ASSESSMENT OF SHARED E-SCPPTER SAFETY

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Abstract: The goal of the paper was to assess the safety of riding shared e-scooters and determine the causes of accidents involving them. Primary data for the research were obtained through a combination of quantitative and qualitative content analysis based on deep learning by analysing data from the WoS database entered into the VOSviewer system. A quantitative observation method was used to determine the number of shared e-scooter users who do not use safety equipment such as helmets. The data obtained were processed using the Wilcoxon test designed to test the homogeneity of two random samples in the univariate case. The observation of shared e-scooter users and social networks of e-scooter service providers showed that safety equipment is not adequately used; in addition, the users often do not know the traffic rules and often violate them. Of the 256 monitored cases of using shared e-scooters, none of the users wore a safety helmet. It can thus be concluded that it is necessary to promote the rules of the safe use of shared e-scooters. Further research could focus on proposing a methodology for assessing traffic accidents involving e-scooters and a general overview of recommendations for e-scooter safe use.

Keywords: Micro-mobility, shared mobility, public transport, electric scooters, injury, wearing helmet

1 Introduction

The concept of Smart City (SC) as a tool to improve the citizens´ quality of life is gaining importance in the agenda of policymakers (Vochozka & Machová, 2018). SC sustainable transport requires smart and environmentally friendly technical solutions (Ghorbanzadeh et al., 2019). An approach to respond to this call is the transition to shared mobility services (X. Li et al., 2018). Based on these new modes of transport and the development of information and communication technologies, the concept of “mobility as a service” has emerged recently (Wells et al., 2021), which offers “door-to-door” service without the necessity of owning a private vehicle (Lu et al., 2018). The new modes of transport, such as shared vehicles or shared rides are beginning to increase their market share at the expense of traditional modes of transport, e.g., automobiles, public transport, and taxi services (Moreno et al., 2018). New types of mobility, including e-scooters and e-bikes, have been recently introduced in many towns in the world (Bielinski & Wazna, 2020). E-scooters have become a popular kind of micro-mobility for urban transportation, offering its users a flexible option for mass first and last-mile travel (Yang et al., 2020). The use of e-scooters would also significantly reduce the production of CO2 (Jung & Koo, 2018). Urban transport planners see e-scooters as an alternative to individual car transport, while the public has welcomed the idea of using e-scooters with both enthusiasm and skepticism, as towns have to face unforeseen consequences such as irresponsible riding, cluttering, or vandalism (Gossling, 2020). Short-term rental scooters owned and operated by start-up companies inundated towns almost overnight, promising a disruption to the urban transportation status quo (McKenzie, 2019). The use of e-scooters could reduce local congestion; however, drivers of two-wheeled motor vehicles are very prone to a high risk of injury on roads (Allem & Majmundar, 2019). From the very beginning of the use of e-scooters, an increasing number of patients have been hospitalized due to injuries caused by riding e-scooters (Moftakhar et al., 2021). For this reason, the use of e-scooters raises concerns related to the safety of their riders and pedestrians. The most common causes of these accidents include ignorance of traffic rules and the recklessness of e-scooter riders (Trivedi et al., 2019). Another frequent cause of many accidents involving e-scooters is alcohol or other drugs that negatively affect the reactions of e-scooter users while riding (Kobayashi et al., 2019), and such accidents then result in hospital overcrowding caused by the hospitalization of such patients (Bloom et al., 2021). E-scooter riders most often come to hospitals with contusions, abrasions, lacerations, fractures, and head injuries; patients often even need surgery (Brownson et al., 2019)

2 Research goal

The goal of the paper is to assess the safety of riding shared e-scooters and to identify the causes of traffic accidents involving them.

By answering research questions, it will be possible to determine how operators of shared e-scooters try to avoid traffic accidents involving shared e-scooters that they rent to users. The important thing is to find out whether e-scooter users that ride them on roads know all the traffic rules.

RQ1: What are the current measures taken by shared e-scooter providers to prevent accidents involving shared e-scooters

Next, it is necessary to determine how the operators of shared e-scooters try to protect the health of their users in the case of an accident involving e-scooters they rent to users, or whether the measures indicated by the operators are sufficient.

RQ2: What are the current measures to reduce the health impact in accidents involving e-scooters? Is safety equipment used rather by men or women?

Finally, it is necessary to determine the ways to reduce the number of traffic accidents involving e-scooters and caused by e-scooter users. This is related also to the formulation of general recommendations for e-scooter users.

RQ3: How can accidents involving shared e-scooters be avoided?

