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Algorithmic HRM and Labour Supply in Platform Work: Scheduling Autonomy as a Mechanism and Transparency as a Boundary Condition

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Abstract: This study examines how algorithmic human resource management (HRM) functions as manpower governance in platform work by shaping workers' scheduling autonomy and, in turn, their labour supply. Using a three-wave time-lagged panel design with platform workers, algorithmic control intensity and transparency/explainability were measured at Time 1, scheduling autonomy at Time 2, and labour supply was captured as hours worked over the prior period at Time 3. Structural equation modelling with bootstrapping showed that higher algorithmic control intensity is associated with lower scheduling autonomy, while higher scheduling autonomy is associated with greater labour supply. Scheduling autonomy significantly mediates the relationship between algorithmic control intensity and labour supply, supporting an autonomy-based mechanism through which algorithmic HRM affects workforce utilisation in platform work. However, transparency/explainability does not significantly weaken the autonomy-reducing effect of algorithmic control intensity, suggesting that informational clarity alone may be insufficient to preserve workable discretion under intensive control. The findings clarify how algorithmic HRM shapes labour supply and refine platform-governance arguments by showing the limits of transparency as a protective mechanism.

Keywords: Algorithmic HRM, Algorithmic Control Intensity, Scheduling Autonomy, Labour Supply, Platform Work, Algorithmic Transparency, Manpower Governance, Workforce Utilisation

INTRODUCTION

Platform work is increasingly organised through algorithmically mediated HR systems that function as a labour-governance infrastructure rather than a simple matching technology. These systems allocate tasks, evaluate performance through continuously updated metrics (e.g., ratings and acceptance rates), and enforce discipline via automated incentives, penalties, and deactivation threats (Chen, 2024; Mbare et al., 2024; Park & Ryoo, 2023; van Zoonen et al., 2024; Zhou et al., 2025). As a governance architecture, algorithmic HRM can improve operational efficiency and service reliability, yet it also introduces a workforce sustainability tension: the very controls designed to stabilise service delivery may raise the effective cost of participation—through uncertainty, schedule frictions, and perceived risk—thereby weakening the conditions that sustain workers' continued labour-market engagement, particularly when rules are experienced as opaque and the risk of adverse outcomes becomes part of everyday work (Brougham & Haar, 2024; Chen & Chen, 2025, 2026; Kaur & Verma, 2025; Sharma et al., 2026). From a manpower perspective, the core question is therefore not whether algorithmic management exists, but how the intensity of algorithmic control reshapes workers' labour-supply decisions—how much labour input (hours) they provide and how reliably they remain available as usable capacity—over time.

This study treats labour supply as the focal labour-economic outcome because it directly captures workforce utilisation and capacity buffers in platform labour markets. Labour supply reflects a behavioural response—how much labour workers choose to provide under a given governance regime—making it central to manpower planning and service continuity (Álvarez-Fernández et al., 2025; Cortadas-Guasch, 2024; Kotyrlo, 2025; Lee et al., 2026; Villamaina & Acciari, 2025). When labour supply contracts, platforms face system-level consequences: thinner capacity buffers, longer fulfilment times, and greater exposure to demand shocks. Conversely, when labour supply is sustained, operational stability can be achieved without relying exclusively on escalating surveillance or punitive controls. Accordingly, labour supply operationalises the manpower problem IJM readers prioritise: stabilising labour input under fluctuating demand.

Despite rapid growth in research on algorithmic management, three gaps limit our ability to explain labour supply dynamics in platform work. First, much empirical work prioritises perceptions and reactions: fairness, stress, satisfaction, trust, while leaving labour supply under-analysed as a core economic outcome (Baiocco et al., 2022; Li & Cheng, 2026; Mbare et al., 2024; Zhou et al., 2025). This creates a mismatch between what is often theorised (governance and control) and what ultimately matters for manpower utilisation (participation and hours supplied). Second, existing explanations frequently move too quickly from control to downstream outcomes (e.g., wellbeing or turnover) without sufficiently specifying the behavioural mechanism through which control becomes economically consequential in workers' day-to-day work design (Arora et al., 2025; Q. Gong et al., 2025; Jo et al., 2024; Rombaut & Guerry, 2018; Wei et al., 2025). Without an explicit mechanism, it remains unclear how algorithmic HRM alters the effective terms of participation in ways that translate into measurable labour input. Third, actionable boundary conditions for algorithmic governance remain underdeveloped. Transparency and explainability are often advanced as normative remedies, yet they are rarely theorised and tested as participation-relevant sensemaking infrastructure that could reshape how workers interpret constraints, anticipate consequences, and adapt their hours under automated rules and feedback (T. Gong, 2025; Jianu et al., 2025; Zheng & Zhu, 2026). As a result, evidence is limited on whether informational clarity can meaningfully preserve behavioural discretion in high-control settings.

