



Workload and Customer Rating Pressure as Antecedents of Burnout: Examining the Mediating Role of Job Stress in the Ride-Hailing Context

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Submitted: 28-03-2026	Review: 10-04-2026	Revision: 17-04-2026	Accepted: 01-05-2026
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Abstrak

Penelitian ini bertujuan untuk menganalisis pengaruh workload dan customer rating pressure terhadap burnout dengan job stress sebagai variabel mediasi dalam konteks pengemudi ride-hailing. Penelitian ini menggunakan pendekatan kuantitatif dengan data yang dikumpulkan dari 160 pengemudi ride-hailing di Kota Makassar dan dianalisis menggunakan Partial Least Squares Structural Equation Modeling (PLS-SEM). Hasil penelitian menunjukkan bahwa customer rating pressure memiliki pengaruh yang lebih kuat terhadap job stress dibandingkan workload, yang mengindikasikan dominannya peran tekanan algoritmik dalam membentuk kondisi psikologis pengemudi. Job stress terbukti berpengaruh signifikan terhadap burnout serta berperan sebagai mekanisme mediasi utama. Workload berpengaruh terhadap burnout baik secara langsung maupun tidak langsung (mediasi parsial), sedangkan customer rating pressure hanya berpengaruh secara tidak langsung melalui job stress (mediasi penuh). Temuan ini menunjukkan bahwa burnout pada pekerja gig tidak hanya dipicu oleh beban kerja fisik, tetapi lebih banyak dipengaruhi oleh tekanan psikologis yang berasal dari sistem evaluasi berbasis platform. Penelitian ini memberikan kontribusi dengan menunjukkan bahwa tidak semua job demands bekerja melalui mekanisme yang sama, serta menekankan pentingnya tekanan algoritmik dalam ekonomi digital..

Kata kunci: workload, customer rating pressure, job stress, burnout, gig economy.

Abstract

This study examines the effects of workload and customer rating pressure on burnout, with job stress as a mediating variable, in the ride-hailing context. Using a quantitative approach, data were collected from 160 ride-hailing drivers in Makassar, Indonesia, and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings reveal that customer rating pressure has a stronger impact on job stress compared to workload, highlighting the critical role of algorithmic management in shaping drivers' psychological conditions. Job stress is found to significantly influence burnout and serves as a key mediating mechanism. While workload directly and indirectly affects burnout (partial mediation), customer rating pressure influences burnout only indirectly through job stress (full mediation). These results suggest that burnout among gig workers is not merely driven by physical job demands but is primarily shaped by psychological pressures embedded in platform-based evaluation systems. This study contributes to the literature by demonstrating that not all job demands operate through the same pathways, emphasizing the dominance of algorithmic pressure in the gig economy. The findings offer practical implications for platform providers and policymakers to design more sustainable and worker-friendly systems.

Keywords: workload, customer rating pressure, job stress, burnout, gig economy.

INTRODUCTION

The rapid expansion of the digital economy has fundamentally transformed labor structures, particularly through the emergence of platform-based work such as ride-hailing services ([Halik et al., 2024](#)). This sector, characterized by algorithmic management and flexible employment arrangements, has created new opportunities while simultaneously introducing complex occupational challenges. Ride-hailing drivers operate under high levels of uncertainty, income variability, and performance-based evaluation systems, which may significantly affect their psychological well-being ([Bokányi & Hannák, 2020](#); [Chen et al., 2023](#)). In this context, workload and customer rating systems have emerged as critical determinants shaping drivers' work experiences ([Kellogg et al., 2019](#); [Wood et al., 2019](#)).

Workload in the ride-hailing context extends beyond traditional physical demands to include time pressure, long working hours, and the need to meet algorithmically determined targets ([Lee et al., 2015](#)). Unlike conventional employment settings, drivers often face unpredictable demand patterns and must continuously adapt to platform incentives and penalties ([Cramer & Krueger, 2016](#); [Hall & Krueger, 2018](#)). Excessive workload has been consistently associated with adverse psychological outcomes, including fatigue, emotional exhaustion, and decreased job satisfaction ([Bakker & Demerouti, 2017](#); [Parker et al., 2021](#)).

In addition to workload, customer rating pressure represents a unique stressor inherent in platform-based work. Rating systems function as both performance evaluation tools and mechanisms of control, directly influencing drivers' access to future work opportunities ([Kellogg et al., 2019](#)). Drivers with low ratings may face reduced visibility, temporary suspension, or even permanent deactivation from the platform ([Wood et al., 2019](#)). This creates a continuous pressure to maintain high ratings, often leading drivers to prioritize customer satisfaction at the expense of their own well-being. Recent studies suggest that such rating systems can induce anxiety, emotional labor, and stress, particularly when ratings are perceived as unfair or uncontrollable ([Kellogg et al., 2019](#); [Lee et al., 2015](#)).

Burnout, defined as a psychological syndrome characterized by emotional exhaustion,

depersonalization, and reduced personal accomplishment, has become increasingly prevalent among gig workers ([Schaufeli, 2017](#)). In the ride-hailing sector, burnout is often exacerbated by the absence of organizational support, job insecurity, and continuous exposure to customer demands. Empirical evidence indicates that both excessive workload and performance pressure contribute significantly to burnout levels among platform workers ([Kellogg et al., 2019](#); [Wood et al., 2019](#)).

However, the mechanisms through which workload and customer rating pressure influence burnout are not always direct. Job stress plays a crucial mediating role in this relationship. Job stress arises when individuals perceive a mismatch between job demands and their capacity to cope effectively ([Ganster & Rosen, 2013](#); [Hobfoll et al., 2018](#)). In high-pressure environments such as ride-hailing, workload and rating systems may first trigger stress responses, which subsequently lead to burnout if prolonged or unmanaged. Recent empirical studies highlight job stress as a key explanatory variable linking work demands to psychological outcomes in gig economy settings ([HAFEEZ et al., 2023](#); [Lang et al., 2023](#)).

Despite growing interest in gig economy research, there remains limited empirical investigation that simultaneously examines workload and customer rating pressure as antecedents of burnout while incorporating job stress as a mediating mechanism, particularly in developing countries such as Indonesia. Most prior studies have focused on either workload or algorithmic control independently, leaving a gap in understanding the combined effects of these stressors in shaping driver well-being.

To further illustrate the urgency of this issue, several recent studies and industry reports provide empirical evidence regarding working conditions and psychological risks in ride-hailing services:

Table 1. Empirical Evidence on Work Conditions and Psychological Risks in Ride-Hailing

Study	Context	Key Findings
Wood et al.(2019)	Gig workers (global)	High autonomy is offset by algorithmic control leading to work intensification
Cramer & Krueger (2016)	Ride-hailing drivers	Long working hours increase fatigue and reduce well-being

Study	Context	Key Findings
Kellogg et al. (2019)	Platform economy	Algorithmic management creates constant performance pressure
Lee et al. (2015)	Ride-hailing drivers	Customer ratings significantly increase anxiety and emotional stress
HAFEEZ et al. (2023)	Gig workers (Asia)	Job stress mediates the relationship between job demands and burnout

Source: Compiled from various sources(2026)

The urgency of this research lies in the increasing dependence on gig-based employment, particularly in developing economies where ride-hailing services serve as a primary source of income for many individuals. While these platforms offer flexibility and accessibility, they also expose workers to unregulated work conditions, psychological pressure, and limited social protection. Understanding how workload and customer rating pressure contribute to burnout through job stress is essential not only for academic advancement but also for informing platform policies and labor regulations that promote sustainable and humane working conditions.

