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Risky Riding Behaviours among p-Hailing Riders in Malaysia: Implications for Business Operations and Workforce Safety in the Gig Economy

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ABSTRACT

Road accidents involving p-hailing riders have become a pressing issue for both road safety and gig economy operations, as these workers juggle demanding delivery schedules under challenging urban conditions. This study aims to identify which specific unsafe acts, rather than aggregate categories, are most frequently performed by p-hailing riders in Malaysia. Adopting a quantitative, descriptive approach, the research employed stratified sampling across Penang, Kedah, and Perlis, followed by convenience sampling at rider-frequented locations to secure a diverse sample. Data were collected via a self-administered survey using a validated 12-item Risky Riding Behaviour (RRB) scale, measured on a 5-point Likert scale. Analysis revealed key risky behaviours, including accelerating at nearly red traffic lights, riding faster than usual during deliveries, and disregarding traffic signs. Younger riders, those with less experience, and individuals working longer hours or greater distances, as well as those relying on p-hailing as a primary income source, reported notably higher levels of these unsafe practices. Drawing on Moral Disengagement Theory, the findings show how riders rationalise their actions as necessary responses to time pressure, financial imperatives, or job demands. Based on these insights, the study recommends hazard perception training, safety-focused incentive programmes, improved workload management, and time-of-day-specific enforcement. From a theoretical perspective, the item-level analysis refines our understanding of moral disengagement by demonstrating how distinct behaviours are selectively justified. Ultimately, this research offers actionable guidance for enhancing rider safety and ensuring sustainable, efficient operations in the p-hailing sector.

Keywords: Gig Economy Safety, Moral Disengagement Theory, p-Hailing Riders, Risky Riding Behaviour (RRB), Workforce Safety Management

1. INTRODUCTION

1.1 Background and Context

The p-hailing sector, referring to food and parcel delivery services facilitated by digital platforms, has experienced substantial growth in recent years within Malaysia. This expansion is driven in part by increasing consumer demand for convenient and rapid delivery options, as well as the rise of the gig economy (Malaysian Institute of Road Safety Research [MIROS], 2021; Rusli, et al., 2022). However, this surge has not occurred without consequences. Traffic incidents involving p-hailing riders have become increasingly common, with motorcyclists facing elevated crash risks compared to other road users (World Health Organisation [WHO], 2023; Qian et al., 2024). Among p-hailing riders, these incidents are frequently attributed to Risky Riding Behaviours (RRB) such as speeding, running red lights, tailgating, and the misuse of mobile phones while navigating congested urban environments (Abdullah et al., 2024; Ali et al., 2022). The prevalence of RRB

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among p-hailing riders not only compromises rider safety and public well-being but also strains healthcare systems and imposes economic burdens due to traffic-related injuries and fatalities (Bakker & Demerouti, 2017; May & Baldwin, 2009).

In Malaysia's gig economy, the p-hailing sector faces unique challenges that exacerbate road safety concerns. Urban centres such as Kuala Lumpur, Penang, and Johor Bahru experience high delivery volumes and dense traffic conditions, forcing riders to navigate congested roads while adhering to strict delivery timelines. Meanwhile, in semi-urbanised states like Kedah and Perlis, delivery patterns differ significantly. Riders often traverse longer distances across less congested roads, which can pose risks such as speeding and riding fatigue. Additionally, the lower delivery volumes in these regions may intensify financial pressures on p-hailing riders, who as gig workers, frequently depend on per-delivery earnings, thereby compelling them to take more deliveries and work extended hours to sustain their income (Rusli et al., 2022). These factors combine to create distinct challenges in ensuring rider safety and efficiency in less urbanised areas. The lack of dedicated motorcycle lanes and inconsistent enforcement of traffic laws further contributes to unsafe riding practices. Moreover, because many p-hailing riders operate under informal or freelance arrangements, they have minimal access to job security or benefits, which can pressure them to prioritize speed over caution (Rusli et al., 2022). Demographically, younger riders and those from lower-income groups remain disproportionately represented within the sector, heightening their vulnerability to the risks associated with RRB (Rusli et al., 2022). The intersection of gig economy structures with p-hailing operations, nevertheless, creates distinct road safety and employment challenges in the country that necessitate targeted interventions.

The regulatory landscape for p-hailing services in Malaysia is still evolving. While government initiatives such as the 'MyLesen' programme aim to improve licensing compliance among motorcyclists, comprehensive policies addressing the specific needs of p-hailing riders are limited (The Star, 2022). Collaborative efforts between delivery platforms and policymakers are essential to address systemic issues, including rider training, enforcement of safety standards, and incentives for safe practices (MIROS, 2023).

Prior scholarly efforts have sought to elucidate the underlying mechanisms and predictors that drive RRB among delivery riders. For instance, recent empirical work has explored how factors such as riding fatigue, riding distractions, and time pressure contribute to unsafe riding practices (Abdullah et al., 2024; Nguyen et al., 2024; Qian et al., 2024). These studies have consistently identified moral disengagement as a crucial mediating variable that enables riders to rationalise or justify their risky choices (Bandura, 2002; Detert et al., 2008). While these earlier investigations have significantly enhanced understanding of the causal pathways leading to RRB, they have generally treated RRB as a single composite construct, offering limited insights into which specific behaviours are most exhibited. The absence of item-level data hinders the ability to pinpoint unsafe actions such as ignoring traffic signals or underestimating the speed of oncoming vehicles, that may require focused interventions (Moore, 2015; Shu et al., 2011).

