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Drunk or Sober? Number of alcohol units perceived to be safe before riding e-scooter

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ABSTRACT

Riding an e-scooter under the influence of alcohol is one of the most frequently reported risky behaviours among riders in various countries, especially in the Nordic countries. What is the Number of Alcohol Units perceived to be Safe (NAUS) before riding an e-scooter? Who is more likely to report higher perceived alcohol tolerance before riding an e-scooter? What is the level of risk perception in this transport domain? The current study advances the literature by aiming to address these questions. Using a cross-sectional survey (n = 395) in Trondheim, Norway we developed an integrated model combining a path analysis with negative binomial regression to predict NAUS before riding an e-scooter. Results show that (i) around 56 % of participants reported that it is safe to consume one or more units of alcohol prior to riding an e-scooter, (ii) younger people, frequent users of e-scooters, individuals with low education, and people with lower perceived risks of an accident were more likely to report higher NAUS. Alcohol health warnings and random blood alcohol concentration tests on e-scooter sites could be prioritised among these segments of the population, and (iii) there is a rather high risk perception in this transport domain. We found that there are strong connections between higher risk perception, worry and fewer NAUS. Policymakers could highlight risks of accidents by e-scooters under the influence of alcohol.

1. Introduction

Electric scooters (e-scooters) are becoming increasingly popular as a mode of micro mobility (Orozco-Fontalvo et al., 2022; Wang et al., 2022). They serve as excellent first-/last-mile transportation options and for short distances in urban spaces (Wang et al., 2022). However, despite the rapid growth in popularity of e-scooters, their initial use was not strictly regulated by applicable regulations in many cities, resulting in safety challenges. E-scooter riding under the influence of alcohol is one of the most frequently reported risky behaviours among riders in various countries (Farley et al., 2020; Gioldasis et al., 2021; Blomberg et al., 2019), especially in the Nordic countries (Karlsen and Fyhri, 2021). For instance, half of e-scooter riders in Oslo, Norway, reported that they had ridden while under the influence of alcohol.[1] A recent survey in Norway showed that nine out of ten respondents believe that some form of alcohol limit is needed for people using an e-scooter.[2] Accordingly, the Norwegian Public Roads Administration has proposed a blood alcohol limit of 0.2, similar to the national car driving legislations.[3] However, there is a sharp increase in e-scooter crashes in Norway leading to a call for efficient rules and enforcement. According to hospital reports in Oslo, around half of such crashes are under the influence of alcohol.[4] Although other risk-taking behaviours such as smartphone use or illicit substance use can be important causes of traffic crashes by micro-mobility options (Gioldasis et al., 2021), riding under the influence of alcohol is one of the most common risk-taking behaviours among riders in the Nordic countries (Karlsen and Fyhri, 2021; Stigson et al., 2021).

Although a few previous studies have investigated sociodemographic characteristics putatively related to riding e-scooter under the influence of alcohol, little is known about (i) what the Number of Alcohol Units perceived to be Safe (from here on abbreviated as “NAUS”) by people before riding an e-scooter is. It has been argued that perception of a specific behaviour can be associated with actual behaviour in the

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[1] https://www.toi.no/transport-and-behaviour/half-of-e-scooter-riders-in-oslo-have-driven-while-under-the-influence-of-alcohol-article36921-1257.html.
[2] https://norwaytoday.info/news/almost-all-norwegians-want-an-alcohol-limit-for-those-driving-electric-scooters-new-survey-shows/.
[3] https://www.politiet.no/rad/trafikk/sikkerhet-i-trafikken/elsykkel-og-elsparkesykkel/.
[4] https://www.eltis.org/in-brief/news/oslo-adopts-restrictions-e-scooters.

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transport domain (Nordfjærn et al., 2021). Considering this, we believe that NAUS can serve as a proxy for actual behaviour (riding under the influence of alcohol), (ii) how different sociodemographic and travel attributes are associated with NAUS before riding an e-scooter, and (iii) how risk perception including probability assessment of an incident, the severity of possible consequences, and worry can predict NAUS. The current study could have policy implications. First, the results can help policymakers better understand how much alcohol is perceived as safe before using e-scooters in different segments of the population. Second, findings can provide information about which sociodemographic groups are more prone to report higher perceived alcohol tolerance when riding an e-scooter. Third, the study can reveal whether it is relevant to conduct risk perception interventions related to this specific transport domain.

