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HOW TO INCREASE URBAN ROAD SAFETY: AN INTEGRATED MODEL FOR PREDICTING PEDESTRIAN BEHAVIOUR BASED ON PSYCHOLOGICAL AND EXTERNAL FACTORS

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Abstract. The study investigates the factors influencing pedestrian decisions to commit temporal violations at signalized intersections, with the aim of enhancing urban road safety. To achieve this, an integrated model combining subjective components from the Theory of Planned Behaviour (TPB) and the Prototype Willingness Model (PWM) with relevant external factors was developed and validated. The findings underscore the significance of

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external factors – such as pedestrian red signal duration, vehicle flow, roadway length, and the presence of a median refuge island – alongside willingness and perceived behavioural control as key predictors of pedestrian behaviour. Intentions, in contrast, showed limited influence, highlighting the dominance of social-reactive pathways over reasoned decision-making in pedestrian violations. The study contributes a novel, comprehensive framework for understanding pedestrian behaviour by integrating psychological and situational predictors, thereby providing valuable insights for the design of safer urban intersections.

Keywords: external factors, integrated model, pedestrians, prototype willingness model, signalized intersections, temporal violations, theory of planned behaviour.

Introduction

According to the data published by the World Health Organization (WHO), 1.19 million people were killed in traffic accidents in 2021 across the globe, which is equivalent to 15 road traffic deaths per 100 000 individuals. In 2019, road traffic injuries were the leading cause of death for children and youth aged 5 to 29 and the 12th leading cause of death for all age groups (WHO, 2023). More than half of those killed were pedestrians, motorcyclists, and cyclists. Globally, pedestrians account for 23% of all traffic accident fatalities (WHO, 2023). Pedestrians are a particularly vulnerable category of road users, as they face serious consequences if involved in traffic accidents due to the lack of physical protection and the large disparity in mass relative to motor vehicles (Shinar, 2017). As this significantly increases the likelihood of serious injury or death compared to vehicle drivers and passengers, it is crucial to develop effective measures for enhancing pedestrian safety.

Understanding and addressing pedestrian traffic-rule violations is critical, as their frequency is strongly linked to an increased risk of collisions, particularly at signalized intersections. Although pedestrian violations do not always lead to traffic accidents, their frequency is positively correlated with the risk of collisions. For example, King et al. (2009) found that temporal (the noncompliance with traffic lights) and spatial (crossing the roadway where this is not allowed) pedestrian violations can increase crash rates at signalized intersections by up to eightfold. Mukherjee and Mitra (2019) similarly found a direct correlation between the frequency of temporal violations and fatal crashes at 24 signalized intersections, and confirmed these findings in a later study by analysing data collected at 55 signalized intersections (Mukherjee & Mitra, 2020). Specifically, the authors found that a 1% increase in pedestrian violations increases the frequency of fatal accidents by approximately 1.589-fold (Mukherjee & Mitra, 2020). More recently, Kumar and Ghosh (2022) established that pedestrian temporal violations, especially those committed at the end of the red-light signal, significantly contribute to increased conflict rates that can potentially lead to serious traffic accidents at signalized intersections. It is evident from these discussions that most studies in this domain focus on intersections, where interactions between pedestrians and vehicles are most frequent, rendering them particularly dangerous locations (Brosseau et al., 2013; Cao et al., 2016).

To understand the risks associated with pedestrian violations, it is crucial to explore the specific phases of crossing behaviour during which such decisions are made. According to Geruschat et al. (2003), pedestrian behaviour when crossing the roadway consists of three phases: *the roadway access phase*, during which the pedestrian visually follows 'crossing decision elements' (primarily traffic signals at intersections); *the waiting phase*, which mirrors the access phase but involves more intensive focus on vehicles; and *the crossing phase*, in which the pedestrian looks ahead or focuses on potentially dangerous zones while crossing. Based on this division, it is unclear at which stage the pedestrian decides to illegally cross the roadway, i.e., whether this decision is made during the roadway access phase, the waiting phase, or if the decision has already been made, and the pedestrian is evaluating the possibility of executing the pre-planned action.

These uncertainties regarding the specific phase of decision-making underline the need to investigate whether pedestrian violations are deliberate or arise from spontaneous opportunities encountered at intersections. Findings reported in pertinent literature and the existing knowledge raise numerous research questions. First, it remains to be established whether pedestrian violations are premeditated actions or if pedestrians decide to commit violations upon approaching an intersection, if they find an opportunity they are willing to take. Although pedestrian behaviour is typically explained by the theory of planned behaviour (TPB); this theory is based on the assumption that intentions are the strongest predictor of pedestrian behaviour. Consequently, the predictive power of basic and extended subjective constructs with respect to intentions is examined without considering the possibility that pedestrian behaviour may not follow a reasoned path.

Observing pedestrian behaviour immediately before red-light crossing, Dommes et al. (2015) concluded that the majority of these pedestrians focus on oncoming vehicles rather than the traffic light, supporting the conclusion that violations are premeditated actions. On the other hand, findings reported by Demir et al. (2019) point to the stronger predictive power of pedestrian willingness (compared to intentions) to seize an opportunity to commit a violation. Additionally, since the basic Prototype Willingness Model (PWM) does not include perceived behavioural control (PBC) – which has been identified as one of the most important predictors of intentions and a significant predictor of pedestrian behaviour – the question arises whether including PBC in the model could provide a better prediction of pedestrian red-light crossings.

Attempts to create an integrated TPB-PWM model have been made by Lee et al. (2016), Demir et al. (2019), Tang et al. (2020), Wang and Xu (2021), Liu, Chen, and Pei (2023), Wang et al. (2023), and Liu and Liu (2024), but only Demir et al. (2019)

focused on pedestrian violations. These authors noted that the TPB-PWM model explains 1% more variance in pedestrian violations than the PWM model. Similarly, Tang et al. (2020) established that red-light violations can be better explained by the TPB-PWM model compared to the PWM model, but only to the extent of 0.1% of the variance. Although Tang et al. (2020) concluded that the integrated model could marginally better predict red-light violations, their study focused on electric bicycle riders. On the other hand, the results of other studies demonstrated the significant superiority of the TPB-PWM model in explaining road users' behaviour in general (Wang & Xu 2021; Liu, Chen, & Pei, 2023; Wang et al., 2023; Liu & Liu, 2024). Therefore, there are evident ambiguities in the results obtained in prior research regarding the efficacy of the TPB-PWM model in explaining road users' behaviour. Furthermore, only the study conducted by Demir et al. (2019) focused on pedestrians, but even in this case, aggregated pedestrian violations were analysed.

Given the evidence provided above, it can be concluded that the capacity of the integrated model encompassing TPB and PWM constructs (as well as the PWM model itself) for predicting pedestrian red-light crossings has not received adequate research attention, despite indications of its superior efficacy in forecasting road users' behaviour compared to the TPB, necessitating further investigation.

Since pedestrians make decisions about crossing in a complex traffic system, it needs to be ascertained whether subjective components are sufficient to understand the pedestrian decision-making process, or if their decision results from the interaction of subjective and external factors. According to the TPB creator Ajzen (1985), behaviour is also conditioned by external factors, which represent limiting elements and provide a link between intentions and behaviour.

In order to understand pedestrian behaviour at signalized intersections, there have been attempts to integrate subjective and external predictors (e.g., Yagil, 2000; de Lavalette et al., 2009), but these models did not include behaviour predictors defined by the TPB and PWM. Shen et al. (2020) developed an integrated model comprising TPB constructs, conformity tendencies, and external factors. The authors developed their model on a sample of delivery drivers, focusing on their intentions to run a red light at intersections. The integrated model (TPB, conformity tendency and external factors) explained an additional 11% of the variance in intentions compared to the basic TPB model.

