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Distracted on duty: A theory-based exploration of influences leading to mobile phone distracted riding among food delivery workers

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ABSTRACT

Using mobile phones while riding is a form of distracted riding that significantly elevates crash risk. Regrettably, the factors contributing to mobile phone use while riding (MPUWR) among food delivery riders remain under-researched. Addressing this literature gap, the current study employs the Job Demands-Resources (JD-R) model and various socio-economic factors to examine the determinants of MPUWR. The research incorporates data from 558 delivery workers in Hanoi and Ho Chi Minh City, Vietnam. The study utilizes two analytical methods to empirically test the hypotheses, considering non-linear relationships between variables: Partial Least Square Structural Equation Modelling (PLS-SEM) and Artificial Neural Network (ANN). The results reveal mixed impacts of factors connected to job resources. Although social support appears to deter MPUWR, work autonomy and rewards seemingly encourage it. Furthermore, a predisposition towards risk-taking behaviour significantly impacts the frequency of mobile phone usage among delivery riders. Interestingly, riders with higher incomes and those who have previously been fined by the police exhibit more frequent mobile phone use. The findings of this study present valuable insights into the crucial factors to be addressed when designing interventions aimed at reducing phone use among food delivery riders.

1. Introduction

Mobile Phone Use While Riding (MPUWR) is a risky behavior associated with road crashes. Although an increasing number of studies aim to understand the motives behind this behavior to prevent MPUWR (Nguyen-Phuoc et al., 2020b, Nguyen et al., 2020, Rusli et al., 2020), there is a dearth of knowledge regarding MPUWR in professional contexts, such as food delivery riding (Zhang et al., 2020). It is noteworthy that, compared to conventional riders, commercial riders face unique challenges (Wu and Loo, 2016, Nguyen-Phuoc et al., 2020a). For them, mobile phone use is essential as it serves as the main interface between the riders and the algorithm that provides real-time location-based services (e.g., tracking positions, finding routes to destinations), along with order and customer details. As a result, MPUWR is a prevalent risky behavior among this group. According to Nguyen-Phuoc et al., (2020a), 28.6 % of 602 app-based taxi motorcyclists in Vietnam regularly or often engage in MPUWR, whereas only 10 % display the second most common behavior (i.e., neglecting signals). The rise of delivery riding as a popular employment option worldwide, fueled by online shopping trends during the COVID-19 pandemic (Nguyen et al., 2021), underscores the necessity to investigate the factors intrinsic to food delivery activities that are associated with MPUWR.

The existing literature on phone use among food delivery riders is largely descriptive (Zhang et al., 2020, Zheng et al., 2019, Nguyen-Phuoc et al., 2020a, 2023). We contend that prior research has some limitations. Firstly, MPUWR is often studied alongside other risky riding behaviors, which does not allow the identification of activity-specific factors impacting MPUWR. Past research on distracted driving suggests that unique task-specific factors determine engagement in distracted driving (Oviedo-Trespalacios et al., 2018a,b). Secondly, job factors associated with MPUWR need systematic consideration. Prior research has shown that organizational psychology theories can be

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useful in explaining risky riding behaviors (Nguyen-Phuoc et al., 2022a). Lastly, the analytical approach of prior research, reliant on logistic regression and structural equation modelling, overlooks non-linear relationships among factors influencing MPUWR (Zabukovšek et al., 2019).

This study aims to address the research gaps mentioned above by analysing the factors influencing the frequency of MPUWR behaviours among delivery riders in Vietnam. A theoretical model is developed based on the Job Demands – Resources (JD-R) model, commonly used to investigate the reasons for unsafe working outcomes (Bronkhorst, 2015, Barbier et al., 2013, Nahrgang et al., 2011). It has also been applied in the delivery riding context to explain engagement in risky riding behaviours and road safety compliance (Nguyen-Phuoc et al., 2022a). A newly proposed methodology, which integrates Partial Least Squares Structural Equation Modelling (PLS-SEM) with Artificial Neural Network (ANN), is presented to discern the significance of these determinants. Specifically, ANN is utilized to better model and scrutinize non-linear and non-compensatory relationships between factors influencing MPUWR, as identified by the PLS-SEM approach. This study is innovative in its proposal of a theory-driven conceptual framework to explain engagement in MPUWR. The research was conducted in two major cities in Vietnam (Hanoi and Ho Chi Minh City), both of which have experienced significant growth in e-shopping and, consequently, delivery services over the years, especially during the COVID-19 era (Nguyen et al., 2021).

2. Background

Mobile phone use is one of the most common distractions on the road, and it is associated with a high number of crashes and injuries (Shaaban et al., 2020, Asbridge et al., 2012, Tractinsky et al., 2013, Oviedo-Trespalacios et al., 2016, McEvoy et al., 2005, Forgays et al., 2014). Antecedents of phone use on the road have been thoroughly investigated in the literature using theoretical frameworks. For example, Ajzen's (1985) theory of planned behavior has been widely utilized to understand the psychosocial antecedents of mobile phone use on the road (Rozario et al., 2010, Walsh et al., 2008, Przepiorka et al., 2018, Eijigu, 2021, Gauld et al., 2017). In these studies, attitudes appear to be the most influential predictor, compared to variables such as perceived behavioural control and subjective norms (Sullman et al., 2021, Tian and Robinson, 2017, Gauld et al., 2017, Phuksuksakul et al., 2021). However, this finding might not be applicable in the context of professional drivers/riders, as mobile phones can also be used for work-related services such as GPS and communication with other stakeholders. For food delivery services, delivery service apps are used by riders to check order information, navigate the route, contact customers, and sometimes compete with other co-workers for orders (Zhang et al., 2020, Oviedo-Trespalacios et al., 2022). Despite the importance of job factors on mobile phone use while riding (MPUWR) among professional drivers/riders, the current literature has concentrated on specific factors and proxy indicators, e.g., working experience (Claveria et al., 2019, Troglauer et al., 2006), psychological perceptions (Nguyen-Phuoc et al., 2020b), and personal traits (Zhang et al., 2020). The lack of a work-specific theory examining the working environment in studies of mobile phone use while on the road is a crucial gap in the literature that could potentially improve the health outcomes of delivery riders. To address this gap, we propose the framework presented in Fig. 1, which is explained in the following sections.

3. Hypotheses development

3.1. Job demands-resources model

The job demands-resources (JD-R) model was introduced by Demerouti et al. (2001), who categorized aspects of work into two primary factors: demands and resources. Under the effect of job demands, employees are prone to exhaustion and burnout, leading to withdrawal behaviors (Demerouti et al., 2001). Compensating for such negative impacts, job resources at workplace foster employee-company relationship, represented by strong commitment and work productivity among employees (Bakker and Demerouti, 2007). When job demands surpass job resources, employers are more likely to experience job strain

