Heliyon 10 (2024) e23735

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Development and evaluation of a scale to measure nurses' unsafe driving behaviour while commuting

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A R T I C L E I N F O

Keywords:
Driving behaviour
Commute
Scale development
Factor analyses
Psychometric
Nurses

A B S T R A C T

Driving is the most prevalent form of commuting for most workers but is also perhaps the most hazardous mode of travel with unsafe driving contributing significantly to road traffic accidents. Despite nurses having been reported as being at higher risk of commuter-related accidents over the last three decades, little is known about unsafe driving behaviours among nurses while commuting, which is unique from other driving routines. Additionally, the lack of appropriate tools to measure such behaviours is apparent. This study aims i) to identify unsafe driving behaviours among nurses while commuting and ii) to develop a scale to assess nurses' unsafe commuting driving behaviours. The study employed a multiphase and multimethod approach to develop the scale, which was subject to stringent validation and evaluation. Themes were specified via the Nominal Group Technique (NGT). Six themes were identified namely: i) violations and reckless driving, ii) negative emotions, iii) drowsy driving iv) mind wandering, v) error and vi) carelessness. Content and face validity were sought through expert review. A total of 442 nurses' data were collected across multisite hospitals for evaluation. Exploratory factor analysis (EFA) resulted in recovered structure and was confirmed through Confirmatory Factor Analysis (CFA) with structural equation analyses being conducted to test predictive validity. All constructs met adequate validity and reliability. Nurses' unsafe driving behaviours while commuting were identified with a novel scale to assess them being both developed and validated. The resulting MyUDWC scale is a suitable tool for measuring nurses' unsafe driving behaviours while commuting.

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https://doi.org/10.1016/j.heliyon.2023.e23735
Received 23 July 2023; Received in revised form 5 December 2023; Accepted 12 December 2023
Available online 21 December 2023
2405-8440/

1. Introduction

Every day, as countless individuals embark on their daily commutes, they are unwittingly exposed to the potential hazards that lurk on the roads. According to the World Health Organisation (WHO), 3700 people die on the roads every day, while approximately 1.35 million people die each year from road traffic accidents (RTAs) [1]. In the United States, Australia, and Europe, more than a third of work-related motor vehicle accident fatalities occur while commuting [2]. Considering the context of this study, however, it may be that "accident" should perhaps more appropriately be referred to as collision due to their predominantly avoidable nature. Even more relevant is the fact that ninety percent of RTAs are caused by human factors [3], with behavioural factors and human errors being among the primary causes [4–6]. The concept of unsafe driving behaviour extends beyond mere traffic violations; it encompasses a broad range of behaviours that imperil public safety on the road. These behaviours, such as aggressive driving, distracted driving, and road rage, can contribute to a significant number of accidents and collisions on our roadways [7–9]. Such accidents often result in injuries, fatalities, and immeasurable emotional distress for those involved and their families.

One context where unsafe driving behaviours come into stark focus is during daily commuting [10]. There has been a significant increase in commuting times across the globe, with 26.15% of Bangkok residents commuting one to 2 h every day, 36.66% in Istanbul, 32.72% in Sao Paolo, and 28% in New York [11]. Commuting, especially in densely populated urban areas, necessitates navigating through heavy traffic, adhering to tight schedules, and contending with the stressors inherent in the daily grind. Commuting can also induce route familiarity which influences the way individuals process their thoughts and ultimately their behaviour [12]. Familiarity with the route in turn contributes to complacency when commuting causing cognitive control to decrease resulting in a tendency to drift into auto-mode [12,13], thereby making drivers vulnerable to errors. Overall, individuals may exhibit a range of behaviours that compromise road safety when faced with these challenges. These behaviours not only put the commuters themselves at risk but also endanger the lives of fellow road users, amplifying the potential for accidents and their devastating consequences.

Despite the prevalence of commuting as a daily activity for a significant portion of the population, this aspect of unsafe driving has remained conspicuously underexplored in previous research and measurements [14–16]. Existing scales and questionnaires such as Driver Behaviour Questionnaire (DBQ) [17] and Occupational Driver Behaviour Questionnaire (ODBQ) [18] designed to examine driving behaviours primarily focused on general or occupational drivers, often overlooking the specific challenges commuters face during their daily journeys [4,19–24]. Previous research has indicated that DBQ scales do not have a clear factor structure within occupational settings [18]. Meanwhile, ODBQ, on the other hand, does not take errors and lapses into consideration, lacks home-related components, which are an integral part of commuting, lacks emotion-related components, and does not include items relevant to occupational driving environments, such as texting while driving. This critical oversight has led to a dearth of understanding regarding the distinct factors contributing to unsafe driving behaviours in the context of daily commuting [18].

Among the diverse groups of commuters, nurses emerge as a demographic facing distinctive and elevated risks. It is well established that nurses are among the most frequently involved in drowsy driving in the world, with a prevalence ranging between 13 and 80 % [16,25,26]. A recent study concluded that nurses were among the most frequently involved in commuting accidents of all professions. There was significant variation in the frequency of commuting collisions among nurses (36.45 %) when compared to paramedics (21.54 %), and administrators (20.34 %) [$\chi^2 = 10.55$, $p<0.05$] [27]. Further evidence of this problem can be found in the increase of approximately 15–18 % in commuting collisions among healthcare workers including nurses in France [28,29] and Malaysia [14,15] over the past year. Nurses worldwide frequently work irregular hours, which can include early morning or late-night shifts, and their roles within the healthcare system are indispensable. An analysis of a cohort study of shift workers found that, expressed as a ratio, the

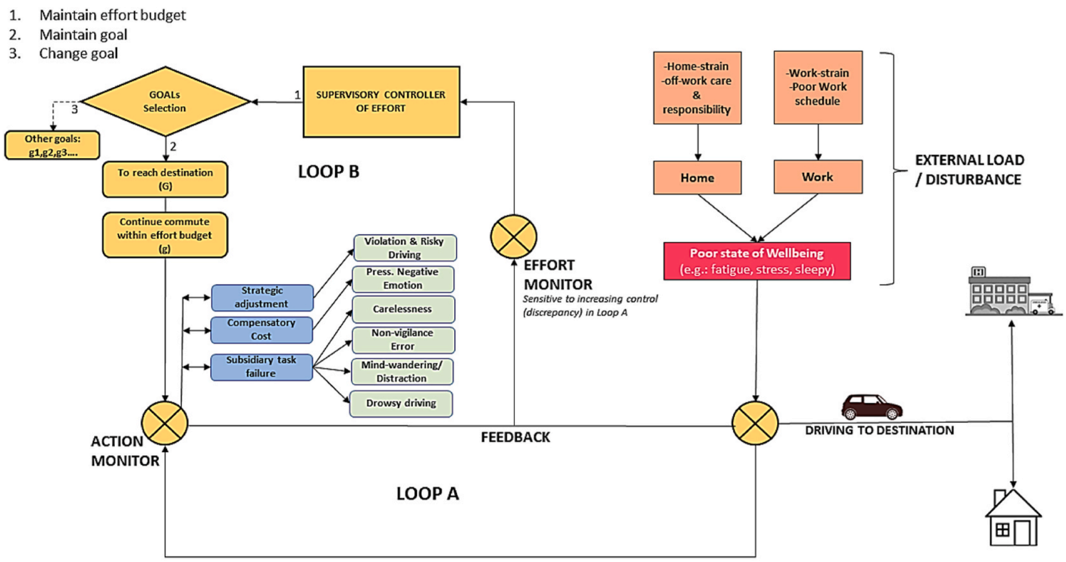

Fig. 1. The conceptual framework for unsafe driving while commuting after Hockey's CCM.