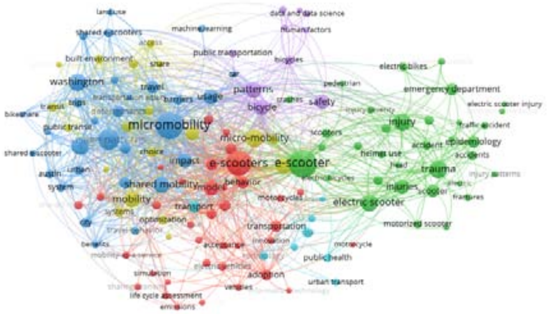
3 Literature research

Shared mobility includes the systems of public transport and shared mobility supporting first and last-mile travel, which means mobility as a service, and stimulation of further demand for travelling by other than private means of transport (Meng et al., 2020). Increased accessibility of these newly emerging types of mobility, which includes dockless systems of bike and e-scooter sharing, provides citizens, workers, and town visitors with a comfortable alternative to more established modes of transport (Gehrke et al., 2022). In the last decade, there has been a rapid increase in shared mobility (Hu & Creutzig, 2022), which could improve the economic situation of marginalized groups of people, as well as reduce CO2 emissions (Leat et al., 2022). However, (Turon et al., 2020) state that the increase in shared mobility services has brought various types of problems not occurring or occurring to a limited extent within the traditional systems. Therefore, shared mobility services are analysed from various perspectives, of which safety-related issues are particularly important for both users and operators (Turon et al., 2019). A similar conclusion was made by (Gehrke et al., 2022), who point to the need for policies supporting shared mobility services through provisions for secure infrastructure (Davis et al., 2020). Developing methodologies for measuring and evaluating the impacts of shared mobility including the safety of its use has thus become essential for city authorities (Kearney et al., 2019). Road safety is one of the major problems in transport system management. Safety analyses usually assess the frequency of accidents and the effects of measures taken on the number of accidents. The emergence of new mobility types makes safety assessment more challenging, as there are usually not enough data and the effects of these services on demand and the effectiveness of the broader network are not completely known (Feizi et al., 2022). Similarly to (Turon et al., 2019), a growing number of researchers are dealing with the concept of various safety and security issues in relation to shared mobility, such as bike, car, or e-scooter sharing. The popularity of e-scooters is given by their availability, accessibility, and low price (Sikka et al., 2019). (Caspi et al., 2020) argue that people use e-scooters almost exclusively in city centres, regardless of the wealth of districts, although less wealthy areas showing a high rate of using e-scooters are those with the large student populations, which indicates that this means of transport is commonly used by students and young people. Along with the increased use of e-scooters, there is also a growing number of accidents involving e-scooters. However, little is known about the risk factors for accidents and injuries related to e-scooter use (Tian et al., 2022). (Siebert et al., 2021) state that there has been only limited research on the relationship between the ergonomics and safe use of e-scooters and it is unclear whether e-scooter riders are aware of prevailing e-scooter-related regulations and whether they adhere to the existing traffic rules. The authors identified several problems that cause accidents involving shared e-scooters: intoxication by alcohol or other drugs, ignorance of traffic rules, riders´ brake unreadiness, lack of knowledge about the scooter braking system, and two riders riding one scooter. (Haworth et al., 2021) presented the results of their research, claiming that more than 90 % of e-scooters, about 50 % of shared bikes, and approx. 25 % of private bikes were ridden on the footpath and about 40 % of them were within 1-m distance of at least one pedestrian. Research conducted by (Kobayashi et al., 2019) focused on the factor of intoxication in the users of e-scooters. About 79 % of patients were tested for alcohol; 48 % had blood alcohol levels > 80 mg/dl. A urine toxicology test was performed in 60 % of the patients, with 52 % of them being positively tested. (Bekhit et al., 2020) even state that more than 25 % of accidents involving e-scooters are directly caused by riding while drunk. Compared to other modes of transport, such as cars and bicycles, the safety of e-scooters is significantly understudied. In addition to individual e-scooter riders´ behaviour (e.g., swinging, hard braking, etc.), it is also necessary to focus on safety problems resulting from increased vibration, changes in speed, and proximity to surrounding objects (Ma et al., 2021). If e-scooter riders rode the same distance in km as drivers of motor vehicles, there would be about 254 times more injuries than in the case of accidents involving motor vehicles (Salas-Nino, 2022). Research conducted by (Moftakhar et al., 2021) dealt with the number of accidents involving e-scooters. They found that a higher number of accidents are recorded in the late afternoon and peak at 8 pm. However, the highest number of patients (39.2 %) were injured in the early evening hours (between 8 pm and 1:59 am), with the most threatened group being young adults (aged 19-39). Shared e-scooter users do not use protective equipment and therefore more injuries occur (Beck et al., 2020). According to (Ma et al., 2021) 95 % of shared e-scooter users did not wear a safety helmet, which resulted in hospitalization due to minor head injuries or concussions, exceptionally even ICH or skull fractures. While the probability of suffering a head injury and hospitalization of persons injured on e-bikes was 17.1 %, the percentage was nearly three times higher for e-scooters (Siebert et al., 2021). For e-scooter injuries, the average hospitalization time is 3 days and often causes unnecessary occupation of hospital beds (Uluk et al., 2020). The authors also stated that 42 % of the hospitalized did not have a driving licence. Similarly, (Kim et al., 2021) point to the need to educate e-scooter riders on the importance of wearing protective equipment such as helmets and on the traffic rules.