Based on the background described above, the research problems can be formulated as follows:

1. Does workload significantly influence job stress among ride-hailing drivers?
2. Does customer rating pressure significantly influence job stress?
3. Does job stress significantly influence burnout?
4. Does workload significantly influence burnout?
5. Does customer rating pressure significantly influence burnout?
6. Does job stress mediate the relationship between workload and burnout?
7. Does job stress mediate the relationship between customer rating pressure and burnout?

LITERATURE REVIEW

Grand Theory: Job Demands–Resources (JD-R) Theory

This study is primarily grounded in the Job Demands–Resources (JD-R) Theory, which has become one of the most widely used frameworks

in explaining employee well-being and burnout across various occupational contexts. The JD-R model posits that every occupation is characterized by specific job demands and job resources, which jointly influence employees' psychological outcomes ([Bakker et al., 2023](#); [Bakker & Demerouti, 2017](#)).

Job demands refer to aspects of work that require sustained physical or psychological effort and are therefore associated with physiological and psychological costs ([Schaufeli, 2017](#)). These include workload, time pressure, emotional demands, and performance expectations. Conversely, job resources refer to aspects of work that help achieve work goals, reduce job demands, or stimulate personal growth ([Park et al., 2021](#)).

The JD-R model explains burnout through the health impairment process, in which excessive job demands deplete employees' mental and physical energy, eventually leading to stress and burnout. Empirical evidence consistently supports that high job demands are positively associated with stress and burnout across different sectors ([Bakker et al., 2023](#); [Bakker & Demerouti, 2017](#)).

In the context of ride-hailing platforms, workload and customer rating pressure can be conceptualized as job demands that continuously require drivers to exert effort under uncertain and often stressful conditions. Therefore, JD-R theory provides a strong theoretical foundation for examining how these demands contribute to job stress and burnout.

Supporting Theory: Conservation of Resources (COR) Theory

In addition to JD-R theory, this study is also supported by the Conservation of Resources (COR) Theory, which explains how individuals strive to obtain, retain, and protect their resources ([Hobfoll, 1989](#)). According to this theory, stress occurs when individuals perceive a threat of resource loss, actual resource loss, or insufficient return on resource investment.

Recent studies have applied COR theory to explain burnout, suggesting that continuous exposure to job stressors leads to resource depletion, which ultimately results in emotional exhaustion and burnout ([Halbesleben, 2006](#)).

In ride-hailing work, drivers invest significant resources such as time, energy, and emotional regulation to maintain performance and ratings ([Bokányi & Hannák, 2020](#)). When these efforts are not adequately rewarded or are continuously threatened (e.g., through poor

ratings), drivers are more likely to experience stress and burnout (Almazrouei et al., 2025).

Key Constructs and Operational Definitions

a. Workload

Workload refers to the amount and intensity of work tasks that individuals are required to complete within a given period. In contemporary work settings, workload encompasses not only physical demands but also cognitive and emotional pressures (Spector & Jex, 1998).

In the gig economy, workload is often characterized by long working hours, unpredictable demand, and pressure to meet algorithmic targets. Excessive workload has been shown to significantly increase stress levels and reduce psychological well-being (Grandey, 2000; Pencavel, 2015).

Workload is measured as drivers' perceived intensity of work demands, including working hours, task volume, and time pressure (Pencavel, 2015; Spector & Jex, 1998).

b. Customer Rating Pressure

Customer rating pressure refers to the psychological pressure experienced by workers due to performance evaluation systems based on customer feedback (Wood et al., 2019). In platform-based work, ratings directly influence job continuity, income, and access to opportunities (Cheng et al., 2020; Putri et al., 2023).

Algorithmic rating systems create a constant need for workers to maintain high performance, often leading to emotional labor and anxiety. Recent studies indicate that rating systems function as a form of digital control that intensifies worker stress (Kellogg et al., 2019; Lee et al., 2015).

Customer rating pressure is defined as the perceived pressure to maintain high customer ratings to avoid penalties or loss of work opportunities (Kellogg et al., 2019; Rosenblat & Stark, 2016).

c. Job Stress

Job stress is defined as a psychological response that occurs when job demands exceed an individual's capacity to cope effectively (Spector & Jex, 1998). It reflects a state of tension, anxiety, and emotional strain resulting from work-related pressures.

Within the JD-R framework, job stress is considered a direct consequence of excessive job demands and serves as a precursor to burnout. Empirical studies confirm that job stress plays a mediating role between job demands and burnout (Halbesleben, 2006; Hobfoll et al., 2018).

Job stress is measured as the level of psychological strain experienced by drivers due to work-related demands and pressures (Lang et al., 2023).

d. Burnout

Burnout is a psychological syndrome characterized by emotional exhaustion, depersonalization, and reduced personal accomplishment (Maslach & Jackson, 1981). It is widely recognized as a consequence of prolonged exposure to chronic job stressors.

According to recent literature, burnout emerges when employees are unable to recover from sustained stress, leading to decreased motivation, reduced performance, and negative well-being outcomes (Bakker et al., 2023; Schaufeli, 2017).

Burnout is measured through indicators of emotional exhaustion, cynicism, and reduced professional efficacy among ride-hailing drivers (Lang et al., 2023).

Hypothesis Development

Workload and Job Stress

Based on JD-R theory, workload is a primary job demand that requires continuous effort, leading to psychological strain. Empirical studies consistently show that excessive workload increases job stress (Bakker & Demerouti, 2017).

H1: Workload has a positive effect on job stress.

Customer Rating Pressure and Job Stress

Customer rating systems impose continuous performance evaluation, which creates psychological pressure (Wood et al., 2019). This pressure can trigger stress, especially when outcomes are perceived as uncertain or uncontrollable (Kellogg et al., 2019).

H2: Customer rating pressure has a positive effect on job stress.

Job Stress and Burnout

Job stress represents a critical antecedent of burnout (Spector & Jex, 1998). Prolonged stress leads to emotional exhaustion and reduced coping

capacity, ultimately resulting in burnout (Lang et al., 2023; Parker et al., 2021).

H3: Job stress has a positive effect on burnout.

Workload and Burnout

High workload directly contributes to burnout by depleting individuals' physical and psychological resources, especially when recovery opportunities are limited (Hobfoll, 1989).

H4: Workload has a positive effect on burnout.

Customer Rating Pressure and Burnout

Continuous exposure to rating pressure can lead to emotional exhaustion and burnout, particularly when workers feel constantly evaluated (Kellogg et al., 2019).

H5: Customer rating pressure has a positive effect on burnout.

Mediating Role of Job Stress

According to JD-R and COR theories, job demands first trigger stress responses, which then lead to burnout. Several studies confirm that stress mediates the relationship between workload and burnout (HAFEEZ et al., 2023; Lang et al., 2023).

H6: Job stress mediates the relationship between workload and burnout.