chances of an RTA or near-miss after an extended shift were respectively 2.3 (95 % CI = 1.6–3.3) and 5.9 (95 % CI = 5.4–6.3) [30]. The demanding nature of their profession often results in fatigue and heightened stress levels, both of which can adversely impact driving behaviours. The combination of irregular schedules, fatigue, and stress places nurses at a heightened likelihood of engaging in unsafe behaviours while driving during their daily commutes [31–34]. It has also been found that nurses often think about work while driving [18], which diminishes attention toward safe driving and results in unsafe driving behaviours. Nurses ruminate while driving, probably because they have difficulty detaching themselves from their work environment [35,36], with results from the previous study showing that ruminating was significantly related to various unsafe driving behaviours [37]. Despite this, potential unsafe driving behaviours among nurses have still not been well researched.

Recognizing the unique risks faced by nurses and the insufficiencies of existing measurements, there arises an imperative need for a rigorously designed tool tailored specifically to this population. Thus, in order to intervene in the root causes of commuting collisions among nurses, unsafe driving behaviours among them should be investigated and addressed. A specific scale that measures unsafe driving behaviour while commuting among nurses could then be developed and used in future studies relating to the intervention of

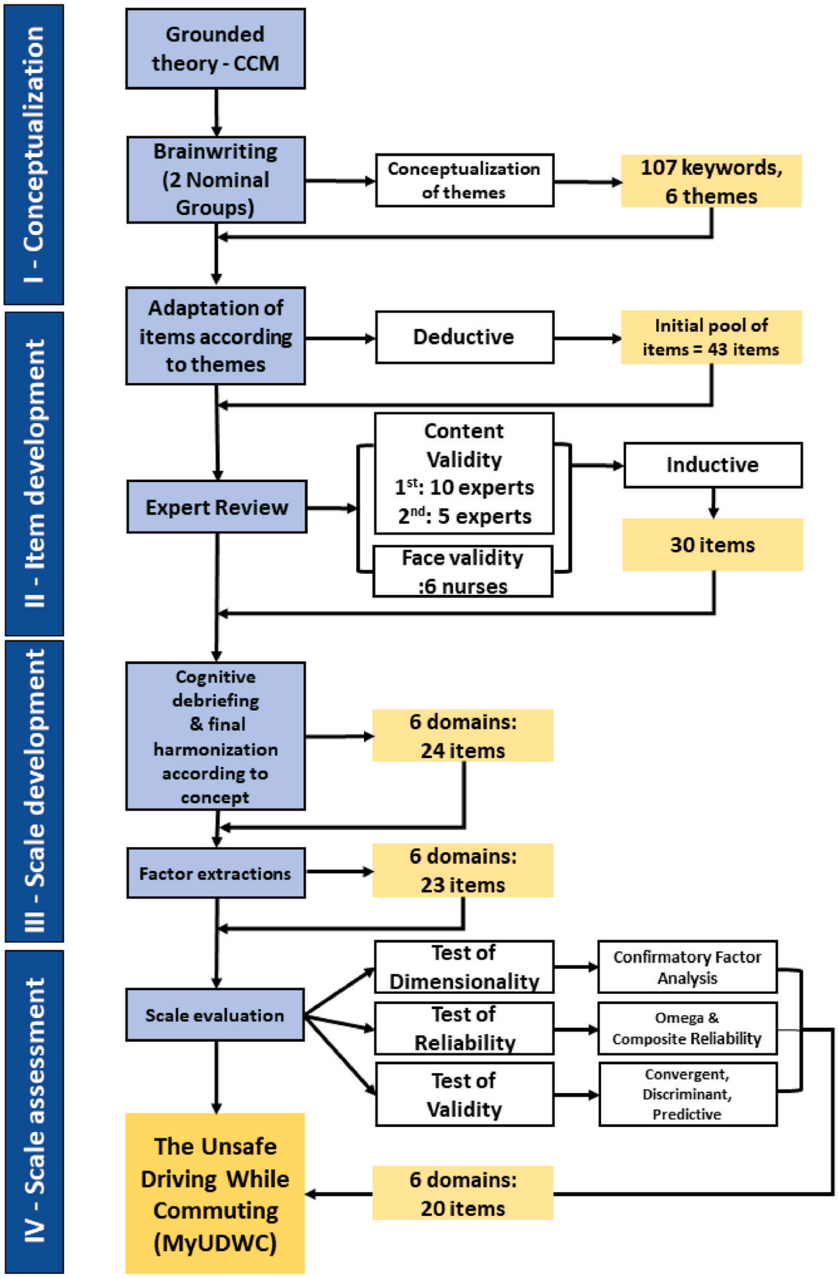

Fig. 2. The flowchart of MyUDWC development and validation.

commuting incidents and collisions among nurses.

2. The underpinning theory

The present study is primarily grounded by the Hockey's Compensatory Control Model (CCM) [38]. Compensatory control is a mechanism used to fulfil the requirement for a measure that is too difficult to implement at a given time. Fig. 1 illustrates the conceptual framework for unsafe driving while commuting following the adaptation of Hockey's Compensatory Control Model (CCM).

During commuting, compensatory control refers to alternative controls that drivers take when they encounter disturbances, a common example of which is poor state of wellbeing resulting from fatigue, stress or sleepiness. These states of wellbeing can be influenced not only by the commuting but also something which is disassociated with the driving, such as home factors, which can include home strain, off-work tasks and responsibilities leading to persistent fatigue, or work factors, such as poor scheduling and insufficient recovery leading to acute fatigue or a drowsy state during or prior to driving. Overall, these factors may also interact synergistically leading to poor state of physical and mental wellbeing.

As driving is a complex task, it involves a combination of both physical and mental health, with safety depending very much on the wellbeing of the driver. In the event of disturbances, drivers can choose an effort budget and goal that suits their needs; drivers can change their goals and preserve their effort. Nevertheless, if the goal is still to arrive at the destination utilising only a certain amount of effort, several consequential actions may occur. The first action involves a strategic adjustment such as speeding, taking a shortcut, or engaging with driving strategies that reduce the load on the driver. The second action that may occur is the compensatory cost, which refers to increased activation of the psychoaffective-physiological systems in response to disturbances and sustained coping effort. This can lead to physical reactions, like increased heart rate and sweating, as well as psychological symptoms such as feeling overwhelmed, anxiety leading to driving in anger, or frustration. Finally, subsidiary task failure refers to narrowing attention towards the driving, such as mind-wandering, distraction to non-driving related activities, brief dozing off and loss of focus while driving. These three compensatory controls are the manifestation of unsafe driving behaviour while commuting.