Primary data are obtained using many methods (Lim et al., 2018). Information obtained through observation represent important data for evaluation and research (Bian et al., 2019). Observation is an empirical research method used for quantitative and qualitative research focused on understanding the real-time development of behaviour and interaction, which makes it particularly significant for examining the processes associated with the generation and adoption of creative ideas (Katz-Buonincontro & Anderson, 2020). Indirect observation largely involves the analysis of textual material obtained either indirectly from the transcriptions of audio recordings of verbal behaviour in a natural setting (e.g., conversations, group discussions), or directly from posts (e.g., statuses, tweets, forums) (Teresa Anguera et al., 2018). (Izquierdo & Anguera, 2021) mention the need for choosing between qualitative and quantitative observation methods. recommend combining both methods to achieve the best results. For examining a large number of processes and events to focus on specific information rather than collect detailed information, the most suitable method is quantitative observation (Zyphur & Pierides, 2020).

Relevant materials for content analysis will be selected using deep learning, which provided useful tools for processing and analysis of large data volumes (Zhao et al., 2019). Another method used is extracting accurate information from raw sensor data (H. Li et al., 2018). (Wang et al., 2019) use methods based on deep learning in sensor-based activities. However, (Guo et al., 2021) state that deep learning is still in its infancy due to the unique challenges data processing pose. As an alternative, they propose the use of neural networks, which can be more suitable in certain situations. Figure 1 shows a suitable combination of keywords through visualization of networks using deep learning.

Figure 1. Keywords visualization (Source: Autor via VOSviewer)



(Source: Autor via VOSviewer)

A suitable method for data processing can be content analysis (Miwa, 2022). When collecting data using content analysis, this method has similar features to the observation method (Thaker et al., 2018). According to (Dehnavieh et al., 2019), content analysis can be used for data processing. Qualitative content analysis is a research methodology conducted either through induction or deduction. The inductive approach uses data collected at the beginning of the research, while in the case of deductive, i.e. directed approach, research is based on existing theories to set up information that guides the research (Kibiswa, 2019). (Lindgren et al., 2020) state that qualitative content analysis and other “standardized” methods are sometimes considered technical tools used for basic, superficial, and simple text classification and their results may lack sufficient accuracy. (Ham et al., 2019) also state that the accuracy of the results of quantitative analysis depends on the analysts´ experience. (Cavalcanti et al., 2020) use content analysis to find recurrent key events related to the given issue.

To answer research hypotheses, statistical methods of data processing will be used. Calculating confidence interval for the population mean enables determining how the mean of the obtained samples differs from the actual population mean (Ivkovic & Rajic, 2021). This method is used by many researchers to determine how representative the obtained results are for the whole population. The creation of the interval is based on statistical methods and includes both the upper and lower limit (Julious, 2019). Statistical analyses include the determination of the so-called significance level, as the higher the confidence of the selected analysis, the more accurate its results are, i.e., inverse proportionality applies. In general, significance level expresses the probability of rejecting the null hypothesis – the lower the significance level, the more difficult it will be to reject the null hypothesis. A frequently asked question related to quantitative research is how to compare two samples that include a combination of paired and unpaired observation (Derrick & White, 2022). Ignoring the violation of the error normality assumption is a mistake that may cause inconsistencies in the analysis of variance results. To verify whether this assumption is met or violated, normality tests, such as the Shapiro-Wilk test can be used (de Souza et al., 2023). Shapiro-Wilk tests confirm the normality of distribution. When examining the reproducibility of experiments in different test samples, it is suitable to use two-sample tests (Shan, 2022). The Wilcoxon test is designed to test the homogeneity of two random samples in the univariate case (Liu et al., 2022). It is a rank-based method for one- and two-sample tests when the univariate data are not normally distributed (Ouyang et al., 2022).