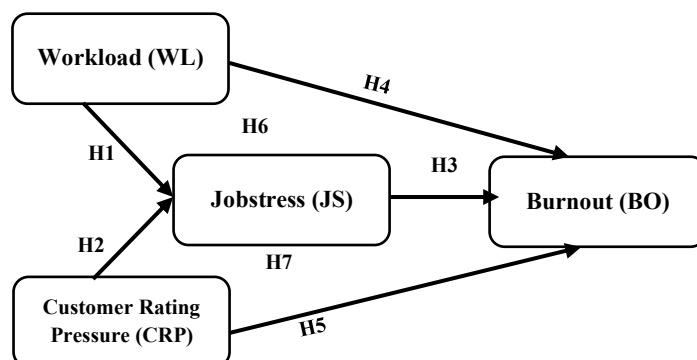
Similarly, customer rating pressure is expected to influence burnout indirectly through job stress, as continuous evaluation creates psychological strain (Kellogg et al., 2019; Wood et al., 2019).

H7: Job stress mediates the relationship between customer rating pressure and burnout.

To synthesize the theoretical arguments derived from the Job Demands–Resources (JD-R) Theory and the Conservation of Resources (COR) Theory, this study proposes a conceptual framework that illustrates the structural relationships among the key variables. Specifically, workload and customer rating pressure are positioned as job demands that influence burnout both directly and indirectly through job stress as a mediating variable. This framework reflects the underlying mechanism through which work-related pressures in the ride-

hailing context translate into psychological strain and eventual burnout.

Accordingly, the conceptual model of this study is presented in **Figure 1**.



Source: Author's conception (2026)

Figure 1. Research Conceptual Framework

RESEARCH METHODS

Research Design

This study employs a quantitative research approach with an explanatory design to examine the causal relationships among workload, customer rating pressure, job stress, and burnout in the ride-hailing context. A quantitative approach is appropriate as it enables hypothesis testing and the examination of relationships between latent variables using statistical analysis (Hair et al., 2022).

A cross-sectional survey design is utilized, where data are collected at a single point in time from respondents. This design is widely used in behavioral and management research to capture perceptions and attitudes efficiently (Sekaran & Bougie, 2017). Furthermore, this study adopts a causal modeling approach, as it aims to analyze both direct and indirect (mediating) relationships among variables (Hair et al., 2021).

Population and Sample

The population of this study consists of ride-hailing drivers operating in Makassar City, Indonesia, who are actively engaged in platform-based transportation services. Makassar is selected as the research location due to the rapid growth of ride-hailing services and the high dependence of urban mobility on digital transportation platforms.

This study applies a non-probability sampling technique, specifically purposive sampling, to ensure that only respondents who meet the research criteria are included. The selection criteria are as follows:

1. Active ride-hailing drivers registered on a digital platform
2. Have a minimum of six months of working experience
3. Actively working within the last three months
4. Willing to participate voluntarily in the study

The total sample size in this study is 160 respondents, which is considered adequate for PLS-SEM analysis. According to methodological guidelines, PLS-SEM is suitable for small to medium sample sizes and complex models ([Hair et al., 2021](#)). Additionally, recommendations suggest that the minimum sample size should be 5–10 times the number of indicators used in the model ([Hair et al., 2019](#)). Given that this study employs 4 indicators for each construct, the total number of indicators supports the adequacy of the selected sample size.

Research Location and Time

This research is conducted in Makassar City, Indonesia, one of the major urban centers with a high penetration of ride-hailing services. The city provides a relevant empirical context due to its dynamic transportation ecosystem and increasing reliance on platform-based work.

Data collection is carried out over a period of approximately two months, allowing sufficient time to gather responses and ensure data quality. The questionnaires are distributed online to facilitate access and participation among respondents.

Data Collection Technique

Primary data are collected using a structured questionnaire administered through an online survey platform. This approach is efficient and widely used in quantitative research, particularly in studies involving geographically dispersed respondents ([Memon et al., 2025](#)).

All measurement items are adapted from previously validated scales in the literature to ensure content validity. Responses are measured using a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree), which is commonly used in behavioral research to capture respondents' perceptions (Sugiyono, 2020).

Operationalization of Variables

In this study, all constructs are conceptualized as reflective latent variables, where the observed indicators are assumed to

represent manifestations of the underlying constructs ([Hair et al., 2022](#)). The operationalization of variables is based on well-established scales from prior literature, with slight contextual adaptation to fit the ride-hailing environment.

Workload is defined as the perceived intensity and quantity of work demands experienced by ride-hailing drivers, including time pressure, working hours, and task burden. This construct reflects the extent to which drivers perceive their work as physically and mentally demanding. The measurement items are adapted from previous studies on job demands and workload in flexible work environments ([Bakker et al., 2023](#); [Bakker & Demerouti, 2017](#); [Schaufeli, 2017](#)).

Customer Rating Pressure refers to the psychological pressure felt by drivers to maintain high customer ratings in order to secure continued access to work opportunities. This construct captures the perceived importance of ratings and the anxiety associated with performance evaluation systems in platform-based work. The items are adapted from studies on algorithmic management and performance monitoring in the gig economy ([Kellogg et al., 2019](#); [Lee et al., 2015](#)).

Job Stress is conceptualized as a psychological response arising from the imbalance between job demands and an individual's coping capacity. It reflects feelings of tension, anxiety, and emotional strain related to work. The measurement items are adapted from established job stress scales widely used in organizational research ([Pencavel, 2015](#); [Spector & Jex, 1998](#)).

Burnout is defined as a psychological syndrome characterized by emotional exhaustion, reduced motivation, and mental fatigue resulting from prolonged exposure to work-related stressors. This study focuses primarily on the emotional exhaustion dimension, which is considered the core component of burnout. The items are adapted from the Maslach Burnout framework and recent empirical studies ([Lang et al., 2023](#); [Maslach & Jackson, 1981](#); [Schaufeli, 2017](#)).

All constructs are measured using a **five-point Likert scale**, ranging from 1 (strongly disagree) to 5 (strongly agree).

Table 2. Measurement Items

Variable	Code	Measurement Items	Source
Workload	WL1	I have to work for long hours to meet my daily targets	(Bakker et al., 2023; Bakker & Demerouti, 2017; Schaufeli, 2017)
	WL2	My job requires me to work under high time pressure	
	WL3	I often feel that my workload is excessive	
	WL4	I have to continuously work without sufficient rest	
Customer Rating Pressure	CRP1	I feel pressured to maintain a high customer rating	(Kellogg et al., 2019; Lee et al., 2015; Wood et al., 2019)
	CRP2	My job security depends on my customer ratings	
	CRP3	I feel anxious when receiving customer ratings	
	CRP4	I must always satisfy customers to avoid negative ratings	
Job Stress	JS1	I feel stressed due to my work demands	(Pencavel, 2015; Spector & Jex, 1998)
	JS2	My job makes me feel tense and anxious	
	JS3	I find it difficult to relax after work	
	JS4	I feel emotionally drained because of my job	
Burnout	BO1	I feel emotionally exhausted from my work	(Lang et al., 2023; Maslach & Jackson, 1981; Schaufeli, 2017)
	BO2	I feel fatigued when I think about my work	
	BO3	I feel less motivated to continue my work	
	BO4	I feel mentally drained after working	

Source: Adapted from previous research (2026)

Data Analysis Technique

This study employs Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS software to analyze the data. This method is selected due to its suitability for

predictive-oriented research, its robustness in handling complex models, and its ability to accommodate data that do not meet strict normality assumptions (Hair et al., 2021; Santosa, 2018). In addition, PLS-SEM is particularly appropriate for studies involving latent constructs and mediation analysis, as it allows for simultaneous estimation of measurement and structural models (Hair et al., 2019).