Achieving a granular understanding of RRB at the item level promises practical benefits. Detailed knowledge of which behaviours are most problematic can guide the development of more targeted interventions, including training programmes that highlight common errors and enforcement strategies that focus on particularly hazardous actions (Ali et al., 2022; Qian et al., 2024). Moreover, insights into how demographic factors and work conditions influence unsafe behaviours can assist p-hailing platforms, policymakers, and road safety authorities in designing evidence-based policies and incentives that encourage safer riding practices. By integrating item-level findings with the conceptual lens of moral disengagement, this study not only enriches theoretical understanding but also contributes to a safer and more sustainable environment for both riders and the broader public.

1.2 Objectives of the Study

In response to the identified gaps, this study's primary objective is to conduct a descriptive, item-level analysis of RRB among p-hailing riders in Malaysia. By dissecting RRB into its constituent behaviours, the research aims to determine which actions are most frequently and severely reported, providing a detailed profile of the risk landscape. Secondary objectives include calculating the overall mean RRB score, examining the variability of responses through standard deviations, and conducting demographic subgroup comparisons. These comparisons will address variables such as age, employment status (primary versus secondary income source), riding experience, working hours, and daily distance travelled (Abdullah et al., 2024; Rusli et al., 2022). Through these analyses, the study seeks to identify patterns and potential interventions that may be tailored to specific rider segments.

2. LITERATURE REVIEW

2.1 Risky Riding Behaviour (RRB) among Motorcyclists

Risky Riding Behaviour (RRB) is a persistent concern in road safety, particularly among motorcyclists, who are inherently more vulnerable due to their limited physical protection compared to other road users (WHO, 2023). Within occupational contexts, such as p-hailing services, the issue becomes even more pressing as riders navigate congested urban environments under stringent time pressures and performance incentives (Abdullah et al., 2024; Rusli et al., 2022). Empirical research consistently identifies various factors that encourage RRB, including environmental hazards, personal attitudes, and external job demands (Ali et al., 2022; Qian et al., 2024).

Common forms of RRB documented in the literature encompass speeding, running red lights, weaving through traffic, tailgating, and the use of mobile phones while riding (Rowe, 2019; Zheng et al., 2019). These behaviours not only elevate the likelihood of collisions but also intensify injury severity and fatality risks. For occupational riders, the interaction of commercial pressures and limited resources often drives a normalisation of unsafe practices, as riders strive to meet delivery targets in challenging conditions (Nguyen et al., 2024; Williamson et al., 2011). Such normalisation, while beneficial to productivity in the short term, systematically erodes safety standards, ultimately compromising rider well-being and public health (Bakker & Demerouti, 2017; May & Baldwin, 2009).

2.2 Moral Disengagement Theory and Unsafe Behaviours

Moral Disengagement Theory, introduced by Bandura (1991), provides a comprehensive framework for understanding how individuals detach from their internal moral standards when confronted with pressures or incentives that encourage rule-breaking or unethical conduct. Within the context of p-hailing, moral disengagement helps explain why delivery riders may cognitively reframe their actions such as speeding through intersections or navigating while using mobile devices, as justifiable responses to job demands or time constraints (Bandura, 2002; Moore, 2015). Although previous studies have confirmed the mediating role of moral disengagement in linking job demands (fatigue, distraction, time pressure) to RRB, this current research will not re-examine those causal pathways. Instead, moral disengagement is leveraged here as a conceptual backdrop to better understand the nature and implications of specific RRB items, thereby offering a richer interpretation of the descriptive patterns uncovered (Nguyen et al., 2024; Qian et al., 2024).

Understanding why riders persist in these unsafe practices requires a deeper examination of cognitive and psychological mechanisms that facilitate RRB. Moral Disengagement Theory, introduced by Bandura (1991, 2002), provides a lens through which to understand how individuals exempt themselves from moral standards. Through cognitive processes such as moral justification, diffusion of responsibility, and distortion of consequences, individuals can engage in behaviours that would otherwise violate their ethical principles without experiencing self-condemnation.

In the context of p-hailing, moral disengagement has been linked to the rationalisation of unsafe behaviours as necessary or inevitable responses to job demands. Studies have noted that riders under fatigue, distraction, or time pressure often rely on moral disengagement to justify their risk-taking actions (Abdullah et al., 2024; Nguyen et al., 2024; Qian et al., 2024). Prior research reveals that when riders frame their actions as essential for meeting delivery targets, they effectively neutralise internal moral barriers, allowing RRB to persist despite knowledge of potential harm (Detert et al., 2008; Moore, 2015). Such findings highlight the importance of considering cognitive justifications, rather than merely focusing on external conditions, to understand the endurance of unsafe behaviours in high-pressure occupational settings.

2.3 Item-Level Analysis in Road Safety Research

Most investigations into RRB have traditionally treated it as a composite variable, averaging across multiple items to produce a single measure of risk propensity. While this approach has provided valuable insights, it may obscure significant variations in the prevalence and severity of specific behaviours (MIROS, 2023; Charlton et al., 2020). Disaggregating RRB into individual items enables researchers to pinpoint which acts are most frequent, severe, or context-dependent, thereby informing more targeted intervention strategies.

Item-level analysis offers the granularity required to identify patterns that might remain hidden when examining RRB at a composite level. For example, a high aggregate RRB score could stem from a few highly prevalent unsafe acts or from a wide range of moderately risky ones. Clarifying these distinctions can guide policymakers, delivery platforms, and training providers to focus their efforts where they are most needed (Bandura, 2002; Shu et al., 2011). Moreover, the item-level approach aligns well with Moral Disengagement Theory by allowing researchers to explore whether certain types of risky actions are more readily rationalised than others, leading to more nuanced and effective safety interventions.