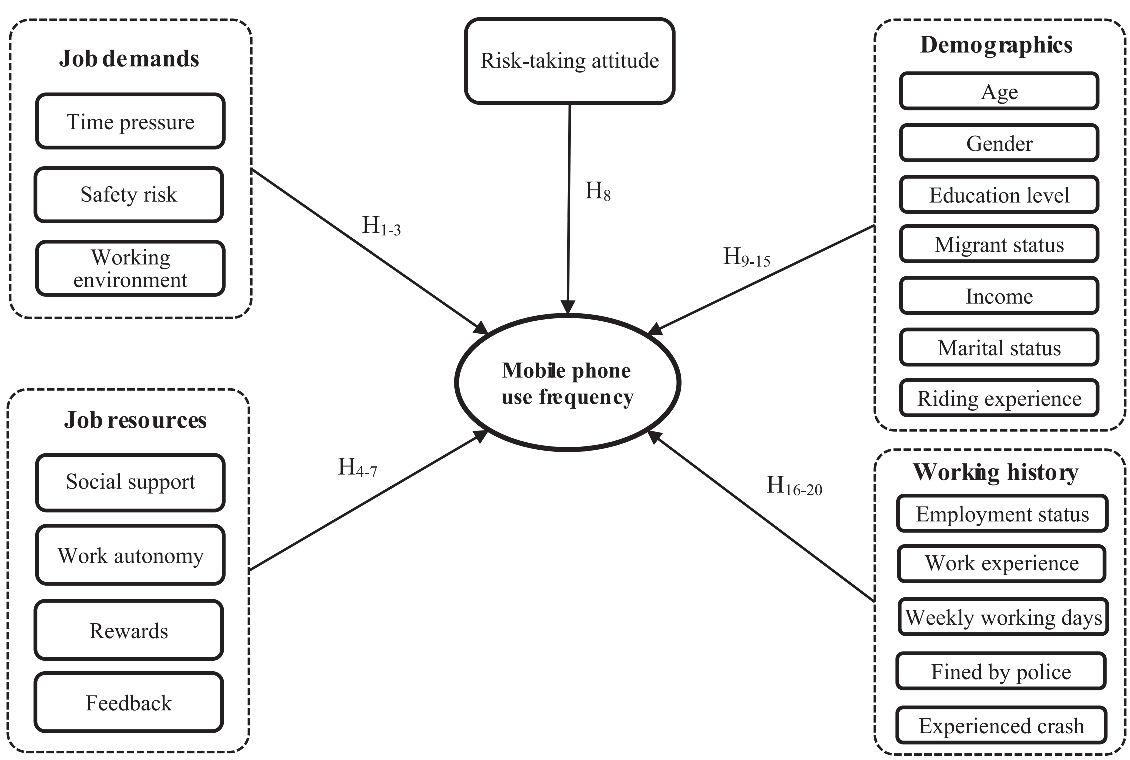

Fig. 1. Proposed conceptual model.

(Bakker and Demerouti, 2007).

Job demands are defined as "those physical, psychological, social, or organisational aspects of the job that require sustained physical and/or psychological (cognitive and emotional) effort or skills and are therefore associated with certain physiological and/or psychological costs" (Demerouti et al., 2001). Several complex job demands are present in food delivery riding. First, delivery riders are remunerated based on the number of delivered orders and penalties for delayed deliveries, which creates time and performance pressures (Zheng et al., 2019, Oviedo-Trespalacios et al., 2022, Nguyen-Phuoc et al., 2022a). Numerous empirical studies showed that time pressure is a common stressor among professional drivers (Silla and Gamero, 2018, Cœugnet et al., 2013, Dorn et al., 2010) triggered by the lack of time to fulfil job-related tasks (Kinicki and Vecchio, 1994). Second, delivery riders frequently engage in multitasking as their work requires them to simultaneously control their vehicle and interact with their phones. Previous research demonstrated that phone use is more commonly observed among delivery riders than private riders (Oviedo-Trespalacios et al., 2022). Third, motorcyclists are inherently vulnerable compared to car users as they are at a higher risk of severe injury in case of a crash. Lack of protection against collisions and exposure to air pollution are some of the problems that they experience to a larger extent compared to motor vehicle drivers (Martínez-Buelvas et al., 2022). A key consideration is that whilst road crashes and injuries may be rare events, riders will still suffer psychological costs due to their risky working environment (Nahrgang et al., 2011).

Whilst limited studies have scrutinised the relationship between work-related demands and riders' hand-held mobile phone use frequency, some hypotheses can be designed following previous work on phone use while driving. Regarding time pressure, as most delivery riders experience time pressure (Landy et al., 1991, Zheng et al., 2019), they are most likely to prioritise speeding instead of engaging in distracted driving which results in lower speeds (Oviedo-Trespalacios et al., 2019a). Regarding perceived crash risk, there have been contradictory findings. Numerous studies show that riders and drivers perceiving substantial crash risks tend to avoid phone use while on the road (Oviedo-Trespalacios et al., 2017a, Hallett et al., 2011, Nguyen-Phuoc et al., 2020b, Almansoor and Jahan, 2021, Truelove et al., 2019, Jamil et al., 2021). Alternatively, some studies suggest that individuals who intend to use mobile phones while on the road can have a large risk awareness (Walsh et al., 2008, Nurullah et al., 2013, Ivers et al., 2009). This can be explained by external (including work), practical, social, and psychological benefits, which can influence their risk appraisal (Atchley et al., 2011, Creaser et al., 2015, White et al., 2007). The pivotal role that mobile phones have for food delivery riders could also influence risk appraisal. Finally, the complexity of the environment also adds to the riders' demands influencing decisions to engage in mobile phone use while in control of the motorcycle. Arguably, riding on certain types of roads (i.e., uneven surfaces, slippery roads, crowded areas with many pedestrian lanes, junctions, and roundabouts) requires investing more attentional resources compared to simpler roads. Naturally, as suggested by distracted driving research, more complex roads reduce their capacity to engage in phone use as both phone use and vehicle control are competing for attentional resources (Onate-Vega et al., 2020). Based on this evidence, the following hypotheses were formulated:

H1: *Time pressure is significantly associated with mobile phone use frequency*
H2: *Safety risk is significantly associated with mobile phone use frequency*
H3: *Working environment is significantly associated with mobile phone use frequency*

'Job resources' is defined as "those physical, psychological, social, or organizational aspects of the job that may do any of the following: (a) be functional in achieving work goals, (b) reduce job demands at the associated physiological and psychological costs, (c) stimulate personal growth and development." (Demerouti et al., 2001). To buffer the negative consequences of job demands (e.g., high perceived risk), social support is a vital job resource at the organisational and interpersonal levels (Cheung et al., 2021, Conchie et al., 2013, Bakker and Demerouti, 2007), which creates a safety climate at workplaces. Social support, which reflects "overall levels of helpful social interaction available on the job" (Karasek and Theorell, 1990), can perform not only through management/ leadership (e.g., organisational policies about payment, practices, and procedures) but also through safety-oriented assistance or reminders among colleagues (Hall et al., 2010, Andrei et al., 2020, Swedler et al., 2015, Cheung et al., 2021). Furthermore, delivery riders are regarded as lone workers whose activities are executed in isolation from their co-workers and without direct or close supervision (Hughes and Ferrett, 2011). Social support interventions should be more effectively implemented relatively to traditional workplaces (Huang et al., 2014).