The present study is unique because it includes all TPB and PWM constructs, as well as a greater number of external factors that have been most frequently reported in pertinent literature as influencing pedestrian behaviour. Its further distinction stems from its sole focus on pedestrian red-light crossings at signalized intersections. The only study in which PWM was employed in predicting pedestrian behaviour was conducted by Demir et al. (2019). However, these authors did not consider external factors and analysed a wide range of pedestrian violations (including red-light crossings, crossing outside marked pedestrian crossings, and diagonal roadway crossings) without a clear distinction of predictors by types of violations.

The remainder of the paper is organized into sections covering the literature review, methodology, results, and conclusions.

1. Literature review

As the decision to cross the road is a complex process conditioned by a large number of factors, it has attracted considerable research aiming to identify the factors that influence the decision-making involved in illegal pedestrian crossings, as well as to determine the strength of their influence. A comprehensive review of extant literature indicates that the influencing factors can be broadly divided into subjective factors and external (situational) factors.

1.1. Subjective factors

One of the most commonly used theories to explain pedestrian behaviour is the *Theory of Planned Behaviour (TPB)* (Barton et al., 2016; Xiao et al., 2021; Liu, Li, and Hu, 2023). According to the core TPB concept, attitudes, subjective norms (SN), perceived behavioural control (PBC), and intentions are the main behaviour predictors.

Several models based on the TPB have been developed and their ability to predict pedestrians' intentions to commit temporal violations has been extensively tested. For example, Evans and Norman (1998) found that the TPB-based model explained 49% of the variance in pedestrians' intentions to cross the road on red light at pelican crossings, while Zhou et al. (2009) reported that an expanded TPB model explained 34% of the variance in pedestrian intentions. Zhou and Horrey (2010) developed an integrated model specifically aimed at adolescent pedestrians, accounting for the TPB components, as well as gender, age, conformity, and sensation seeking. Their model explained 27% and 39% of the variance in intentions in the non-conformity and conformity scenario, respectively. Numerous researchers have also expanded the basic TPB concepts in order to predict pedestrian behaviour (Xu et al., 2013; Zhou et al., 2016; Demir et al., 2019; Xiao et al., 2021; Liu, Li, and Hu, 2023). The TPB model developed by Demir et al. (2019) explained 39% of the variance in intentions and 42% of the variance in pedestrian violations (both temporal and spatial). As a part of their investigation, Xiao et al. (2021) utilised the TPB model to examine the violations committed by younger pedestrians at signalized intersections. The model explained 10% of the variance in intentions and 11% of the variance in pedestrian behaviour. More recently, Liu, Li, and Hu (2023) have examined illegal pedestrian crossings, including red-light and diagonal crossings. The model based on the core TPB constructs explained 49.9% of the covariance in intentions and 18.4% of the covariance in pedestrian behaviour. Using this expanded model, Xu et al. (2013) explained 63% of the variance in pedestrian temporal violations.

In an earlier study, Diaz (2002) developed a TPB-based model of pedestrian violations, errors, and lapses, and reported that all predictors – including attitudes, SN, and PBC, mediated by intentions – had a statistically significant explanatory power. Attitudes were the strongest predictor of intentions, followed by SN and PBC. Likewise, Liu, Li, and Hu (2023) found that attitudes, descriptive norms, perceived severity, and perceived benefit had a statistically significant influence on pedestrian violations. The results reported by Xiao et al. (2021) similarly suggest that all TPB constructs are significant predictors of pedestrians' intentions to cross the road during a red signal. Nonetheless, SN was the strongest predictor of pedestrian intentions, while PBC was the weakest. These authors further noted that intentions were the only predictor with a direct and significant influence on pedestrian behaviour at signalized intersections. On the other hand, in a large number of studies, PBC was the strongest predictor of intentions (Evans & Norman, 1998, 2003; Holland & Hill, 2007; Zhou et al., 2009; Zhou & Horrey, 2010; Xu et al., 2013; Barton et al., 2016). According to Barton et al. (2016), the reason for such results may be the fact that, although pedestrians are aware of the risks involved in illegal road crossing, as it is part of their daily routine, it is considered easy to perform, which significantly reduces the perception of risk.

A growing body of research highlights the importance of understanding pedestrian behaviour through theoretical frameworks, among which the *Prototype Willingness Model (PWM)* has shown potential for explaining risky crossing decisions. Only one study was found in which PWM was used to predict illegal roadway crossings by pedestrians (Demir et al., 2019). PWM model explains an additional 11–17% of the variance in intentions and an additional 23% of the variance in pedestrian violations compared to the TPB model. Demir et al. (2019) also found that willingness was a stronger predictor of pedestrian violations than intentions. As a part of their investigation, Mirzaei-Alavijeh et al. (2019) also adopted the PWM perspective, but they did not predict pedestrian behaviour. Nonetheless, these authors successfully developed a psychometric scale for safe road crossings by adolescent pedestrians based on PWM.

An *integrated TPB – PWM model*, consisting of all constructs defined by the TPB and PWM, in the context of predicting pedestrian behaviour, was developed by Demir et al. (2019). The TPB-PWM model explained a higher percentage of variance in intentions (56%), willingness (44%), and behaviour (66%), compared to the TPB (39% variance in intentions and 44% in behaviour) and PWM (50% variance in intentions, 39% in willingness, and 65% in behaviour) models. Accordingly, the authors concluded that intentions and willingness were statistically significant predictors of pedestrian violations, with willingness having a stronger impact. They further noted that prototype perception was a stronger predictor of pedestrian behaviour compared to all TPB components except PBC.

As no further studies were identified in which PWM and integrated TPB-PWM model were applied to explain and predict pedestrian behaviour, the literature review was expanded to include other categories of road users.

The authors concur that the PWM model is superior in predicting the behaviour of road users compared to the TPB model (Elliot et al., 2017; Frater et al., 2017; Tang et al., 2020; Esmaeli et al., 2022; Zhao et al., 2023; Pei et al., 2023; Wang et al., 2023). Furthermore, they concur that the integrated TPB-PWM model explains a greater variance in behaviour compared to the TPB model (Liu, Chen, and Pei, 2023; Liu and Liu, 2024). A majority of studies have demonstrated that the integrated TPB-PWM model is even more effective than the PWM model (Lee et al., 2016; Tang et al., 2020; Wang and Xu, 2021; Zhao et al., 2023; Liu and Liu, 2024), though some research presents conflicting results (Pei et al., 2023; Wang et al., 2023).

From the references presented above, it is evident that the PWM and integrated TPB-PWM models are often superior to the TPB model in predicting the behaviour of road users. Additionally, the model incorporating PWM components is frequently used to examine behaviours of road users of all age groups (Esmaeli et al., 2022; Wang et al., 2023; Pei et al., 2023; Liu and Liu, 2024) even though, in its original form, this theory was intended for younger populations. As Gibbons et al. (2020) noted, such a trend is expected as many risky behaviours are intentional to a certain extent. However, as each individual has their limits, the risk above that threshold is typically determined by willingness, even among adults.

1.2. External factors

Pertinent literature is also reviewed to provide a deeper understanding of external factors that can influence pedestrian violations at intersections. The goal is to identify key external factors and their potential impact on pedestrian temporal violations at signalized intersections.

Waiting time is one of the key and most frequently identified factors, with longer waiting times for the green light significantly increasing the likelihood of pedestrian temporal violations (Yang and Sun, 2013; Chen et al., 2017; Gong et al., 2019; Ma et al., 2020; Wu et al., 2021; Afshari et al., 2021; Zhu, Sze, and Bai, 2021; Zhu, Sze, and Feng, 2021; Raoniar et al., 2022; Ghomi and Hussein, 2022; Liu et al., 2022). According to the findings reported by Tiwari et al. (2007), Ren et al. (2011), Guo et al. (2011), Guo et al. (2012), Brosseau et al. (2013), Koh et al. (2014), and Zhang and Deng (2019), pedestrians become more impatient as the waiting time increases, which may prompt them to commit violations. For example, Guo et al. (2011) and Guo et al. (2012) established that, after 50 seconds of waiting, almost half of the pedestrians decided to cross the road during the red light, while about 10% of risk-prone pedestrians would attempt to cross within the first three seconds. Afshari et al. (2021) similarly demonstrated that, for each additional second of waiting, the likelihood of temporal violations increases by 2.2%. Based on the evidence presented above, the rate of pedestrian temporal violations at intersections increases with longer waiting times, which are directly related to the duration of the red signal for pedestrians.