To address these gaps, we theorise scheduling autonomy as the key mechanism linking algorithmic control to labour supply. We conceptualise algorithmic control intensity as the extent to which platforms monitor, evaluate, and sanction worker behaviour through automated rules and performance metrics (Deng et al., 2025; Kinowska & Sienkiewicz, 2020; Liu et al., 2025; Sharma et al., 2026; Zha et al., 2026). Drawing on job design and labour-supply response logic, we argue that higher control intensity constrains scheduling autonomy—workers' practical ability to choose working times, sustain participation, and decline tasks without disproportionate access penalties. When autonomy is tightened, the non-wage "cost" of supplying labour increases: participation becomes less manageable, perceived risk rises, and workers are more likely to adjust their hours and engagement to regain control or reduce exposure to automated sanctions (Hackman & Oldham, 1976; Karasek, 1979). In labour-economic terms, reduced autonomy operates as a participation constraint that lowers the net utility of supplying additional hours (even if headline pay is unchanged), producing a contraction in labour input.

We also examine transparency/explainability as a boundary condition for this autonomy channel. When decision rules, performance feedback, and consequences are clearer, workers may be better able to anticipate constraints and manage trade-offs, potentially weakening how strongly control intensity translates into reduced autonomy (Brink et al., 2024; T. Gong, 2025; Jianu et al., 2025; F. Wang et al., 2025; Y. Wang, 2025). Here, transparency is treated as informational predictability, not necessarily contestability (the ability to challenge or alter decisions), which sharpens interpretation of boundary effects. This framing advances algorithmic HRM research beyond broad ethical prescriptions by specifying a testable governance lever. Accordingly, this study contributes by (i) centring labour supply as the manpower outcome that links algorithmic HRM to workforce utilisation, (ii) specifying scheduling autonomy as an economically consequential mechanism through which algorithmic control affects labour input, and (iii) evaluating transparency as a boundary condition with direct implications for platform governance and workforce sustainability. We test these arguments using a time-lagged panel design with platform workers and report downstream tests on earnings volatility and exit intention as boundary evidence.

Theory and Hypotheses

Conceptual framing: Algorithmic HRM as manpower governance

Platform work is governed by algorithmic HRM, where core people-management functions are executed through data-driven rules. Algorithms allocate tasks, monitor behaviour, evaluate performance (e.g., ratings, acceptance rates), and enforce compliance through automated incentives, penalties, and deactivation risk (Arora et al., 2025; Chen & Chen, 2025; Q. Gong et al., 2025; T. Gong, 2025; Liu et al., 2025; Tutar & Battal, 2025). As manpower governance, these systems structure access to work and discipline at scale (Azevedo et al., 2023; Li & Cheng, 2026; Zhao & Syed, 2026). We define algorithmic control intensity (ACI) as the extent to which automated rules constrain and direct worker behaviour. From a labour-economics perspective, ACI shapes the effective terms of participation, schedule predictability, access stability, and exposure to sanctions, and affects labour supply via non-wage channels (Kadolkar et al., 2024; Li & Cheng, 2026; McDaid et al., 2023). Higher ACI can create schedule frictions, raise participation risk, and increase compliance burdens, lowering the net utility of supplying hours even when pay is unchanged. Labour supply is therefore the key outcome because it captures workforce utilisation and capacity buffers; rising participation costs can reduce hours, induce intermittent inactivity, or encourage multi-homing (Bellesia et al., 2025; Kadolkar et al., 2024; Maffie & Hurtado, 2026).

Algorithmic control intensity and scheduling autonomy (participation constraint)

Job-design and labour-supply response logics converge on a simple implication: when control intensifies, discretion shrinks. In platform work, higher algorithmic control intensity embeds behavioural expectations into allocation rules, monitoring signals, and automated consequences. Workers' ability to choose when to log on, how long to remain active, and whether to decline specific orders becomes practically constrained when access to future tasks and earnings opportunities is tied to metric compliance (e.g., acceptance rates, cancellation thresholds) and the threat of throttling or deactivation (Cameron, 2024; T. Gong, 2025; McDaid & Free, 2025; Williams & Rani, 2026; Yu et al., 2025). We therefore treat scheduling autonomy (SA) not as a general preference for flexibility, but as a participation constraint that determines

how manageable and sustainable labour input is under algorithmic governance. When autonomy is tightened, the non-wage cost of supplying labour rises, making participation harder to maintain.
H1. *Algorithmic control intensity is negatively associated with scheduling autonomy.*

Scheduling autonomy and labour supply (workforce utilisation)

In platform work, scheduling autonomy increases the utility of participation by allowing workers to align labour input with shifting personal constraints, alternative income sources, and real-time earning opportunities (Alauddin et al., 2025; Pilatti et al., 2024; Uysal & Boyraz, 2024). Autonomy reduces non-wage participation costs—schedule frictions, uncertainty about whether choices will be penalised, and the opportunity costs of committing time to a platform whose demands can change quickly. When workers can decide when to work, how long to stay active, and which tasks to accept without disproportionate access penalties, supplying labour becomes more manageable and sustainable. In labour-market terms, scheduling autonomy lowers the "participation price" of providing labour, thereby increasing the likelihood that workers maintain or expand their hours and engagement. We define labour supply as a behavioural economic outcome—hours worked and participation intensity—which directly proxies workforce utilisation and the availability of capacity buffers in platform labour markets (Alauddin et al., 2025; Jiang et al., 2024; Pilatti et al., 2024; Stecher et al., 2025; Zhang et al., 2025).
H2. *Scheduling autonomy is positively associated with labour supply.*