Regarding task-level resources, job autonomy, feedback, and rewards are significant dimensions (Bakker and Demerouti, 2007). Job autonomy indicates the degree of employees' freedom and independence in performing occupational tasks such as scheduling, decision-making, and goal-setting (Wall et al., 1995, Morgeson and Humphrey, 2006, Breaugh, 1985). High job control would motivate employees to gain the initiative to assist customers and satisfy their individual demands (Chen and Chen, 2014). Although there exists controversy concerning work autonomy in the IT-enabled sharing economy (Hua et al., 2020), Wang et al. (2021)' findings showed that delivery riders obtain freedom and flexibility in many aspects, such as cash transfer, working hours, and gestures. In addition, driver reward programs, which are applied as an employee incentive scheme for delivery service providers, have been expanded, especially in the aftermath of COVID-19 (Chapman, 2021). Rewards can be offered in the form of financial incentives, recognition/ approval, and career opportunities (i.e., promotion prospects, job security, and status consistency) (Siegrist, 1996). For example, after a fixed period, cash rewards will be offered to recognise outstanding riders who completed a certain number of orders, maintained high customer ratings, and had low cancellation rates. Demerouti et al. (2001) also attested that performance feedback is the primary job resource of employees in transportation. Particularly, food delivery applications allow customers to give feedback to food delivery riders as soon as goods are successfully delivered. Hence, in addition to constructive feedback from supervisors and managers, customer feedback also enhances the understanding of customers' demands among food delivery riders, thereby motivating them to be work more effectively in next deliveries.

H4: *Social support is significantly associated with mobile phone use frequency*
H5: *Work autonomy is significantly associated with mobile phone use frequency*
H6: *Rewards are significantly associated with mobile phone use frequency*
H7: *Feedback is significantly associated with mobile phone use frequency*

3.2. Socio-economic characteristics

Socio-economic variables are widely regarded as significant determinants of risky road behaviours. Among personal characteristics, age and gender have been examined in connection with risky behaviours (Oviedo-Trespalacios and Phillips, 2021; Nurullah et al., 2013; Sullman et al., 2015). In general, older drivers tend to avoid phone use while on the road (Oviedo-Trespalacios et al., 2019b). Concerning gender, studies have found higher rates of handheld mobile phone use among male drivers (Walsh et al., 2008; Lyon et al., 2020; Truong et al., 2016; McDonald et al., 2018b). In a developing country context, like Malaysia, female motorcyclists were found to use mobile phones more frequently while riding than their male counterparts (Rusli et al., 2020). However, Oviedo-Trespalacios et al., (2017a) found no gender-based difference in reported mobile phone use likelihood. Although age and gender have been extensively studied in the context of drivers' mobile phone use behaviour, fewer studies have focused specifically on delivery riders.

Regarding education, several studies suggest that drivers with higher educational attainment are more likely to engage with mobile phones while driving, valuing their time highly (Márquez et al., 2015; Montuori et al., 2021; Donkor et al., 2018; Ismeik et al., 2015; Martínez-Gabaldón et al., 2019). However, this positive association may not hold for food delivery riders, who often use their phones for work-related purposes.

From a psychological standpoint, attitudes, defined as an individual's beliefs and feelings towards an object or situation, play a critical role. The literature suggests that a more positive attitude towards road safety diminishes intentions to dial or text while driving (Walsh et al., 2008; Nemme and White, 2010; Oviedo-Trespalacios et al., 2017a; Oviedo-Trespalacios, 2018; Nguyen-Phuoc et al., 2020b). Further, Sullman et al. (2021) empirically demonstrated that attitudes substantially influence mobile phone usage rates in challenging driving conditions.

The relationship between migrant status and income with MPUWR is not well-established in the literature. While a direct correlation between migrant status and mobile phone engagement among professional drivers has yet to be evidenced, migrant delivery riders have been observed to exhibit more risky behaviours such as red-light running (Talaat and Yuan, 2017), speeding (Shepherd, 2017), and mobile phone use (Zhou, 2018). Migrant drivers who move to larger cities often face the considerable pressure of not only earning a living but also supporting their families. They may resort to dangerous driving behaviours to complete delivery tasks faster and maximise their wages. Higher incomes among drivers are correlated with increased incidences of mobile phone use while driving (McDonald et al., 2018a; Li et al., 2014; Nurullah et al., 2013).

In terms of marital status, Shulman and Cauffman (2014) argued that single young adults are more prone to risky behaviours while driving, such as using mobile phones, feeling they have less to lose, aligning with findings by Martínez-Gabaldón et al., 2019. Another plausible explanation is that single drivers tend to be more socially active than their married counterparts, increasing their desire to use mobile phones ubiquitously, even while driving (Claveria et al., 2019).

Although riding experience has been widely recognized as a significant determinant of mobile phone usage frequency while driving, there is some debate about the nature of this effect. Some researchers (e.g., Donkor et al., 2018; Ismeik et al., 2015) have found that more experienced drivers tend to engage in improper behaviour while driving, including using their mobile phones. However, these findings conflict with other studies suggesting that drivers who have held a valid license for a longer duration have a lower incidence of phoning while driving (Oviedo-Trespalacios, 2018; Montuori et al., 2021; Oviedo-Trespalacios et al., 2018a,b; Sullman and Baas, 2004; Terry and Terry, 2015; McEvoy et al., 2007; Oviedo-Trespalacios et al., 2017a; Klauer et al., 2014). Notably, Oviedo-Trespalacios (2018) confirmed that every additional year of holding a valid driving license corresponds to a 3 % decrease in the hourly incidence of texting, calling, and browsing events by drivers. The following hypotheses were formulated:

H8: *Risk-taking attitude is significantly associated with mobile phone use frequency*
H9: *Age is significantly associated with mobile phone use frequency*
H10: *Gender is significantly associated with mobile phone use frequency*
H11: *Education level is significantly associated with mobile phone use frequency*
H12: *Migrant status is significantly associated with mobile phone use frequency*
H13: *Income is significantly associated with mobile phone use frequency*
H14: *Marital status is significantly associated with mobile phone use frequency*
H15: *Riding experience is significantly associated with mobile phone use frequency*

3.3. *Working history*

Occupational factors such as employment status, work experience, weekly working days, fines by police, and experienced crashes. Individuals who drive more days per week often engage in distractions such as mobile phone conversations (Prat et al., 2017), which is consistent with the finding of Nguyen-Phuoc et al. (2020b)'s study about app-based motorcycle taxi drivers. The authors also signified that employment status was not a determinant of MPUWR since part-time drivers (e.g., students) and full-time ones can have the equivalent number of working hours. However, in human resource literature, it is evidenced that temporary workers have a lower commitment to rule compliance and obligations compared to full-time or permanent employees (Sharma and Warkentin, 2019, De Cuyper et al., 2008). Other studies (e.g., Ismeik et al., 2015, Nurullah et al., 2013) also found a relationship between employment status and mobile phone usage while driving despite utilising different employment status categories. Furthermore, experienced cohorts expressed compliance with safety procedures better than their inexperienced counterparts, which was evidenced in occupational safety literature (Ayim Gyekye and Salminen, 2010). It is indicated that novice riders whose working experience within six months reported a high rate of road safety violations (Shin et al., 2019, Byun et al., 2020). Based on the above arguments, three hypotheses are stated concerning the impact of delivery riders' employment status, work experience, and weekly working days on safety-related behaviour, including MPUWR.

Although there has not yet been research proving the association between experienced fines by police and increased frequency of mobile phone use, Truelove et al. (2021) revealed that heightened awareness of the penalty for MPUWR would deter and reduce engagement in this illegal behaviour. When individuals perceive a greater likelihood of being punished for the offence, the penalty can play the role of an inhibitor of ongoing recidivism (Nagin et al., 2015, Piquero et al., 2011, Homel, 1988). In addition, interestingly, it was explored that drivers who had experienced one or more traffic crashes were likely to continue performing distracted behaviour of mobile phone use (Zhou et al., 2020, Petzoldt, 2020, Brubacher et al., 2017, Oviedo-Trespalacios, 2018). To conclude, this study posits that delivery riders who have been fined by police and experienced traffic crashes would influence the propensity of using hand-held mobile phones while riding.