1.1. The state of the art in e-scooter safety and alcohol consumption

The state of the art in e-scooter safety and alcohol consumption can be categorised into three streams of research. The first stream has dealt with the prevalence of different types of injuries among e-scooter riders. The second stream has evaluated general safety patterns of e-scooter use, and the third stream of research, consisting of only a few studies, has tried to explore sociodemographic correlates of riding under the influence of alcohol. Examples for each stream are presented in the following paragraphs.

A retrospective study among 89 individuals who sustained e-scooter accidents in Germany, showed that 28 % of the persons were under the influence of alcohol. More than half of the riders suffered trauma to the head or face (Kleinertz et al., 2021). Another study in Berlin reported that e-scooter usage while under the influence of alcohol carries a high risk of serious head, face, and extremity injuries (Graef et al., 2021). Using patient-related and incident-related data as well as a survey concerning e-scooter use in Germany, Uluk et al. (2022) found that consumption of alcohol was associated with traumatic brain injuries. Bianchi et al. (2021) showed that accidents involving e-scooters can cause serious kidney damage and these incidents are expected to increase. Farley et al. (2020) estimated US injury trends from 2014 to 2019. They showed that alcohol consumption accounts for 88.1 % of e-scooter injuries in 2019. Assessing e-scooter injuries among riders in Paris, alcohol consumption was reported in 49 % of the cases. Based on 70 e-scooter injuries recorded in Turkey, Genc Yavuz et al. (2022) showed that 2.9 % of the patients had a Blood Alcohol Concentration (BAC) of >10 mg/dl. According to 468 scooter-related injuries recorded in Denmark, Blomberg et al. (2019) found that e-scooter riders (18–25 years of age) were likely to be under the influence of alcohol or drugs. According to a study conducted on 103 injured e-scooter riders in USA, 79 % of the subjects were tested for alcohol, and 48 % had BAC above 80 mg/dL (Kobayashi et al., 2019). According to the 2018 dockless e-scooter accident data in Austin, Texas, Azimian and Jiao (2022) found that most of these injuries occurred in densely populated urban areas such as city centers.

Recent studies in Brisbane, Australia, showed that private e-scooter riders engage in fewer illegal behaviours than shared e-scooter riders (Haworth et al., 2021a, 2021b), which seems to indicate that especially the free floating e-scooter fleets are prone to be used by people under the influence of alcohol. Based on an online survey of 337 German e-scooter users and non-users, Petzoldt et al. (2021) discovered that less than half of the participants knew the legal BAC. On the basis of two Swedish accident data sets, Stigson et al. (2021) concluded that alcohol-related accidents are more likely to occur at weekends and at night. As asserted by Ma et al. (2021), alcohol restrictions are listed as one of 16 key attributes of municipal guidelines for users of shared e-scooters in the US that should be considered by more actionable guidelines. According to text mining of news reports on 169 e-scooter crashes in the US, riding under the influence of alcohol is one of the reasons why e-scooter crashes occur (Yang et al., 2020). Based on the studies reported above, it can be safely concluded that alcohol use is a major component contributing to serious accidents with e-scooters.

Employing a face-to-face road survey (N = 459) among e-scooter riders in Paris, France, Gioldasis et al. (2021) investigated the effect of riders' attributes (i.e., gender, age, income, job status, occupation category, education degree, marital status, e-scooter ownership, e-scooter use) on the frequency of riding under the influence of alcohol. The cited study used a self-reported question to measure riding after drinking. Young and male e-scooter riders are the most likely to consume alcohol and drugs. Teenagers and young adults aged 17 to 24 were the most likely to engage in such behaviour. Approximately 40 % of the 17-to-24-year-old riders reported riding an e-scooter after drinking alcohol. Further, riders of e-scooters who have used them for a longer period tend to consume alcohol more frequently. The researchers speculated that riders who are familiar with this transport mode are more likely to take risks (i.e., a risk habituation process). However, the authors did not find significant effects of variables such as place of living, income, educational degree, job status, and household composition on riding under the influence of alcohol. An experimental study (medical examinations) was recently conducted by Zube et al. (2022) to investigate whether alcohol has an effect on e-scooter riding. The study was conducted on 57 subjects (28 females and 29 males) and 6 consistently sober subjects (three females and three males). They showed that alcohol significantly impairs the performance of e-scooter riders, even at rather low BAC levels (0.21 to 0.40 g/kg), indicating that alcohol can negatively affect e-scooter riding.