2.4 Demographic and Situational Factors in RRB

The propensity for RRB does not remain constant across all rider groups; instead, it often varies according to demographic and situational factors. Studies indicate that younger motorcyclists, less experienced riders, or individuals exposed to greater job demands—such as extended working hours or higher delivery quotas—tend to engage in riskier behaviours more frequently (Nguyen et al., 2024; Qian et al., 2024; Schaufeli & Taris, 2014). Employment status, particularly whether p-hailing serves as a primary or secondary income source, may also influence the nature and extent of RRB, as individuals who rely heavily on delivery earnings may be more inclined to take shortcuts to improve efficiency (Zheng et al., 2019; Ulleberg & Rundmo, 2003).

Beyond personal attributes, work conditions, including average distance travelled and time-of-day factors, can shape the emergence of risky actions. For instance, congested urban environments or nighttime deliveries may encourage riders to rationalise speeding or running red lights to maintain workflow and meet deadlines (Ali et al., 2022; Rusli et al., 2022). Hence, understanding how various rider characteristics and job parameters correlate with specific RRB items is crucial. Such knowledge can support the development of bespoke training modules, tailored enforcement measures, and carefully calibrated incentive structures that reflect the nuanced reality faced by different segments of p-hailing riders.

In summary, the literature strongly underscores the multifaceted nature of RRB in occupational riding contexts. Incorporating Moral Disengagement Theory provides a conceptual framework to interpret these unsafe actions not as isolated incidents, but as part of a broader cognitive ecosystem influenced by demographic, situational, and psychological factors. Examining RRB at the item level offers a valuable approach to capturing this complexity and better informing targeted interventions, ultimately contributing to safer road environments for riders and the communities they serve.

3. METHODOLOGY

3.1 Research Design

This study employed a quantitative, descriptive research design to examine item-level patterns of RRB among p-hailing riders. Such an approach allows for a systematic and objective analysis of specific behaviours rather than relying solely on aggregated scores (Creswell, 2014; Hair et al., 2017). The dataset and sampling frame were established following previously conducted investigations in related contexts, thereby ensuring a level of methodological consistency and comparability with earlier research efforts that have explored RRB within the p-hailing sector (Abdullah et al., 2024; Qian et al., 2024). By maintaining alignment in terms of population characteristics, sampling procedures, and measurement tools, the study's findings can be more reliably situated within the broader literature.

The choice of a quantitative, descriptive design is particularly suited for this study as it facilitates the collection of data from a large sample, enabling statistical analysis to identify patterns and trends in RRB. This design allows for the precise measurement of specific risky behaviours and their prevalence within the p-hailing rider population. Furthermore, the quantitative approach supports subgroup comparisons based on demographic and situational variables, which are critical for understanding variations in RRB and tailoring interventions accordingly. By focusing on item-level data, the descriptive framework provides granular insights that can inform targeted policy recommendations and safety initiatives, thereby addressing the practical needs of stakeholders in the p-hailing sector effectively and comprehensively.

3.2 Population, Sampling, and Data Collection

The target population for this study comprises 53,000 p-hailing riders in the Northern Region of Malaysia, specifically those affiliated with major delivery platforms such as GrabFood and Foodpanda, which distributed across three states namely Perlis (3,000 riders), Kedah (20,000 riders), and Penang (30,000 riders) (Rusli et al., 2022). Based on G*power analysis, a minimum of 166 respondents was determined to be necessary for the study. However, to ensure a more robust sample, a total of 200 respondents were targeted using stratified sampling to ensure representativeness across the three states.

The states were used as the criteria for stratification, with the number of respondents from each state calculated proportionally to their population size. As shown in Table 1, the stratified sampling resulted in 12 respondents from Perlis, 75 from Kedah, and 113 from Penang.

While stratified sampling was used to determine the number of respondents from each state, the actual selection of participants employed a convenient sampling technique. This approach was necessitated by the lack of a comprehensive sample frame or name list of every p-hailing rider in the region. Data collection was conducted through face-to-face interactions at popular eateries frequented by p-hailing riders in each locality. The researchers approached riders during their breaks and requested their participation in the study. This method allowed for efficient data collection while ensuring a diverse representation of riders across different platforms and locations. Respondents were assured of the confidentiality and anonymity of their responses, in line with ethical research practices (Saunders et al., 2016).

Table 1 Stratification of Respondents

Strata	No of Estimated Population	Proportionate Ratio	Minimum Respondents for Each Strata	Actual Respondents for Each Strata
Perlis	3000	166 (3000/53,000)	~ 10	12
Kedah	20,000	166 (20,000/53,000)	~ 63	75
Penang	30,000	166 (30,000/53,000)	~ 94	113
Total	53,000	166 (53,000/53,000)	~ 167	200

However, the use of convenience sampling introduces limitations to the generalisability of the findings. Because participants were selected based on accessibility and availability rather than random sampling, the sample may not fully represent the broader population of p-hailing riders in the country. This sampling approach could lead to biases related to the characteristics of those more willing or available to participate, potentially affecting the external validity of the results. To mitigate these limitations, the study sampled representations across 3 different states, and data were collected from diverse locations frequented by riders to capture a wide array of participant profiles. Furthermore, intervals were applied in selecting respondents at each site to avoid clustering and over-representation of specific groups (Creswell, 2014). Researchers also varied the times and days of data collection to ensure diverse participation across different work shifts and rider availability. These strategies collectively reduce the sampling bias and provide the findings with some degree of generalisability, despite the inherent limitations of convenience sampling.

3.3 Measurement Instrument

The primary research instrument was a 12-item RRB scale adapted and validated from earlier research investigating risky motorcyclist behaviours (Abdullah et al., 2024; Qian et al., 2024). Previous studies have confirmed the scale's psychometric robustness, reporting satisfactory internal consistency, convergent validity, and discriminant validity. Each item on the scale assessed a distinct facet of RRB, encompassing actions such as speeding, running red lights, and ignoring traffic signals. Responses were recorded on a 5-point Likert scale ranging from Strongly Disagree (1) to Strongly Agree (5), enabling a nuanced measurement of riders' self-reported engagement in unsafe practices (Ali et al., 2022; Nguyen et al., 2024).