H16: *Employment status is significantly associated with mobile phone use frequency*
H17: *Work experience is significantly associated with mobile phone use frequency*
H18: *Weekly working days are significantly associated with mobile phone use frequency*
H19: *Experienced fines by police are significantly associated with mobile phone use frequency*
H20: *Experienced crash is significantly associated with mobile phone use frequency*

4. Methods

4.1. *Survey*

The instruments for the survey were adapted from the extant literature on constructs tested in this study (see Table A1). Specifically, time pressure, safety risk, and working environment were measured by four (Demerouti et al., 2001, Zheng et al., 2019), three (Gregory, 2020), and three (Demerouti et al., 2001) items, respectively. Twelve attitudinal statements deployed by Breaugh (1999); Cheung et al. (2021);

Demerouti et al. (2001); Radic et al. (2020) were utilised to assess social support at organise and co-worker levels, work autonomy, feedback, and rewards (see Table 1). The measurement of risk-taking attitude was implemented via the use of four items (Iversen, 2004) while we adopted four items to evaluate mobile phone use frequency. A Likert scale using seven points was devised to gather the riders' views on statements. The survey was originally devised in English and interpreted into Vietnamese for practical purpose. The questionnaire's validity was obtained based on the review and comments of an expert panel with four transport researchers and two practitioners. A pilot test with ten riders was undertaken to detect potential issues occurring during the large-scale survey. The questionnaire was finalised with some minor revisions made.

4.2. Data collection

Data were collected in Hanoi and Ho Chi Minh City between 10 April 2021 and 9 May 2021. During this time, the effective management of the COVID-19 pandemic allowed us to carry out face-to-face interviews with riders at public places where riders usually gathered while waiting for orders. Our surveyors, who are trained students, directly issued invitations to the riders. Prior to participating in the primary survey, participants were required to provide their informed consent, which included details about the voluntary nature of participation, the associated risks and benefits, and the procedures in place to maintain confidentiality. Once they agreed, participants were provided with paper-based questionnaires and asked to complete the questionnaire form before receiving an incentive of approximately 1 USD. An alternative to completing the survey for riders was to provide oral answers for surveyors to note into the form. Of more than 600 forms distributed, 572 were successfully re-collected. However, due to the lack of reliability and missing data, 14 were eliminated, resulting in the final sample of 558 responses utilised for further factor analyses.

4.3. Data analysis

For accomplishing hypothesis testing purposes, PLS-SEM was used because it is broadly demonstrated to model the relationships among latent variables in an extension of theory from a sample with a limited size and/or a non-normal distribution (Hair et al., 2010). Furthermore, there has been a growing preference for the use of PLS-SEM in transport safety analyses (Nguyen-Phuoc et al., 2022b, Zhang et al., 2019, Ngoc et al., 2023). However, PLS-SEM has its own disadvantages. Indeed, Partial Least Squares Structural Equation Modeling (PLS-SEM) can only detect linear relationships, whereas the human decision-making process often includes non-linear and sophisticated interactions. Consequently, PLS-SEM may oversimplify the ways in which factors influence behaviors (Chan and Chong, 2012). To address this limitation, previous researchers have proposed an enhanced methodological approach that incorporates two machine learning algorithms, namely Bayesian Networks (BN) and Artificial Neural Networks (ANN), to validate the results obtained from PLS-SEM. Díez-Mesa et al. (2018) introduced a two-step method for examining service quality using Bayesian Networks (BN) and SEM. First, significant dimensions of service quality are extracted from the BN and subsequently validated by SEM. In contrast, ANN, though methodologically distinct from BN, is not designed to test hypotheses. Instead, it utilizes the significant factors identified in the PLS-SEM step to construct ANN models. This multi-analytical approach combines the strengths of PLS-SEM in testing hypotheses within a complex conceptual framework with ANN's ability to model non-linear relationships. ANN, inspired by the structure of the human brain, is a commonly used machine learning algorithm for recognizing non-linear and complex relationships. ANN models often yield more robust and accurate predictions compared to linear models (Zabukovšek et al., 2019). To date, ANN has proven effective in scrutinizing complementary factors and verifying PLS-SEM results in SEM-based studies across various fields, including e-learning (Elareshi et al., 2022), media entrepreneurship (Roshandel-Arbatani et al., 2019), adoption of quality management systems (Miloševć et al., 2022), and cryptocurrency adoption (Sohaib et al., 2020). A recent review by Albahri et al. (2022) underscores the growing prevalence of SEM-ANN hybrid models across 11 research categories while highlighting the potential for applying this method in diverse fields, such as transportation and safety. Given the advantages of the hybrid model based on PLS-SEM and ANN as mentioned above, we employed this method to test the proposed theoretical framework.

Table 1
Survey respondent characteristics.

Demographics	n	%	Working history	n	%
Age (years)			*Employment status*		
Mean (SD)	25.68 (5.55)		Part-time	303	54.3
Gender			Full-time	255	45.7
Male	494	88.5	*Work experience (years)*		
Female	64	11.5	Mean (SD)	1.12 (0.79)	
Level of education			*Weekly working days (days/week)*		
High school diploma	96	17.2	Mean (SD)	6.15 (1.01)	
College degree	207	37.1	*Fined by police*		
Bachelor degree	183	32.8	No	423	75.8
Master degree	32	5.7	Yes	135	24.2
Other	40	7.2	*Experience crash*		
Migrant status			No	299	53.6
Migrant	313	56.1	Yes	259	46.4
Non-migrant	245	43.9			
Income (million VND/month)					
Mean (SD)	8.62 (4.50)				
Marital status					
Single	409	73.3			
Married	149	26.7			
Years with a riding license (years)					
Mean (SD)	5.43 (4.15)				

5. Results

5.1. Descriptive statistics

Table 1 give information about the characteristic of survey respondents. An overwhelming majority of the respondents were male delivery riders (88.5 %) compared to their female counterparts (11.5 %). Slightly more than half (56.1 %) of the riders were migrants, while 43.9 % of them were non-migrants. The most common level of education among the riders was college degree with 37.1 %, which was closely followed by bachelor degree at 32.8 %. A smaller portion of the sample held either a high school diploma (17.2 %), master's degree (5.7 %) or other certifications (7.2 %). The mean income of the delivery riders was 8.62 million VND monthly and their mean weekly working week lasted 6.15 days. The statistics also noted that the riders held their riding license for a mean of 5.43 years, but the mean work experience among them is only 1.12 years. With regard to their working record, only 24.2 % of the delivery riders were ever fined by police, while up to 46.4 % were involved in traffic crashes.

5.2. Measurement model evaluation

Confirmatory factor analysis was performed to evaluate the validity and reliability of the proposed measurement model. Following Hair et al. (2016)'s guidelines, internal consistency reliability, convergent validity, and discriminant validity were the three major criteria examined during this stage.