The study therefore aims to determine unsafe driving behaviours among nurses while commuting in Malaysia, in accordance with the CCM, following which, the intention is to develop and validate a scale for measuring unsafe driving behaviour among nurses during commuting.

3. Methodology

A multiphase, multimethod approach was employed to achieve our objectives incorporating best practices for instrument development and validation [39]. There were four main phases in the study: conceptualization, item development, scale development, and scale evaluation. A diagram of this study process is shown in Fig. 2.

3.1. Phase 1: conceptualization

3.1.1. Determining the unsafe driving behaviour while commuting

The aim of Phase 1, which was conducted at the beginning of this study, was to identify the unsafe driving behaviour of nurses while commuting. The domain specification involved two strategies, namely inductive and deductive. For inductive outcomes, keyword identification pertinent to unsafe driving while commuting was performed through a nominal group technique (NGT). Two focus groups were carried out among the traffic safety research and practice group ($n = 9$) and frequent commuters among hospital nurses ($n = 10$). The participants were recruited through purposeful sampling with a convenience strategy. All members of both groups had to have been licensed drivers for at least 10 years. Additionally, for the traffic safety research and practice group, the inclusion criteria were experience in teaching, practicing, or research in traffic safety or occupational health and safety for at least 5 years. The inclusion criteria for the second group were hospital nurses with 5 years working experience and who drove to work every day by themselves.

As participants commenced the NGT, they were presented with a scenario: *A nurse drives to work while experiencing poor physical or mental health.* Researchers ensured that all participants understood the scenario. A question was then posed: "*As a nurse commuting to work, how do you describe the way you drive if you are experiencing poor physical or mental wellbeing?*" In this exercise, participants were instructed to reflect on the scenario and answer the question in their own words.

During the focus group, three core phases of NGT were adopted [40]: (1) silent generation of ideas following the opening statement, (2) collection of key ideas in a round-robin format, and (3) key ideas clarified, following which the ideas were sorted into identified themes. For deductive, the literature review focused on the background theories and mapping of the existing driving behaviour scales. Themes relevant to the concept were finalized by consensus among the authors.

3.2. Phase 2: items development

A pool of initial items was generated after the researchers agreed upon themes. This involved mixing new item suggestions and adaptations of existing scales from other relevant scales. This technique applied a deductive approach toward item generation, which was followed by two rounds of expert review. Ten domain experts were invited to the initial content validation assessment: three traffic safety researchers, three practitioners, three occupational health physicians, and one Malay language expert with a safety engineering background. Five domain experts performed a second round of quantitative content validation involving two public and occupational health doctors, one occupational safety and health academician, one traffic safety researcher officer, and one traffic safety practitioner. Experts were chosen for their expertise and experience in traffic safety and questionnaire development. The expert panel then gave their professional judgment of each item within each dimension. A content validity analysis was conducted on the resulting items, providing both qualitative and quantitative evaluations of necessity, relevance, comprehensiveness, and representativeness. Content validity indexes (CVI), content validity ratios (CVR), Kappas and face validity index (FVI) were all counted. The process calculation of CVI, CVR, Kappas and FVI are provided in Appendix A.

The analysis of expert evaluations and face validation results was conducted to assess their outcomes. Items were subsequently reviewed and standardized as needed, categorized as approved, modified, eliminated, or merged accordingly. Prior to assessing the scale's validity, a cognitive debriefing involving six nurses who are frequent commuters was undertaken. Subsequently, alignment and adjustment of constructs and their respective items were performed based on the obtained feedback and the associated conceptual framework. This systematic procedure aimed to ensure the suitability of items, preparing them for distribution.

3.3. Phase 3: scale development

3.3.1. Sampling, setting and data gathering

A cross-sectional cluster sample of nurses in 3 zones (northern, eastern and central) of Peninsular Malaysia from 10 tertiary hospitals was conducted from August 1, 2021 to September 30, 2021. It was at a time when Malaysia was transitioning to a National Recovery Plan following the COVID-19 pandemic. Within each zone, three hospitals were random proportionately selected. Ten persons in charge (PICs) were each assigned a random hospital to sample nurses within the zone. In consideration of the different technical restrictions imposed by the COVID-19 pandemic and for convenience of respondents, the questionnaire was administered online (using Google Forms) to minimize attrition. Potential respondents were selected by simple random sampling from each hospital's sample frame, and the final sample was composed of 442 nurses. The target population is Malaysian nurses who work in hospital and commute to work by driving. The sample was randomly divided, leaving 135 nurses to be analyzed by exploratory factor analysis (EFA) and 307 nurses to be analyzed by confirmatory factor analysis (CFA) (Table 1). This was in alignment with Bujang's recommendation (the ratio of the minimum number of items to the minimum number of samples) is 1:3 [41] and the classic suggestion of 2–20 person per items [42].

Within nursing professionals, nurse managers are Matrons and Sisters. While the Matron is responsible for the smooth functioning of departments or hospitals, the sister is responsible for patient care administration in the respective units or wards. Staff nurses serve as implementers in providing patient care in their respective units, and community nurses (including midwives) and assistant nurses are responsible for assisting staff nurses in the delivery of patient care.

3.3.2. Exploratory factor analysis (EFA)

Exploratory Factor Analysis (EFA) was conducted to pinpoint a reduced set of factor patterns within the concept of Unsafe Driving While Commuting, elucidated by its constituent items. To achieve this, the Principle Axis Factoring method coupled with oblique rotation (Promax) was employed. Considering findings from prior studies on driving behaviour scales, it was anticipated that

Table 1
Sociodemographic of participants for EFA (n = 135) and CFA (n = 307).

Participant's characteristics	Frequency (%) or mean (±SD)	
	EFA (n = 135)	CFA (n = 307)
Age	35.91 (±5.94)	36.77 (±6.65)
Gender		
Male	10 (7.4)	12 (3.9)
Female	117 (86.7)	295 (96.1)
Marital Status		
Unmarried	14 (10.4)	23 (7.5)
Married	117 (86.7)	271 (88.3)
Divorced	4 (3)	13 (4.2)
At least 1 Family Dependency		
Yes	115 (85.2)	262 (85.3)
No	20 (20 (14.8)	45 (14.7)
Job Position		
Assistant Nurse	1 (0.7)	14 (4.6)
Community Nurse	9 (6.7)	37 (12.1)
Staff Nurse	91 (67.4)	171 (55.7)
Sister	34 (25.2)	78 (25.4)
Matron	–	7 (2.3)
Commuting Accident Involvement		
Yes	36 (26.7)	83 (27)
No	99 (73.7)	224 (73)
Commuting Near Miss Involvement		
Yes	73 (54.1)	152 (49.5)
No	62 (45.9)	155 (50.5)

constructs would exhibit intercorrelations. Additionally, inter-factor correlations are common in the social sciences. Eigenvalues exceeding 1.0 were used as a criterion for the analysis in SPSS Ver. 25. The preliminary labels assigned to the individual components of Unsafe Driving While Commuting were reassessed to ensure consistency in their conceptual meaning as implied by the corresponding items. Standardized factor loadings (λ) and the Omega coefficient (Ω) were employed as metrics to assess the constituent items in the derived structure for each component. The set threshold for standardized factor loading (λ) was established at 0.60 or higher, while communalities were considered acceptable at 0.50. Moreover, the reliability coefficient (Ω) was computed, with values of 0.70 or above denoting a satisfactory level of reliability [43,44].