The data analysis is conducted in two main stages, namely the evaluation of the measurement model (outer model) and the structural model (inner model). The measurement model evaluation aims to ensure that all constructs meet the required standards of reliability and validity. Convergent validity is assessed by examining factor loadings and the Average Variance Extracted (AVE), where values above the recommended thresholds indicate that the indicators adequately represent their respective constructs (Hair et al., 2019; Haryono, 2017). Internal consistency reliability is evaluated using Composite Reliability and Cronbach's Alpha, ensuring that the measurement items consistently reflect the underlying variables. Furthermore, discriminant validity is assessed through the Fornell-Larcker criterion and the Heterotrait-Monotrait Ratio (HTMT) (Fornell & Larcker, 1981; Henseler et al., 2015), confirming that each construct is empirically distinct from others. These procedures are widely recognized as standard practices in SEM-based research to ensure measurement quality (Hair et al., 2019).

Following the validation of the measurement model, the analysis proceeds to the structural model evaluation, which focuses on testing the proposed hypotheses. The relationships among variables are examined through path coefficients, which indicate both the direction and strength of the effects. The explanatory power of the model is assessed using the coefficient of determination (R^2), while the effect size (f^2) is used to evaluate the relative impact of each exogenous variable on the endogenous constructs. In addition, model fit indices is examined using the blindfolding procedure to assess the model's predictive capability (Hair et al., 2019).

To determine the statistical significance of the hypothesized relationships, this study employs a bootstrapping procedure with 5,000 resamples. This approach enables the estimation of standard errors and confidence intervals for both direct and indirect effects, thereby providing robust support

for hypothesis testing. The use of PLS-SEM is particularly advantageous in this context, as it allows for reliable mediation analysis without imposing strict distributional assumptions ([Hair et al., 2021](#)).

RESULTS AND DISCUSSION

Overview of Research Object

This study focuses on ride-hailing drivers operating in Makassar City, Indonesia, who actively engage in platform-based transportation services. The rapid growth of ride-hailing platforms has significantly transformed urban mobility in Makassar, making it a relevant context for examining work-related psychological conditions such as job stress and burnout.

Ride-hailing drivers represent a unique category of workers within the gig economy, characterized by flexible working arrangements, algorithmic management, and performance evaluation systems based on customer ratings. These working conditions expose drivers to various job demands, including high workload and continuous performance pressure, which may influence their psychological well-being.

The respondents in this study consist of drivers who meet the predefined criteria, including active engagement in ride-hailing services and a minimum of six months of work experience. A total of 160 valid responses were collected and used for further analysis.

Respondent Characteristics

To provide a clearer understanding of the sample profile, respondent characteristics are presented based on gender, age, education level, and work experience.

Table 3. Respondent Characteristics (n = 160)

Characteristics	Category	Frequency	Percentage (%)
Gender	Male	138	86.3%
	Female	22	13.7%
Age	< 25 years	28	17.5%
	25–34 years	72	45.0%
	35–44 years	41	25.6%
	> 44 years	19	11.9%
	High School	102	63.8%
Education			

Characteristics	Category	Frequency	Percentage (%)
Work Experience	Diploma	28	17.5%
	Bachelor Degree	30	18.7%
	< 1 year	36	22.5%
	1–3 years	78	48.8%
	> 3 years	46	28.7%

Source: Primary data processed (2026)

The data indicate that the majority of respondents are male drivers in the productive age group (25–34 years), with high school education and 1–3 years of work experience. This profile reflects the typical demographic composition of ride-hailing drivers in urban Indonesia.

Descriptive Statistical Analysis

Descriptive statistical analysis is used to provide an overview of the data distribution and respondents' perceptions of each measurement item. This analysis helps researchers understand the central tendency (mean), dispersion (standard deviation), and response patterns before conducting further inferential analysis. In quantitative research, descriptive statistics play a crucial role in identifying whether the data are relatively homogeneous, detecting potential anomalies, and providing initial insights into how respondents perceive each construct (Ghozali, 2021).

Specifically, the mean value indicates the average level of agreement of respondents toward each statement, while the standard deviation reflects the variability of responses. A higher mean suggests stronger agreement, whereas a lower standard deviation indicates more consistent responses among respondents ([Hair et al., 2019](#)).

Table 4. Descriptive Statistical Analysis

Code	Variable	Mean	Standard Deviation
WL1	Workload	3.944	1.038
WL2	Workload	3.869	1.119
WL3	Workload	3.756	1.011
WL4	Workload	3.475	0.922
CRP1	Customer Rating Pressure	3.844	1.143
CRP2	Customer Rating Pressure	3.850	1.168
CRP3	Customer Rating Pressure	3.631	1.053

Code	Variable	Mean	Standard Deviation
CRP4	Customer Rating Pressure	3.344	0.969
JS1	Job Stress	3.769	0.903
JS2	Job Stress	3.825	0.978
JS3	Job Stress	3.975	1.095
JS4	Job Stress	3.837	1.060
BO1	Burnout	3.350	0.937
BO2	Burnout	3.587	1.142
BO3	Burnout	3.206	0.982
BO4	Burnout	3.256	0.924

Source: Smart-PLS output (2026)

Referring to Table 2 (Measurement Items), the descriptive results indicate several important insights:

1. Workload (WL)

The mean values for workload indicators range from 3.475 to 3.944, indicating that respondents generally agree that they experience relatively high work demands. The highest mean (WL1 = 3.944) suggests that drivers strongly perceive long working hours as a major aspect of their job. Meanwhile, WL4 (mean = 3.475) indicates that although drivers feel continuous work pressure, it is slightly less dominant compared to time-related demands.

Workload in the ride-hailing context is primarily driven by time pressure and long working hours, consistent with the conceptual definition in **Table 2**.

2. Customer Rating Pressure (CRP)

The mean scores range from 3.344 to 3.850, indicating moderate to high perceived pressure related to customer ratings. CRP2 (mean = 3.850) shows that respondents strongly agree that job continuity depends on ratings, reinforcing the role of algorithmic control. However, CRP4 (mean = 3.344) is slightly lower, suggesting that not all drivers feel equally pressured to constantly satisfy customers.

Customer rating systems are perceived as important but variably stressful, depending on individual experiences.

3. Job Stress (JS)

All job stress indicators show relatively high mean values (3.769 to 3.975), with JS3 (mean = 3.975) being the highest. This indicates

that many drivers find it difficult to relax after work, reflecting sustained psychological strain.

This aligns strongly with the theoretical expectation that high job demands translate into psychological stress, confirming the JD-R mechanism at the descriptive level.

4. Burnout (BO)

Burnout indicators show slightly lower mean values (3.206 to 3.587) compared to workload and stress. BO2 (mean = 3.587) indicates moderate fatigue, while BO3 (mean = 3.206) suggests that loss of motivation is present but not yet severe.

Burnout is present but at a moderate level, suggesting that while drivers experience stress, it has not fully escalated into severe burnout for all respondents.