To establish the reliability and convergent validity of the constructs of interest, Cronbach's alpha (CA), indicator loadings, Composite reliability (CR), and Average Variance Extracted (AVE) were recorded in

Table 3. Specifically, CA values were used to determine internal consistency among the components. All CA values ranged between 0.806 and 0.896, satisfying the 0.70 criterion (Fornell and Larcker, 1981), thus depicting acceptable internal consistency reliability for the constructs. Meanwhile, factor loading, CR, and AVE were examined to validate the convergence among proposed measurement items in their associated constructs. Table 2 illustrated that the loading value of 30 measurement items was over 0.7 and therefore was further examined. All CR values were over 0.7, with the lowest of 0.878, confirming good convergent validity. Similarly, AVE coefficients fell between 0.676 (Time pressure) and 0.906 (Social support at organisation level), which significantly exceeded the threshold value of 0.5 (Fornell and Larcker, 1981). Given the statistics mentioned above, it can be concluded that the convergence validity of the proposed measured model was empirically verified.

Discriminant validity was estimated based on Fornell-Larcker criterion (Fornell and Larcker, 1981) to determine the uniqueness of each construct in comparison with other constructs within the model. The result of this process is recorded in Table 3, verifying that the discriminant validity of all constructs was obtained. Particularly, the square root of AVE for each reflective construct surpassed its correlation with other constructs in the structural model.

5.3. Structural model evaluation

5.3.1. Model fit tests

Two indices, including the standard root mean square residual (SRMR) and the Normed Fit Index (NFI), were assessed to check the PLS-SEM model fit in the current study. A model fit is considered strong when NFI value achieves a minimum value of 0.8 (Henseler et al., 2016) and SRMR is less than 0.08 (Hu and Bentler, 1998). As depicted in Table 4, SRMR (=0.039) and NFI (=0.807) values met the requirements for the fit indices, verifying that the proposed model fit the data well.

Table 2
First-order model evaluation.

Constructs	Items	Loadings	CA	CR	AVE
Time pressure (TPR)			0.846	0.893	0.676
	TPR1	0.833			
	TPR2	0.830			
	TPR3	0.861			
	TPR4	0.762			
Safety risk (SAR)			0.884	0.929	0.813
	SAR1	0.890			
	SAR2	0.937			
	SAR3	0.877			
Working environment (WEN)			0.806	0.878	0.708
	WEN1	0.694			
	WEN2	0.899			
	WEN3	0.914			
Social support (Organise level) (SSO)			0.896	0.950	0.906
	SSO1	0.959			
	SSO2	0.944			
Social support (Co-worker level) (SSW)			0.828	0.897	0.744
	SSW1	0.866			
	SSW2	0.905			
	SSW3	0.816			
Work autonomy (WAU)			0.874	0.923	0.799
	WAU1	0.861			
	WAU2	0.924			
	WAU3	0.896			
Feedback (FDB)			0.853	0.932	0.872
	FDB1	0.940			
	FDB2	0.927			
Rewards (REW)			0.883	0.944	0.895
	REW1	0.953			
	REW2	0.939			
Risk-taking attitude (RTA)			0.890	0.923	0.750
	RTA1	0.830			
	RTA2	0.869			
	RTA3	0.868			
	RTA4	0.894			
Mobile phone use frequency (MPF)			0.886	0.922	0.747
	MPF1	0.785			
	MPF2	0.855			
	MPF3	0.906			
	MPF4	0.904			

5.3.1.1. Predictive capability evaluation. Predictive accuracy, examined by the coefficient of determination (R^2), and predictive relevance, examined by coefficient Q^2, are critical in evaluating a SEM. Specifically, higher predictive accuracy is associated with a higher R^2 value within the range of 0 and 1 (Hair et al., 2019), while predictive relevance among the endogenous variables can be verified with a positive Q^2 value (>0) (Henseler et al., 2009). The result suggested that mobile phone usage frequency only had a weak predictive capability ($R^2 = 0.273$), but it did have medium predictive relevance ($Q^2 = 0.184$).

5.3.1.2. Relationships. The results of the examination of the proposed relationships are recorded in Table 4. The test confirmed the relationship of eight latent constructs with mobile phone use frequency (MPF) with a corresponding empirical t-value higher than 1.96 with significance level of 5 % (Hair et al., 2016). In particular, safety risks, as a part of job demands, were found to have a positive influence on MPF ($\beta_{SAR\rightarrow MPF} = 0.120$, t = 2.386, p = 0.017). On the contrary, social support from organisations, as a part of job resources, had a negative effect on MPF ($\beta_{SSO\rightarrow MPF} = -0.170$, t = 4.273, p = <0.001). Given work autonomy and rewards were normally considered to be the components of job resources, the positive impacts on MPF have been found in this study ($\beta_{WAU\rightarrow MPF} = 0.103$, t = 2.179, p = 0.029 and $\beta_{REW\rightarrow MPF} = 0.116$, t = 2.373, p = 0.018, respectively). Negative attitude, specifically towards risk-taking behaviours, could influence the riders' mobile phone usage ($\beta_{RTA\rightarrow MPF} = 0.170$, t = 3.66, p = <0.001). Out of the seven demography constructs evaluated, only migrant status and income had an effect on phone usage frequency ($\beta_{IMM\rightarrow MPF} = -0.100$, t = 2.458, p = 0.014 and $\beta_{INC\rightarrow MPF} = 0.098$, t = 1.972, p = 0.049, respectively). In terms of working history, only experiencing a fine by the police positively affected MPF ($\beta_{FIN\rightarrow MPF} = 0.117$, t = 2.845, p = 0.004).

5.4. Artificial neural network (ANN)

In order to predict the normalised importance of the determinants of MPUWR frequency among food delivery riders, ANN was implemented in this study. Eight significant independent constructs from the PLS-SEM path analysis (i.e., SAR, SSO, WAU, REW, RTA, IMM, INC and FIN) were taken as the input neurons for the ANN model (Liébana-Cabanillas et al., 2017) (Fig. 2). Using a feed-forward-back-propagation (FFBP) algorithm, ANN can predict the analysis outcomes with minimized errors in training process (Leong et al., 2020a). Additionally, the sigmoid function as the activation function was used for the input and hidden layers. A 10-fold cross-validation approach was also engaged to minimise the errors and to evade the over-fitting possibility (Ooi et al., 2018). Finally, according to Leong et al. (2018), the data were classified into two parts: 90 % of the data were analysed for learning and 10 % for testing to identify the Root Mean Square of Errors (RMSE) values. The results revealed that the average value of RMSE of the training and testing process were fairly small at 0.1445 and 0.1391, sequentially (Table 5). Thus, an excellent model fit was confirmed.

Sensitivity analysis was carried out to compute the normalised importance of the input neurons in the ANN model (Karaca et al., 2019). Firstly, the average relative importance of eight neural networks was computed. Then, the normalised importance of each of the input neurons was the ratio of relative importance of an input neuron to the highest relative importance in the ANN model (Leong et al., 2020b). Table 6 revealed that SAR (100.0 %), RTA (93.0 %) and WAU (81.1 %) are in the top 3 of the most important predictors of MPUWR frequency. They were followed by REW (72.4 %), SSO (71.9 %), INC (45.7 %), FIN

Table 3
Fornell-Larcker criterion assessing discriminant validity.