1.2. Risk perception

Risk perception has been analysed from two different perspectives: "risk as analysis" or "risk as feelings" (Loewenstein et al., 2001; Slovic et al., 2013; Rundmo and Nordfjærn, 2017; Backer-Grøndahl and Fyhri, 2009). In the first case, a person attempts to evaluate the source of risk in accordance with their knowledge, reasoning, and logic. In the second instance, emotional responses are triggered by sources of risk. However, also a rational and subjective assessment of risk can produce feelings such as worry, and anxiety. The subjective assessment of a risk involves two elements: subjective evaluations of probability of a hazardous event and perceived potential severity of its consequences. Risk as feelings is the emotional component of the risk assessment (often worry). Whereas it is often considered that perception of risk is purely cognitive (Nordfjærn et al., 2021), dread may be seen as a reflection of emotion (Sjøberg, 1999). However, worry and concern, for example, should not be considered part of the risk perception itselfbut rather as an effect of perceived risk.

Several studies have demonstrated that risk perception can explain risk-taking behaviour in traffic safety (Nordfjærn et al., 2021; Rundmo and Nordfjærn, 2017). Rundmo and Nordfjærn (2017) argued that subjective probability assessment of an accident, expected severity of consequences and worry can be used as predictors of risk-taking behaviour. It is also assumed that the two factors of "risk as analysis" (i.e., subjective probability assessment of an accident and expected severity of consequences) can be correlated with each other and can also explain worry as an anticipated emotional outcome (Rundmo and Nordfjærn, 2017). Therefore, we develop our hypothesised model to test how risk perception might explain NAUS as a cognition.

According to the literature, it can be summarised that riding an e-scooter under the influence of alcohol is a substantial safety challenge. However, it is less clear (i) what level of alcohol is perceived safe before riding an e-scooter, and (ii) to what extent the levels of perceived risk regarding accidents and sociodemographic characteristics influence NAUS.

1.3. Contributions of the current study

What is the perceived number of alcohol units people think they can

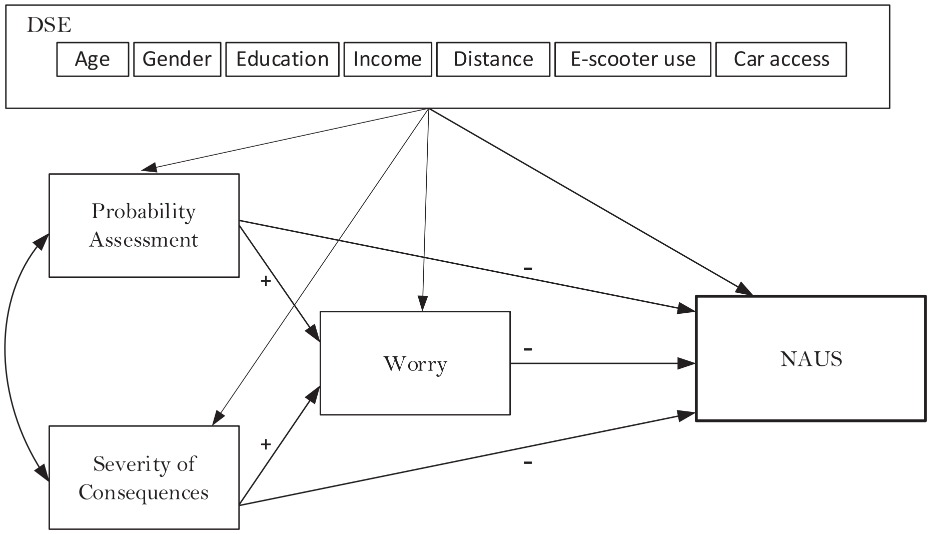


Fig. 1. Hypothesised model of the study explaining NAUS.

safely consume before riding an electric scooter (NAUS)? Which groups of people are more likely to report higher alcohol perception before riding an e-scooter? Does risk perception influence the NAUS? The current study aims to answer these questions which fill a gap in the literature review reported above. Firstly, we estimate the number of alcohol units perceived to be safe by people before riding an e-scooter (NAUS). A Norwegian alcohol measurement standard defines one "unit" as one glass of beer (4.5 %) or a glass of wine (12 %), or 2/4cl of hard liquor (40 %). The concept of the "unit" is well established in the general Norwegian population. Furthermore, we test how risk perception alongside demographic and socioeconomic variables, and travel attributes predict NAUS. Our major contribution to the state of the art is to examine relationships between risk perception components and NAUS. What are the levels of risk perception in this transport domain?