Measurement Model Evaluation (Outer Model)

The outer model, also known as the measurement model, is used to evaluate the relationship between latent constructs and their observed indicators. Its primary purpose is to ensure that the measurement instruments used in the study are both reliable and valid. In the context of PLS-SEM, the outer model assessment focuses on examining indicator reliability, internal consistency reliability, convergent validity, and discriminant validity ([Hair et al., 2019](#)).

Indicator reliability is assessed through outer loadings, which reflect how strongly each indicator represents its underlying construct. Internal consistency reliability is evaluated using Cronbach's Alpha and Composite Reliability (CR), ensuring that the indicators consistently measure the same construct. Convergent validity is assessed through the Average Variance Extracted (AVE), which indicates the extent to which a construct explains the variance of its indicators. These criteria are essential to confirm that the measurement model is adequate before proceeding to the structural model analysis ([Hair et al., 2021](#)).

Table 5. Outer Model Measurement Results

Construct	Indicator	Outer Loading	Cronbach's Alpha	Composite Reliability (CR)	AVE
Workload	WL1	0.898	0.898	0.909	0.766
	WL2	0.880			
	WL3	0.914			
	WL4	0.804			

Construct	Indicator	Outer Loading	Cronbach's Alpha	Composite Reliability (CR)	AVE
Customer Rating Pressure	CRP1	0.908	0.911	0.919	0.789
	CRP2	0.912			
	CRP3	0.904			
	CRP4	0.826			
Job Stress	JS1	0.838	0.888	0.895	0.749
	JS2	0.814			
	JS3	0.910			
	JS4	0.897			
Burnout	BO1	0.853	0.885	0.893	0.744
	BO2	0.899			
	BO3	0.839			
	BO4	0.858			

Note: All values satisfy recommended thresholds: Outer Loadings > 0.70; AVE > 0.50; α & CR > 0.70
Source: Smart-PLS Output (2026)

The results of the outer model evaluation indicate that all constructs meet the required criteria for reliability and validity.

First, indicator reliability is confirmed as all outer loading values exceed the recommended threshold of 0.70. The loadings range from 0.804 to 0.914, indicating that each indicator has a strong correlation with its respective construct. For instance, WL3 (0.914) and CRP2 (0.912) demonstrate particularly strong contributions in representing workload and customer rating pressure, respectively.

Second, in terms of internal consistency reliability, all constructs show Cronbach's Alpha values above 0.70, ranging from 0.885 to 0.911, while Composite Reliability (CR) values range from 0.893 to 0.919. These results indicate a high level of consistency among the indicators within each construct. Notably, Customer Rating Pressure exhibits the highest reliability (CR = 0.919), suggesting that its indicators are highly consistent in measuring the construct.

Third, convergent validity is established as all AVE values exceed the minimum threshold of 0.50, ranging from 0.744 to 0.789. This indicates that each construct explains more than 50% of the variance in its indicators. Customer Rating Pressure shows the highest AVE (0.789), suggesting strong explanatory power.

Overall, these findings confirm that the measurement model is both reliable and valid, and all constructs are adequately measured by their respective indicators (Hair et al., 2019).

Table 6. Discriminant Validity (Fornell-Larcker Criterion)

Construct	Workload	Customer Rating Pressure	Job Stress	Burnout
Workload	0.875			
Customer Rating Pressure	0.642	0.888		
Job Stress	0.701	0.689	0.865	
Burnout	0.655	0.632	0.742	0.863

Source: Smart-PLS output (2026)

The Fornell-Larcker criterion is used to assess discriminant validity, which ensures that each construct is empirically distinct from other constructs in the model (Fornell & Larcker, 1981). According to this criterion, the square root of the AVE for each construct (diagonal values) must be greater than its correlations with other constructs (Hair et al., 2019).

Based on **Table 6**, all diagonal values are higher than the corresponding inter-construct correlations. For example, the square root of AVE for Workload (0.875) is greater than its correlations with Customer Rating Pressure (0.642), Job Stress (0.701), and Burnout (0.655). Similarly, Customer Rating Pressure (0.888) shows higher values compared to its correlations with other constructs.

For Job Stress, the diagonal value (0.865) exceeds its correlations with Workload (0.701), Customer Rating Pressure (0.689), and Burnout (0.742). Likewise, Burnout (0.863) also satisfies the criterion, as it is higher than its correlations with all other constructs.

These results indicate that each construct shares more variance with its own indicators than with other constructs, thereby confirming that discriminant validity has been successfully established (Hair et al., 2019).

Structural Model Evaluation (Inner Model)

The structural model evaluation aims to assess the predictive capability and the strength of relationships among latent constructs in the proposed model. This evaluation includes the examination of the coefficient of determination (R^2), effect size (f^2), and model fit indices. These measures provide insight into how well the model explains the endogenous constructs and the relative importance of exogenous variables (Hair et al., 2021).

Coefficient of Determination (R-Square). The coefficient of determination (R^2) indicates the proportion of variance in endogenous constructs explained by their predictor variables. Higher R^2 values indicate greater explanatory power of the model (Hair et al., 2019).

Table 7. R-Square Results

Endogenous Variable	R-Square	Interpretation
Job Stress	0.421	Moderate
Burnout	0.442	Moderate

Source: Smart-PLS output (2026)

The coefficient of determination (R^2) values indicates the extent to which the endogenous variables are explained by their respective predictors in the model.

The R^2 value for job stress (0.421) suggests that workload and customer rating pressure jointly explain 42.1% of the variance in job stress. This indicates a moderate level of explanatory power, meaning that while these job demands play an important role in shaping job stress, there are still other factors outside the model that may contribute to drivers' psychological strain.

Similarly, the R^2 value for burnout (0.442) shows that workload, customer rating pressure, and job stress collectively explain 44.2% of the variance in burnout. This also falls within the moderate category, indicating that the model provides a reasonable explanation of burnout, although additional variables—such as social support, coping mechanisms, or financial pressure—may further enhance the model's explanatory capability.

Overall, these findings suggest that the proposed model has adequate predictive relevance, particularly in capturing the role of job demands and stress in explaining burnout among ride-hailing drivers, while also highlighting the potential for further model development.

Effect Size (F-Square). Effect size (f^2) measures the impact of each exogenous variable on endogenous constructs (Hair et al., 2019). It evaluates how much an endogenous variable's R^2 changes when a specific exogenous variable is removed from the model.

Table 8. Effect Size (f^2) Results

Relationship	f^2 Value	Effect Size
Workload → Job Stress	0.058	Small
Customer Rating Pressure → Job Stress	0.502	Large
Job Stress → Burnout	0.248	Medium
Workload → Burnout	0.068	Small
Customer Rating Pressure → Burnout	0.011	Very Small (Negligible)

Source: Smart-PLS output (2026)

The effect size (f^2) results reveal important insights into the relative influence of each predictor in the model.

First, customer rating pressure has a very strong effect on job stress ($f^2 = 0.502$), which falls into the large category. This indicates that rating-related pressure is the most dominant factor influencing psychological stress among ride-hailing drivers. In other words, the platform-based evaluation system plays a more critical role in shaping stress compared to traditional workload factors.

In contrast, workload shows only a small effect on job stress ($f^2 = 0.058$). This finding is quite interesting and somewhat counterintuitive, as traditional job demand theory often positions workload as a primary stressor. In this context, it suggests that psychological pressure from ratings outweighs physical or time-based workload demands.