For the purposes of this paper, content analysis and conventional quantitative observation will be used to collect primary data. The findings will be analysed using quantitative content analysis, which will enable answering all formulated research questions.

3 Materials and methods

The data necessary for answering the first research question will be obtained through qualitative content analysis of documentation provided by the Regional Directorate of the Traffic Police of the Czech Republic, specifically from České Budějovice, a town situated in the centre of Europe with nearly 100 000 inhabitants. Currently, the police does not keep records of accidents involving e-scooters but it is able to provide information about all traffic accidents involving either Bolt or Lime, which are the only companies providing shared e-scooters in České Budějovice. The data provided for the period from 1 January 2021 to 1 December 2022 monitor the following aspects of accidents: date, time, the severity of injury of the shared e-scooter user, and the name of the company that provided the given e-scooter. This enables determining the time and period in which this type of accident occurs. Along with content analysis of documents provided by the police, the method of deep learning will be used to obtain data from articles on the topic of “electric scooter injuries, e-scooter injuries, e-scooter accidents, and e-scooters“ published between 1 January 2018 and 1 December 2022. Based on the keywords, articles dealing with this issue will be selected where the reasons why accidents involving e-scooters occur will be sought for. The results will be used as the basis for answering the third research question.

To answer the second research question, it is necessary to determine what injuries typically occur in accidents involving shared e-scooters. Qualitative content analysis will be used to analyse published research available via Web of Science, which focuses on the issue of accidents involving e-scooters using deep learning, on the aforementioned topics of “electric scooter injuries, e-scooter injuries, e-scooter accidents, and e-scooter“. The data will identify the most common consequences of accidents happening to e-scooter users, which enables making recommendations for the providers on which direction they should take to ensure greater user safety. This research question will also use the observation method. Quantitative observation will be used to monitor the users of shared e-scooters in České Budějovice from 1 November 2022 to 1 December 2022 between 10:00 and 4:00 with the aim to determine the level of user protection, especially the number of shared e-scooter users that wear safety helmets and other protective features, which may result in better protection of their health, the gender classification of users, and the length of the ride. As in the case of the previous research question, there will be used the data provided by the Police of the Czech Republic, which keeps records of the severity of injuries in accidents involving shared e-scooters. To determine whether the providers sufficiently protect the health of the users of their e-scooters, Instagram profiles of companies providing shared e-scooters will be monitored. Here, quantitative content analysis will be used to monitor the number of users wearing safety helmets between 1 January 2021 and 1 December 2022 and whether users are encouraged by the providers to use protective equipment. Another subject of observation will be whether users follow the established rules they should follow when riding e-scooters.

For the purposes of the paper, hypothesis H1 is formulated as follows: women spend less time riding shared e-scooters without wearing safety helmets compared to men.

The third research question concerns the formulation of general recommendations to avoid accidents involving e-scooters. Here, the most important data is information provided by the police about accidents that occurred in the last year and the analysis of their causes, places and time of these accidents. Based on these findings, measures to prevent the occurrence of this type of accident will be formulated. This information thus represents primary data that will be examined using qualitative content analysis. Subsequently, the research will use the data obtained through the previous research questions, especially the general recommendations provided by individual companies operating shared e-scooters. Here, qualitative content analysis will be used to examine the development of the rules of companies Bolt, Lime, and Uber between 1 January 2020 and 1 December 2022. The obtained data will represent the main risk factors e-riders encountered in the last two years, and along with other data, future possible threats will be predicted.

Next, it is necessary to analyse the obtained quantitative and qualitative variables. To calculate two-sided confidence interval for the population mean, first the mean x for the sample size and standard deviation for the sample set $s_{(x)}$, as the population standard deviation is not known. The quantile of the standard normal distribution is determined at the number of observed users n. The significance level α, which reflects the error rate of the test, is determined according to the number n. The above variables enable calculating two-sided confidence interval for the pouplation mean μ, limited by upper and lower interval *(G_d and G_h)*

The calculation is based on the following formula (Abu-Shawiesh & Saghir, 2019):

$$\bar{x} - [u_{(1-\frac{\alpha}{2})} * \frac{s_{(x)}}{\sqrt{n}}] \leq \mu \leq \bar{x} - [u_{(1+\frac{\alpha}{2})} * \frac{s_{(x)}}{\sqrt{n}}],$$

where:
x – arithmetic mean of the length of the journeys [min];
$s_{(x)}$ – standard deviation for the selected sample set [min];
α - level of significance [%];
n – number of samples;
μ - two-sided confidence interval for the population mean [min];

To verify the assumption of data normality, it is necessary to confirm or reject the formulated null hypothesis, for which alternative hypothesis needs to be formulated as well. First, it is necessary to determine the significance level α, which is usually determined at 5 %.