Scheduling autonomy as a mechanism linking control intensity to labour supply

The manpower effects of algorithmic HRM need not follow a simple "control lowers supply" logic. Governance becomes utilisation-relevant when it restricts workers' effective ability to participate. We argue that algorithmic control intensity (ACI) reduces labour supply primarily by tightening scheduling autonomy (SA)—the practical discretion to choose working times, sustain activity, and manage task acceptance without triggering access penalties (Milanez et al., 2025). As SA shrinks, participation is harder to reconcile with competing obligations and risk management, raising non-wage participation costs and prompting workers to reduce hours supplied (Alauddin et al., 2025; Zhou et al., 2025). This autonomy channel specifies a behavioural transmission mechanism from governance intensity to labour input, moving beyond perception-based accounts toward an economically consequential explanation for workforce utilisation in platform work (Zhang et al., 2025).
H3. *Scheduling autonomy mediates the relationship between algorithmic control intensity and labour supply.*

Transparency/explainability as a boundary condition on the control–autonomy link

Transparency/explainability operates as sensemaking infrastructure in algorithmic HRM but takes two distinct forms. First, informational clarity concerns how clearly workers understand rules and how behaviours map onto outcomes (e.g., rejecting orders, logging off, pausing activity) that affect metrics, allocation priority, and access to earning opportunities (Arora et al., 2025; Q. Gong et al., 2025; T. Gong, 2025; Peng et al., 2025; Talwar et al., 2026). Clearer rules reduce perceived arbitrariness and uncertainty, improving predictability and enabling more informed scheduling choices under automated governance. Second, contestability/enforcement transparency concerns whether workers can challenge decisions and sanctions (e.g., throttling, deactivation) and whether enforcement is proportionate and reviewable; this is closer to procedural control and may be necessary when constraints are binding.

Here, transparency/explainability is conceptualised primarily as informational clarity. It is theorised to moderate the upstream control–autonomy link by weakening the extent to which intensified algorithmic control reduces scheduling autonomy: when rules and consequences are clearer, workers can better anticipate constraints and manage trade-offs to preserve practical autonomy. However, because informational clarity does not alter enforcement power, buffering may be limited under high-control regimes.

H4. *Transparency/explainability moderates the algorithmic control intensity–scheduling autonomy relationship such that the negative association is weaker when transparency/explainability is higher.*

Conceptual framework

Figure 1 summarises a parsimonious framework that positions algorithmic HRM as manpower governance with direct relevance to workforce utilisation in platform labour markets. The model specifies algorithmic control intensity (ACI) as a governance lever that shapes labour supply not primarily through immediate attitudinal reactions, but through a core job-design participation constraint: scheduling autonomy (SA). When autonomy is constrained, workers adjust their hours and participation intensity, producing observable changes in labour supply (LS). The framework also incorporates transparency/explainability (TR) as a boundary condition on the first-stage link, testing whether informational clarity alters how strongly control intensity translates into reduced autonomy.

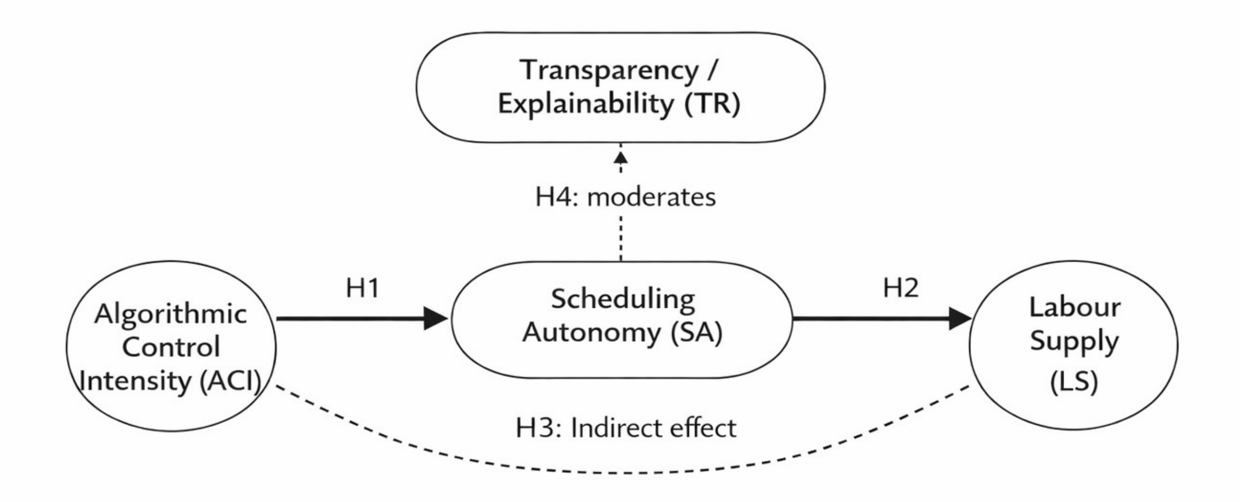

Figure 1. Conceptual framework: Algorithmic HRM as manpower governance (moderated mediation).