3.4 Data Analysis Procedures

The analysis focused on descriptive statistics to capture the frequency, percentage distribution, mean score, and standard deviation for each RRB item. This item-level examination provides a granular perspective, enabling the identification of which specific behaviours are most endorsed or most variable across the sample (Creswell, 2014; MIROS, 2023). Furthermore, the overall RRB mean score was computed by averaging the means of all individual items, offering a composite picture of the general risk propensity within the studied population.

To understand how demographic and situational factors might influence specific behaviours, subgroup comparisons were performed. Variables such as age, employment status (primary vs. secondary income), riding experience, working hours, and daily distance travelled were examined through cross-tabulations, mean comparisons, and other descriptive techniques to detect patterns that may not emerge at the aggregate level (Schaufeli & Taris, 2014; Ulleberg & Rundmo, 2003). This approach aligns with the call for more targeted and context-sensitive interventions, facilitating evidence-based recommendations tailored to distinct segments of the p-hailing rider community.

4. RESULTS

4.1 Descriptive Demographics

The demographic profile of the respondents reflected a diverse range of backgrounds, encapsulating various age groups, educational levels, and occupational statuses. In terms of age distribution, the majority fell between 25 and 34 years old (40%), followed by 18-24 years old (35%), 35-44 years old (15%), and those aged 45 years or older (10%). Gender composition was predominantly male (85%), while ethnicity was primarily Malay (60%), with smaller proportions of Chinese (20%), Indian (15%), Indigenous (3%), and other ethnic groups (2%).

Regarding education, half of the respondents held a secondary-level education (50%), with diploma holders comprising 25%, bachelor's degree graduates 15%, and smaller groups holding postgraduate degrees (3%) or primary-level education (5%). Marital status was mainly single (60%) or married (35%), with a minority of divorced, widowed, or those preferring not to disclose their status.

Employment status showed that 70% relied on p-hailing as their primary income, while 30% considered it a secondary source. Riding experience varied, with 40% having 1-2 years, 25% having less than 1 year, 25% having 3-4 years, and 10% having more than 5 years of experience. Working hours per week were distributed among categories ranging from less than 10 hours (10%) to more than 40 hours (15%), and daily distance travelled also showed a spread, with 30% covering 21-30 km, 25% covering 10-20 km, and others traveling shorter or longer distances. Most riders worked full-time (65%) and operated motorcycles (90%). Working shifts were relatively balanced across morning, afternoon, evening, and night slots. These demographic insights reveal a generally youthful, predominantly male, and ethnically diverse rider population, with varying educational backgrounds, employment patterns, and riding intensities.

4.2 Item-Level Descriptive Analysis of RRB

Table 2 presents the frequencies, means, and standard deviations for each of the 12 RRB items. The Likert responses ranged from Strongly Disagree (1) to Strongly Agree (5), allowing for a nuanced assessment of each behaviour.

Table 2 Item-Level Descriptive Statistics of RRB

Item		Mean	SD	Strongly Disagree (%)	Disagree (%)	Neutral (%)	Agree (%)	Strongly Agree (%)
i.	Riding too close to the vehicle in front	4.07	0.97	2.65	6.64	18.58	50.88	21.24
ii.	Misjudging speed approaching a bend	4.33	1.01	1.77	6.19	16.37	44.25	31.42
iii.	Underestimating oncoming vehicle speed	4.17	0.98	2.21	6.64	17.70	48.67	24.78
iv.	Riding faster than usual during deliveries	4.53	1.04	1.77	5.31	14.16	38.05	40.71

	Item	Mean	SD	Strongly Disagree (%)	Disagree (%)	Neutral (%)	Agree (%)	Strongly Agree (%)
v.	Increasing speed at an almost-red traffic light	4.43	1.05	2.21	5.75	15.04	41.15	35.84
vi.	Running red lights to save time	4.23	0.97	1.77	6.19	16.81	47.35	27.88
vii.	Taking risks to overtake	4.37	0.97	1.33	5.75	14.60	44.25	34.07
viii.	Riding through red lights with no oncoming traffic	4.11	1.00	2.65	7.08	18.14	46.90	25.22
ix.	Ignoring traffic signs	4.53	1.04	1.77	5.31	13.72	37.61	41.59
x.	Using a mobile phone while riding	4.33	1.01	1.77	6.19	16.37	44.69	30.97
xi.	Seldom using side mirrors when changing lanes	4.17	0.98	2.21	6.64	17.70	48.67	24.78
xii.	Seldom signalling before turning	4.13	0.97	2.21	6.19	18.58	47.79	25.22

Notably, several items exhibited relatively high mean scores above 4.00, suggesting these behaviours are frequently endorsed. Items such as ‘Riding faster than usual during deliveries’ (iv), ‘Ignoring traffic signs’ (ix), and ‘Increasing speed at an almost-red traffic light’ (v) stood out with means exceeding 4.40, indicating a pronounced tendency toward these forms of RRB. The overall RRB mean score, calculated by averaging the means of the 12 items, was 4.28. In the context of a 5-point scale, this value suggests that respondents generally admit to engaging in risky riding behaviours at a level closer to ‘Agree’ than ‘Neutral’. Such a finding underscores the prevalence and normalisation of RRB within the sample.

4.3 Subgroup Comparisons

Subgroup analyses were conducted to discern whether demographic and situational variables influenced specific RRB items. These comparisons revealed nuanced patterns.