Vehicle flow is another important factor influencing pedestrian behaviour at intersections. Specifically, Yagil (2000), Koh (2014), Dommes et al. (2015), Diependaele (2019), Ma et al. (2020) and Ghomi and Hussein (2022) established a negative correlation between vehicle flow and the pedestrian red-light crossing frequency. Based on the findings yielded by regression models, Afshari et al. (2021) similarly concluded that a single-vehicle increase in traffic flow resulted in a 9.5% reduction in the likelihood of pedestrians crossing during the red light. Zhang and Deng (2019) observed that longer vehicle following intervals in traffic flow significantly increased the chances of pedestrian temporal violations. Applying the same approach, Gong et al. (2019) demonstrated that only 5.1% of pedestrians crossed the road during the red light when the gap between vehicles was between 0 and 2 seconds. These results are expected because the gap between vehicles increases when traffic flow is lower (Yang et al., 2015).

According to Yagil (2000), *the presence of waiting pedestrians* reduces the frequency of violations by females more strongly than males. Other authors similarly noted that the *presence of pedestrians already crossing during the red light* increases the likelihood that an individual will also commit this violation irrespective of gender (Guo et al., 2011; Guo et al., 2012; Yang et al., 2015; Afshari et al., 2021; Zhu, Sze & Bai, 2021; Raoniar et al., 2022). These tendencies are explained by the theory of conformity, whereby individuals follow group behaviour to align with social norms or reduce social isolation (Guo et al., 2011).

The presence of a *median refuge island* has also been identified as a factor that increases the number of pedestrian temporal violations (de Lavalette et al., 2009; Li & Fernie, 2010; Zhang et al., 2016; Wang et al., 2020; Ghomi & Hussein, 2021), because it motivates pedestrians to make two-phase crossings. Koh et al. (2014) investigated the combined impact of median refuge islands and the number of traffic lanes, concluding that the likelihood of risky crossings is 248% higher on a four-lane road with a median island compared to roads with six or seven traffic lanes.

Available evidence also indicates that the number of pedestrians who decide to cross during the red light is affected by the *road width* (number of traffic lanes, pedestrian crossing length) (de Lavalette et al., 2009; Ren et al., 2011; Brosseau et al., 2013; Koh et al., 2014). According to Afshari et al. (2021), increasing the length of the pedestrian crossing by one meter reduces the likelihood of temporal violations by 13.9%. Similar conclusions were reached by Yang and Sun (2013), Diependaele (2019), Ghomi and Hussein (2021), and Zhu, Sze, and Bai (2021), who found a negative correlation between the number of traffic lanes (pedestrian crossing length) and pedestrian temporal violations. Zhu, Sze, and Bai (2021) posit that this inverse link arises because the perception of greater risk and the longer time required to cross a wider intersection encourages pedestrians to behave more cautiously. Yet, these arguments are challenged by Gong et al. (2019) and Wu, Guo, and Yin (2021) who report a positive correlation between the pedestrian crossing length and the temporal violation rate.

Findings yielded by numerous studies further show that pedestrians walking in groups are less prone to temporal violations (Ren et al., 2011; Brosseau et al., 2013; Koh et al., 2014; Dommes et al., 2015; Chen et al., 2017; Gong et al., 2019; Zhu, Sze, and Bai, 2021, Raoniar et al., 2022). Specifically, Koh et al. (2014) found that the likelihood of temporal violations for pedestrians moving in group decreased by 246% compared to those crossing alone. Similarly, Gong et al. (2019) established that, if pedestrians were moving in a group of six or more members, the violation rate was only 4.8%. Conversely, individual pedestrians are more prone to violations as they have the flexibility to adjust their walking speed according to the interval between oncoming vehicles.

The presence of a *countdown timer* on pedestrian traffic lights has a significant impact on reducing temporal violations because it provides pedestrians with clear information about the remaining time until the signal changes (Brosseau et al., 2013). Chen et al. (2017) found that intersections with a countdown timer had 15% fewer pedestrian temporal violations compared to intersections without a timer. Similar conclusions were reached by Lipovac et al. (2013), de Lavalette et al. (2013), Chen et al. (2017), Diependaele (2019), Gong et al. (2019), Guo et al. (2019), Marić et al. (2021), and Ghomi and Hussein (2022). In contrast, Biswas et al. (2017) reported a higher percentage of pedestrian temporal violations per cycle at intersections with a timer (3.2 violations per cycle) compared to intersections without a timer (2 violations per cycle). Also, as Ristić et al. (2024) concluded, the presence of countdown timers significantly would influence pedestrian behaviour by reducing start-up times and enhancing the efficiency of green signal utilisation.

2. Materials and methods

The overall research flow, from motivation to implications, is summarised in Figure 1, providing an overview of the research key stages.

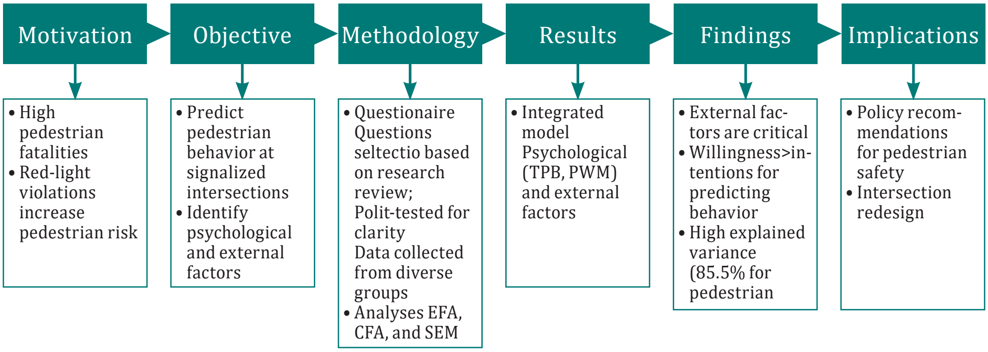

Figure 1. Study flow diagram

2.1. Psychological theories

The *Theory of Planned Behaviour* identifies attitudes, subjective norms, perceived behavioural control, and intentions as key predictors of behaviour. Attitude represents an individual's belief that certain behaviour will bring favourable or unfavourable consequences. For example, a pedestrian's belief that crossing the road at a red signal will save time is indicative of a positive attitude toward violation. Subjective norms are defined as beliefs that people close to the individual will approve or condemn a certain behaviour, while perceived behavioural control represents the individual's perception of their own abilities to implement the behaviour with a relative ease or difficulty (Zhou et al., 2016). Whereas these three factors influence behaviour through intention, the impact of PBC can be direct, especially when an individual believes that their abilities exceed the difficulty of a certain task (Ajzen, 1991). This concept is depicted in Figure 2.