Algorithmic control intensity (ACI) reduces scheduling autonomy (SA) (H1), while higher SA increases labour supply (LS) (H2). SA mediates the ACI–LS relationship (H3). Transparency/explainability (TR) moderates the ACI–SA link, weakening the negative association at higher TR (H4).

METHOD

Research design

This study employs a quantitative, time-lagged panel design to test a moderated mediation model linking algorithmic HRM to labour supply through scheduling autonomy. Temporal separation is used to strengthen causal ordering and reduce common method concerns. Algorithmic control intensity (ACI) and transparency/explainability (TR) are measured at Time 1 (T1), scheduling autonomy (SA) at Time 2 (T2), and labour supply (LS) at Time 3 (T3), operationalised as hours worked over the prior 14 days. The time lag between T1 and T2 was 14 days, and the time lag between T2 and T3 was 14 days (i.e., a total separation of 28 days from T1 to T3). This sequencing aligns the theorised autonomy channel with an observable labour-economic outcome that captures workforce utilisation.

Context and sampling

The study focuses on active platform workers in Indonesia's order-based, app-mediated on-demand labour market, where task allocation, performance evaluation, and access to earning opportunities are governed by algorithmic systems (Goel et al., 2024; Makmun et al., 2025; Masta & Kaushiva, 2024; Ray et al., 2025). In this setting, algorithmic dispatch allocates orders and platform standing is shaped by continuous performance metrics (e.g., customer ratings, acceptance and cancellation thresholds, and related compliance indicators) that can affect future task access. Enforcement under algorithmic governance may include reduced dispatch priority ("throttling"), temporary restriction, or deactivation, making access to work contingent on metric compliance. Participants were recruited through online worker communities and peer networks with eligibility screening to ensure current platform activity (worked within the prior 14 days). Surveys were administered across three waves and responses were matched using anonymous unique panel codes. To maintain panel retention, each wave was designed to be brief and mobile-friendly and was supported by reminders and wave-based incentives (Haji et al., 2025; Majhi et al., 2025; Stopher & Jones, 2003).

Measures and operationalisation

Perceptual constructs—ACI, TR, and SA—were measured using 5-point Likert scales (1 = strongly disagree; 5 = strongly agree). Labour supply (LS) was treated as an observed behavioural outcome and measured as hours worked on the platform over the past 14 days at T3. This recall window balances accuracy and behavioural representativeness: it is short enough to reduce memory error yet long enough to capture typical work patterns and intra-month variability in platform labour input. Full item wording, coding, and formats are reported in **Table 1**.

To improve robustness, LS values were screened for implausible entries and outliers. Responses below zero and those exceeding feasible weekly limits were flagged and treated as outliers. Robustness checks re-estimated models using (i) winsorised hours (top/bottom 1%) and (ii) log-transformed hours (ln[hours + 1]) to address skewness; conclusions were compared across specifications.

Table 1. Measurem'ent and operationalisation (5-point Likert unless stated)

Construct	Code	Item wording / operational definition	Scale
Algorithmic Control Intensity (ACI)	ACI1	The platform closely monitors my work activities through digital metrics.	Likert (1–5)
	ACI2	My access to tasks/orders is strongly influenced by automated performance indicators (e.g., ratings/acceptance).	
	ACI3	Automated incentives and penalties strongly shape how I must behave to keep receiving tasks/orders.	
	ACI4	There is a noticeable risk of automated sanctions (e.g., throttling/deactivation) when performance falls short.	
Transparency/ Explainability (TR)	TR1	I can understand why the platform assigns me certain tasks/orders and not others.	Likert (1–5)
	TR2	The platform provides clear criteria used to evaluate my performance.	
	TR3	When an outcome affects me, the platform provides understandable reasons for it.	
	TR4	There are clear and accessible procedures to challenge or correct platform decisions.	

Construct	Code	Item wording / operational definition	Scale
Scheduling Autonomy (SA)	SA1	I can decide when to start and stop working on the platform.	Likert (1–5)
	SA2	I have flexibility to adjust my working hours when needed.	
	SA3	I can decline tasks/orders without fearing disproportionate negative consequences.	
Labour Supply (LS)	LS1	Total hours worked/active on the platform in the past 14 days.	Numeric (hours)
	LS2 (optional)	Total completed tasks/orders in the past 14 days.	Numeric (count)

Analytic strategy

Hypotheses were tested using PLS-SEM with bootstrapping. PLS-SEM was chosen because the model is prediction-oriented and includes a moderated mediation (interaction) structure, combining reflective constructs with an observed behavioural outcome (hours worked), and is suitable under potential non-normality. We first assessed the reflective measurement model (loadings, reliability, AVE, and discriminant validity) (Cafferkey et al., 2024; Özgül & Demir, 2025; Yuliati et al., 2025). We then estimated structural paths for H1 (ACI → SA) and H2 (SA → LS), and tested moderation (H4) by adding an interaction term (ACI × TR) predicting SA; ACI and TR were mean-centred prior to forming the interaction, and collinearity was checked using VIF (Gomes et al., 2025; Nguyen et al., 2025; Tran Pham & Doan, 2026). The indirect effect (H3) was evaluated using bootstrapping with 5,000 resamples (Hair, 2022; Sarstedt et al., 2022; Shmueli et al., 2019), Model quality was additionally evaluated using SRMR (approximate fit) and Q^2 (predictive relevance). Attrition diagnostics compared baseline characteristics of completers versus dropouts (Rogelberg & Stanton, 2007; Taylor et al., 1996).