H_0: men and women spend equal amount of time riding shared e-scooters without wearing safety helmets

H_1: women spend less time riding shared e-scooters without wearing safety helmets.

Observations are converted into normal variables. The Shapiro-Wilk test is then used to confirm the assumption of data normality, which enables confirming or rejecting the null hypothesis. After applying the Shapiro-Wilk test for confirming the assumption of data normality, a p-value is obtained, which needs to be compared with the significance level α. If the resulting p-value of the Shapiro-Wilk test is greater than α, the null hypothesis is not rejected. If the p-value of the Shapiro-Wilk test is less than α, the null hypothesis is rejected.

To verify the rejection of the H_0 and if the assumption of data normality is not met, another tool needs to be applied, such as a final non-parametric two-samples Wilcoxon test. After entering the obtained data into the computing system, the p-value for the Wilcoxon test is calculated, which is also compared with the significance level α. The same rule applies for the Wilcoxon as for the Shapiro-Wilk test, i.e., if the resulting p-value is greater than α, the null hypothesis is not rejected; if the p-value is less than α, the null hypothesis is rejected and the alternative hypothesis is accepted.

4 Results

E-scooter sharing companies naturally try to ensure the safest possible rides for users. However, they often do not take adequate measures to make the use of e-scooters safer. Therefore, there were successively analysed applications for renting scooters, companies´ social networks and websites targeted at Czech users, where the operators of e-scooter sharing services should encourage the users to ride safely. The first analysed company was Bolt, which encourages users to ride safely the first time they use the app but it is not possible to look at the rules of using e-scooters later. However, Bolt provides clear basic information on the rules of using e-scooters on its website. The website of Lime only refers to the mobile app where e-scooters can be unlocked. Here, when using the app for the first time, the user must agree to the terms of use, which also briefly and in small letters mentions the safety rules of riding the e-scooter. As for Uber, on its website, the company only states that it also operates shared e-scooters and bikes, but provides a direct link to the application which is rather focused on providing taxi and other Uber services. For better illustration, Table 1 shows the rules and recommendations presented on the websites and mobile apps of the aforementioned companies.

Table 1. Rules and recommendations for using e-scooters provided by individual companies

	Bolt	Lime	Uber
Prohibited riding under the influence of alcohol	yes	yes	yes
Prohibited tandem riding	yes	yes	yes
Recommended riding on cycle paths	yes	yes	no
Prohibited riding on pavements	no	no	no
Compliance with traffic rules	yes	yes	yes
Recommended checking the functionality of the e- scooter	yes	yes	no
Recommended familiarization with the e-scooter	yes	yes	no
Recommended use of a safety helmet	yes	yes	yes
Introduction of slow zones	yes	yes	yes

(Source: mobile apps and websites of Uber, Bolt, Lime)

Monitoring the consequences of accidents is an important factor in understanding this issue. For this purpose, conducted research has been analysed. Research conducted by Genc Yavuz et al. (2022) focused on a total of 70 patients who were provided treatment in the emergency department. The consequences of traffic accidents involving e-scooters were superficial soft-tissue injuries (45.7 %; n=32) and head injuries (40 %; n = 28). Based on medical examination performed, orthopedic fractures and sprains were found in 18.5 % (n = 13) of patients, and jaw fractures in 11.4 % (n = 8). About 4.3 % (n = 3) of patients had worn a safety helmet. Brownson et al. (2019) conducted research on a similar topic, with the following findings: 180 patients were admitted to the hospital due to the consequences of a traffic accident involving e-scooters. The median hospital stay length was 4.0 hours, and the interquartile range (IQR) was 18.4 hours. The most common injuries included contusions, abrasions, and lacerations (65.6 %), fractures (41.7 %), and head injuries (17.2 %). Every fifth patient (22.2 %) needed surgery. Only three patients (1.6 %) had worn a safety helmet. Of all patients treated, 23.3 % had consumed alcohol; of all patients with a head injury, 41.9 % had consumed alcohol.