This study's conceptual framework is based mainly on risk perception, worry, and NAUS. Our focus is on risk perception[5] and worries in this context. As illustrated in Fig. 1, it is hypothesised that an increased perceived assessment of accident probability, perceived judgment of the severity of consequences, and worry are associated with fewer perceived units of alcohol that can be safely consumed before riding an e-scooter. Additionally, it is hypothesised that increased perceived assessment of accident probability and perceived severity of consequences are positively related to worry. In addition, the direct effects of demographic, socioeconomic, and travel attributes (DSE) on NAUS were taken into account in the model. DSE variables were also considered as potential correlates of each of the risk perception factors. Such correlates can also have implications for policy and planning regarding risk campaigns. We can figure out, for example, if the probability assessment of having an accident is a significant explanator of NAUS, which segments of the sample (females versus males or highly educated versus lowly educated) are more likely to have stronger subjective probability assessments.

2. Method

2.1. Procedure and sampling

A self-completion survey with a cross sectional design was used to gather data. Convenience sampling was used to establish the sample. Firstly, convenience sampling took the form of orally recruiting participants at a fixed physical location, in this case, two shopping centres in Trondheim, Norway, during February 2022 (one of them was in the city centre and is less car-orientated, whereas the other was more peripherally located and is more car-orientated). Participants were asked if they wished to participate in a quick digital survey that was completely voluntary and anonymous. Secondly, snowball sampling was conducted by the respondents themselves sending a link to the survey to acquaintances (via SMS, email, and online messaging), with the hope that they would in turn pass it on to their acquaintances, and so on. Eight psychology students served as research assistants in the project and were responsible for carrying out the data collection. Data collection took place between Monday the 21st of February and Monday the 28th of February between the hours of 10:00 and 16:00. When it came to age and gender, it was attempted to recruit as diverse a sample as possible, however, this was challenging since there were, on average, more women present at the shopping centres than men. Lastly, before participation, the participants were all informed about confidentiality issues, such as anonymity and the security of their data.

Table 1
Sample characteristics.

Attribute	(n, %)	Attribute	(n, %)
Age	14–24 (n = 108, (27 %) 25–39 (n = 77, 19 %) 40–59 (n = 102, 26 %) 60–98 (n = 109, 28 %)	Gender	Men (n = 169, 42.7 %) Women (n = 223, 56.3 %)
Education	Primary school (n = 23, (5.8 %) High school (n = 130, (32.8 %) University (n = 223, (56.3 %) Other (n = 19, (4.8 %)	Income*	A lot less (n = 98, 24.7 %) Less (n = 86, 21.7 %) Average (n = 123, 31.1 %) More (n = 73, 18.4 %) A lot more (n = 15, 3.8 %)

* Annual income compared to the average brut in Norway (587,600 NOK).

The sample consisted of 396 individuals, of which, 86 participants took part through the snowball approach. However, one of the participants did not consent to having the data used in the study and was excluded from the sample. Of the remaining 395 individuals, 223 (56.3 %) were female, 169 (42.7 %) were male, one reported other gender and two respondents did not respond the gender item. Population statistics in Trondheim show that 49 % of citizens are female and 51 % male. As shown in Table 1, the age group 14–24 consisted of 108 (27 %) individuals. The next group (25–39 years old) consisted of 77 (19 %)

[5] The risk is perceived for the individual/general level (so implied general).

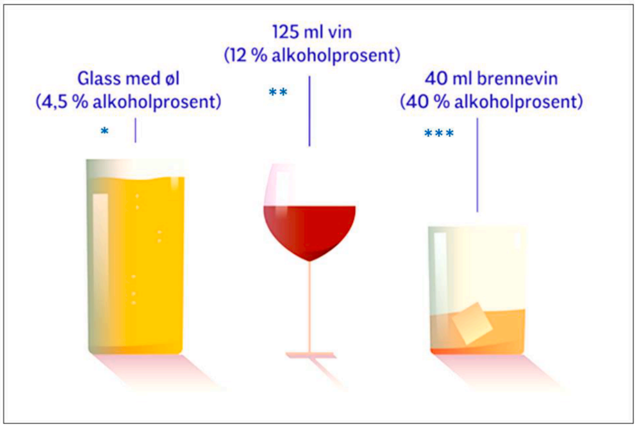


Fig. 2. The definition of unit of alcohol which was illustrated in the Norwegian language questionnaire (*: one glass of beer (4.5 %), **: a glass of wine (12 %), ***: 40 ml of strong liquor (40 %)) (The indicated units have about the same amount of alcohol when considering the differences in amount of liquor in the different units. The Norwegian alcohol measurement standard defines one "unit" as one glass of beer (4.5 %) or a glass of wine (12 %), or 40 ml of hard liquor (40 %). The indicated units are usually presented to improve face validity in validated measures of risky alcohol consumption, such as the Alcohol Use Disorders Identification Test (AUDIT) (Saunders et al., 1993). In Norway, the concept of the "unit" is well-established in the general population. However, we also mentioned this point in the questionnaire in case some of the participants were unfamiliar with this issue.).