Data collection procedure

Data were collected in three waves. At T1, participants provided informed consent and completed measures of algorithmic control intensity (ACI) and transparency/explainability (TR). At T2 (approximately two weeks after T1), participants completed the scheduling autonomy (SA) measure. At T3 (approximately two weeks after T2), participants reported labour supply as total hours worked on the platform over the prior 14 days. Responses were matched using anonymous panel codes generated at T1. Data quality procedures included eligibility screening, attention checks, and duplicate-response controls; retention was supported through reminders and incentives.

Additional downstream tests (reported as boundary evidence)

To avoid over-extending the core model while still informing workforce-sustainability debates, we conducted supplementary downstream analyses linking labour supply to earnings volatility (computed from weekly earnings over a short window) and exit intention as boundary evidence. These tests are reported exploratorily and interpreted cautiously, because short-horizon earnings volatility is likely to be driven by platform allocation rules, incentive cycles, and market demand conditions in addition to individual labour input. Accordingly, results are presented as associational boundary evidence rather than as extensions of the core causal chain.

RESULTS AND DISCUSSION

Sample retention and attrition

A three-wave panel design was implemented. In total, 900 platform workers completed T1, 663 participated at T2 (73.7% retention), and 469 completed T3 (52.1% retention from T1; 70.7% from T2) (**Table 2**). All hypothesis tests use the matched three-wave panel (N = 469).

Baseline comparisons between T3 completers and dropouts showed no significant differences in demographics, work characteristics (income dependence, multi-homing), or T1 constructs (ACI, TR) (all $p > 0.20$; gender χ^2 $p = 0.775$). As a sensitivity check, we also estimated an attrition model (logit) predicting dropout from baseline variables (age, tenure, income dependence, multi-homing, ACI, TR); results indicated no systematic predictors of attrition, consistent with limited attrition bias. The final analytic sample had a mean age of 31.3 years and mean platform tenure of 16.3 months; 33.9% reported multi-homing.

Table 2. Sample retention and attrition checks

Wave	N	Retention (%)	Mean age	Mean tenure (months)	Mean income dependence (1–5)	Multi-homing (%)
T1	900	100.0	31.5	16.6	3.00	35.6
T2	663	73.7	31.5	16.3	2.98	34.5
T3 (analytic panel)	469	52.1	31.3	16.3	2.94	33.9

Attrition diagnostics (T3 completers vs dropouts): age $p = 0.468$; tenure $p = 0.392$; income dependence $p = 0.204$; multi-homing $p = 0.281$; ACI $p = 0.672$; TR $p = 0.840$; SA $p = 0.360$; gender χ^2 $p = 0.775$.

Descriptive statistics and correlations

Table 3 summarises descriptive statistics and score correlations for the focal variables (analytic panel; N = 469). Reported patterns are consistent with the upstream mechanism: ACI is negatively related to SA, and SA is positively related to labour supply. Labour supply (LS) is measured as total hours active over the prior 14 days (M = 44.77, SD = 9.74). LS was screened for implausible values and outliers; robustness checks using winsorised hours (1% tails) and log-transformed hours (ln[hours + 1]) produced substantively unchanged inferences. Across these alternative specifications, the direction and statistical significance of the core relationships remained unchanged.

Table 3. Descriptive statistics and correlations (analytic panel; N = 469)

Variable	Mean	SD	Min	Max	1	2	3	4
1. Algorithmic Control Intensity (ACI)	3.01	1.30	1.00	5.00	1.00			
2. Transparency/Explainability (TR)	2.98	1.26	1.00	5.00	r12	1.00		
3. Scheduling Autonomy (SA)	3.04	1.30	1.00	5.00	r13	r23	1.00	
4. Labour Supply (LS; hours/14 days)	44.77	9.74	13.90	71.80	r14	r24	r34	1.00

Notes: ACI, TR, and SA are mean scores of indicators measured on a five-point scale. LS is total hours active on the platform in the past 14 days.

Measurement model assessment

The measurement model showed strong indicator reliability and construct validity for ACI, TR, and SA (**Table 4**). All reflective loadings exceeded recommended thresholds (0.735–0.923), internal consistency was high (Cronbach's α = 0.896–0.902; CR = 0.914–0.935), and convergent validity was supported (AVE = 0.728–0.827). Discriminant validity was satisfactory, with all HTMT ratios below conservative thresholds and the highest observed value for the ACI–SA pair (HTMT = 0.488; **Table 5**). Labour supply (LS) was operationalised as a single observed behavioural outcome (hours worked over the prior 14 days) and was therefore modelled as an endogenous variable in the structural model rather than as part of the reflective measurement model. The interaction term (TR×ACI) was also specified in the structural model and was not assessed as a reflective construct.