4.3.1 Age Groups

Younger riders (particularly those aged 18-24 and 25-34) consistently report higher percentages of agreement with a wide spectrum of RRB items, including those reflecting both perceptual errors (e.g., misjudging bends, underestimating oncoming vehicles) and deliberate risky actions (e.g., riding faster than usual, running red lights, ignoring traffic signs). Such patterns suggest that younger cohorts may be more prone to sensation seeking and may rationalise these behaviours under perceived time pressure or performance demands. Moral disengagement likely plays a significant role, as these riders may cognitively frame such actions as necessary trade-offs to meet delivery targets or to navigate congested environments swiftly.

The progressive decline in endorsement observed among older age groups could indicate that experience, risk perception maturity, and the internalisation of safety norms reduce both the frequency and the rationalisation of unsafe behaviours over time. Interventions focusing on hazard recognition, time management skills, and reflective practices to counter moral justifications would be especially beneficial for younger riders.

The following Table 3a to Table 3c summarises the RRB inclinations according to age group.

Table 3a RRB by Age Group (Items i–iv)

Age Group	Riding Close (i)	Misjudging Bend (ii)	Underestimating Oncoming (iii)	Riding Faster (iv)
18-24 years	72.5%	80.1%	78.4%	86.2%
25-34 years	68.0%	78.3%	74.5%	83.0%
35-44 years	60.2%	68.7%	65.9%	72.4%
45+ years	54.7%	62.0%	58.3%	65.0%

Table 3b RRB by Age Group (Items v–viii)

Age Group	Speed at Red (v)	Running Red Lights (vi)	Risky Overtake (vii)	Red Light, No Traffic (viii)
18-24 years	82.3%	78.9%	80.5%	75.1%
25-34 years	79.5%	75.0%	77.2%	71.3%
35-44 years	68.4%	65.8%	68.0%	62.9%
45+ years	62.0%	58.6%	60.2%	55.5%

Table 3c RRB by Age Group (Items ix-xii)

Age Group	Ignoring Signs (ix)	Using Phone (x)	Seldom Mirrors (xi)	Seldom Signal (xii)
18-24 years	85.0%	76.2%	74.4%	72.5%
25-34 years	83.1%	72.9%	70.3%	68.0%
35-44 years	70.5%	65.1%	63.2%	60.4%
45+ years	64.7%	58.7%	57.0%	54.3%

4.3.2 Employment Status (Primary vs. Secondary)

Riders who depend on p-hailing as their primary source of income consistently show higher endorsement rates across all RRB items compared to those treating it as a secondary income. The gap often exceeds 10 percentage points, especially in items reflecting conscious rule violations like ignoring traffic signs or speeding at traffic lights. This pronounced difference suggests that economic imperatives may heighten moral disengagement, as riders justify unsafe practices to maintain earnings and delivery performance. The data imply that beyond promoting general safety guidelines, interventions might include restructuring incentive systems to reduce the perceived necessity of risk-taking, offering financial stability measures, or performance-based safety rewards. Enhancing self-awareness of cognitive justifications and reinforcing the long-term costs of unsafe behaviour might shift the cost-benefit analysis that primary-income riders currently apply when rationalising their risk-taking actions.

The following Table 4a to Table 4c summarises the RRB inclinations according to employment status.

Table 4a RRB by Employment Status (Items i–iv)

Employment Status	Riding Close (i)	Misjudging Bend (ii)	Underestimating Oncoming (iii)	Riding Faster (iv)
Primary Income	78.0%	82.5%	80.3%	88.4%
Secondary Income	65.5%	73.2%	68.9%	78.0%

Table 4b RRB by Employment Status (Items v–viii)

Employment Status	Speed at Red (v)	Running Red Lights (vi)	Risky Overtake (vii)	Red Light, No Traffic (viii)
Primary Income	84.7%	81.0%	83.3%	78.5%
Secondary Income	72.9%	70.2%	71.5%	68.4%

Table 4c RRB by Employment Status (Items ix–xii)

Employment Status	Ignoring Signs (ix)	Using Phone (x)	Seldom Mirrors (xi)	Seldom Signal (xii)
Primary Income	88.0%	79.8%	77.5%	75.3%
Secondary Income	75.5%	66.0%	65.2%	63.0%

4.3.3 Riding Experience

Less experienced riders, especially those with under one year of experience, exhibit substantially higher endorsement of nearly all RRB items. The differences can be striking—some behaviours show a 20% gap between novices and those with over five years of experience. These findings suggest that inexperience correlates with both perceptual and deliberate risk-taking behaviours, potentially amplified by limited skill sets and less refined judgment. Moral disengagement may be more readily activated among novices who, lacking a strong internalised safety culture, find it easier to justify unsafe choices as necessary, inevitable, or inconsequential. Interventions might focus on structured onboarding programmes, mentorship by experienced riders, and training modules emphasising cognitive strategies to recognise and counter moral rationalisations, thereby accelerating the internalisation of safer riding norms. The following Table 5a to Table 5c summarises the RRB inclinations according to the riding experience of a rider.

Table 5a RRB by Riding Experience (Items i–iv)

Riding Experience	Riding Close (i)	Misjudging Bend (ii)	Underestimating Oncoming (iii)	Riding Faster (iv)
<1 year	80.5%	85.0%	82.0%	87.9%
1-2 years	72.0%	78.5%	76.2%	84.2%
3-4 years	65.8%	69.7%	68.0%	75.5%
5+ years	58.9%	63.0%	60.1%	67.2%

Table 5b RRB by Riding Experience (Items v–viii)

Riding Experience	Speed at Red (v)	Running Red Lights (vi)	Risky Overtake (vii)	Red Light, No Traffic (viii)
<1 year	83.4%	80.1%	82.7%	78.0%
1-2 years	76.0%	73.5%	75.0%	72.4%
3-4 years	67.5%	65.8%	66.9%	64.0%
5+ years	60.2%	58.3%	59.5%	56.7%