A controversial topic is primarily wearing safety helmets, which should be the most important safety factor when riding e-scooters. For this reason, the content analysis method was used to monitor posts on the Instagram profiles of individual companies that provide the services of shared e-scooters between 1 January 2021 and 1 December 2022. These companies include Bird, which is widely represented all over the world, especially in the USA, and Bolt and Lime, which provide their services directly in České Budějovice. Within the analysis of social networks, attention was paid to e-scooter users that were wearing safety helmets in posted photos and videos. In addition to monitoring wearing helmets, there were also monitored persons using mobile phones while riding e-scooters. The results of the analysis are shown in Table 2.

Table 2. Results of Instagram profiles´ analysis concerning the e-scooter users´ health protection

Company	**Number of users wearing helmet**	**Number of users not wearing helmet**	**Number of users using a mobile phone**
Bird	13	119	5
Lime	53	82	6
Bolt	10	8	0

(Source: Author)

In parallel with the analysis of the companies´ profiles on social networks, primary data were collected using the method of observation when the population sample of shared e-scooter users in the České Budějovice district was observed between 1 November 2022 and 1 December 2022. Currently, there are more than 11,000 users of shared e-scooters registered in České Budějovice, for whom 261 e-scooters are available for rent. The subject of the investigation was the use of safety equipment, mainly safety helmets, the gender of the users, and the length of the ride. In total, there were monitored 256 e-scooter users, who used the services of Bolt or Lime. Of the 256 monitored cases (statistical units), no e-scooter user was wearing a safety helmet or using safety equipment.

In the period 1 January 2022 – 1 December 2022, the Regional Directorate of the Traffic Police in the South Bohemian region recorded a total of 10 accidents involving shared e-scooters. The data are presented in Table 3. These are distorted data since the information is inaccurate. No source, whether the database of the Czech Police, scientific articles, etc., provides information on the precise number of accidents involving e-scooters in the last year. The actual number is assumed to be several times higher but it is not easily obtained due to the fact that the majority of accidents occurring are not dealt with by the Police of the Czech Republic, since there are mostly superficial injuries only when the intervention of the emergency services is not necessary and users do not have to seek medical help. Such accidents are thus not recorded in any database.

Table 3. Overview of traffic accidents involving shared e-scooters in České Budějovice

Date	Time	Injury severity	Damage [in thousand CZK]	Company
3 May 2022	22:34	1 person injured	0	Lime
5 May 2022	21:45	1 person injured	10	Bolt
20 May 2022	18:48	1 person injured	32	Bolt
2 June 2022	1:56	1 person injured	25	Lime
15 June 2022	16:21	1 person injured	0	Bolt
15 June 2022	23:06	1 person injured	0	Bolt
2 July 2022	19:59	1 person injured	0	Bolt
13 July 2022	21:28	1 person injured	0	Lime
28 July 2022	23:49	1 person injured	5	Bolt
29 July 2022	0:36	1 person injured	5	Bolt

(Source: Policie ČR)

For effective prevention, it is necessary to identify the causes of these accidents. Usually, it is a combination of several causes. The content analysis performed within research conducted on this issue, the following findings were obtained: Kobayashi et al. (2019) deal with the intoxication of e-scooter users where 79 % were tested for alcohol, with a blood alcohol level of 48 % of them being > 80 mg/dl. Bekhit et al. (2020) even argue that more than 25 % of accidents involving e-scooters are directly caused by riding while drunk. Another major cause is fast rides. Beck et al. (2020) conducted a study that included 149 accidents involving e-scooters and found that 60 % of the accidents were caused by fast rides, loss of balance, and failure to adapt the speed to the surface of the road. Due to this, e-scooter users most often experience accidents caused by slipping on a non-standard road surface, such as cobblestones, tram tracks, pedestrian crossings, and horizontal road markings. According to Meyer et al. (2022), these were causes of more than 7 % of the total 356 cases analysed. Another cause of accidents is the use of one e-scooter by two and more users. According to a survey conducted by Bolt, 15 % of all rides recorded in 2021 were those where one e-scooter was ridden by more than one user. According to their findings, another common cause of accidents is that users do not fully concentrate on riding, e.g., due to using their mobile phones or listening to music, which negatively affects concentration and distorts auditory perception.

Calculation of two-sided confidence interval for the population mean:

x = 11.75 [min];
$s_{(x)}$ = 5.67899966 [min];
α = 5 [%];
n = 256;
11. 0543 [min] $\leq \mu \leq$ 12.44468 [min] with 95% confidence and a deviation of 2.5 % for both upper and lower interval.

The formulated null hypothesis H_0 was rejected on the basis of the results of the Shapiro-Wilk test of the assumption of normality since the resulting p-value is 0.000000:

α = 5 [%];
p-value < α = H_0 is rejected;
0.0000 < 0.05;
Where:
α = significance level;

The assumption of data normality is thus not met. Therefore, a final non-parametric two-sample Wilcoxon test must be applied using the calculation software. The resulting p-value was 0.009248.