Table 4. Measurement model summary (outer loadings, reliability, and convergent validity)

Construct	Indicators (n)	Loading range	Cronbach's α	CR (ρc)	AVE
Algorithmic Control Intensity (ACI)	4	0.842–0.907	0.902	0.931	0.772
Transparency/Explainability (TR)	4	0.735–0.921	0.899	0.914	0.728
Scheduling Autonomy (SA)	3	0.893–0.923	0.896	0.935	0.827

Notes: Labour supply (LS) was operationalised as a single observed behavioural outcome (hours worked over the prior 14 days) and was therefore not assessed as part of the reflective measurement model. The interaction term (TR×ACI) was modelled in the structural model and was not treated as a reflective construct.

Table 5. HTMT matrix for reflective constructs

Construct	1	2	3
1. Algorithmic Control Intensity (ACI)	—		
2. Transparency/Explainability (TR)	0.412	—	
3. Scheduling Autonomy (SA)	0.488	0.115	—

Notes: HTMT values are reported only for the reflective constructs included in the measurement model. Labour supply (LS) and the interaction term (TR×ACI) were excluded because they were not modelled as reflective constructs. All reported HTMT values were below conservative threshold levels, supporting discriminant validity.

Structural model and hypothesis testing (direct effects)

Figure 2 summarises the estimated structural model for the hypothesised autonomy channel (moderated mediation). Overall, the model explains meaningful variance in scheduling autonomy and labour supply (Table 6), indicating that algorithmic control and job-design discretion capture an important share of utilisation-relevant behaviour in this setting.

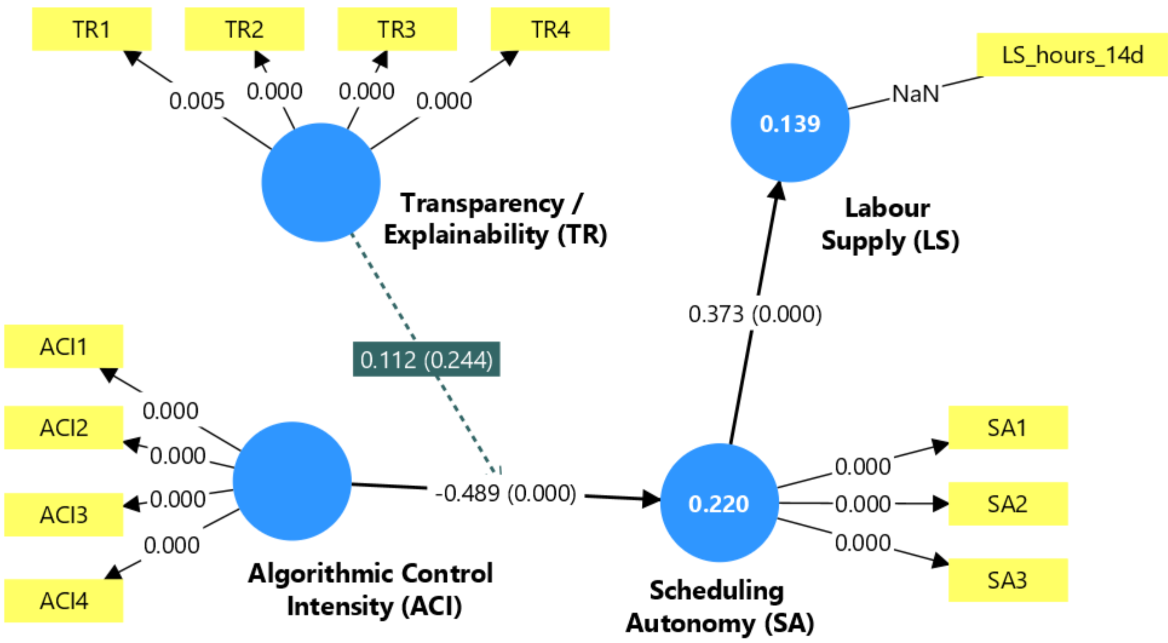

Figure 2. Structural model results (core model)

Figure 2 summarises the estimated structural model for the hypothesised autonomy channel (moderated mediation). Overall, the model explains meaningful variance in scheduling autonomy and labour supply (Table 6), indicating that algorithmic control and job-design discretion capture an important share of utilisation-relevant behaviour in this setting.

As reported in **Table 6**, algorithmic control intensity is negatively associated with scheduling autonomy, supporting **H1**. Scheduling autonomy is positively associated with labour supply (hours), supporting **H2**. In contrast, neither the main effect of transparency/explainability on autonomy nor the interaction term is statistically significant; therefore, the hypothesised buffering moderation is not supported (**H4 not supported**).