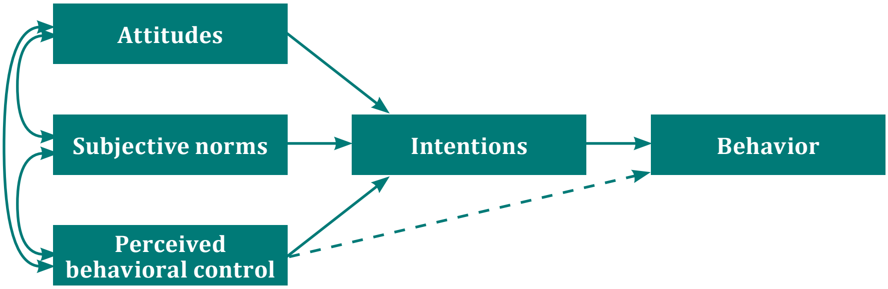

Figure 2. The concept of the theory of planned behaviour (adapted from Ajzen, 1991)

According to the *Prototype Willingness Model*, the rational actions described by the TPB are possible predictors of behaviour, but are not the sole ones. From another psychological point of view, behaviour is more spontaneous, conditioned by the current situation, and largely depends on prototype perception (Gibbons et al., 1998). In other words, when confronted with a situation that encourages certain behaviours, especially risky ones, individuals' actions are not conditioned by pre-planned intentions, but by the willingness to take advantage of the opportunity (Ajzen, 2011). For example, if there are no oncoming vehicles, a pedestrian may decide to cross the road during a red signal, although they did not intend to do so beforehand (Demir et al., 2019). The PWM posits that two paths, namely reasoned and social-reactive, lead to behaviour (Figure 3).

In line with the TPB, the reasoned path includes attitudes and SN, whereby PBC is excluded. On the other hand, in addition to attitudes, SN, and intentions, the social-reactive path includes prototype perception, as well as willingness. In this context, willingness denotes inclination toward taking advantage of the opportunity, and prototype is defined as an opinion about persons who represent typical representations of a certain behaviour and consists of prototype similarity and prototype favourability (Demir et al., 2019). In the case of pedestrian violations, prototype similarity is determined by how strongly the pedestrian, deciding to cross the road illegally, identifies with those who typically do so. Prototype favourability refers to pedestrians' opinions about individuals who frequently cross the road illegally.

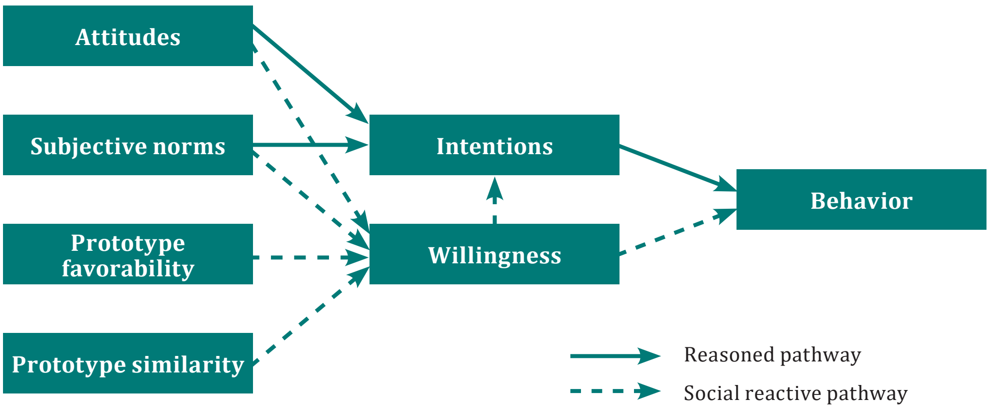

Figure 3. The concept of the prototype willingness model (adapted from Demir et al., 2019)

When discussing the PWM, several questions must be asked: (1) Is willingness a stronger predictor of behaviour compared to intentions? (2) Can the PWM concepts be effectively used to predict pedestrian behaviour? and (3) Does integrating the

TPB and PWM (by including willingness and prototype perception into the TPB) contribute to better behaviour prediction (Ajzen, 2011)? As PWM effectiveness in predicting illegal road crossings has so far received limited scholarly attention, these questions are highly pertinent. The hypothetical integrated TPB-PWM concept, which has been examined within this study, is illustrated in Figure 4.

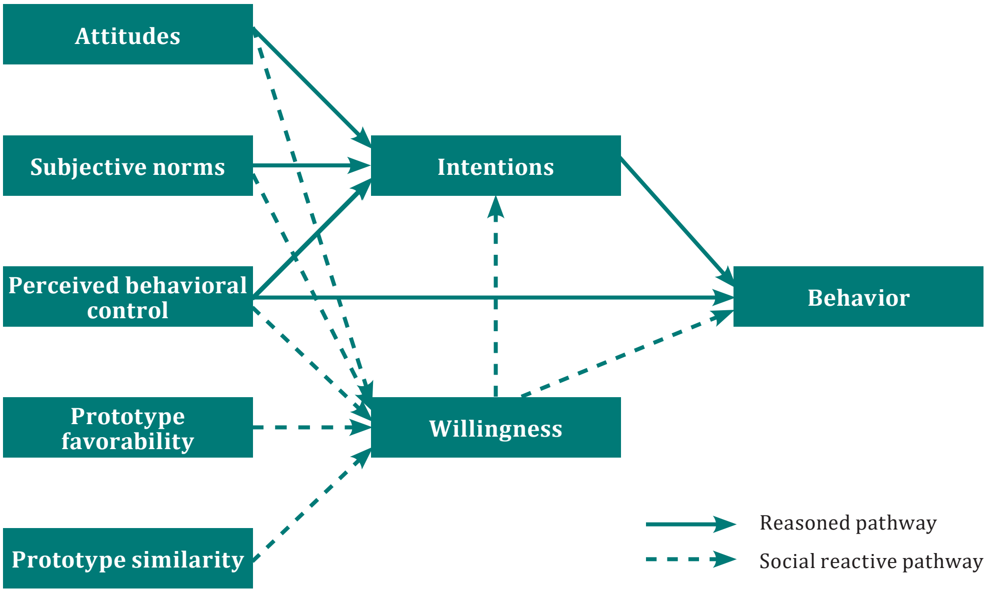

Figure 4. Integrated TPB-PWM concept (adapted from Wang et al., 2023)

2.2. Development and adaptation of the questionnaire

The questionnaire development process commenced with the selection and modification of questions/items utilised in other studies on traffic safety, based on the previously described psychological theories, as well as external factors. The preliminary version of the questionnaire was evaluated by experts in traffic safety and a psychologist. Once their feedback was incorporated, the questionnaire was tested on a sample of 56 students, who were subsequently invited to share their perspectives on the clarity of the questions. Based on the obtained results, additional modifications were made to the questionnaire, resulting in its final version.

2.3. Measures

The questionnaire included items addressing both subjective factors based on the TPB and PWM and external factors. External factors were measured via the following nine items, reflecting the influential factors most frequently considered in previous studies: arriving at the intersection at the moment the red light turns on, the duration of the red signal on the pedestrian traffic light, the presence of a median refuge island, the roadway width (number of traffic lanes), walking in a group, the presence of a countdown timer on the pedestrian traffic light, the behaviour of other pedestrians (presence of pedestrians waiting for the green signal and presence of pedestrians crossing during the red signal), and vehicle flow. All items required a response on a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree) or from 1 (never) to 7 (always). Attitudes, SN, and PBC were measured via five items each. Prototype favourability was measured through six items, and three items related to prototype similarity. All items required responses on a 7-point Likert scale, ranging from 1 (strongly disagree) to 7 (strongly agree) or from 1 (never) to 7 (always).

2.4. Data collection and respondents

The data required for this investigation were obtained via an anonymous online survey conducted from January to February 2024. The questionnaire was distributed via social media and the academic network of the University of Novi Sad. This method yielded a sample of 764 respondents, which was heterogeneous in terms of demographic characteristics (gender, age, level of education) and geographical location. After eliminating incomplete responses and outliers, data provided by 592 respondents remained and was used for model development.

For the purpose of model validation, an additional sample of 288 respondents (197 of whom were included in the analysis) was collected through anonymous in-person surveys of high school and university students. This research phase was carried out in March 2024. Both studies were conducted within the territory of the Republic of Serbia.