individuals and, the penultimate group (40–59 years old) consisted of 102 (26 %) individuals. The final age group, consisting of people aged 60 years or older, included 108 individuals (28 %). Moreover, the minimum age was 14 and the maximum was 98 years, and the mean and standard deviation were 43.82 and 19.93 years respectively. Further, 23 (5.8 %) individuals completed primary school, 130 individuals (32.8 %) high school, 223 (56.3 %) university and the remaining 19 (4.8 %) people reported "other" education. Finally, 307 (77.5 %) individuals had an average or lower income, and 88 (22.3 %) individuals had an above average income.

2.2. Questionnaire

A total of 14 items were used to capture the research questions and aims. At the end of the questionnaire, demographic items were included (age and gender). Participants had four options for gender, "male", "female", "other", or "prefer not to say".

To collect information about participants' income, they were asked to indicate whether they earned about the same as the Norwegian national average (587 600 NOK[6] per year), slightly less, a lot less, slightly more or a lot more. A scale of 1 to 5 was used; 1 is a lot less, 3 is average, and 5 is a lot more than the national average. Participants were also presented with four response categories regarding their highest level of education. The four categories were arranged from lowest to highest education level; "primary school", "secondary/high school", "university", and "other". We also asked respondents if they owned an e-scooter and had access to a car ("yes" or "no").

A few questions were asked regarding travel attributes or situational factors. The participants were asked to indicate the perceived walking time in minutes to the city centre, (minimum value 0 and maximum 99). The participants were also asked how often they used a shared electric scooter.[7] In this case, seven answer options were available; "daily", "once a week", "once a month", "a few times a year", "yearly", "never used, but interested", and "never used, and not interested".

Regarding risk perception, three statements were used including "Riding an electric scooter under the influence of alcohol is likely to result in an accident", "An accident while riding an electric scooter under the influence of alcohol may be very severe", and "I feel concerned about the risks of using an electric scooter under the influence of alcohol", which measure perceived probability, perceived severity of consequences and worry, respectively. These statements were evaluated with a five-point Likert scale ranging from 1) strongly disagree to 5) strongly agree.

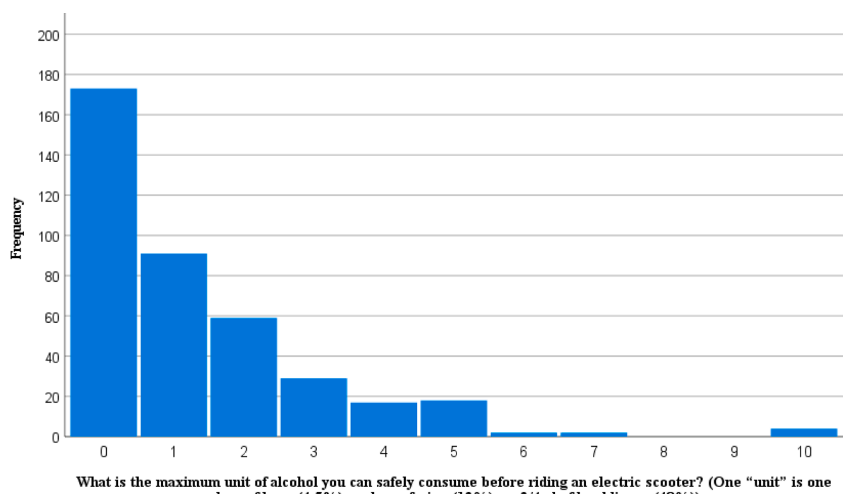
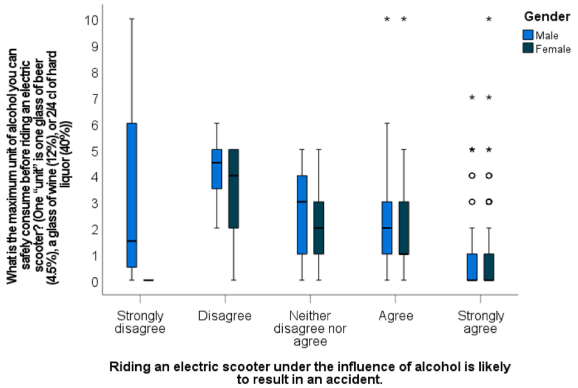


Fig. 3. Frequency of units of alcohol perceived to be safe by respondents.