Table 6. Direct effects and hypothesis testing (bootstrapping, 5,000 resamples; core model)

Hypothesis	Path	O	M	STDEV	t	p	Decision
H1	ACI → SA	-0.489	-0.487	0.087	5.587	$p<0.001$	Supported
H2	SA → LS	0.373	0.372	0.079	4.725	$p<0.001$	Supported
—	TR → SA	0.063	0.057	0.148	0.425	0.671	Not significant
H4	TR×ACI → SA	0.112	0.108	0.096	1.165	0.244	Not supported

Table 7 summarises the model's explanatory power (R^2), local effect sizes (f^2), and predictive relevance (Q^2). The model explains 22.0% of the variance in scheduling autonomy and 13.9% in labour supply. Effect sizes reinforce the central mechanism: algorithmic control intensity contributes meaningfully to explaining scheduling autonomy ($f^2 = 0.259$), and scheduling autonomy contributes moderately to labour supply ($f^2 = 0.162$), whereas transparency-related effects (TR → SA; TR×ACI → SA) are small. Predictive relevance is supported, with Q^2 values above zero for both endogenous constructs ($Q^2(SA) = 0.115$; $Q^2(LS) = 0.151$).

Table 7. Explanatory power (R^2) and local effect sizes (f^2) (core model)

Endogenous construct	R^2	R^2 adjusted	Predictor → Outcome	f^2
Scheduling Autonomy (SA)	0.220	0.196	ACI → SA	0.259
			TR → SA	0.004
			TR×ACI → SA	0.017
Labour Supply (LS)	0.139	0.131	SA → LS	0.162

Note: f^2 values are reported for predictors included in the core structural model.

Indirect effects and moderated mediation

Bootstrapped indirect-effect estimates support the autonomy mechanism (Table VII). The indirect effect of algorithmic control intensity on labour supply via scheduling autonomy (ACI → SA → LS) is significant, supporting H3 and indicating that control becomes utilisation-relevant primarily by constraining practical autonomy. In contrast, transparency-related indirect effects (TR → SA → LS) and the interaction-based conditional indirect effect ((TR×ACI) → SA → LS) are not significant (**Table 8**), suggesting no evidence that transparency buffers the control–autonomy channel. This null moderation is consistent with the distinction between informational clarity and contestability/enforcement: clearer rules may improve predictability without altering access penalties, leaving autonomy structurally constrained in high-control settings.

Table 8. Indirect effects (bootstrapping, 5,000 resamples; core model)

Effect	Indirect path	O	M	STDEV	t	p	Decision
—	TR → SA → LS	0.024	0.021	0.057	0.412	0.680	Not significant

Effect	Indirect path	O	M	STDEV	t	p	Decision
—	(TR×ACI) → SA → LS	0.042	0.040	0.037	1.118	0.264	Not significant
H3	ACI → SA → LS	-0.182	-0.180	0.047	3.849	0.000	Supported

Additional downstream tests (boundary evidence; not part of the core model)

As boundary evidence, we examined short-horizon downstream associations linking labour supply to earnings volatility (CV) and earnings volatility to exit intention. These tests do not form part of the core autonomy model and are interpreted cautiously. The results show no robust associations (**Table 9**), and explanatory power for these outcomes is low (R^2 volatility = 0.011; R^2 exit intention = 0.039). Taken together, the evidence suggests that the empirically reliable mechanism in this study operates up to labour supply, whereas short-window earnings volatility and exit intentions are likely shaped by additional forces beyond individual hours supplied (e.g., allocation dynamics and market conditions).

Table 9. Downstream boundary tests (supplementary; bootstrapping, 5,000 resamples)

Path	O	STDEV	t	p
Labour Supply (LS) → Earnings volatility (CV)	-0.105	0.104	1.007	0.314
Earnings volatility (CV) → Exit intention	0.198	0.201	0.985	0.325

Note: Earnings volatility is measured as the coefficient of variation (CV) computed from weekly earnings over a short window (higher CV = higher volatility / lower stability).

Discussion

Mechanism summary: how algorithmic governance becomes utilisation-relevant

The results support the upstream autonomy mechanism. Algorithmic control intensity is negatively associated with scheduling autonomy, and lower autonomy is associated with reduced labour supply. The significant indirect effect shows that algorithmic governance becomes economically consequential mainly by constraining discretion over participation: control does not merely shape attitudes, it limits when and how long workers can work, which translates into measurable labour input.

This reframes algorithmic HRM as a manpower governance lever. Metric-based allocation, monitoring, and automated sanctions narrow practical flexibility and raise the non-wage cost of participation. Workers respond behaviourally by adjusting hours supplied; the evidence supports an indirect autonomy pathway linking algorithmic control intensity to labour supply.

By contrast, transparency/explainability does not buffer the control–autonomy link. Informational clarity, as operationalised here, does not materially weaken autonomy loss under intensified control. The null moderation is informative: transparency alone may not relax participation constraints when allocation and sanction structures remain unchanged.

Theoretical contributions

First, the study strengthens the bridge between HRM and labour economics by locating algorithmic HRM within labour-supply response logic. Rather than focusing on perceptions of fairness, stress, or satisfaction, the analysis centres on labour supply as a behavioural economic outcome directly relevant to workforce utilisation. By demonstrating that scheduling autonomy mediates the relationship between control intensity and hours supplied, the study identifies a concrete mechanism through which digital governance affects manpower capacity.