Constructs	AVE	RTA	FDB	SAR	REW	MPF	SSW	SSO	TPR	WAU	WEN
RTA	**0.750**	**0.866**									
FDB	**0.872**	0.243	**0.934**								
SAR	**0.813**	0.258	0.395	**0.901**							
REW	**0.895**	0.216	0.599	0.315	**0.946**						
MPF	**0.747**	0.266	0.275	0.340	0.299	**0.864**					
SSW	**0.744**	0.241	0.371	0.372	0.353	0.240	**0.863**				
SSO	**0.906**	0.040	0.032	−0.081	0.026	−0.173	0.189	**0.952**			
TPR	**0.676**	0.220	0.165	0.326	0.119	0.112	0.181	0.136	**0.822**		
WAU	**0.799**	0.355	0.400	0.446	0.419	0.338	0.426	−0.061	0.229	**0.894**	
WEN	**0.708**	0.265	0.287	0.310	0.217	0.196	0.246	0.088	0.400	0.273	**0.842**

Table 4
Results of hypothesis testing.

Path Relation (Hypothesis)	Path Coefficient (ß)	*SD*	*t*-value	*p*-value	Results
Job demands					
Time pressure (TPR) -> MPF	−0.033	0.044	0.759	0.448	Rejected
Working environment (WEN) -> MPF	0.080	0.045	1.782	0.075	Rejected
Safety risk (SAR) -> MPF	0.120*	0.050	2.386	0.017	***Supported***
Job resources					
Social support (Co-worker level) (SSW) -> MPF	0.086	0.048	1.776	0.076	Rejected
Social support (Organise level) (SSO) -> MPF	−0.170**	0.040	4.273	<0.001	***Supported***
Work autonomy (WAU) -> MPF	0.103*	0.047	2.179	0.029	***Supported***
Rewards (REW) -> MPF	0.116*	0.049	2.373	0.018	***Supported***
Feedback (FDB) -> MPF	0.029	0.054	0.548	0.584	Rejected
Attitude					
Risk-taking attitude (RTA) -> MPF	0.170**	0.046	3.664	<0.001	***Supported***
Demography					
Age (AGE) -> MPF	−0.139	0.080	1.754	0.079	Rejected
Gender (GEN) -> MPF	0.035	0.036	0.980	0.327	Rejected
Education level (EDU) -> MPF	−0.053	0.039	1.355	0.176	Rejected
Migrant status (IMM) -> MPF	−0.100*	0.041	2.458	0.014	***Supported***
Income (INC) -> MPF	0.098*	0.050	1.972	0.049	***Supported***
Marital status (MAR) -> MPF	0.045	0.050	0.915	0.360	Rejected
Riding experience (RIE) -> MPF	0.001	0.067	0.019	0.985	Rejected
Working history					
Employment status (EMS) -> MPF	−0.100	0.053	1.895	0.058	Rejected
Work experience (WOE) -> MPF	0.014	0.043	0.329	0.742	Rejected
Weekly working days (WWD) ->MPF	0.027	0.042	0.641	0.522	Rejected
Fined by police (FIN) -> MPF	0.117**	0.041	2.845	0.004	***Supported***
Experienced crash (CRA) -> MPF	0.036	0.040	0.902	0.367	Rejected

Notes: ** $p < 0.01$, * $p < 0.05$.

(39.5 %) and IMM (32.6 %).

Figure A1 illustrates the difference between the results of the SEM and ANN approaches in terms of ranking the predictors of mobile phone use frequency among food delivery riders.

6. Discussion

6.1. Theoretical implications

MPUWR among motorcycle riders has been explored by a large number of scholars (Truong et al., 2018, Nguyen-Phuoc et al., 2020a, Rusli et al., 2020). However, studies focusing on phone use behaviour among commercial riders have been limited. This study proposes a theory-driven approach to investigate mobile phone usage behaviour among food delivery riders in a low middle country. From a theoretical perspective, a key finding is that the two main constructs of the JD-R model, job demands and job resources, appear to explain why delivery riders engage in MPUWR from a work-related perspective. As such, this study distinguishes itself from earlier studies that only considered very specific occupational factors such as riding history (Papakostopoulos and Nathanael, 2021, Zhang et al., 2020, Claveria et al., 2019).

In previous research, the perceived safety risk is considered as a job demand in the framework of the JD-R model (Falco et al., 2021, Xia et al., 2020) and the positive link between perceived risk and negative outcomes such as job burnout or job satisfaction was also confirmed (Day et al., 2009, Nahrgang et al., 2011). In this study, the perceived safety risk is a component of job demand which is found to positively influence the frequency of MPUWR. One explanation for this is that increased risk awareness can amplify their optimism bias, as they may develop more accurate mental models of risk. This aligns with prior research indicating that individuals intending to use mobile phones while driving exhibit heightened risk awareness (Walsh et al., 2008; Nurullah et al., 2013; Ivers et al., 2009; Oviedo-Trespalacios et al., 2017b). Alternatively, the necessity of work and income for livelihood may overshadow their risk perceptions, resulting in a disconnect between their perceptions and the frequency of phone use while riding. It is important to note that mobile phones are essential tools for these workers. Delivery riders rely on mobile phones for various tasks such as routing, customer contact, and operational and financial monitoring. This might compel riders to use their phones during journeys despite being aware of associated risks. Based on the previous findings, one can argue that delivery riders are doubly vulnerable due to their job design and their status as road users. Consequently, both the industry and road authorities must collaborate to restrict phone use while riding. A promising approach for road authorities is to rectify inaccurate risk perceptions, while the industry should investigate how correct app designs can result in reduced instances of distracted riding.

Regarding job resources, three factors are found to significantly impact the frequency of MPUWR, including social support (organizational level), work autonomy, and rewards. Social support is found to reduce MPUWR by alleviating the mental burden on delivery drivers. Havârneanu et al. (2019) explain that reducing job-related stress for drivers will help them cope better with other job challenges. In contrast, the findings show that work autonomy is positively associated with MPUWR. This is consistent with previous studies showing that safety

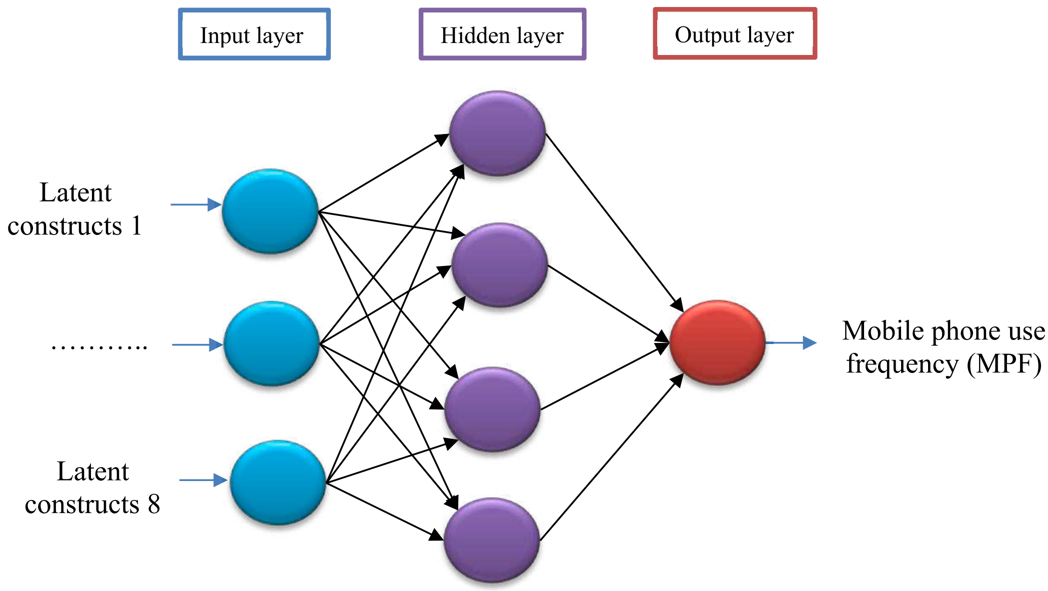

Fig. 2. Architecture of a multilayer perceptron ANN model.