0.009248 < α;

The alternative hypothesis assuming that the average time spent without wearing a safety helmet is the same for both men and women can thus be accepted.

5 Discussion

RQ1: What are the current measures taken by shared e-scooter providers to prevent accidents involving shared e-scooters?

The issue of accidents involving shared e-scooters should be dealt with mainly by companies providing this service. However, such companies are primarily interested in increasing their profit rather than the safety of e-scooter users. When examining individual recommendations provided by such companies with the aim to increase the safety of e-scooter users, three companies were analysed, namely Uber, Lime, and Bolt. In this respect, Bolt was rated the best. On its website, Bolt offers e-scooter riders the Bolt Scooter School where both potential and current users can learn how to use e-scooter safely, familiarize themselves with the scooter and with the rules and regulations that need to be followed when riding e-scooters. This training can be seen also in the application used for renting e-scooters but only when using it for the first time; later, it is not possible. This is considered a significant shortcoming given that the application is the only tool necessary for using this service. On its website, Lime provides a link to the mobile app where, unlike Bolt, it is possible to see the rules and conditions of using e-scooters anytime. Of the companies analysed, Uber is rated the worst, as compared to the above companies, it mentions the same rules but ignores the recommendations that could reduce the number of accidents involving e-scooters, such as the recommendation to check the functionality of the brakes, familiarization of users with the e-scooters, and the recommendation to ride on cycle paths. None of the companies analysed informs the users about the prohibition of riding on pavements, although this regulation is stipulated in the road traffic rules of the Czech Republic. However, this regulation is significantly absent in the conditions of the use of shared e-scooters. Due to the users´ unawareness of this regulation, there is a greater number of accidents caused by collisions between e-scooter riders and pedestrians.

RQ2: What are the current measures to reduce the health impact in accidents involving e-scooters? Is safety equipment used rather by men or women?

The operation of these services includes efforts to reduce the number of accidents as well as the adoption of measures to mitigate the consequences of accidents involving shared e-scooters. When analysing individual consequences, it was found that more than 60 % of patients that were given treatment in the emergency department had superficial soft-tissue injuries, while more than 40 % had suffered a head injury. Head injury was evaluated as one of the most serious injuries associated with e-scooter riding, despite of the fact it can be easily eliminated by wearing safety helmets. The use of safety helmets and other safety equipment should be promoted even by the providers of these services. When analysing the profiles of Lime, Bird, and Bolt on social networks, Bolt was again rated the best one as only in 44 % of cases, it showed users who were not wearing helmets and not even once did it show a user using a mobile phone while riding an e-scooter. As for Lime, 60 % of its posts showed e-scooter riders who were not wearing safety helmets and 6 e-scooter riders who used mobile phones. Of the three analysed companies, Bird shows the highest number of posts with e-scooter users not wearing safety helmets (nearly in 90 % of cases). The formulated hypothesis H_1 was fully confirmed. Within the monitored period, not a single e-scooter user was seen wearing a safety helmet. On the basis of the calculated average length of riding without a safety helmet for men and women, men were proven to spend longer time riding e-scooter without a helmet. The wearing of safety helmets and other protective equipment when riding e-scooters is not sufficiently promoted, unlike e.g. in the case of cycling, although proportionally, three times more e-scooter users than cyclists need treatment in the emergency department (Arbel et al., 2022). The analysed companies providing shared e-scooters ignore a substantial part of the Czech legislation, namely the obligation of cyclists (a category that includes also e-scooter users) to wear safety helmets. None of the analysed shared e-scooter providers informs the users about this obligation, although they set the minimum age for using e-scooters at 16 years. E-scooter users thus not only endanger their health but also violate the laws of the Czech Republic.

RQ3: How can accidents involving shared e-scooters be avoided?