Second, the findings clarify the role of job design in platform labour markets. Scheduling autonomy operates as a participation constraint: when autonomy is compressed, the effective "price" of supplying labour increases. This positions algorithmic control intensity not merely as a coordination technology, but as a structural determinant of labour input. In doing so, the study advances theorising on how platform governance architectures shape aggregate workforce availability.

Third, the non-significant moderation refines transparency arguments in algorithmic management research. Transparency is often framed as a corrective to algorithmic power asymmetries. However, the present evidence suggests that informational clarity alone may not restore autonomy when structural allocation rules remain intact. This identifies a boundary condition: transparency without redesign of control architecture may have limited impact on participation-relevant outcomes.

Boundary conditions and downstream limits

The null moderation indicates that transparency/explainability did not reliably weaken the control–autonomy link in this setting. This is consistent with the distinction between informational clarity and contestability/enforcement: clearer rules may improve predictability without reducing access penalties or enforcement power, leaving autonomy structurally constrained under high control. Downstream tests should therefore be interpreted as boundary evidence only. Short-horizon earnings volatility is likely driven by allocation algorithms, incentive cycles, and demand conditions, such that additional hours supplied may not stabilise income within a brief window; similarly, volatility-driven exit intentions may unfold over longer horizons than observed here. Overall, the evidence supports the proposed mechanism up to labour supply (control → autonomy → hours), while downstream income risk and exit dynamics remain contingent on broader structural and temporal factors beyond the model.

Why this matters for manpower planning and platform governance

The practical implication is straightforward. When algorithmic control erodes scheduling autonomy, platforms face a predictable utilisation response: workers reduce or adjust participation. This has direct consequences for capacity buffers, fulfilment reliability, and demand responsiveness. Governance design is therefore not only an ethical issue but a manpower planning decision.

Platforms seeking stable labour supply cannot rely solely on intensified control or transparency messaging. Preserving workable autonomy may function as a capacity-management lever, supporting sustained participation without escalating surveillance intensity. Minimum governance standards can operationalise this lever: (i) auditability of allocation and sanction decisions (traceable logs and reason codes), and (ii) accessible appeal pathways with timely review to correct erroneous enforcement. These standards do not remove algorithmic control, but they reduce arbitrary participation risk and stabilise access to work—conditions that support more reliable labour input. In this sense, the study shifts the discussion from fairness rhetoric to workforce sustainability mechanics.

Implications

Practical implications for platform and HR design

Workforce capacity in platform work is shaped by governance choices that constrain or preserve scheduling autonomy. Two design levers follow. First, protect workable autonomy by introducing proportional “guardrails” (e.g., limited rejections, short offline windows) without triggering disproportionate access penalties. Second, upgrade transparency into actionable governance by providing clear reason codes for allocation and performance outcomes, and fast, visible appeal routes for correcting errors that affect access. Together, these measures reduce participation frictions and help stabilise labour input—an outcome directly relevant to utilisation and service reliability. In manpower terms, these minimum viable standards (reason codes, audit trails, and appeal routes) reduce access uncertainty and stabilise labour supply by lowering non-wage participation costs.

Policy implications for decent work and labour-market stability

Policy can focus on governance features that affect participation constraints. Three priorities are: (1) minimum transparency standards (core criteria disclosure and meaningful explanations for adverse outcomes), (2) auditability and contestability (records of automated decisions plus accessible review and correction), and (3) workforce sustainability monitoring that tracks utilisation risk indicators (e.g., persistent earnings volatility and local supply instability) to flag emerging retention pressures. These steps align algorithmic governance with decent-work objectives while supporting manpower planning. By reducing participation risk and improving contestability, these standards help prevent sudden contractions in local labour supply that undermine service continuity.

Limitations and future research

Three limits guide next steps. First, evidence from one platform segment and one national context limits portability; comparative studies across platforms and institutional settings are needed. Second, earnings were self-reported and volatility was captured over a short window; future work should use payout logs/administrative records, alternative risk metrics, and longer horizons. Third, although the three-wave design strengthens temporal ordering, stronger causal inference would benefit from longer panels or quasi-experiments that leverage policy/algorithm changes over time. Longer observation windows and richer institutional variation are also needed to assess whether the null transparency moderation reflects structural enforcement constraints (beyond informational clarity) and to further rule out subtle attrition-based selection effects.

CONCLUSION

This study shows how algorithmic HRM becomes labour-economics-relevant in platform work: control intensity reduces scheduling autonomy, and autonomy loss reduces labour supply. The findings position autonomy as a participation constraint that translates governance intensity into measurable workforce utilisation. Transparency, as modelled here, does not reliably buffer the control–autonomy link, and short-horizon downstream tests provide limited evidence that hours supplied map directly into earnings volatility or exit intentions. From a manpower planning and platform governance perspective, the implication is direct: governance designs that erode workable autonomy compress effective labour input and thin local capacity buffers, with consequences for service reliability and labour-market stability.

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