Regarding burnout, job stress demonstrates a moderate effect ($f^2 = 0.248$), confirming its central role as a key predictor of burnout. This supports the theoretical assumption that stress acts as a primary mechanism through which job demands translate into burnout.

Meanwhile, the direct effects of workload ($f^2 = 0.068$) and customer rating pressure ($f^2 = 0.011$) on burnout are relatively small and negligible. This indicates that both variables influence burnout primarily indirectly through job stress, reinforcing the mediating role of job stress in the model.

Model Fit. Although PLS-SEM is primarily prediction-oriented, model fit indices can still be used to assess the overall fit of the model (Henseler et al., 2015).

Table 9. Model Fit Indices

Model Fit Index	Value	Threshold	Interpretation
SRMR	0.053	< 0.08	Good Fit
NFI	0.875	> 0.90	Marginal Fit

Source: Smart-PLS output (2026)

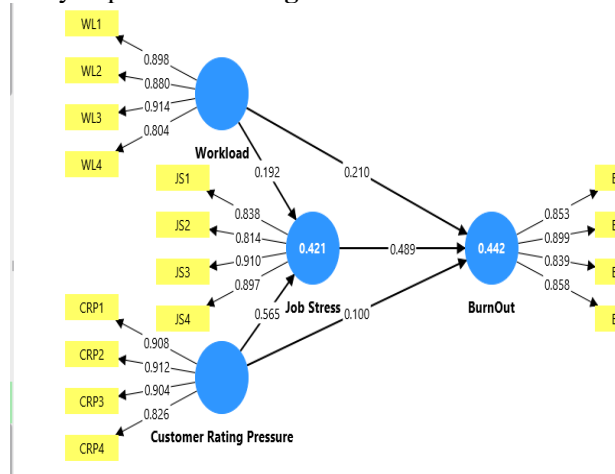
The model fit results indicate that the proposed model demonstrates an acceptable level of overall fit. The Standardized Root Mean Square Residual (SRMR) value of 0.053 is below the recommended threshold of 0.08, indicating a good fit between the observed and predicted correlations (Hair et al., 2019).

However, the Normed Fit Index (NFI) value of 0.875 is slightly below the recommended threshold of 0.90, suggesting a marginal fit. This implies that while the model performs reasonably well, there is still room for improvement in terms of model specification or inclusion of additional relevant variables (Hair et al., 2019).

Overall, despite the marginal NFI value, the model can still be considered adequately fit for predictive analysis, particularly within the context of PLS-SEM, which prioritizes prediction over strict model fit criteria.

To further illustrate the structural relationships among the constructs and provide a visual representation of the hypothesized model, the results of the Structural Equation Modeling (SEM) analysis are presented graphically. This figure displays the path coefficients and the direction of relationships between workload, customer rating pressure, job stress, and burnout, thereby offering a comprehensive overview of the tested model.

Accordingly, the structural model of this study is presented in **Figure 2**.



Source: Smart-PLS output (2026)

Figure 2. Structure Equation Model**Hypothesis Testing Results****Table 10.** Hypothesis Testing Results

Hypothesis	Relationship	Path Coefficient	t-value	p-value	Result
H1	Workload → Job Stress	0.192	2.612	0.009	Supported
H2	Customer Rating Pressure → Job Stress	0.565	8.601	0.000	Supported
H3	Job Stress → Burnout	0.489	5.772	0.000	Supported
H4	Workload → Burnout	0.210	2.835	0.005	Supported
H5	Customer Rating Pressure → Burnout	0.100	1.152	0.249	Not Supported
H6	Workload → Job Stress → Burnout	0.094	2.303	0.021	Supported
H7	Customer Rating Pressure → Job Stress → Burnout	0.277	4.717	0.000	Supported

Source: Smart-PLS output (2026)

The results of hypothesis testing provide strong empirical evidence supporting most of the proposed relationships in the model, with one notable exception.

First, workload has a positive and significant effect on job stress (H1 supported; $\beta = 0.192$, $p = 0.009$). This finding indicates that increased work demands contribute to higher levels of psychological strain among ride-hailing drivers. However, the relatively modest coefficient suggests that workload is not the dominant source of stress in this context.

Second, customer rating pressure exhibits a strong and highly significant effect on job stress (H2 supported; $\beta = 0.565$, $p < 0.001$). This result highlights that rating-based performance evaluation is the most influential factor driving stress among drivers. Compared to workload, rating pressure appears to exert a substantially stronger psychological impact.

Third, job stress has a significant positive effect on burnout (H3 supported; $\beta = 0.489$, $p < 0.001$). This confirms that prolonged exposure to stress leads to emotional exhaustion and reduced well-being, consistent with both the Job

Demands–Resources (JD-R) theory and the Conservation of Resources (COR) theory.

Fourth, workload directly influences burnout (H4 supported; $\beta = 0.210$, $p = 0.005$), although the magnitude of this effect is relatively small. This suggests that workload contributes to burnout not only indirectly through stress but also through a direct pathway.

In contrast, customer rating pressure does not have a significant direct effect on burnout (H5 not supported; $\beta = 0.100$, $p = 0.249$). This is a critical finding, indicating that rating pressure alone does not immediately lead to burnout unless it first induces psychological stress.

Regarding mediation effects, both indirect relationships are statistically significant. Job stress mediates the relationship between workload and burnout (H6 supported; $\beta = 0.094$, $p = 0.021$), indicating a partial mediation effect, as the direct relationship (H4) remains significant.

Furthermore, job stress also mediates the relationship between customer rating pressure and burnout (H7 supported; $\beta = 0.277$, $p < 0.001$). Given that the direct effect (H5) is not significant, this indicates a full mediation effect, where customer rating pressure influences burnout entirely through job stress.

Discussion

Workload and Job Stress (H1)

The findings confirm that workload has a positive and significant effect on job stress. This result indicates that increased working hours, time pressure, and task intensity contribute to psychological strain among ride-hailing drivers. From the perspective of the Job Demands–Resources (JD-R) theory, workload represents a core job demand that requires sustained effort, which in turn leads to energy depletion and stress.

However, the relatively modest effect size suggests that workload is not the primary stressor in this context. This can be explained by the nature of ride-hailing work, where drivers often have some degree of flexibility in managing their working hours. As a result, workload becomes a manageable demand, rather than an uncontrollable stressor. This finding aligns with recent studies indicating that flexibility can buffer the negative effects of workload in gig work settings ([Kellogg et al., 2019](#); [Wood et al., 2019](#)).

Novel insight: Workload still matters, but it is not the dominant stress trigger in platform-based work.

Customer Rating Pressure and Job Stress (H2)

Customer rating pressure is found to have a strong and significant effect on job stress, making it the most influential predictor in the model. This finding reflects the growing importance of algorithmic management, where performance is continuously monitored and evaluated through customer feedback systems.

Unlike workload, rating pressure is often perceived as uncontrollable and uncertain, as drivers cannot fully predict or influence customer ratings. This uncertainty creates psychological tension and anxiety. From the perspective of the Conservation of Resources (COR) theory, this condition represents a threat to valuable resources (e.g., income, job security), thereby triggering stress.

This result is consistent with prior studies showing that rating systems act as a form of digital control that intensifies worker stress ([Kellogg et al., 2019](#); [Lee et al., 2015](#)).

Novel contribution: This study highlights that algorithmic pressure outweighs traditional workload in shaping job stress.