As there are many causes of accidents involving e-scooters, it is not possible to formulate a simple recommendation that would reduce the number of accidents involving both shared and private e-scooters. If all e-scooter-related accidents and falls were recorded, it would be possible to set speed limits in the e-scooter system in places where accidents often occur in the same way that speed limits are set e.g. in the case of cars. Speed is one of the main causes of accidents and e-scooter providers are beginning to realize this fact gradually. Therefore, in recent years, they started to implement such measures in places with a large concentration of people. However, these places are often pedestrian zones where, with only a few exceptions, bicycles and e-scooters are prohibited, and the providers of shared e-scooters do not inform the users about this fact. A large number of accidents, including those involving e-scooters, are caused by alcohol or drugs. This problem has been addressed in transport from the very beginning of the automotive industry, and unfortunately, e-scooters are no exception, mainly due to their availability in town centres, where there are a lot of bars and pubs. The users often prefer using e-scooters to waiting for night bus lines or taxis and then they often break the law by riding e-scooters under the influence of alcohol. Nevertheless, the solution to this problem is not in the hands of e-scooter providers but rather in the hands of the authorities that control compliance with the law. The police do not deal with e-scooter users and cyclists to the same extent as e.g. with car drivers. If this category was paid greater attention to, along with the enforcement of penalties, e-scooter users would be more careful not to ride them under the influence of alcohol. Another common cause of accidents is tandem riding. This problem can be solved by e-scooter providers as well as the responsible authorities since tandem riding cannot be overlooked and can thus be easily fined. From the side of e-scooter providers, tandem riding can easily be prevented by system modification. Since e-scooters are smart devices, it is possible to calculate the approximate weight of the user on the basis of the power expended to achieve a desired speed, and based on this calculation, tandem riding can easily be detected. E-scooters are designed to carry a maximum weight of 100 kg. If this weight is exceeded, which usually occurs in the case of tandem riding, the e-scooter can be automatically deactivated. Bolt has already developed software that should be able to monitor the weight of the rider that uses the e-scooter and is thus able to detect whether another rider started to use the scooter. At that point, the scooter should be deactivated.

6 Conclusion

The goal of the paper was to assess the safety of riding shared e-scooters and to identify the causes of accidents involving them. The goal of the paper was thus fully met.

E-scooters have recently become a discussed topic in larger towns´ town halls. It shall be noted that the main safety issues concerning e-scooters are not e-scooters as such but their users. If all the rules set by e-scooter providers were followed, the number of accidents would be significantly reduced. Currently, e-scooter users are the reason why the number of accidents involving e-scooters is three times higher than in the case of bicycles. The cornerstone for ensuring safety is training aimed at making users familiar with e-scooters and the regulations they must follow. Such training should be provided by e-scooter rental companies to users when they use e-scooters for the first time, and companies should ensure that they successfully complete the training.

The safety of riding e-scooters does not depend only on preventing the occurrence of accidents, but also on the use of both active and passive safety features. If shared e-scooter riders started to use safety helmets, the passive safety of users would significantly increase, since according to the research results, 40 % of e-scooter riders treated after an accident had suffered a head injury. This recommendation cannot be targeted at one gender only as the unwillingness to wear safety helmets applies to all users. The wearing of safety helmets is not sufficiently promoted by the analysed companies on their social network profiles, although they recommend their wearing. For example, on its social network profile, the company Bird shows only 10 % of users that are wearing safety helmets. Users should be recommended by e-scooter providers to use these passive safety features. Also, it is necessary to make users familiar with the legislation concerning the mandatory wearing of safety helmets in a given country.

Relevant authorities should focus on the reduction of the number of accidents involving e-scooters and the enforcement of penalties associated with this type of mobility. In the Czech Republic, e-scooter users are classified as drivers subject to the same regulations as passenger car drivers, and offences and crimes can be easily fined and enforced. According to the research conducted by Bekhit et al. (2020), about 40 % of patients treated after an accident involving e-scooters had been under the influence of alcohol, which is in the Czech Republic punishable by a fine of $ 1,000 – 2,000 and possible revocation of a driving licence for a period 6 – 12 months. Similarly, companies providing e-scooters should also participate in the reduction of the number of accidents in several ways, e.g. by monitoring places with a frequent ocurrence of accidents and limiting the speed in these places, mapping pedestrian zones where e-scooters are prohibited because of a large concentration of pedestrians or other obstacles, which may result in a lower number of accidents in these risky areas, deactivation of e-scooters in these areas, and modification of software used in e-scooters that would prevent tandem riding.

There are two major limitations to this research. From the perspective of reducing the number of accidents, it is an absence of keeping records of accidents involving e-scooters in the legislation of the Czech Republic. Due to this, it is not possible to sufficiently analyse this type of accidents in order to obtain primary data, which would enable a better understanding of this issue and propose suitable measures to reduce the number of accidents. The limitation in terms of passive safety features is the unavailability of safety helmets. Although it is known that head injuries are of common occurrence, there is no system created to ensure sufficient safety features for users of these shared mobility means, such as e-scooters, bicycles, and e-bikes.

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Primary Paper Section: A

Secondary Paper Section: AP, AQ