This methodological structure not only enabled the collection of relevant data for model development but also allowed for its effective validation by applying it to two distinct samples, ensuring the reliability and validity of the obtained results.

For data analysis and visualization, the following tools were used: Microsoft Excel, IBM SPSS Statistics 23, IBM SPSS AMOS 26, and CorelDRAW X7.

The research was approved by the ethics committee of the Faculty of Technical Sciences in Novi Sad.

3. Results

In the first step, a preliminary data analysis was conducted, which involved the elimination of incomplete responses and outliers. Table 1 presents the descriptive statistics for the main and test samples used in this study.

The age range in the main sample spanned from 17 to 73 years, with a mean age of 34.68 years and a standard deviation of 12.09, indicating a diverse age distribution. In contrast, the test sample had a narrower age range, from 15 to 26 years, with a mean age of 18.85 years and a smaller standard deviation of 2.29. This highlights that the test sample predominantly consisted of younger individuals, offering a more homogenous subset compared to the broader demographic representation in the main sample.

Regarding daily walking distances, the main sample reported distances ranging from 0 to 12 km per day, with an average of 4.73 km and an SD of 2.65. The test sample exhibited a slightly different range, from 1 to 10 km, and a marginally higher mean of 5.15 km with a lower SD of 2.46. These differences suggest a more consistent walking pattern among the test sample participants, likely reflecting their status as high school students and the associated routines of this age group.

The gender distribution was balanced across both samples. In the main sample, males accounted for 51.7% and females – 48.3%, while in the test sample, males accounted for 48.7% and females – 51.3%. This near-equal representation of genders in both samples ensures a balanced perspective in the analysis and contributes to the robustness of the research findings.

Table 1. Descriptive statistics and frequencies for the main and the test sample

Variable		N	Min	Max	Mean	SD	Percentage, %
Age		592 (197)	17 (15)	73 (26)	34.68 (18.85)	12.09 (2.29)	
Km per day (by walking)		592 (197)	0 (1)	12 (10)	4.73 (5.15)	2.65 (2.46)	
Gender	Males	306 (96)					51.7 (48.7)
	Females	286 (101)					48.3 (51.3)
Total		592 (197)					100 (100)

Note: The data related to the sample used for testing is shown in brackets

3.1. Exploratory (EFA) and confirmatory factor analysis (CFA)

Principal component analysis (PCA) was conducted on the main data set to reduce the number of indicators and establish the factor structure. Initially, all items (33 items) were included in the analysis, except those related to self-reported pedestrian violations, intentions, and willingness. The results of the initial factor analysis indicated low factor loadings for certain items. Items with factor loadings less than 0.4, as well as items that were grouped around multiple factors, were eliminated from further analysis. After several iterations, the number of items was reduced to a total of 24. Subsequently, an EFA was conducted.

Before conducting the EFA, the suitability of the data for its implementation was examined. Bartlett's test of sphericity $\chi^2 = 9213.163$, $p < 0.001$ was statistically significant, indicating good factorability of the data. The KMO value of 0.927 shows that the sample size is adequate for the analysis. Using the Kaiser criterion and scree plot, six factors were identified with eigenvalues greater than 1, which was confirmed by the scree plot analysis. The six factors explained a total of 71.64% of the variance.

In the next step, CFA was used to examine the factor structure of the model obtained from the EFA. The suitability of the six-factor model, which consisted of 24 items, was tested. The initial model was tested, and the fit index results were good. The standardized factor loadings of the 6-factor model ranged from 0.60 to 0.94. CFA-validated six-factor model of pedestrian behaviour predictors is shown in Figure 5. The fit indices for both the main and test samples are presented in Table 2.

Table 2. Fit indices for the main and test samples

Fit indices	χ^2/df	RMSEA	CFI	TLI	PClose
Main sample	2.649	0.053	0.957	0.950	0.147
Test sample	1.701	0.060	0.946	0.938	0.056

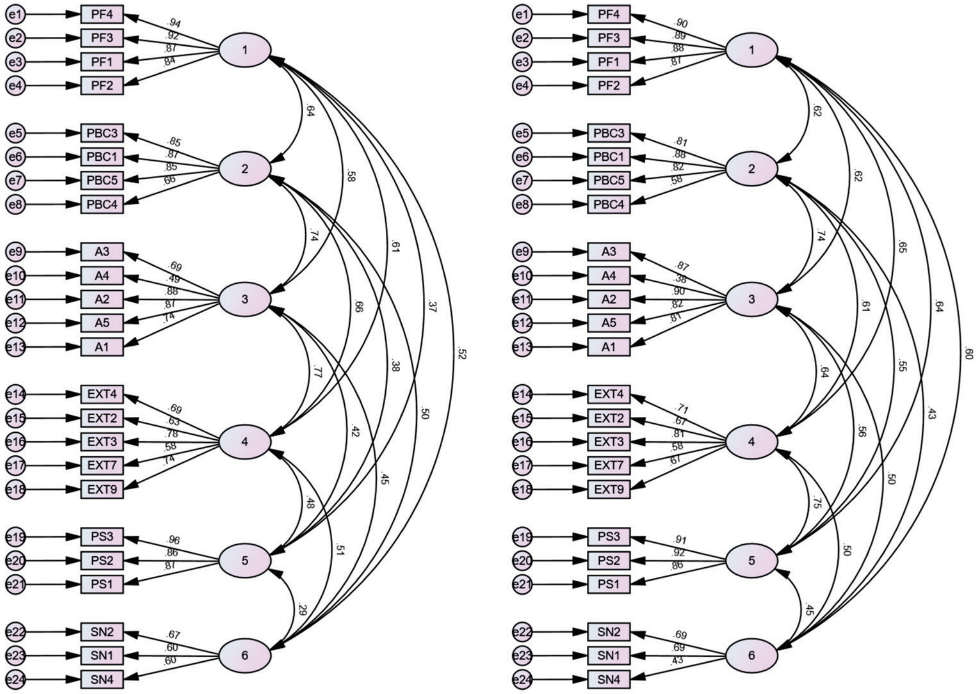

Figure 5. CFA-validated six-factor model of pedestrian behaviour predictors (the main and test samples, respectively)

Common fit indices used to evaluate model suitability included: χ^2/d*f,* RMSEA, CFI, TLI, and PClose. For χ^2/d*f*, values below 3 indicate a good model fit (Kline, 2023). For RMSEA, values less than 0.05 are considered excellent fit (Wang & Wang, 2019), those in the 0.05–0.08 range indicate acceptable fit (Browne & Cudeck, 1993; Hair et al., 1998; Byrne, 2016), values from 0.08 to 0.10 indicate mediocre fit (Kline 2015, 2023), and those exceeding 0.10 indicate a poor fit (Byrne, 2016; Hair et al., 2019). For CFI and TLI, values greater than 0.95 indicate an excellent fit, while those above 0.90 indicate an acceptable fit (Bentler, 1990; Hu & Bentler, 1999; Hair et al., 2019). Finally, for PClose, values greater than 0.05 indicate a good model fit (Browne & Cudeck, 1993).

The standardised factor loadings for the six-factor model on the test sample ranged from 0.43 to 0.91 (Figure 5). The fit index results for the test sample indicate a satisfactory model fit. These indices are consistent with the results obtained from the analysis of the main sample, suggesting that the model is stable and can be generalized to a broader population. Although the fit index values are somewhat lower for the test sample, they are still within acceptable limits, supporting the model's validity. The factor structure is identical for both the main and test samples, and the similarity of the factor loadings between these two data sets further confirms the model's robustness.

3.2. Development of an integrated model: Structural equation modelling (SEM)

Based on a comprehensive review of pertinent literature, an integrated hypothetical model was conceptualised, containing subjective factors (TPB and PWM constructs) as well as external factors identified in previous research, adopted through EFA, and confirmed through CFA analysis.