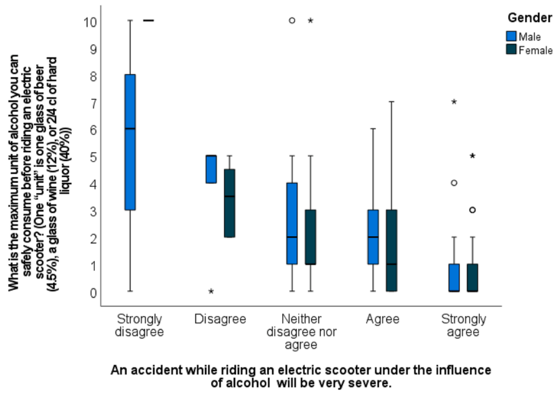
An additional picture-based question was also asked to measure the units of alcohol people think they can safely consume before riding an electric scooter. As illustrated in Fig. 2, we asked the following question: "What is the perceived number of units of alcohol you can safely consume before riding an electric scooter? (One "unit" is one glass of beer (4.5 %), a glass of wine (12 %), or 40 ml of hard liquor (40 %))". The answer scale was 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10 and more.

[6] One Norwegian Kroner (NOK) is equal to about 0.1 USD.

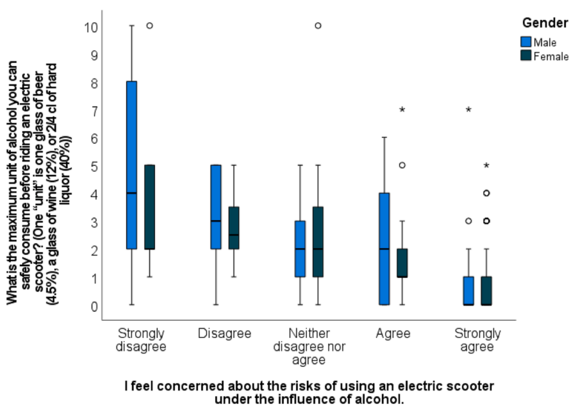
[7] Shared e-scooter system is a service where e-scooters are rented on a short-term basis. There is no fixed location for the e-scooters and they are typically picked up and dropped off at specific points within the service area.



a) Probability assessement



b) Severity of consequences



c) Worry

Fig. 4. Self-reported maximum units of alcohol across different levels of agreement with risk perception items by gender.

2.3. Modelling approach

To test the hypothesised model (Fig. 1) an integrated model combining path analysis (a type of multiple regression analysis) with a count data model was developed. Since the measured outcome variable of the study is the units of alcohol people think that they can safely consume before riding an electric scooter (NAUS), a series of count (i.e., nonnegative integer values) models including Poisson regression, Negative binomial regression, and Zero-inflated versions of the cited models were developed to capture (1) the count nature, (2) distribution, and (3) potential inflation of zero values of the dependent variable.

Table 2
Variables tested in the analyses.

Variable	Descriptive	Mean	SD	%
Demographic and socioeconomic				
Age	Ranging from 14 to 98	43.82	19.93	
Age1424	1: Age of [14–24], 0: Otherwise	0.27	0.44	27 %
Age2539	1: Age of [25–39], 0: Otherwise	0.19	0.39	19 %
Age4059	1: Age of [40–59], 0: Otherwise	0.26	0.43	26 %
Age6098	1: Age of [60–98], 0: Otherwise	0.28	0.44	28 %
GEN	1: The respondent is a female; 0: otherwise	0.57	0.49	57 %
EDU	1: The respondent has a university degree; 0: otherwise	0.56	0.49	56 %
INC	1: The respondent’s annual income is greater than the average in Norway (587,600 NOK* or 66,302 USD); 0: otherwise	0.22	0.41	22 %
CAR	1: The respondent has access to a car; 0: otherwise	0.76	0.42	76 %
AccessES	1: The respondent owns a e-scooter; 0: otherwise	0.04	0.20	4 %
Travel attributes				
CBD	Average walking time (minute) from home to the city centre	53.67	30.77	–
E-USE	1: daily (0.8 %), 2: once a week (6.1 %), 3: once a month (6.1 %), 4: a few times per year (18.2 %), 5: yearly (6.6 %), 6: never used but would be interested (12.4 %), 7: never used and will never be used (49.9 %)			
Risk perception				
Probability	1: strongly disagree; 2: disagree; 3: neither disagree nor agree; 4: agree; 5: strongly agree	4.56	0.84	–
Severity	1: strongly disagree; 2: disagree; 3: neither disagree nor agree; 4: agree; 5: strongly agree	4.24	0.91	–
Worry	1: strongly disagree; 2: disagree; 3: neither disagree nor agree; 4: agree; 5: strongly agree	4.26	1.10	–

* At the time of writing, 1 NOK (Norwegian Krone) was worth around 0.11 USD.