Table 5
Results of RMSE for training and testing process.

Network	Training				Testing			
	Sample	SSE	MSE	RMSE	Sample	SSE	MSE	RMSE
1	505	10.9690	0.0217	0.1474	53	0.8930	0.0168	0.1298
2	500	10.0320	0.0201	0.1416	58	1.0890	0.0188	0.1370
3	512	9.1700	0.0179	0.1338	46	0.9100	0.0198	0.1407
4	509	10.5400	0.0207	0.1439	49	0.7340	0.0150	0.1224
5	494	11.4160	0.0231	0.1520	64	1.2780	0.0200	0.1413
6	514	11.4400	0.0223	0.1492	44	0.9250	0.0210	0.1450
7	502	10.5910	0.0211	0.1453	56	1.0990	0.0196	0.1401
8	516	10.1350	0.0196	0.1401	42	0.8180	0.0195	0.1396
9	504	9.5300	0.0189	0.1375	54	1.2030	0.0223	0.1493
10	502	11.8550	0.0236	0.1537	56	1.1870	0.0212	0.1456
Average		10.5678	0.0209	0.1445		1.0136	0.0194	0.1391
SD		0.8249	0.0017	0.0060		0.1727	0.0020	0.0075

SSE = Sum square of error; MSE = Mean square of error; RMSE = Root mean square of error.

Table 6
Results of sensitivity analysis.

Network	SAR	SSO	WAU	REW	RTA	IMM	INC	FIN
1	0.210	0.163	0.153	0.180	0.170	0.052	0.022	0.050
2	0.198	0.120	0.147	0.130	0.157	0.060	0.119	0.072
3	0.156	0.134	0.101	0.138	0.183	0.083	0.129	0.076
4	0.281	0.130	0.108	0.115	0.129	0.031	0.118	0.087
5	0.018	0.198	0.209	0.152	0.207	0.057	0.083	0.077
6	0.223	0.059	0.277	0.162	0.140	0.047	0.020	0.073
7	0.213	0.155	0.066	0.206	0.206	0.041	0.047	0.067
8	0.179	0.136	0.147	0.108	0.142	0.055	0.150	0.082
9	0.170	0.128	0.133	0.133	0.163	0.056	0.131	0.086
10	0.218	0.118	0.172	0.026	0.239	0.127	0.034	0.067
Average	0.186	0.134	0.151	0.135	0.174	0.061	0.085	0.074
Normalised	100.0 %	71.9 %	81.1 %	72.4 %	93.0 %	32.6 %	45.7 %	39.5 %
ANN order	1	5	3	4	2	8	6	7
SEM order	3	1	6	5	1	7	8	4

culture and peer influence are protective factors against phone use while driving (Luria, 2018). The work autonomy of delivery riders seems to lead them to perceive the freedom to use mobile phones while riding to better handle customer orders and search for locations. This is consistent with the nature of the job, as these delivery riders are often seen as independent contractors. This study also confirms the positive link between rewards and the frequency of MPUWR. Delivery companies often reward their riders for completing a certain number of orders within a defined timeframe. To earn more, the riders are likely to engage in risky riding behaviours such as MPUWR (Scott-Parker and Weston, 2017). This finding is consistent with that of Papakostopoulos and Nathanael (2021) regarding the delivery industry in Athens. Overall, this further highlight that the industry has direct responsibility for this behaviour.

The effect of personal characteristics such as migrant status, income, and fine history on the frequency of MPUWR among delivery drivers was confirmed. These findings reveal that riders who are migrants from other cities, have a high income, and have been fined by the police tend to use mobile phones while riding more frequently. These results are in line with the findings of Nguyen-Phuoc et al., (2020b) and Zhang et al. (2020) in their papers on motorcycle riders and food delivery workers, respectively. Additionally, a risk-taking attitude is associated with the frequency of MPUWR. In this study, the measurement of risk-taking attitude assesses whether drivers consider the risk acceptable. Consequently, riders with higher scores are more comfortable taking risks and rationalizing them. Specifically, riders with higher risk-taking attitudes tend to engage in the risky behaviour of MPUWR. As emphasized in previous research, this suggests that drivers lack the protective influence of understanding the risk, leading to increased mobile phone use during demanding riding conditions (Oviedo-Trespalacios et al., 2017b). Risk-taking attitude is identified as the second strongest predictor of MPUWR frequency. This finding represents an opportunity, as it suggests that attitude-based interventions can be easily developed and implemented with relatively high success.

A combination of PLS-SEM and ANN models is used to increase the accuracy and reliability of the proposed model's findings. As such, this study contributes to dealing with the limitation of PLS-SEM in which the linear and compensatory models are complemented with the usage of non-linear and non-compensatory of ANN models. Hence, this study has contributed to the advancement in research methods as well as provided a new approach to studying road users' behaviours.

6.2. Practical implications

This paper presents various opportunities for practical implications aimed at reducing the frequency of phone use among delivery riders, thereby enhancing their safety and that of other traffic participants. Delivery riding services should take the lead in mitigating existing work-related safety risks by easing job demands. Several strategies address the unpredictable and volatile environment of delivery riding, such as providing accurate and timely information about weather, transportation routes, and road infrastructure. This enables drivers to navigate potentially hazardous situations during deliveries. With clear and updated delivery plans, the incidence of crashes should theoretically decrease, as drivers would be less inclined to use their handheld devices for on-the-go information.

A more conducive working environment, coupled with improved remuneration or job resources, can help relieve the stress associated with income and financial strain on drivers. This is particularly relevant for migrant drivers, who often shoulder heavier burdens of family support, leading to riskier riding for maximum earnings (McDonald et al., 2018a, Li et al., 2014, Nurullah et al., 2013). Specifically, regular compulsory training and education sessions on the dangers of MPUWR could prove valuable for seasoned riders, whose confidence in their riding capacity can lead to unsafe behaviours (Castanier et al., 2013, Zhang et al., 2020). By shifting riders' attitudes towards risky behaviours, we can expect a reduction in the frequency of such behaviours. Conversely, delivery organisations must reassess and modify their approach, which often prioritises speed over safety in delivery, for the well-being of their employees or partners (Papakostopoulos and Nathanael, 2021). Furthermore, increased remuneration for riders would allow them to make fewer trips, easing their financial burden and reducing risky riding behaviours like mobile phone use and aggressive riding (Wang et al., 2019). This strategy would also benefit the delivery organisation through improved employee retention and enhancement of the company's public image.

Finally, this study acknowledges and advocates the establishment of social support frameworks for delivery riders, especially migrant riders. Social support and a safe work environment can significantly foster the safety of delivery riders by reducing mobile phone usage frequency. For instance, management allowing breaks in riders' schedules has been found to decrease the likelihood of phone usage (Claveria et al., 2019). Moreover, since typical generic safety mandates are often ineffective in promoting safe behaviours (Papakostopoulos and Nathanael, 2021), specific communities and unions representing delivery riders' rights and interests could help bridge the gaps in existing policies. These organisations can provide safety training, facilitate the sharing of work experiences, serve as information portals or communication points, thereby proving invaluable for inexperienced drivers to enhance their job performance and reduce unsafe riding behaviours like mobile phone usage.