3.4. Phase 4: scale assessment

3.4.1. Confirmatory factor analysis (CFA) and construct reliability (CR)

The purpose of CFA is to validate My-UDWC both convergently and discriminantly after EFA [45]. A construct's convergence validity is determined by the proportion of variances that are shared between indicators of the construct [44]. In determining convergent validity, three statistics are taken into account: (a) standardized factor loadings, (b) average variance extracted (AVE), and (c) composite reliability (CR) [43]. Statistical factor loading refers to the correlation between factors and variables. As for AVE, it is calculated as the average percentage of variance explained among the items of a construct in Structural Equation Modeling (SEM) [44]. Furthermore, CR refers to the degree of reliability and internal consistency of the items that are representative of a latent construct during the SEM procedure. Accordingly, the three statistical measures have the following cut-off values: (a) Standardized factor loading (λ) of ≥ 0.50, AVE of ≥ 0.50 and composite reliability of ≥ 0.60 [44].

The objective of model fit evaluation is to determine if the data are fit by a CFA model [42]. As part of the present study, the assessment of the adequacy of a CFA model relied on multiple fit indices and their respective thresholds. These indices comprised the chi-square ($\chi 2$), the normed chi-square ($\chi 2/df$) between 3 and 5 [46], a RMSEA of 0.05–0.10 represents the root mean square error of approximation [47], Tucker-Lewis index (TLI) of 0.90 or greater and comparative fit index (CFI) of 0.90 or higher [48]. Additionally, the fit quality of various models was compared based on the AIC [49] and CAIC criteria [50].

The discriminant validity of a construct is determined by the degree to which it differs from another construct and its indicator [51]. An analysis of discriminant validity relies on the examination of cross-loading between constructs, error variance between and within constructs, and error distribution between and within constructs [44]. If cross-loading is not present, the discriminant validity is warranted. Alternatively, the Fornell and Larcker criterion can be used to examine discriminant validity in a more rigorous manner [52]. The discriminant validity of a variable is assured if the square root of the AVE exceeds its correlation coefficient with another variable.

3.4.2. Predictive validity

Predictive validity was investigated first by examining the relationship between work demands, off-work demands and unsafe driving behaviour while commuting. Secondly, the conceptual framework integrated a state of wellbeing as precedent for the external disturbances. In testing this hypothesis, the roles of fatigue state as mediator from external disturbances to unsafe driving while commuting were examined. According to Work-Home Resources model (WH-R), fatigue from one domain or context, such as home, can overflow into another context or domain, such as work, even though potentially unrelated [53]. As such, the mediating role of i) acute fatigue in the relationship between work demands and unsafe driving while commuting, and ii) persistent fatigue in the relationship between off work demands and unsafe driving while commuting through bootstrapping were examined. A structural model was used to analyse these relationships.

The following constructs were collected from respondents and measured:

Work Demands. Work Demands were assessed via items measuring physical, mental and emotional work demands adapted from the shortened Demand-Induce Strain Compensation Questionnaire 3.1 (DISQ-S 3.1) [54]. It has three items respectively for each construct. The responses were based on bipolar interval from 1 (strongly disagree) to 10 (strongly agree). Items were coded such that higher scores indicated a greater degree of work demand. An example of an indicator included "*I have to perform a lot of physically strenuous tasks to carry out my job*". To ensure that physical, mental and emotional work demands were loaded onto a latent work demand variable, the uni-dimensionality of work demands by a second order construct was examined. The model fits the data satisfactorily, $\chi^2/(25) = 3.91, p < 0.001$; comparative fit index = 0.94; Tucker–Lewis index = 0.92; goodness fit index = 0.94, and all indicators loaded well (>0.40). Based on a review of the modification indices, it appears that correlating errors between two mental work demand items would lead to better model fit. The final model fit had good fit indexes $\chi^2/(25) = 2.63, p < 0.001$; comparative fit index = 0.97; Tucker–Lewis index = 0.96; goodness fit index = 0.97.

Off-Work (Home) Demands. Off-Work (Home) Demands were measured with one item each of physical, mental and emotional work demands adapted from the shortened DISC Questionnaire 3.1 [54]. Reliability was assessed via Omega coefficient (Ω) resulting in a figure of 0.84. Off-Work (Home) Demands were loaded by all items as indicators of an underlying off-work demand latent variable. The model fitted the data satisfactorily, $\chi^2/(1) = 5.79, p = 0.016$; comparative fit index = 0.99; Tucker–Lewis index = 0.97; goodness fit index = 0.98, and all indicators loaded well (>0.40). The AVE was 0.64 and composite reliability (CR) was 0.83. The RMSEA is not reported in the presence of small degrees of freedom (df) for a model and small sample sizes. Because it often indicates that a model is poorly fitted, even if the model has been properly specified [55].

Acute Work Fatigue. Acute Work fatigue is measured by Occupational Fatigue Recovery Scale (OFER-15) – IR [56]. The responses are based on a six-point agreement scale between scores of 0 (strongly disagree) and 6 (strongly agree) applied equally across five items. Reverse items were recoded accordingly. The score is measured by the sum of all items divided by 30, followed by a multiplication factor of 100. Higher scores indicated a greater degree of acute fatigue. Omega coefficient (Ω) value for present sample was 0.84.

Persistent Work Fatigue. Persistent Work fatigue is measured by Occupational Fatigue Recovery Scale (OFER-15) – IR [56]. The responses are based on a six-point level of agreement between 0 (strongly disagree) to 6 (strongly agree) applied to five items. Reverse items were recoded accordingly. The score is measured by the sum of all items divided by 30, followed by a multiplication factor of 100. Higher scores indicated a greater degree of persistent fatigue. Omega coefficient (Ω) value for present sample was 0.72.

4. Results

A total of six themes emerged following two NGT focus groups, based on 107 keywords generated. The themes are as follows: (1) violation and risky driving, (2) negative emotions, (3) drowsy driving, (4) mind-wandering, (5) carelessness, and (6) error. Table 2 demonstrates the initial items generation and pooling based on emerged themes as guided by Hockey's dimensions.

4.1. Face & content validity

The item-face validity indexes (I-FVI) (43 items) ranged from 0.5 to 1.0 with FVI-Ave being 0.84. The first round of expert review evaluation for item-level content validity indexes (I-CVI) (43 items) ranged from 0.6 to 1.0. For content validity ratio (CVR), the scores ranged from 0.4 to 1.0 and Kappa coefficient reported a result of 0.49–1.0. The S-CVI/Ave result indicated 0.94 while S-CVI was 0.54 with 24 out of 43 total items in agreement. In addition, 18 new items were generated from expert opinion. Overall items were re-examined for their appropriateness in reference to evaluation by expert review and face validity by nurses. Prior to another round of expert review, 5 items were improved, 10 items were improved and merged, 13 items were eliminated and 9 items were accepted, which yielded 29 items for another round of expert rating.