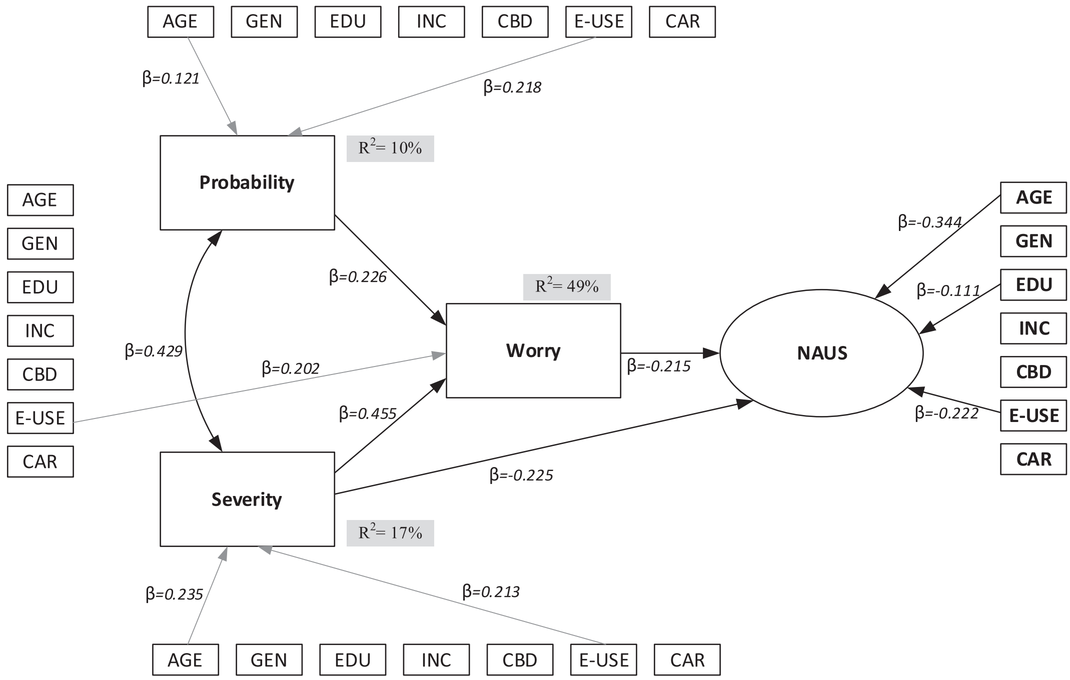
Different demographic and socioeconomic attributes, and risk perception components were entered into these models as observed variables. Finally, the best model was selected based on overdispersion parameter (α) *t*-statistics and other statistics (e.g., goodness-of-fit, Vuong) (Washington et al., 2020). The model selection process and statistical details of count data models are explained in Appendix A.

3. Results

3.1. Descriptives

On average, participants reported that they could safely consume around 1.32 units (SD = 1.74) of alcohol before riding an e-scooter. Approximately 43.8 % (n = 173) of respondents reported that it is not safe to consume any units of alcohol, as illustrated in Fig. 3. Around 56 % (n = 222) of participants reported that it is safe to consume one or more units of alcohol prior to riding an e-scooter. A total of 23 %, 15 %, and 7 % assessed being able to safely consume one, two, and three units of alcohol before riding e-scooters, respectively. Others reported being able to safely consume more units of alcohol before riding e-scooters. About 38 % of participants had used shared e-scooters, while the remainder had not.

Fig. 4 shows the relation between the extent to which respondents agreed or disagreed with risk perception items and the perceived amount of alcohol they can safely consume before riding an e-scooter. It is evident that respondents with a higher perception of risk perceived fewer units of alcohol as safe. It appears that these values do not differ by gender.



Standardised coefficients at 95% CI are shown.

Fig. 5. Explaining NAUS by different factors.

Table 2 lists the variables that were tested in the model. The variables were tested with multiple definitions in the modelling process. For example, the age of respondents was tested both as a continuous variable and several dummy variables in the modelling process, but the continuous form was chosen for the final model because the latter form fitted better in the model.