Job Stress and Burnout (H3)

The results indicate that job stress has a strong and significant effect on burnout. This finding confirms the central mechanism proposed by both JD-R and COR theories, where prolonged stress leads to emotional exhaustion and burnout ([Hobfoll, 1989](#)).

In the ride-hailing context, continuous exposure to stress—such as dealing with customer demands, traffic conditions, and performance expectations—gradually depletes drivers' psychological resources. Over time, this leads to fatigue, reduced motivation, and burnout.

This finding is consistent with previous research demonstrating that job stress is a key predictor of burnout across various occupations ([Bakker & Demerouti, 2017](#); [Schaufeli, 2017](#)).

Key implication: Burnout is primarily a stress-driven outcome, not an immediate reaction to job demands.

Workload and Burnout (H4)

Workload is found to have a direct and significant effect on burnout, although the magnitude is relatively small. This suggests that excessive work demands can directly lead to fatigue and exhaustion, even without passing through psychological stress.

This direct effect may occur due to physical exhaustion, especially when drivers work long hours without sufficient rest (Wood et al., 2019). However, compared to its indirect effect through stress, the direct impact is weaker.

Interpretation: Workload contributes to burnout, but mainly through cumulative strain rather than immediate psychological pressure.

Customer Rating Pressure and Burnout (H5)

Interestingly, customer rating pressure does not have a significant direct effect on burnout. This finding challenges the assumption that all job demands directly lead to burnout.

One possible explanation is that rating pressure operates as a latent psychological stressor rather than a direct cause of exhaustion (Putri et al., 2023). Drivers may initially respond to rating pressure with increased vigilance or emotional regulation, which does not immediately translate into burnout.

Novel insight: Algorithmic pressure does not directly “burn out” workers—it first disrupts their psychological state.

Mediating Role of Job Stress (H6 & H7)

The mediation analysis reveals that job stress significantly mediates the relationship between both workload and burnout (partial mediation), and customer rating pressure and burnout (full mediation).

For workload, the presence of both direct and indirect effects indicates partial mediation, meaning workload influences burnout both directly and through stress.

In contrast, for customer rating pressure, the absence of a significant direct effect combined with a strong indirect effect indicates full mediation. This means that rating pressure affects burnout entirely through job stress.

Theoretical Implications

This study contributes to the literature in several important ways.

First, it extends the JD-R theory by demonstrating that not all job demands function in the same way. While workload operates through both direct and indirect mechanisms, customer rating pressure operates primarily through psychological stress pathways.

Second, this study enriches the COR theory by highlighting how algorithmic pressure represents a resource threat, particularly in terms of job security and income stability.

Third, the findings introduce the concept of “algorithmic stress dominance”, where digital evaluation systems exert stronger psychological effects than traditional workload demands.

Practical Implications

The findings of this study offer several practical implications for platform providers and policymakers.

First, ride-hailing platforms should reconsider the design of customer rating systems, as they significantly contribute to driver stress. Providing more transparent evaluation criteria and appeal mechanisms may help reduce perceived pressure.

Second, interventions aimed at reducing burnout should focus on stress management, rather than solely reducing workload. For example, platforms can provide mental health support, rest incentives, or stress awareness programs.

Third, policymakers should recognize gig workers as a vulnerable group and consider implementing labor protections, particularly in relation to algorithmic management practices.

CONCLUSION

Three key findings emerge from this study: **(1)** *customer rating pressure is the most dominant driver of job stress*, surpassing the influence of traditional workload, which indicates the growing impact of algorithmic management in shaping workers’ psychological conditions; **(2)** *job stress serves as the central mechanism leading to burnout*, confirming that burnout in the ride-hailing context is not an immediate reaction to job demands but rather the result of accumulated psychological strain; and **(3)** *customer rating pressure affects burnout only indirectly through job stress (full mediation)*, while workload influences burnout both directly and indirectly (partial mediation), highlighting that not all job demands operate through the same pathways.

These findings shift the focus from conventional workload-centered perspectives toward a deeper understanding of digital and psychological pressures embedded in platform-based work environments.

Research Limitations and Future Research Directions

This study is subject to several limitations that should be acknowledged. First, the use of a cross-sectional design limits the ability to

establish causal relationships over time. Future studies are encouraged to adopt longitudinal approaches to better capture the dynamic process through which stress evolves into burnout.

Second, this study focuses on a single geographic context (Makassar City), which may limit the generalizability of the findings. Future research could expand the scope to multiple cities or countries to provide comparative insights across different socio-economic and cultural settings.

Third, the model explains a moderate proportion of variance in burnout, suggesting that other relevant factors—such as social support, coping strategies, financial pressure, or job satisfaction—may further enrich the explanatory power of the model. Future studies are encouraged to incorporate these variables to develop a more comprehensive framework.

Additionally, future research could explore moderating variables, such as resilience or digital literacy, to better understand individual differences in responding to job demands and algorithmic pressures.

This study underscores a critical shift in understanding work-related stress in the digital era: the most significant pressures faced by gig workers are no longer purely physical, but increasingly psychological and algorithmic in nature. Recognizing and addressing these invisible stressors is essential for building more sustainable, humane, and resilient platform-based work systems.

REFERENCES

- Almazrouei, H., Alvarez-Torres, F. J., Schiuma, G., & Lopez-Torres, G. C. (2025). The digital creative organisation: are work–life balance, remote working and management support impacting in the creativity? *Measuring Business Excellence, ahead-of-print*(ahead-of-print). <https://doi.org/10.1108/MBE-10-2024-0177>
- Bakker, A. B., & Demerouti, E. (2017). Job demands–resources theory: Taking stock and looking forward. *Journal of Occupational Health Psychology, 22*(3), 273–285. <https://doi.org/10.1037/ocp0000056>
- Bakker, A. B., Demerouti, E., & Sanz-Vergel, A. (2023). Job Demands–Resources Theory: Ten Years Later. *Annual Review of Organizational Psychology and Organizational Behavior, 10*(Volume 10, 2023), 25–53. <https://doi.org/10.1146/annurev-orgpsych-120920-053933>
- Bokányi, E., & Hannák, A. (2020). Understanding Inequalities in Ride-Hailing Services Through Simulations. *Scientific Reports, 10*(1), 6500. <https://doi.org/10.1038/s41598-020-63171-9>
- Chen, X., Bai, S., Wei, Y., & Jiang, H. (2023). How income satisfaction impacts driver engagement dynamics in ride-hailing services. *Transportation Research Part C: Emerging Technologies, 157*, 104418. <https://doi.org/10.1016/j.trc.2023.104418>
- Cheng, Z. (Aaron), Pang, M.-S., & Pavlou, P. A. (2020). Mitigating Traffic Congestion: The Role of Intelligent Transportation Systems. *Information Systems Research, 31*(3), 653–674. <https://doi.org/10.1287/isre.2019.0894>
- Cramer, J., & Krueger, A. B. (2016). Disruptive Change in the Taxi Business: The Case of Uber. *American Economic Review, 106*(5), 177–182. <https://doi.org/10.1257/aer.p20161002>
- Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research, 18*(1), 39–50. <https://doi.org/10.2307/3151312>
- Ganster, Daniel C, & Rosen, Christopher C. (2013). Work Stress and Employee Health: A Multidisciplinary Review. *Journal of Management, 39*(5), 1085–1122. <https://doi.org/10.1177/0149206313475815>
- Ghozali, I. (2021). *Partial Least Square: Konsep, Teknik dan Aplikasi Menggunakan Smart PLS 3.2.9* (3rd ed.). Universitas Diponegoro.
- Grandey, A. A. (2000). Emotional regulation in the workplace: A new way to conceptualize emotional labor. *Journal of Occupational Health Psychology, 5*(1), 95–110. <https://doi.org/10.1037/1076-8998.5.1.95>
- HAFEEZ, S., GUPTA, C., & SPRAJCER, M. (2023). Stress and the gig economy: it's not all shifts and giggles. *Industrial Health, 61*(2), 140–150. <https://doi.org/10.2486/indhealth.2021-0217>