On the second round, The I-CVI, CVR and Kappa coefficient ranged from −0.6 to 1, 0.6 to 1.0 and 0.49 to 1.0 respectively. S-CVI/Ave was 0.95 while S-CVI/UA was 0.83 with 25 total items in agreement. Items were further harmonized subsequent to open ended questions inducted from expert review. The questionnaire consisted of 30 items distributed among 6 constructs. The final harmonization of the scales and cognitive debriefing led to 24 items, ready to be distributed for extraction factors.

4.2. Exploratory factor analysis

The Kaiser–Meyer–Olkin (KMO) measure for sampling adequacy attained a value of 0.88, indicating favourable conditions for factor analysis, as confirmed by the significant result of Bartlett's test of Sphericity ($\chi^2 = 2895.28, p < 0.001$). Subsequently, six oblique factors were derived, each possessing eigenvalues surpassing 1.0, encompassing a total of 23 items. In total, these factors accounted for 73.89% of the variance, exceeding the recommended threshold of 50% [63]. The variance explained by the first factor specifically amounted to 41.58%, falling below the 50% guideline [63]. Table 3 shows the six factors derived from EFA that represent the six components of the Unsafe Driving While Commuting: i) *violation and reckless driving*, ii) *negative emotion* iii) *error* iv) *mind wandering*, v) *drowsy driving* and vi) *carelessness*. It was observed that the items had loadings ranging from 0.678 through 0.965, which were greater than the cut-off value of 0.50 [44]. VRD1 ("*I ran a red light even though it was in the midst of turning* was excluded because the communality value was 0.34, which is < 0.5 [43,44].

4.3. Construct validity

It is crucial to eliminate ambiguity about dimensionality, hence CFA was conducted using a different sample of 307 participants to determine whether EFA proposed a six-factor model with the 23-item scale to assess unsafe driving behaviour while commuting. While the EFA identified six latent factors, there were items that had relatively high loading values (>0.6) in two factors. These items primarily related to VRD and E constructs; and DD and MWD.

Table 2
The Hockey's dimension of CCM, emerging themes for MyUDWC, conceptualization and references.

Hockey's dimensions	MyUDWC Themes	Conceptualization	References
Strategic adjustment	Violation & reckless driving	Violation of road traffic regulations and disregard of the danger or consequences of one's action.	[19,57,58]
Compensatory cost	Negative emotion	Drivers' involvement in pressure and negative emotion driving while commuting.	[19, 57–59]
Subsidiary task failure	Drowsy driving	Drivers' performance reduction in terms of fatigue or drowsiness or sleepiness symptoms while commuting.	[60,61]
	Mind-wandering	Driver's thoughts drift away from the primary task of driving, and preoccupied with unrelated topics while commuting.	[18,62]
	Carelessness	Acts of negligence in which drivers do not take the necessary precautions to ensure their safety and others while commuting.	[19,57]
	Error	Unintentional mistakes made due to lack of situational knowledge and awareness, misjudgement, or attention narrowing while commuting.	[19,57]

Table 3
Exploratory Factor Analysis (EFA), reliability (Omega) and communalities.

	Factor						
	1	2	3	4	5	6	Communalities
PNE1				0.937			0.896
PNE2				0.817			0.723
PNE3				0.822			0.711
VRT1			0.451				0.338
VRT2			0.900				0.824
VRT3			0.886				0.855
VRT4			0.883				0.783
VRT5			0.829				0.791
VRT6			0.748				0.631
VRT7			0.747				0.608
E1	0.924						0.881
E2	0.739						0.569
E3	0.691						0.577
E5	0.898						0.829
C1						0.965	0.979
C2						0.696	0.589
C3						0.678	0.535
DD1		0.930					0.872
DD2		0.950					0.908
DD3		0.866					0.789
DD6		0.894					0.803
IA1					0.839		0.712
IA2					0.903		0.842
IA3					0.793		0.690
Ω (95 % CI)	0.90 (0.78, 0.96)	0.95 (0.92, 0.97)	0.93 (0.84, 0.97)	0.89 (0.81, 0.94)	0.89 (0.84, 0.94)	0.79 (0.64, 0.90)	

A relatively low loading was observed in both E1 (0.65) and VRD3 (0.66) of the initial model. Another item, IA3, showed high modification residual covariances with other items including VRD6 (MI = 21.54) and DD2 (MI = 21.67). In this way, three items were taken out, leading to a six-factor model with 20 items (Table 4; Model 4). Hence, the CFA six-factor model was run with only 20 items dropping E1, VRD3 and IA3 items.

Three alternative CFA models were also tested—uni-dimensionality of subconstructs (Model 1) and two types of five-factor model (Table 4; Model 2 & Model 3). The uni-dimensionality of the subconstructs was assessed by second order construct loaded onto a latent variable named UDWC. The five-factor model was assessed by: i) combining VRD and E; and ii) combining DD and IA as a single construct along with the remaining factors.

Model fit assessments should include at least one fitness measure from each of the three categories: absolute fit, incremental fit, and parsimonious fit [44]. Results showed that the 5-factor model was a poor fit compared to the uni-dimensionality (Model 1) and 6-factor models (*Model 4 & 5*). As can be seen in Table 4, the values for the Akaike's Information Criterion (AIC) and the Consistent Akaike's Information Criterion (CAIC) for the 1-factor model (*Model 1*) and 6-factor model (*Model 4 & 5*) were lower than the values for the 5-factor model (*Model 2 & 3)*. As for the 6-factor model, Model 5 has better fit than Model 4.

Despite the fact that the χ^2 is significant, the model still fits because it will reject the model in nearly all cases when large samples are used [64,65]. This study used a sample size of 307, which is sensitive to a sample size of more than 200 [66]. Model apprehension for Model 5 was reported in RMSEA coefficient as 0.07, which indicates a satisfactory fit. Likewise, GFI: 0.90. The incremental fit indices also indicate that both tests are appropriately fitted since they obtained CFI and TLI of 0.95 and 0.93, respectively. As a final analysis, parsimony fit indices indicated a good fit, as the $\chi2/df$ is 2.62, thus the model fits well. It was observed that the uni-dimensionality factor (Model 1) fits poorly compared with the 6-factor model (Model 5). However, the indices were still in the range of an acceptable fit (*$\chi2/df$:3.21; RMSEA: 0.08; TLI 0.91; CFI: 0.92*). Thus, Model 1 and Model 5 demonstrated the construct validity. As a result of the total fit indices (absolute, incremental, parsimony) being met, the overall fit indices for the full model were

Table 4
Model fit comparison.