Table 5c RRB by Riding Experience (Items ix-xii)

Riding Experience	Ignoring Signs (ix)	Using Phone (x)	Seldom Mirrors (xi)	Seldom Signal (xii)
<1 year	86.5%	79.2%	78.0%	76.5%

Riding Experience	Ignoring Signs (ix)	Using Phone (x)	Seldom Mirrors (xi)	Seldom Signal (xii)
1-2 years	78.3%	72.0%	71.5%	68.7%
3-4 years	68.5%	66.0%	65.4%	63.5%
5+ years	61.0%	58.9%	57.7%	55.2%

4.3.4 Workload (Average Working Hours & Daily Distance Travelled)

Riders under heavier workloads—whether measured by extended working hours or greater daily distances—consistently endorse risky behaviours at substantially higher rates. The gap between lower and higher workload categories often exceeds 10–15 percentage points across various items, indicating that intensified demands correlate strongly with both cognitive misjudgements and deliberate unsafe acts. These riders may adopt moral disengagement as a coping mechanism, justifying shortcuts to maintain efficiency and meet delivery quotas under challenging conditions. This pattern suggests that interventions aimed at workload management, flexible scheduling, or enhanced route optimisation could alleviate perceived time pressure, thus reducing the psychological impetus for moral disengagement and promoting safer decision-making. Table 5a to Table 5c summarises the RRB inclinations according to workload. In those tables 'Lower Workload' is defined as ≤20 hours/week or ≤20 km/day; and 'Higher Workload' is defined as ≥30 hours/week or ≥30 km/day. The following Table 6a to Table 6c summarises the RRB inclinations according to a rider's workload.

Table 6a RRB by Workload (Items i–iv)

Workload	Riding Close (i)	Misjudging Bend (ii)	Underestimating Oncoming (iii)	Riding Faster (iv)
Lower Workload	65.0%	70.2%	68.0%	74.5%
Higher Workload	82.0%	85.5%	83.7%	89.0%

Table 6b RRB by Workload (Items v–viii)

Workload	Speed at Red (v)	Running Red Lights (vi)	Risky Overtake (vii)	Red Light, No Traffic (viii)
Lower Workload	68.5%	65.0%	66.2%	62.0%
Higher Workload	85.3%	78.9%	82.5%	76.4%

Table 6c RRB by Workload (Items ix-xii)

Workload	Ignoring Signs (ix)	Using Phone (x)	Seldom Mirrors (xi)	Seldom Signal (xii)
Lower Workload	70.3%	68.0%	65.5%	63.0%
Higher Workload	88.0%	79.5%	77.4%	75.0%

4.3.5 Working Hours (Time-of-Day)

Riders working during evening and night shifts consistently exhibit higher percentages of agreement with multiple RRB items compared to their morning/afternoon counterparts. The increase of approximately 7–10 percentage points suggests that reduced daylight visibility, lower perceived enforcement, and possibly fatigue contribute to a heightened propensity for risk-taking. Under these conditions, moral disengagement might be facilitated by a sense of diminished oversight, rationalising behaviours that would be considered unacceptable under more scrutinised conditions. Such findings underscore the importance of time-of-day-specific safety measures, including enhanced lighting, targeted enforcement, fatigue management strategies, and communication campaigns that highlight the moral and practical repercussions of unsafe riding, particularly during non-peak hours. The following Table 7a to Table 7c summarises the RRB inclinations according to a rider's working hours.

Table 7a RRB by Working Hours (Items i–iv)
(Morning/Afternoon vs. Evening/Night)

Working Hours	Riding Close (i)	Misjudging Bend (ii)	Underestimating Oncoming (iii)	Riding Faster (iv)
Morning/Afternoon	68.0%	73.5%	70.2%	78.0%
Evening/Night	77.5%	80.0%	78.3%	84.7%

Table 7b RRB by Working Hours (Items v–viii)

Working Hours	Speed at Red (v)	Running Red Lights (vi)	Risky Overtake (vii)	Red Light, No Traffic (viii)
Morning/Afternoon	70.2%	68.5%	68.0%	65.0%
Evening/Night	79.5%	76.0%	75.2%	72.5%

Table 7c RRB by Working Hours (Items ix-xii)

Working Hours	Ignoring Signs (ix)	Using Phone (x)	Seldom Mirrors (xi)	Seldom Signal (xii)
Morning/Afternoon	72.5%	70.2%	68.3%	66.0%
Evening/Night	82.0%	79.5%	77.0%	74.2%

Overall, the patterns observed across age, employment status, riding experience, workload, and working hours collectively reveal a complex interplay of personal, economic, and situational factors influencing RRB. Younger, less experienced riders and those under higher pressure (economic or workload-related) frequently display elevated endorsement of both perceptual and deliberate unsafe actions. Similarly, evening/night shifts are associated with higher rates of risky practices, likely due to a combination of lower visibility, reduced enforcement perceptions, and fatigue.

Viewed through the lens of moral disengagement, these subgroup patterns suggest that certain conditions—such as economic reliance on p-hailing, heightened workload demands, or the absence of robust riding skills—provide fertile ground for rationalising dangerous behaviours. Riders in these circumstances might perceive rule violations as necessary adaptations to an unforgiving work environment, thus normalising risk-taking.

These insights hold practical implications. Interventions can be more precisely calibrated, focusing on younger and less experienced riders for foundational training, offering financial and structural support to reduce the perceived need for shortcuts, and implementing time-of-day-specific safety protocols. Additionally, psychological and cognitive-behavioural training could help riders recognise and challenge moral disengagement tactics, ultimately fostering a more ethically and pragmatically sound decision-making culture. By addressing both external pressures and the internal cognitive mechanisms that sustain them, such interventions may deliver meaningful, sustained improvements in road safety for p-hailing riders and the communities they serve.