The section presents the procedure for developing and evaluating several models using SEM analysis. In fact, the model that explained the highest percentage of variance in pedestrian behaviour was adopted. In all models developed and examined as part of this study, pedestrian behaviour (i.e., red-signal roadway crossings at signalized intersections) was the ultimate dependent variable.

The fit indices and the percentage of explained variance for all models are provided in Table 3.

Table 3. The fit indices and the percentage of explained variance for all models

Model type	Fit indices					% of variance explained			Model summary
	χ^2/df	RMSEA	CFI	TLI	PClose	Intentions	Willingness	Behaviour	
TBP	3.49 (a)	0.065 (a)	0.959 (e)	0.949 (e)	0.001 (p)	N/A	N/A	N/A	Unacceptable
PWM	2.73 (e)	0.054 (a)	0.967 (e)	0.960 (e)	0.123 (e)	84.8%	53.8%	80.0%	Acceptable
External factors (EF)	2.66 (e)	0.053 (a)	0.990 (e)	0.984 (e)	0.375 (e)	N/A	N/A	80.5%	Acceptable
TPB + PWM	2.62 (e)	0.052 (a)	0.963 (e)	0.956 (e)	0.215 (e)	85.9%	56.5%	79.7%	Acceptable
TPB + EF	2.92 (e)	0.057 (a)	0.955 (e)	0.946 (a)	0.022 (a)	84.8%	N/A	83.3%	Acceptable
PWM + EF	2.49 (e)	0.050 (a)	0.962 (e)	0.955 (e)	0.466 (e)	84.0%	69.9%	84.8%	Acceptable
TPB, PWM + EF	2.44 (e)	0.049 (e)	0.958 (e)	0.951 (e)	0.599 (e)	86.3%	71.7%	85.5%	**Excellent**

Note: (e) – excellent; (a) – acceptable, (p) – poor

Although the percentages of explained variance are similar across several models, as the fit indices provide additional information about how well the model fits the data, preference should be given to the model with the best fit index values. According to these guidelines, the "TPB, PWM + External factors" model is the best choice both in terms of the percentage of explained variance for all three dependent variables and according to the fit indices. Moreover, only in the integrated model RMSEA is less than 0.05, which indicates an excellent fit. The adopted model will be analysed in more detail in the following section. The graphical presentation of the integrated (TPB, PWM + External factors) SEM model is given in Figure 6.

It is evident that attitudes, SN, and PBC have a direct and strong impact on intentions, with standardised path coefficients of 0.23, 0.15, and 0.33, respectively, which are statistically significant at the $p < 0.001$ level. Intentions did not exhibit a statistically significant impact on pedestrian behaviour. Significant predictors of willingness at the level of $p < 0.001$ are external factors with standardised path coefficients of 0.69 and PBC with a coefficient value of 0.25. External factors, in addition to willingness, also showed a direct and statistically significant effect on behaviour at the level of $p < 0.001$ ($\beta = 0.56$). External factors also exhibit a statistically significant ($p < 0.01$) but weaker impact on intentions with a β-coefficient of 0.25. Pedestrian behaviour is well described by the model, and 85.6% of the variance explained can primarily be attributed to external factors, willingness, and PBC, with a direct and strong impact. To individually assess the influence of external factors on behaviour, the factor loadings for this factor were extracted (see Table 4).

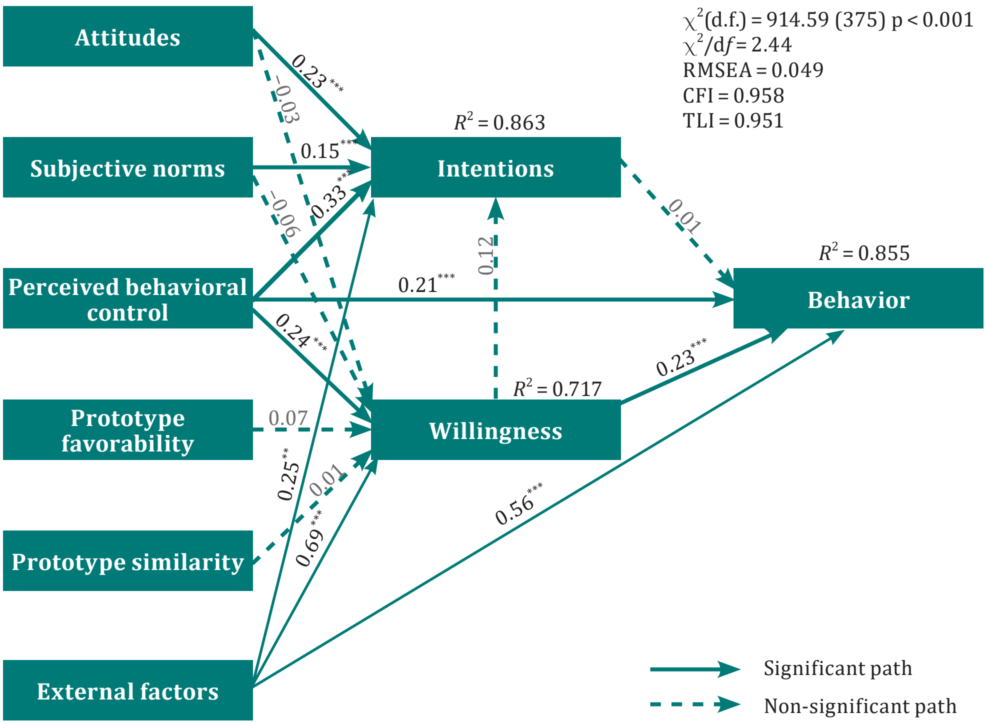

Figure 6. Integrated model for predicting pedestrian behaviour in reduced form (the main model)

Table 4. Factor loadings for external factors

External factors		Red signal duration	Traffic flow	Median refuge island	Turning on the red light at the moment of arrival	Road width
Factor loadings	Main model	0.78	0.74	0.69	0.63	0.58
	Test model	0.81	0.67	0.71	0.67	0.58

3.3. Testing the integrated SEM model

The test model (Figure 7) provides a satisfactory fit to the data (χ^2/df = 1.64, RMSEA = 0.057, CFI = 0.945, TLI = 0.936, PClose = 0.070). The CFI and TLI values below 0.95 can be attributed to the smaller sample size compared to that used for the main model, but these coefficients are still at an acceptable level.

The model indicates that both PBC and SN have a direct impact on intentions, with standardised path coefficients of 0.37 and 0.18, respectively, which are statistically significant at $p < 0.001$ and $p < 0.05$. Attitudes do not exhibit a significant impact on either willingness or intentions, which in turn do not have a statistically significant impact on pedestrian behaviour. Prototype similarity exerts statistically significant influence on willingness, with a β-coefficient of 0.30 ($p < 0.01$). Moreover, external factors exhibit a direct and statistically significant effect on both willingness ($\beta = 0.49$, $p < 0.001$) and behaviour ($\beta = 0.22$, $p < 0.05$). While 88% of the variance in behaviour is explained by the model, which can be attributed to willingness and external factors, willingness emerged as the strongest predictor of pedestrian behaviour ($\beta = 0.59$, $p < 0.001$).