	Absolute fit			Incremental fit		Parsimony	Information theoretic	
	χ^2 (df.)	RMSEA	GFI	CFI	TLI	χ^2/df	AIC	CAIC
Model 1	523.37 (163)*	0.08	0.85	0.92	0.91	3.21	617.37	839.53
Model 2	564.19 (159)*	0.091	0.83	0.91	0.89	3.55	666.19	907.26
Model 3	686.78 (159)*	0.104	0.83	0.89	0.86	4.32	788.78	1029.85
Model 4	598.15 (214)*	0.08	0.85	0.92	0.91	2.80	722.15	1015.22
Model 5	405.74 (155)*	0.07	0.90	0.95	0.93	2.62	555.74	756.65

*Significant $p < 0.001$. Model 1: 1-factor model, 20 items; Model 2: 5-factor model combining VRD & E, 20 items; Model 3: 5-factor model combining DD & MWD; Model 4: 6-factor, 23 items; Model 5: 6-factor, 20 items.

acceptable.

In comparison to the five-factor model, the 6-factor model (Fig. 3) was more parsimonious in fitting the data. The psychometric properties of the measurement model (convergence and discrimination validation) can thus be assessed after the factors structure is confirmed.

4.4. Convergent validity

Table 5 presents the results of convergent validity, as calculated by AVE. According to the AVE values for the following domains: Pressure and Emotion (0.56), Violation and Risky Driving (0.66) Error (0.69), Carelessness (0.716), Drowsy Driving (0.791) and Mind-wandering (0.84), none of the AVE values are below 0.50, which is considered acceptable. Therefore, the final model construct exhibited convergent validity.

4.5. Discriminant validity

Table 6 shows that the correlations between the six main constructs range between 0.212 and 0.665, which are less than the square root of the AVE values, which range from 0.76 to 0.92. It is evident that the constructs have a strong correlation to their respective indicators in comparison to other constructs of the model, indicating good discriminant validity [43,44]. A correlation less than 0.85 is also observed between exogenous constructs [67]. Therefore, the final model constructs are discriminantly valid.

4.6. Predictive validity

After confirming the uni-dimensionality of Unsafe Driving While Commuting (UDWC), the total score for UDWC was calculated. To assess predictive validity, the influence of work demands and off-work demands on unsafe driving while commuting was examined using a structural model based on the Conservation of Resources theory (Fig. 4). The model demonstrated a strong fit to the theoretical framework ($\chi^2 = 179.69$, df = 60, $p = < 0.001$; CMIN/DF = 2.38, RMR = 2.995; GFI = 0.92; CFI = 0.94; NFI = 0.91; IFI = 0.94; RMSEA = 0.081, ranging between 0.067 and 0.094). Additionally, both work demands (β = 0.156, SE = 3.35 *t-value = 2.05 p-value = 0.034*) and off-work demands (β = 0.118, SE = 0.436 *t-value = 2.12 p-value = 0.04*) were found to be significant predictors according to the

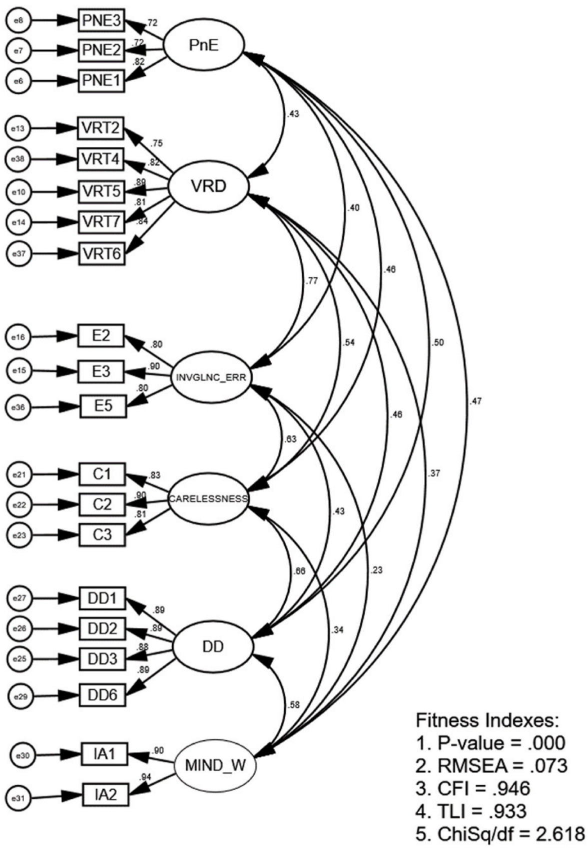

Fig. 3. Confirmatory factor analysis.

Table 5
The mean, SD, skewness, kurtosis and convergent validity.

No	Constructs	Item	Mean	SD	Skewness	Kurtosis	Loading	AVE	CR
1	Negative emotion	PNE1	2.14	1.70	−0.88	−0.87	0.816	0.564	0.795
2		PNE2	2.62	2.05	−1.02	−0.96	0.717		
3		PNE3	1.90	1.45	−0.45	−0.48	0.716		
4	Violation and reckless driving	VRT2	1.79	1.44	−0.37	−0.46	0.746	0.666	0.908
5		VRT4	1.50	1.25	0.80	0.58	0.824		
6		VRT5	1.35	1.03	1.66	1.78	0.886		
7		VRT6	1.65	1.14	0.28	0.38	0.836		
8		VRT7	1.56	1.21	0.49	0.39	0.813		
9	Error	E2	1.36	1.18	2.02	1.93	0.796	0.698	0.874
10		E3	1.42	1.00	1.14	1.41	0.904		
12		E5	1.38	1.02	1.22	1.31	0.801		
13	Carelessness	C1	1.51	1.07	0.20	0.09	0.834	0.716	0.883
14		C2	1.41	1.01	0.71	0.60	0.896		
15		C3	1.82	1.23	−0.34	−0.19	0.806		
16	Drowsy driving	DD1	1.92	1.60	−0.75	−0.83	0.890	0.791	0.938
17		DD2	1.83	1.61	−0.51	−0.66	0.892		
18		DD3	2.19	1.73	−0.89	−0.88	0.884		
19		DD6	1.81	1.54	−0.62	−0.76	0.892		
20	Mind wandering	IA1	2.83	2.23	−1.25	−1.14	0.897	0.844	0.915
21		IA2	3.09	2.36	−1.43	−1.23	0.940		

Table 6
Discriminant validity.

Constructs	VRD	Neg Emo	DD	MWD	C	Error	AVE
VRD	**0.816**						0.666
Neg Emo	0.398**	**0.76**					0.564
DD	0.431**	0.430**	**0.89**				0.791
MWD	0.359**	0.408**	0.535**	**0.92**			0.844
C	0.492**	0.386**	0.621**	0.342**	**0.85**		0.716
Error	0.665**	0.355**	0.386**	0.212**	0.543**	**0.835**	0.698

Note: The square value of the AVE is shown in bold. Off diagonal is a representation of the correlation between dimensions, while AVE is the extracted average variance.

regression analysis.