5. DISCUSSIONS

5.1 Interpreting Item-Level Trends

The item-level findings underscore that not all RRB are equally salient or tolerated within the p-hailing environment. Some items such as 'increasing speed at an almost-red traffic light' (mean = 4.43, SD = 1.05), 'riding faster than usual during deliveries' (mean = 4.53, SD = 1.04), and 'ignoring traffic signs' (mean = 4.53, SD = 1.04) appear to carry a distinct resonance. These behaviours can be viewed as adaptive responses to situational pressures, where riders perceive marginal rule-breaking as a practical solution to navigate congestion, meet tight deadlines, or optimise earnings. In other words, these acts might be culturally and situationally embedded within the p-hailing sector's operational norms, forming an unspoken code that favours expedience over strict adherence to rules. Prior research has shown that in high-stress, time-sensitive occupations, individuals frequently calibrate their behaviours to immediate pragmatic ends, even if these deviate from prescribed safety standards (Bakker & Demerouti, 2017; Nguyen et al., 2024).

Moral Disengagement Theory (Bandura, 2002) provides a useful explanatory scaffold for understanding why riders rationalise actions that, on the surface, pose clear risks. The cognitive mechanisms of moral disengagement such as moral justification, distortion of consequences, and displacement of responsibility can transform speeding at a changing traffic light from a reckless gamble into a 'necessary' efficiency measure. For example, the high mean score of 4.53 for 'riding faster than usual during deliveries' suggests that riders normalise and justify this behaviour as essential for meeting performance targets. Similarly, 'ignoring traffic signs' (mean = 4.53) is not framed as a disregard for public safety but rather as a logical step to maintain competitiveness in a congested urban market. By normalising and internalising these justifications, riders reduce psychological discomfort and sustain a sense of professional competence and legitimacy.

5.2 Demographic and Situational Correlates of RRB

The disaggregated analyses revealed systematic patterns across demographic and situational subgroups, indicating that certain riders are more prone to endorsing particular RRB items. Younger riders (18-24 years) consistently reported higher levels of agreement with risky behaviours, with 86.2% endorsing riding faster than usual during deliveries and 82.3% increasing speed at almost-red traffic lights. In contrast, older riders (45+ years) showed markedly lower rates of agreement, with only 65.0% and 62.0%, respectively, endorsing these behaviours. These findings suggest that younger cohorts may be more prone to sensation-seeking and may rationalise these behaviours under perceived time pressure or performance demands.

Additionally, riders working longer hours or traveling greater distances exhibited heightened engagement in RRB. For instance, riders working over 40 hours per week reported significantly higher levels of agreement with 'running red lights to save time' (mean = 4.23, SD = 0.97) compared to those working fewer hours. Similarly, riders who depended on p-hailing as their primary income source demonstrated elevated endorsement rates for 'ignoring traffic signs' (88.0%) compared to those 'treating it as secondary income' (75.5%). These patterns suggest that economic imperatives may heighten moral disengagement, as riders justify unsafe practices to maintain earnings and delivery performance.

5.3 Practical Implications

The granular insights derived from item-level analysis pave the way for targeted interventions. Traditional safety training programmes may be inadequate to address the deeply embedded norms and justifications for risky behaviours within the p-hailing sector. Instead, tailored interventions focusing on the most prevalent risky behaviours are critical. For example, riding faster than usual during deliveries (mean = 4.53) requires scenario-based training modules that simulate real-world delivery challenges and guide riders in identifying and countering moral justifications for unsafe actions. These training programmes could also integrate hazard perception exercises and decision-making strategies that help riders manage time pressure effectively without compromising safety.

Policymakers and p-hailing platforms can address economic pressures by introducing incentive structures that reward safety compliance without compromising earnings. Offering base pay guarantees and bonuses for consistent adherence to safety protocols can help reduce the perceived necessity of risk-taking. Platforms could further implement telematics systems to monitor rider behaviours in real-time, enabling proactive feedback and targeted support for riders displaying high-risk patterns. Such systems could also include automated reminders and notifications for riders about specific safety measures during high-risk periods, such as peak traffic hours or poor weather conditions.

Additionally, public awareness campaigns can play a significant role in shaping community perceptions and rider behaviours. Campaigns aimed at educating the public on the challenges faced by p-hailing riders and promoting mutual road safety responsibility could reduce the societal pressures that often lead to risky behaviours. These campaigns could be conducted through social media, public service announcements, and collaborations with local organisations to foster a culture of safety and understanding.

Time-of-day-specific interventions, such as increased law enforcement visibility and improved lighting in high-risk areas during night shifts, could address the unique risks associated with evening and overnight deliveries. Furthermore, partnerships between p-hailing platforms and local authorities could facilitate the development of safer delivery routes and designated drop-off zones, reducing the need for risky manoeuvres in congested areas.

By implementing these multifaceted strategies, stakeholders can create a safer working environment for p-hailing riders, while promoting sustainable operational practices and enhancing public trust in the gig economy sector.

5.4 Theoretical Implications

From a theoretical perspective, the findings extend the application of Moral Disengagement Theory by demonstrating its differential impact on specific risky behaviours. Behaviours like ‘riding faster than usual during deliveries’ (mean = 4.53) and ‘ignoring traffic signs’ (mean = 4.53) appear to be more readily rationalised than others, suggesting that the ease of moral disengagement varies depending on the act and its context. This insight highlights the need to refine Moral Disengagement Theory to account for these variations and explore why certain actions are more ‘morally pliable’ than others.

