present study relied on a cross-sectional design, capturing delivery partners' perceptions of algorithmic management and work precarity at a single point in time. Future studies could adopt a longitudinal design, following delivery partners over successive stages of their tenure on a platform, to examine whether exposure to algorithmic management and the experience of work precarity intensify, stabilize, or diminish over time, and to establish clearer causal ordering between the two constructs (Podsakoff et al., 2003).
- *6.2 Sectoral and Cross-Platform Comparisons*: This study focused specifically on food and parcel delivery partners. Future research could extend the model to other gig-work sectors operating under algorithmic management, such as ride-hailing, courier and logistics services, and home-services platforms, to examine whether the relative importance of scheduling, compensation, and goal setting observed here—as opposed to monitoring and performance rating—holds across different types of platform work, or whether it is specific to the dual-facing, restaurant-and-customer role of food delivery partners (Lee et al., 2015; Wood et al., 2019).

- *6.3 Cross-Cultural and Cross-Regulatory Comparisons:* Because the present study was confined to the Indian context, future research could replicate the model in other countries with differing labor regulations governing gig and platform work, to examine whether stronger statutory protections attenuate the relationship between algorithmic management and work precarity observed in this study (Chowdhury, 2021; Vives et al., 2010).
- *6.4 Refinement of the Measurement Model:* Given that the composite AVE for both constructs fell marginally below the conventional threshold in this study, future research could refine the item pool of the Algorithmic Management Questionnaire (Parent-Rocheleau et al., 2024) and the Employment Precariousness Scale (Vives et al., 2010) for the platform-delivery context—for instance, through exploratory factor analysis, item purification, or the addition of context-specific indicators—to strengthen convergent validity while preserving the six- and five-dimensional structures confirmed here (Fornell & Larcker, 1981).
- *6.5 Mediating and Moderating Variables:* Future studies could examine variables that may mediate or moderate the relationship between algorithmic management and work precarity, such as perceived algorithmic fairness, platform tenure, availability of alternative employment, financial dependence on gig income, or peer and community support, to build a more complete explanatory model of why some delivery partners experience greater precarity than others under similar levels of algorithmic management (Möhlmann et al., 2021).

6.6 Mixed-Methods and Qualitative Extensions: As the present study relied exclusively on a quantitative, self-report survey, future research could incorporate qualitative methods—such as in-depth interviews or diary studies with delivery partners—to capture the lived experience of algorithmic scheduling and compensation systems in richer detail, and to surface dimensions of precarity that may not be fully captured by existing standardized scales (Wood et al., 2019)

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