Table 7 presents the findings from the bootstrapping analysis, revealing significant indirect effects in the relationship between work demands and unsafe driving while commuting (β = 0.233, t-value = 3.581). The 95 % boot CI: (LL = 0.135, UL = 0.411) confirms the absence of zero within the interval, indicating mediation. Similarly, in the pathway from Off-Work Demands (OWD) through persistent Fatigue (PF) to Unsafe Driving While Commuting (UDWC), the bootstrapping analysis demonstrated a significant indirect effect (β = 0.352, t-value = 2.247). The 95 % Boot CI: [LL = 0.141, UL = 0.634] also excludes zero, affirming the presence of mediation in this

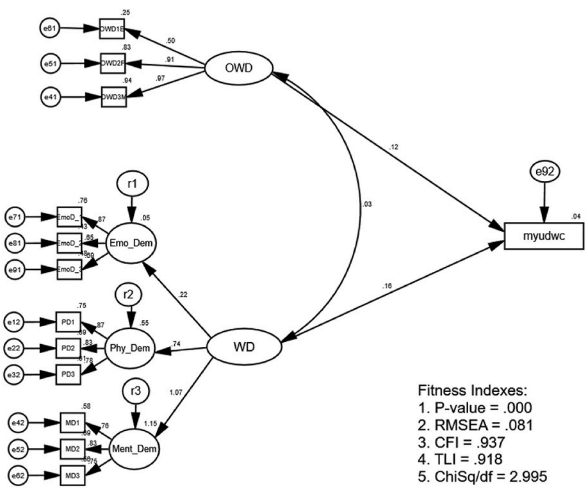

Fig. 4. Path analysis of work demand and off-work demand on unsafe driving while commuting.

relationship.

5. Discussion

5.1. Study findings

This study aimed to both determine unsafe driving behaviours experienced by nurses while commuting, and to develop a questionnaire to assess unsafe driving behaviours among nurses while commuting. A total of six themes were identified, which correspond to three types of performance deterioration as per Hockey's CCM, these themes indicating unsafe driving behaviours while commuting. The themes were 1) violation and reckless driving, 2) negative emotion, 3) drowsy driving, 4) mind-wandering, 5) carelessness, and 6) errors. Based on Hockey's CCM, violations and reckless driving fall into strategic adjustment types. Negative emotion represents CCM's compensatory cost. Meanwhile, drowsy driving, mind-wandering, carelessness and errors represent subsidiary task failures.

Nurses' driving behaviour during their commute possesses several unique characteristics. Firstly, it relates to time sensitivity and strategic adjustments to time; nurses often work on fixed schedules and need to arrive at their healthcare facilities promptly. This time sensitivity can lead to behaviours such as speeding, aggressive driving, or taking risks to avoid being late for duty. These behaviours emerged as violation and reckless driving in MyUDWC. While speeding is incorporated within the same theme, ODBQ positions it as a distinct theme.

In addition, a nurse may want to multitask and stay connected to utilize time efficiently during the commute. Nurses may feel the need to use their cell phones while on the road to manage work-related tasks, such as responding to calls, checking patient information, or coordinating care and updates. The pressure to multitask and use cell phones to save time can increase temptation, besides which, the urgency of healthcare-related communication can justify a perceived necessity to use cell phones while driving, even though it is unsafe. Driving using a cell phone was also identified as one of the items of violations and reckless driving. This item, however, does not appear in the ODBQ as although it was also conceptually included in the broader concept of driving distraction, using a cell phone while driving is an offense considered non-compoundable in Malaysia in accordance with Rule 17 A, LN166/59 [68,69].

Secondly, nurses are particularly susceptible to negative emotion driving since this profession is both demanding and stressful. The ODBQ, however, reveals a lack of emotional driving behaviour as an affective response to the stress caused by work-home commuting. Negative emotion driving can manifest as compensatory cost behaviour in Hockey's CCM, with many nurses experiencing exhaustion, burnout, and work-related stress [36,70,71]. Thus, commuting can be affected by these factors, potentially causing impatience, anger, and aggressive driving. Traffic congestion may worsen the condition [59,72] as a driver might become frustrated and resentful while his vehicle is stationary or moving slowly. Time pressure and long exposure to commuting may catalyse further negative interactions with other road users [59,73].

Thirdly, nurses may become familiar with their commuting routes due to daily travel to and from healthcare facilities. Route familiarity can create a false sense of security and lead to complacency while driving [12]. This diminishes cognitive control and makes the driver more prone to distractions and mind-wandering resulting in a narrowed focus and inattention to the road [74,75]. Also, familiarity with a specific route can lead to a lack of adaptability in response to changing road conditions, construction, or unexpected situations. Instead, drivers may rely on their preconceived notions of the route, leading to resistance in modifying their driving behaviour to suit the circumstances rendering them more vulnerable to errors, carelessness, and poor control of the vehicle [12,13]. These unique characteristics of commuting resulted in the reported findings of emerging themes, namely mind-wandering, error and carelessness respectively. While the concept of inattention is present in the ODBQ and is similar to our construct of mind-wandering, error-proneness and carelessness were absent.

Finally, nurses also commonly work in shifts that include early mornings, late nights, and rotating schedules [76,77]. Shift work can result in fatigue, reduced alertness, and disrupted sleep patterns, which may increase the likelihood of drowsy driving and impaired driving performance [16,78–80]. The emergence of our final construct, namely drowsy driving, highlights this point. People who are drowsy and fatigued can have slower reaction times, decreased vigilance and judgement, and an increased crash risk [81,82]. This is because fatigue can impair the neural pathways that control the body's alertness response [83], leading to impaired decision-making and difficulty concentrating Additionally, the lack of sleep can lead to microsleeps, which can further reduce alertness and increase the risk of an accident [84]. Previous studies have shown that nurses are at increased risk of drowsy driving due to their work-related fatigue [26,79,85].

Table 7
The direct and indirect relationship.

Relationship	B	SE	t-value	CI 95 %
WD → UDWC	0.156	3.35	2.05**	0.00,0.255
OWD → UDWC	0.118	0.436	2.12**	0.043,0.206
WD→ AF → UDWC	0.233	0.065	3.581***	0.135,0.411
OWD → PF → UDWC	0.352	0.157	2.247**	0.141,0.634

Notes: WD, work demands; OWD, off-work demands; AF, Acute Fatigue; PF, Persistent Fatigue; UDWC, Unsafe Driving While Commuting. $^{**}p \leq 0.05$, $^{***}p \leq 0.001$ Sources: Preacher and Hayes (2004, 2008).

5.2. Scales validity

In the validity, content validity of this scale showed excellent agreement among experts and items with excellent content validity indexes across constructs. Validation of the developed item pool was performed by an independent panel of experts selected for their expertise in the fields of traffic safety research, and psychometric and occupational health, which strengthened the validity of its face and content. The process underwent rigorous evaluation and objective rating of content validity by an expert panel.

In the assessment of the constructs, the six domains of the My-UDWC displayed clusters of interrelated measures indicative of unsafe driving. The investigation of My-UDWC uni-dimensionality in the dataset resulted in satisfactory fits to the model. This allows the My-UDWC total score to be used as an additive index for unsafe driving. Nevertheless, our findings suggested a superior fit of the six-factor model (multidimension) than the uni-dimension model; it indicated its subconstructs capture information which the overall score did not explain as a single factor.