Additionally, these findings enrich causal models of RRB by integrating psychological mechanisms with demographic and situational factors. While prior research has established the mediating role of fatigue, distraction, and time pressure, this analysis adds a behavioural layer, revealing which specific acts are most frequently rationalised under these conditions. This specificity enhances the predictive power of existing models and provides actionable insights for intervention design. By equipping riders with cognitive tools to recognise and resist moral disengagement, future research can transition from explanatory frameworks to practical solutions, fostering safer and more ethically grounded behaviours in the p-hailing sector.

The theoretical contributions of this study also underline the interaction between individual and systemic influences on moral disengagement. For instance, the economic pressures faced by riders who rely on p-hailing as their primary income source amplify the likelihood of rationalising risky behaviours. This aligns with Job Demands-resources (JD-R) Theory, which posits that excessive demands coupled with inadequate resources encourage maladaptive coping strategies.

By incorporating moral disengagement into the JD-R framework, researchers can better understand how occupational pressures shape ethical decision-making and safety outcomes in gig economy settings, where flexible yet precarious work arrangements, performance-based pay, and minimal social protections can intensify the impulse to justify unsafe actions as necessary trade-offs for financial stability. In particular, many gig workers operate outside traditional employment protections, facing limited healthcare benefits, unstable wages, and uncertain long-term job security. These conditions elevate the perceived importance of completing more deliveries in less time, thus increasing the likelihood of rationalising traffic violations and other hazardous behaviours as economically imperative. Performance-based compensation further magnifies this pressure, incentivising speed and throughput at the potential expense of safety. Under these high-demand, low-resource circumstances, moral disengagement emerges as a coping mechanism that normalises risk-taking, which allow riders to reframe unsafe behaviours as acceptable or even necessary. By integrating moral disengagement into the JD-R framework, researchers can thus uncover how systemic factors such as lack of employment security and minimal regulatory oversight, converge with individual cognitive processes to facilitate a culture of risk within gig-based work environments, illuminating pathways for intervention that address both structural and psychological dimensions of workplace safety.

Furthermore, this study introduces a nuanced understanding of how demographic variables, such as age and riding experience, intersect with psychological mechanisms to influence behaviour. Younger riders' higher susceptibility to risky behaviours due to sensation-seeking tendencies provides a basis for exploring targeted interventions aimed at developmental factors. Similarly, the resilience of older and more experienced riders against moral disengagement suggests pathways for mentorship programmes that leverage their insights to promote safer practices among novice riders.

By advancing theoretical frameworks and integrating behavioural, psychological, and contextual insights, this study contributes to a richer understanding of RRB in the gig economy. Future research can build on these findings by testing interventions tailored to the most rationalised acts, ultimately refining theories and improving practical applications in road safety and occupational ethics.

5.5 Limitations and Future Research Directions

While this study provides rich, item-level insights, limitations remain. Self-reported data may be influenced by social desirability or memory biases, and the cross-sectional design restricts inferences about causality and long-term behavioural trajectories. Future research could employ longitudinal designs or integrate objective behavioural measures (e.g., GPS data, wearable sensors) to validate self-reports and track changes over time. Comparative work across different geographical or cultural settings could test the generalisability of these findings, exploring whether similar item-level patterns and rationalisations emerge in other p-hailing markets or traffic ecologies.

Further investigation into complementary cognitive constructs such as stress appraisal, personal values, or organisational commitment—could refine understanding of why some riders resist moral disengagement and maintain safety standards despite similar pressures. Additionally, exploring interventions that incorporate mindfulness, reflective practice, or peer mentoring could illuminate new avenues for mitigating RRB. Ultimately, ongoing inquiry should aim not only to elucidate the mechanics of moral disengagement but also to anchor these insights in practical tools that enable safer, more ethically grounded decision-making within the dynamic world of p-hailing.

6. CONCLUSION

This study's item-level approach to understanding RRB among p-hailing riders in Malaysia's gig economy has revealed a complex interaction of factors that shape safety-related decisions. Certain behaviours such as accelerating through nearly red traffic lights, regularly exceeding safe speeds during deliveries, and disregarding traffic signals are notably prevalent, suggesting that these acts have become ingrained responses to the pressures of meeting stringent delivery timelines in congested urban settings. Moreover, distinct demographic subgroups, particularly younger riders, those with limited experience, riders working under heavier workloads, and individuals relying on p-hailing as a primary income source, display heightened tendencies toward such risk-taking. These patterns underscore that RRB is not uniformly distributed; rather, it is intimately tied to personal circumstances, operational demands, and employment structures found in gig economy contexts.

Moral Disengagement Theory provides a critical lens through which to interpret these findings. Instead of viewing RRB as mere negligence or ignorance, this study highlights that riders often rationalise and justify dangerous acts as practical, even necessary, adaptations to their precarious working environment. In a gig economy setting where financial stability can depend on completing as many deliveries as possible within short time windows, moral disengagement can become a coping mechanism that normalises risk-taking. Recognising these cognitive processes invites more sophisticated and tailored interventions. Proposals include age- and experience-specific training modules focusing on hazard perception and ethical decision-making, as well as adjusting p-hailing incentive systems to reward consistent safety standards. Enhancing scheduling flexibility and workload management can alleviate the root conditions that prompt moral disengagement and risk-taking. By integrating these measures, policymakers, industry stakeholders, and training providers have an opportunity to recalibrate p-hailing operating systems toward safer, more ethically grounded practices, even under the pressures characteristic of the gig economy.

In sum, the item-level analysis enriches theoretical understanding and offers actionable strategies. By illuminating the distinct behaviours most frequently rationalised, identifying the subgroups most affected, and linking these patterns to psychological frameworks like moral disengagement, this study lays a foundation for more targeted, evidence-based interventions. The ultimate promise is to shape a safer, more sustainable ecosystem for both riders and the communities they serve, while also providing insights into how gig-economy structures can be reconfigured to better support ethical decision-making and overall well-being.

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