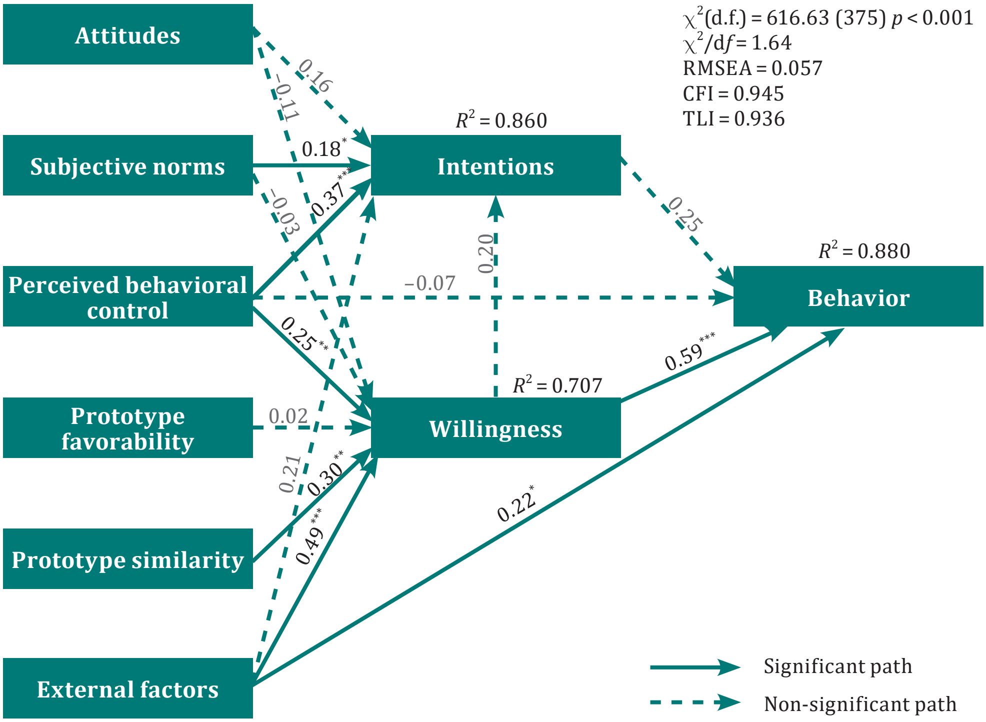

Figure 7. Integrated model for predicting pedestrian behaviour in reduced form (test model)

4. Discussion

4.1. Comparison of the main and the test model

The main and the test models are identical with respect to the predictors of dependent variables and the paths between predictors and dependent variables. In the main model, attitudes, SN, and PBC were significant predictors of intentions, while in the test model, intentions were predicted by SN and PBC. In both models, external factors were the strongest predictor of willingness. Additionally, in the main model, PBC also had a significant impact on willingness, whereas in the test model, both PBC and prototype similarity were significant.

In the main model, significant direct predictors of pedestrian behaviour were external factors, willingness, and PBC, in decreasing order of strength. In the test model, only willingness and external factors were significant direct predictors of pedestrian behaviour.

As noted previously, different samples (in terms of size as well as socio-demographic composition) were utilised for model development and testing. In addition, the data collection methods were different. Those two factors could be the potential reasons for the discrepancies between the main and the test model identified above.

On the other hand, in both models, external factors and willingness were significant direct predictors of pedestrian behaviour, with strong impacts. Finally, the percentage of explained variance in pedestrian behaviour in the test model (88.0%) exceeds the percentage of explained variance in the main model (85.6%). The higher percentage of explained variance in the test model indicates good model generalization and robustness, even when applied to a population with different demographic characteristics.

4.2. Predictive power of the integrated model

The TPB model did not provide a good fit to the data. In an attempt to rectify this issue, paths from attitudes and SN to behaviour were added. However, even this modified model did not fit the data well (χ^2/df = 3.562, RMSEA = 0.065, CFI = 0.959, TLI = 0.947, PClose < 0.001). All other model variants yielded satisfactory but not excellent fit to the data, except for the integrated TPB-PWM-external factors model. Moreover, the integrated model explained the highest percentage of variance in both interdependent variables (intentions and willingness) and the ultimate dependent variable (pedestrian behaviour). Therefore, the integrated model was adopted based on the fit indices and the percentage of explained variance in the dependent variables.

The integrated model explained 86.3%, 71.7%, and 85.5% of variance in intentions, willingness, and pedestrian behaviour, respectively. Analysing pedestrian violations at intersections, Demir et al. (2019) developed an integrated model composed of all TPB and PWM components, which explained 56% of the variance in intentions, 44% of the variance in willingness, and 66% of the variance in behaviour. The percentage of explained variance in pedestrian behaviour in this study is approximately 20% higher compared to that reported by these authors, which is expected since additional (external) factors are included in this model. Apart from behaviour, this model also explained a higher percentage of variance in intentions (approximately 20%) and willingness (approximately 28%).

The results obtained in the present study are consistent with those yielded by previous investigations in the same domain (Liu, Chen, & Pei, 2023; Liu & Liu, 2024; Tang et al., 2020) suggesting that road users' behaviour can be better explained by an integrated (TPB-PWM) model compared to either the TPB or the PWM used in isolation. On the other hand, Pei et al. (2023) found that the percentage of variance in road users' behaviour explained by the integrated model did not exceed that provided by the PWM model, which countered the results obtained in this study. However, the aim of that research was to examine the seatbelt use by rear-seat passengers in vehicles.

In the study conducted by Tang et al. (2020), the modified integrated TPB-PWM model explained 82% of the variance in intentions, 77% of the variance in willingness, and 81% of the variance in electric bicycle riders' red-signal crossings, concurring with the predictive ability of the integrated model developed in this study. Liu, Chen, and Pei (2023) developed an integrated TPB-PWM model to explain adolescent cyclists' behaviour, which explained 72.5% of variance in intentions, 42.3% in willingness, 27.4% in bicycle use for commuting to school, and 28.5% in bicycle use for leisure.

In the integrated TPB-PWM model developed by Liu and Liu (2024), 43.9% of the variance in intentions, 62.4% in willingness, and 37.5% in behaviour (use of child restraint systems by parents) were explained. Analysing the last two studies, two conclusions can be drawn. First, similar to the model developed in this study, previously proposed models explained a higher percentage of variance in interdependent variables (intentions) compared to the ultimate dependent variable (behaviour). This means that the satisfactory prediction of interdependent variables has been achieved, but further work is required to improve the predictive power with respect to the ultimate dependent variable, which can potentially be achieved by examining additional factors. Second, the predictive power of the integrated model developed in this study is significantly greater compared to that reported by other authors (Liu, Chen, & Pei, 2023; Liu & Liu, 2024).

4.3. Predictors of pedestrian behaviour

In accordance with the definition of TPB, in the integrated model, PBC, attitudes, and SN were significant predictors of pedestrian intentions (in descending order of significance), concurring with the findings yielded by most prior studies (Evans & Norman, 1998, 2003; Holland & Hill, 2007; Zhou et al., 2009; Zhou & Horrey, 2010; Xu et al., 2013; Barton et al., 2016). On the other hand, these results are not consistent with the findings reported by Diaz (2002) and Xiao et al. (2021). In the present study, external factors were also significant predictors of intentions.

The most significant predictors of willingness were external factors (with a strong influence), followed by PBC. Contrary to theoretical expectations, prototype favourability and prototype similarity did not have a significant impact on willingness, possibly due to the wide age distribution of the survey sample. The influence of peers on older adults tends to be lower compared to adolescents. This supposition is supported by the test model results, as prototype similarity had a significant influence on willingness when the analysed data were provided by high school and university students.

The strongest influence on pedestrian behaviour came from external factors. Willingness and PBC emerged as equally influential factors on behaviour. On the other hand, intentions did not significantly impact pedestrian behaviour, which contradicts the findings reported by Demir et al. (2019). These authors found a statistically significant correlation between intentions and pedestrian violations. However, the $p < 0.05$ significance level and $\beta = 0.10$ suggest that the influence of intentions on pedestrian violations is small.