6.3. Limitation

While being designed rigorously and carefully, the current study is subject to several limitations. This research relied on the self-reported data of delivery riders recruited conveniently, which would limit the generalisation of the findings. Additionally, it has been reported that the workload of delivery riders significantly increased during the COVID-19 period, primarily because of the rapid growth in e-commerce (Nguyen et al., 2023, 2022). This raises a question regarding how job demands impact MPUWR in the post-pandemic era. Besides, although taking a wide array of factors into account, this research still ignored some potential exploratory variables of MPUWR, such as familiarity with the area of delivery, traffic speed, and job burnout (Márquez et al., 2015, Nahrgang et al., 2011). Because the findings of influential factors can be location-specific; therefore, it is necessary to implement similar research in other areas to validate and extend the results of this work. Furthermore, it will be interesting if future research can clarify the effects of distracted riding due to MPUWR by investigating the association between phone-related crashes and phone use while riding among delivery riders.

7. Conclusion

The exploration of factors contributing to MPUWR in a professional context holds significant interest for both practitioners and researchers. This research presents pioneering work in extending the well-established Job Demands-Resources theory to investigate the frequency of MPUWR among delivery workers in urban areas of an emerging country. In an effort to ensure robust and reliable identification of key factors influencing MPUWR, we utilised a unique combination of Partial Least Squares Structural Equation Modelling (PLS-SEM) and Artificial Neural Networks (ANN).

Our research highlights the importance of optimizing the work environment to enhance safety, with measures such as providing real-time information and tools to avoid hazards during deliveries. Additionally, addressing the unique challenges faced by migrant drivers through improved remuneration and job resources can alleviate financial strain and reduce the propensity for risky riding behaviours. Mandatory and remunerated risk awareness training and a shift in delivery priorities to prioritize safety can also contribute significantly. Lastly, establishing social support frameworks, particularly for migrant riders, can promote safety by filling gaps left by generic safety mandates and offering valuable resources and support. By implementing these recommendations, delivery organizations can contribute to safer roads and improved working conditions for their riders while fostering a positive public image in emerging countries. This study not only advances our theoretical knowledge of risky behaviours in professional contexts but also offers practical implications that can help shape safer operational strategies for delivery services, especially in rapidly urbanising and digitally evolving regions.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

Appendix A

Table A1. Measurement items

Constructs	Dimensions	Measurement items		Mean	SD	Supporting literature
Job demands (JDE)	Time pressure (TPR)	TPR1	I am always in a hurry to fulfill the assignment on time	4.805	1.562	(Demerouti et al., 2001; Zheng et al., 2019)
		TPR2	I often think about the penalty for late delivery	4.792	1.555	
		TPR3	I often worry about late delivery while working because of the time limit for each order	4.896	1.506	
		TPR4	I try to complete the number of orders as many as possible to increase my wage	5.401	1.438	
	Safety risk (SAR)	SAR1	I might be at risk of having some kind of accident on the roads	5.296	1.417	(Gregory, 2020)
		SAR2	I am at greater risk of accidents as I am exposed to roads more time than other people	5.229	1.453	
		SAR3	I worry about being injured as I work with different road and weather conditions	5.197	1.462	
	Working environment (WEN)	WEN1	Delivery riders have to ride motorcycles in adverse road conditions (e.g., poor road surfaces), which increases the risk of accident	5.278	1.481	(Demerouti et al., 2001)
		WEN2	Delivery riders work in all weather, even in bad weather conditions	5.151	1.525	
		WEN3	Delivery riders work in a pressured working environment as they are required to deliver to the right place, sometimes in the dark within a set time frame*	5.131	1.415	
Job resources (JRE)	Social support (Organise level) (SSO)	SSO1	The delivery firms are willing to invest money and effort to improve safety for riders.	4.088	1.603	(Cheung et al., 2021)
		SSO2	The delivery firms seem to care about my safety.	4.102	1.614	
	Social support (Co-worker level) (SSW)	SSW1	Delivery riders who I know expect me to behave safely.	5.043	1.314	(Cheung et al., 2021)
		SSW2	Delivery riders who I know emphasise working safety and make sure to do the same.	5.000	1.378	
		SSW3	Delivery riders who I know remind me to follow safety regulations.	4.982	1.377	
	Work autonomy (WAU)	WAU1	I am allowed to decide how to go about getting my job done.	5.168	1.468	(Breaugh, 1999)
		WAU2	I can decide for myself how to perform my work	5.127	1.483	
		WAU3	I am free to choose the methods to use in carrying out my work.	5.143	1.481	
	Feedback (FDB)	FDB1	I get enough feedback about the quality of my performance	5.073	1.463	(Demerouti et al., 2001)
		FDB2	I always receive feedback about my performance from the customers	5.063	1.489	
	Rewards (REW)	REW1	My performance is rewarded properly	4.957	1.509	(Radic et al., 2020)
		REW2	I receive the recognition I deserve for my work	4.984	1.557	
Risk-taking attitude (RTA)		RTA1	If you are a good rider, it is acceptable to engage in risky riding behaviors sometimes	4.280	1.835	(Iversen, 2004)
		RTA2	Taking chances and breaking a few rules does not necessarily make bad riders	4.527	1.658	
		RTA3	Traffic rules are often too complicated to be carried out in practice	4.491	1.624	
		RTA4	Traffic rules do not need to be respected in bad conditions of road and weather	4.763	1.542	
Mobile phone use frequency (MPF)		MPF1	How often do you use your mobile phone while riding during work time?	3.898	1.505	
		MPF2	How often do you use your mobile phone to navigate while riding during work time?	4.013	1.714	
		MPF3	How often do you use your mobile phone to contact customers while riding during work time?	4.056	1.708	
		MPF4	How often do you use your mobile phone to receive orders while riding during work time?	4.133	1.762	

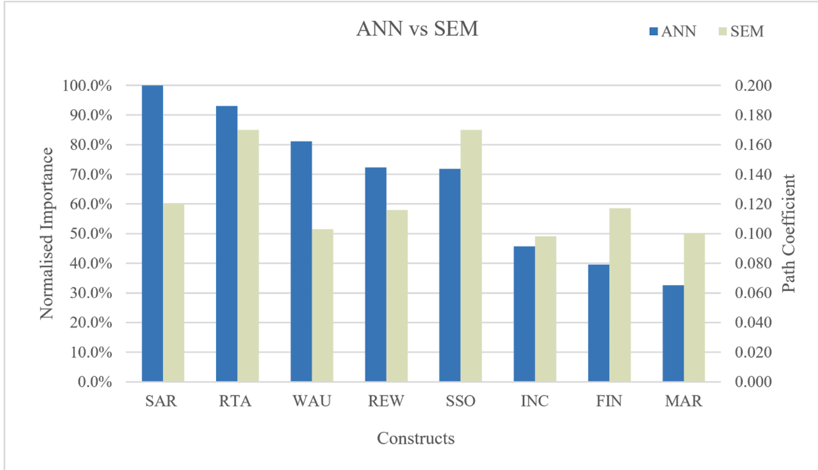

Fig. A1. Normalised important (ANN) vs path coefficient (SEM).

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