- Hair, J. F., Howard, M. C., & Nitzl, C. (2021). Review of Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A Workbook. In *Structural Equation Modeling: A Multidisciplinary Journal* (Vol. 30, Issue 1). <https://doi.org/10.1080/10705511.2022.2108813>
- Hair, J. F., Page, M., & Brunsveld, N. (2022). *Essentials of Business Research Methods* (14th ed.). Routledge. <https://doi.org/10.4324/9780367330743>
- Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2–24. <https://doi.org/10.1108/EBR-11-2018-0203>
- Halbesleben, J. R. B. (2006). Sources of social support and burnout: A meta-analytic test of the conservation of resources model. *Journal of Applied Psychology*, 91(5), 1134–1145. <https://doi.org/10.1037/0021-9010.91.5.1134>
- Halik, J. B., Rantererung, C. L., Sutomo, D. A., Rasinan, D., Daud, M., & Todingbua, M. A. (2024). *Era Disruptif* (J. B. Halik (ed.); 1st ed.). CV. Adanu Abimata. https://books.google.co.id/books?hl=en&lr=&id=kKUDEQAAQBAJ&oi=fnd&pg=PA179&ots=GVM0GTeahE&sig=ixF8ruUsRR4KmAtdE_GYwrlvO4k&redir_esc=y#v=onepage&q&f=false
- Hall, Jonathan V, & Krueger, Alan B. (2018). An Analysis of the Labor Market for Uber's Driver-Partners in the United States. *ILR Review*, 71(3), 705–732. <https://doi.org/10.1177/0019793917717222>
- Haryono, S. (2017). Metode SEM untuk penelitian manajemen dengan AMOS LISREL PLS. *Luxima Metro Media*, 450.
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115–135. <https://doi.org/10.1007/s11747-014-0403-8>
- Hobfoll, S. E. (1989). Conservation of resources: A new attempt at conceptualizing stress. *American Psychologist*, 44(3), 513–524. <https://doi.org/10.1037/0003-066X.44.3.513>
- Hobfoll, S. E., Halbesleben, J., Neveu, J.-P., & Westman, M. (2018). Conservation of Resources in the Organizational Context: The Reality of Resources and Their Consequences. *Annual Review of Organizational Psychology and Organizational Behavior*, 5(Volume 5, 2018), 103–128. <https://doi.org/10.1146/annurev-orgpsych-032117-104640>
- Kellogg, K. C., Valentine, M. A., & Christin, A. (2019). Algorithms at Work: The New Contested Terrain of Control. *Academy of Management Annals*, 14(1), 366–410. <https://doi.org/10.5465/annals.2018.0174>
- Lang, J. J., Yang, L. F., Cheng, C., Cheng, X. Y., & Chen, F. Y. (2023). Are algorithmically controlled gig workers deeply burned out? An empirical study on employee work engagement. *BMC Psychology*, 11(1), 354. <https://doi.org/10.1186/s40359-023-01402-0>
- Lee, M. K., Kusbit, D., Metsky, E., & Dabbish, L. (2015). Working with Machines: The Impact of Algorithmic and Data-Driven Management on Human Workers. *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, 1603–1612. <https://doi.org/10.1145/2702123.2702548>
- Maslach, C., & Jackson, S. E. (1981). The measurement of experienced burnout. *Journal of Organizational Behavior*, 2(2), 99–113. <https://doi.org/10.1002/job.4030020205>
- Memon, M. A., Ramayah, T., Ting, H., & Cheah, J. (2025). PURPOSIVE SAMPLING : A REVIEW AND GUIDELINES FOR QUANTITATIVE RESEARCH. *Journal of Applied Structural Equation Modeling*, 9(1), 1–23. [https://doi.org/10.47263/JASEM.9\(1\)01](https://doi.org/10.47263/JASEM.9(1)01)
- Park, S.-K., Rhee, M.-K., & Lee, S.-W. (2021). The effects of job demands and resources on turnover intention: The mediating roles of emotional exhaustion and depersonalization. *PubMed*, 70(1), 301–309. <https://doi.org/10.3233/WOR-213574>
- Parker, S. L., Dawson, N., Van den Broeck, A., Sonnentag, S., & Neal, A. (2021). Employee motivation profiles, energy levels, and approaches to sustaining energy: A two-wave latent-profile analysis. *Journal of Vocational Behavior*, 131,

103659.
<https://doi.org/10.1016/j.jvb.2021.103659>
- Pencavel, J. (2015). The Productivity of Working Hours. *The Economic Journal*, 125(589), 2052–2076.
<https://doi.org/10.1111/eoj.12166>
- Putri, T. E., Darmawan, P., & Heeks, R. (2023). What is fair? The experience of Indonesian gig workers. *Digital Geography and Society*, 5, 100072.
<https://doi.org/10.1016/j.diggeo.2023.100072>
- Rosenblat, A., & Stark, L. (2016). Algorithmic Labor and Information Asymmetries : A Case Study of Uber ’ s Drivers. *International Journal of Communication*, 10(2016), 3758–3784.
<https://doi.org/10.2139/ssrn.2686227>
- Santosa, P. I. (2018). *Metode Penelitian Kuantitatif: Pengembangan Hipotesis dan Pengujiannya Menggunakan SmartPLS* (Giovanny (ed.); 1st ed.). Penerbit ANDI.
- Schaufeli, W. B. (2017). Applying the Job Demands-Resources model: A ‘how to’ guide to measuring and tackling work engagement and burnout. *Organizational Dynamics*, 46(2), 120–132.
<https://doi.org/10.1016/j.orgdyn.2017.04.008>
- Sekaran, U., & Bougie, R. (2017). *Research Method for Business* (6th ed.). Salemba Empat.
- Spector, P. E., & Jex, S. M. (1998). Development of four self-report measures of job stressors and strain: Interpersonal Conflict at Work Scale, Organizational Constraints Scale, Quantitative Workload Inventory, and Physical Symptoms Inventory. *Journal of Occupational Health Psychology*, 3(4), 356–367. <https://doi.org/10.1037/1076-8998.3.4.356>
- Sugiyono. (2020). *Metode Penelitian Kuantitatif, kualitatif, dan R&D* (Sutopo (ed.); Edisi ke-2). Alfabeta.
- Wood, Alex J, Graham, Mark, Lehdonvirta, Vili, & Hjorth, Isis. (2019). Good Gig, Bad Gig: Autonomy and Algorithmic Control in the Global Gig Economy. *Work, Employment and Society*, 33(1), 56–75.
<https://doi.org/10.1177/0950017018785616>