When interpreting these differences, it should be noted that Demir et al. (2019) analysed three types of pedestrian violations, whereas the current investigation focused specifically on pedestrian red-signal crossings. For instance, in the case of pedestrians crossing outside the marked crosswalks, a rational path makes sense (if it shortens their path), especially during daily commutes via a known route. In contrast, pedestrians approach intersections without knowing in advance whether the traffic light will be red or green upon their arrival. Therefore, they are unlikely to plan an illegal action (crossing during red signal) in advance as they do not know if there is a need for such violation. In the case of red-light crossing, conclusions about the influence of external factors and willingness on pedestrian tendency towards temporal violations are expected. As postulated by the integrated model, if the opportunity arises, pedestrians will cross the roadway despite not planning to do so and despite it being prohibited by the signal. The results of the only study with a similar aim and the same target group (Demir et al., 2019) also point to the dominance of willingness in predicting pedestrian violations over intentions.

As the results of the model developed in the present study indicate that external factors exert the most significant influence on pedestrian temporal violations, they will be analysed in more detail. Based on the factor loadings in the SEM (Table 4), external factors can be interpreted individually, depending on their strength. High factor loadings indicate a significant impact of indicators within the factor. The factor loading was the highest for the "*duration of the red signal for pedestrians*". It is important to note that another indicator pertaining to external factors measured a similar characteristic, which is the moment pedestrians arrive at the intersection when the pedestrian signal changes from green to red. The nature of these two indicators is very similar. Namely, if a pedestrian arrives at the intersection just as the red signal turns on, they will be forced to wait through the entire cycle to cross the roadway. Accordingly, the integrated model implies that, with an increase in waiting time at the intersection, pedestrians' tendency towards temporal violations increases, concurring with the results obtained in all studies examining this phenomenon (Tiwari et al., 2007; Ren et al., 2011; Guo et al., 2011; Guo et al., 2012; Brosseau et al., 2013; Yang & Sun, 2013; Koh et al., 2014; Chen et al., 2017; Gong et al., 2019; Zhang & Deng, 2019; Ma et al., 2020; Afshari et al., 2021; Wu, Guo, & Yin, 2021; Zhu, Sze, & Bai, 2021; Zhu, Sze, & Feng, 2021; Ghomi & Hussein, 2022; Liu et al., 2022).

The next indicator with respect to the factor loading value is "*vehicle flow*". In this study, the term "there are not many vehicles nearby" was used for measuring the indicator related to vehicle flow, in accordance with the results of previous research. The results obtained in all these cases (Yagil, 2000; Koh et al., 2014; Dommes et al., 2015; Yang et al., 2015; Diependaele, 2019; Gong et al., 2019; Zhang & Deng, 2019; Ma et al., 2020; Afshari et al., 2021; Ghomi & Hussein, 2022) show that pedestrians' tendency towards temporal violations increases when vehicle flow is low and vice versa. According to Raoniar et al. (2022), more intense vehicle flow can increase pedestrians' perception of risk, deterring them from crossing during a red signal. However, when traffic flow is low, pedestrians may consider red-signal crossing safe, thus increasing the likelihood of temporal violations. The results of the integrated model developed in this study support this premise, as higher scores in pedestrian temporal violations are positively associated with low vehicle flow.

The next highest factor loading from the group of external factors was obtained for the indicator "*presence of a median refuge island*". According to the integrated model, pedestrians are more inclined to commit temporal violations on roadways divided by a median refuge island, concurring with the findings reported by other authors (de Lavalette et al., 2009; Li & Fernie, 2010; Koh et al., 2014; Zhang et al., 2016; Wang et al., 2020; Ghomi & Hussein, 2021). Thus, it would appear that the presence of a median refuge island, which facilitates two-phase crossings, may motivate pedestrians to commit temporal violations. The last indicator from the group of external factors is the "*width of the roadway/number of traffic lanes*". The integrated model shows that pedestrians are more prone to commit temporal violations on narrower roadways or those with fewer traffic lanes. These results are consistent with those reported by de Lavalette et al. (2009), Ren et al. (2011), Brosseau et al. (2013), Yang and Sun (2013), Koh et al. (2014), Diepandaele (2019), Afshari et al. (2021), Ghomi and Hussein (2021), and Zhu, Sze, and Bai (2021), but counter those obtained by Gong et al. (2019) and Wu, Guo, and Yin (2021).

Analysing the last three indicators jointly (low vehicle flow, presence of a median refuge island, and narrower roadway/fewer traffic lanes), certain conclusions can be drawn from a psychological perspective. Namely, when presented with such directed indicators, respondents in this study showed a greater tendency toward temporal violations. If the roadway has fewer traffic lanes, is divided by a median refuge island, and/or has lower vehicle flow, the complexity of crossing the roadway during a red signal is reduced, thereby reducing the difficulty of the task pedestrians need to accomplish. This can be interpreted as the perception of the ease or difficulty of performing a specific task (PBC), which was identified in the integrated model as a factor that directly influences pedestrians' tendency to commit temporal violations.

In this study, and based on the conclusions reached by other authors, the following indicators were also analysed: pedestrian movement in a group, the behaviour of other pedestrians (conformity tendency), and the presence of a countdown timer on the pedestrian traffic light. These indicators did not form any factor within the EFA, and were thus excluded from further analysis.

Conclusion

The research represents the first comprehensive study as part of which all subjective constructs defined by the Theory of Planned Behaviour and the Prototype Willingness Model, along with external factors, have been analysed, targeting pedestrians as the respondents. During the research, multiple models have been developed, and the best model has been proposed based on two criteria: fit indices and the percentage of explained variance. As a result, an integrated model that includes components of TPB, PWM, and external factors has been proposed.

This integrated model has been tested on a different sample of respondents, and the obtained results supported its robustness. On a theoretical level, this research provides a significant contribution to the current understanding of pedestrian behaviour at signalized intersections, indicating the dominance of the social-reactive pathway over the reasoned (rational) pathway in pedestrians' decision-making processes. The main predictors of pedestrians crossing during a red signal are external factors, willingness, and PBC, while intentions do not have a significant impact. The results further suggest that traffic conditions at the time of arrival at the intersection are crucial for pedestrians' decision to cross during a red signal, indicating the stochastic nature of these decisions.

On a practical level, the research results reported in this paper identify specific types of signalized intersections where pedestrians show a greater tendency for temporal violations. This information can be utilised for targeted interventions aimed at enhancing pedestrian safety in urban environments.

This study has theoretical significance as it is the only one that takes into account all TPB and PWM constructs, as well as external factors to form an integrated model aimed specifically at pedestrians. The obtained results point to the dominance of a social-reactive path compared to a rational path. This means that pedestrians' decision to cross the roadway during red light at signalized intersections is conditioned by the current traffic and situational conditions at the intersection. In other words, if an opportunity to cross during a red signal arises, pedestrians are inclined to take it, even if they have not planned to do so beforehand.

As determined in this study, the propensity to cross the roadway during red light at signalized intersections is predominantly influenced by external factors, with waiting time being the most impactful. This finding points to the need to consider the duration of the red signal for pedestrians in the intersection design and regulation. It is particularly important to reduce the duration of the red signal for pedestrians at intersections with lower vehicle flow, where there are fewer traffic lanes and/or where lanes are divided by a median refuge island, as pedestrians are more prone to temporal violations under such conditions.

The integrated model developed in this study generally explains and predicts pedestrian behaviour well. However, it can be further improved by including new factors. For example, according to the original PWM, past behaviours are one of the predictors of behaviour. Past behaviours have not been considered in this study for methodological reasons, as respondents might find it difficult to differentiate between behaviours in the past six months, during the most recent month, and in the preceding week when responding to the survey. Thus, past behaviours could be incorporated into future studies based on both surveys and observations.

Additionally, in this study, self-reported data have been used in both model development and testing. Although the surveys have been anonymous, respondents might have still felt inclined to provide socially desirable answers. This shortcoming can be overcome in the future by gathering data through temporal violation observations.

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Statement of the Use of Generative AI and AI-assisted Technologies in the Writing Process

The authors declare that no generative AI or AI-assisted technologies were used in the writing process.

Disclosure Statement

The authors declare that they have no competing financial, professional, or personal interests from other parties.

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