Analyses of both exploratory and confirmatory factor relationships provided support for the validity of My-UDWC's construct. In this study, the EFA of My-UDWC explained 73.89% of the variance which yielded the 6-factor model. Validation of My-UDWC factor structures derived from EFAs was undertaken using CFA. The results demonstrated a good fit for the model, confirming its factor structure. In terms of fit indices, the indices achieved met the least fit requirements. All AVE values for each construct were more than 0.5 suggesting a good convergent validity. The constructs were related to their respective indicators in a stronger manner than other constructs in the model, thus indicating a high degree of discriminant validity.

In terms of predictive validity, the work demand and off-work demand variables significantly predicted unsafe driving while commuting. The indirect effects of unsafe driving while commuting were also predicted by work and off-work demands via acute fatigue and persistent fatigue respectively. This feature of fatigue as a link explains the process of unsafe driving while commuting under the influence of work demands and off-work demands. In keeping with recent evidence, commuting has spill-over effects on both the personal and professional lives [86]. In light of the Omega and composite reliability findings, we can conclude both the scales and the sub-dimensions were reliable.

5.3. Practical implication

The main implication of our study for practical measures was aimed towards addressing traffic safety issues among nursing and other healthcare professionals while commuting. Existing data in the Social Security (SOCSO) 2018 annual report showed a significant increase in commuter-related collisions [87] while workplace incidents, conversely, were diminished. Similarly findings stated in the French Health Insurance 2017 Annual Report showed a worrying increase in the number of commuting collisions [88]. In Malaysia, nurses contributed the largest portion (53 %) of total commuter-related incidents among government hospital staff (n = 554) [15]. In a different study, nurses contributed 15.2 per 10 000 workers incidence rate of commuting accidents and represented the largest portion of commuting collisions compared to other healthcare professions [14].

Development and validity of My-UDWC allows a better understanding of drivers' unsafe behaviour while commuting, which is categorized into six different classes. It is believed that the first step towards any behaviour modification training program and an effective road safety campaign within a workplace is by recognizing drivers' profiling. Hence, My-UDWC enables identification of drivers' type of unsafe driving behaviour while commuting. Consequently, a targeted and personalized intervention could be conducted according to drivers' self-profiling. For instance, factors such as negative emotions, violation and risky driving are related to personality, motivation, attitude, knowledge and skills. Among suggested interventions are the establishment of focus groups aimed at understanding respondents' behaviours at a deeper level and providing opportunity for greater reflection, and recommendations for corresponding counselling accordingly. Concurrently, an educational program to mitigate fatigue and sleepiness at the workplace could also address issues for those who are relevant candidates for drowsy driving, invigilance, carelessness and mind wandering factors.

5.4. Strengths and limitations

This study's strength is the systematic methodology employed in the development of this scale. This included the incorporation of a grounded theory for conceptualization, and an expert panel to inductively generate ideas and assess both the content and face validity. The examination of construct, divergent and convergent validity provides further validity to the newly developed scales. The execution of data collection through an open web-based method was cost-effective, comprehensive, and convenient. While the survey was web-based, it still employed random sampling to select participants from 10 major hospitals. Still, interpreting the results should be done with caution. Although the online distribution was employed randomly, it may introduce inherently selection bias, social desirability, and potential understatement of unsafe driving behaviours among participants. This is given that self-reporting on any scale may lead participants to overestimate or underreport certain behaviours in order to appear more socially desirable.

Despite its strength, this study has several limitations that should be noted. First, the study was conducted only among hospital nurses, predominantly female (95 %) which may compromise the generalizability. By fact, nursing profession remains a woman-dominated profession and this scenario does not significantly alter at national level [89] as well as from other countries like Japan [90], China [91], the US [92] and Canada [93]. In order to minimize this concern, a diverse sample of nurses (non-managerial vs managerial, aged more than 18 years old and driving licence holder >1 year) were employed. Future research employing broader criteria of commuters in respect to individual characteristics would offer increased representativeness and additional validity for the scale.

Second, the research applied a cross-sectional design. The participants were assessed at one point in time from one single self-reported source. Therefore, stability and reliability of the scale across time were not concluded due to the absence of test-retest reliability. Moreover, the common method variance (CMV) may have inflated the correlations in present study. Nevertheless, in order to mitigate the CMV, participants were assured of the anonymity and confidentiality of the study. Participation was voluntary and there were no right or wrong answers to the scales. These procedures reduced leaning towards what can be construed as researchers' preferred and more socially desirable answers. Different scale endpoints were used for persistent fatigue and My-UDWC. The Harman one-factor test was also conducted for statistical remedies with unrotated factor solutions. No issues with common method bias were found in this study because the total variance extracted by single factor was 42.74%, which is less than 50 % [94]. In addition, mediating effects were examined to add complexity to the relationship, as guided by established theories.

Whatever the case may be, future validation of driving behaviour should attentively consider CMV during design and analysis phases. To further overcome this issue, future research could evaluate the relationship between relevant factors and commuting behaviour in a longitudinal manner or by using a daily diary study. For instance, a previous study found that job strain influenced commuting safety behaviour at intraindividual level via work-related affective rumination [95]. Next, future researchers could also examine the correlation of respective driver behaviour subscales with objective measures for driving performance (*e.g.: Time Headway, average speed*) and fatigue state (*e.g.: PERCLOS, facial recognition, eye tracking*). This would determine the relationship between objective or existing measures with newly developed scales, thus providing accuracy to the construct validity.

6. Conclusion

This study developed the My-UDWC was guided by the Compensatory Cost Model of Hockey. The development process underwent systematic assessment by panel experts and therefore represents a significant development in illuminating and measuring unsafe driving while commuting among healthcare workers, particularly for Malaysian nursing professionals. The My-UDWC has been proven to be a reliable and valid assessment tool for unsafe driving while commuting among nursing professionals and comprised six factors, "violation and risky driving", "negative emotion", "error", "carelessness", "drowsy driving", and "mind-wandering". The unidimensionality of My-UDWC was examined and subsequently shows acceptable validity. In conclusion, My-UDWC can be applied to measure unsafe driving while commuting with good construct validity and reliability. It could be further improved if present study limitations are taken into consideration in future studies.

Ethical consideration

All participants provided informed consent. Research on this topic was conducted as part of a larger project examining the relationship between daily psychosocial strain and driving behaviour among hospital nurses. The study was approved by the Medical Research and Ethics Committee (MREC), Ministry of Health (KKM/NIHSEC/P20-1860(15) and the Research Ethics Committee, The National University of Malaysia (UKM PPI/111/8/JEP-2021-137).

Data availability statement

This study's data are available on request from its corresponding author. The data are not publicly available due to data owner restrictions.

Additional information

No additional information is available for this paper.

CRediT authorship contribution statement

Hanizah Mohd Yusoff: Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Conceptualization. **Khairil Idham Ismail:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Rosnah Ismail:** Writing – review & editing, Validation, Supervision, Resources, Methodology, Data curation, Conceptualization. **Nor Kamaliana Khamis:** Writing – review & editing, Supervision. **Rosnawati Muhamad Robat:** Writing – review & editing, Supervision. **Jonathan Michael Bryce:** Writing – review & editing, Validation.

Declaration of competing interest

The authors declared no potential conflict of interest.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2023.e23735.

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