3.2. Model testing

A series of count data models were tested step by step. First, a Poisson regression model was developed, and likelihood ratio tests showed that this model was statistically better fitted to the data than a linear regression model. The overdispersion test, however, revealed a variance that was significantly larger than the mean (*t-test* > *1.96, p-value* = *0.01, dispersion* = *0.*129). To address the issue of overdispersion, a negative binomial (NB) model with the same predictors was developed. The likelihood ratio test also indicated that the NB model was significantly better (at CI 95 %) than the Poisson model (*Chisq Pr(>Chisq)* = *0.007*).

In addition, a zero-inflated NB (ZINB) with the same model specification was also tested as 43 % of the values of the dependent variable were zero. Using the Vuong statistic, non-nested hypotheses of ZINB versus NB models were also tested. The result of the Vuong test showed that ZINB cannot be better fitted to the data compared to the NB model. Additionally, the likelihood ratio test revealed that the NB model fitted the data better than the ZINB model. The NB model was selected as the final count model after evaluation of the overdispersion test, Vuong statistic, and likelihood ratio tests.

The estimation results for the integrated model (path analysis combined with NB) are presented in Fig. 5, which is the selected model explaining the perceived units of alcohol people think they can consume before riding an e-scooter. Table 3 provides a more detailed description of the estimates. This table summarizes the estimates of standardised regression weights, residual variances, and squared multiple correlations. Approximately 10 %, 17 %, and 47 % of the variability in probability assessment, the severity of consequences and worry was explained by the path model part.

Among hypothesised associations, we found positive associations between probability assessment and worry of an accident happening while riding e-scooter under the influence of alcohol (*β* = *0.226, p* <*.001*) and severity of consequences and worry (*β* = *0.455, p* <*.001*). The results also show negative associations between severity of consequences and NAUS (*β* = *-0.255, p* <*.001*), and between worry and NAUS (*β* = *-0.215, p* <*.001*). Probability assessment failed to directly relate to NAUS (*β* = *-0.048, p* >*.05*). There was also a significant and positive correlation between probability assessment and severity of consequences (*β* = *0.429, p* <*.001*).

Regarding demographic, socioeconomic and travel attributes, our results show that older respondents (*β* = *-0.344, p* <*.001*), individuals with high education (*β* = *-0.111, p* = *0.035*), and infrequent users of shared e-scooters (*β* = *-0.222, p* <*.001*) were more likely to perceive fewer units of alcohol they can safely consume before riding an e-scooter. However, variables including gender, walking distance to the city centre, income level, access to car, and e-scooter ownership did not significantly predict the perceived number of units of alcohol people think that they can safely consume before riding an e-scooter.

Among the different predictors of the risk perception and worry, only age and use of e-scooter were found to be significant predictors. Other variables including gender, education, income status, perceived walking distance to the city centre, and car access, failed to explain risk perception and worry. Older people perceived a high level of probability assessment (*β* = *0.121, p* <*.05*), and severity of consequences (*β* = *0.235, p* <*.001*). The links between e-scooter use and probability (*β* = *0.218, p* <*.005*), severity of consequences (*β* = *0.213, p* <*.001*) and worry (*β* = *0.202, p* <*.001*) were also found statistically significant. In other words, infrequent users of e-scooters reported higher perceived risks.

4. Discussion

This study aimed to advance the literature by addressing the following research questions: (i) What is the number of alcohol units perceived to be safe (NAUS) before riding an e-scooter? (ii) Who is more

Table 3
Specific estimates in the model (path analysis with a negative binomial outcome).

			Estimate	S.E.	Est./S.E.	p
Unstandardized Regression Weights						
Probability assessment	<—	Age (AGE)	0.005	0.002	2.055	0.040
Probability assessment	<—	Female (GEN)	0.114	0.088	1.302	0.193
Probability assessment	<—	Well educated (EDU)	−0.002	0.082	−0.024	0.981
Probability assessment	<—	High Income (INC)	−0.026	0.096	−0.270	0.787
Probability assessment	<—	Walking time to CBD (CBD)	0.000	0.001	0.148	0.882
Probability assessment	<—	Car access (CAR)	0.134	0.109	1.229	0.219
Probability assessment	<—	E-scooter use (E-USE)	0.107	0.037	2.911	0.004
Severity of consequences	<—	Age (AGE)	0.011	0.003	4.061	0.000
Severity of consequences	<—	Female (GEN)	0.031	0.088	0.351	0.725
Severity of consequences	<—	Well educated (EDU)	−0.096	0.086	−1.110	0.267
Severity of consequences	<—	High Income (INC)	−0.017	0.099	−0.169	0.865
Severity of consequences	<—	Walking time to CBD (CBD)	0.001	0.001	0.966	0.334
Severity of consequences	<—	Car access (CAR)	0.022	0.108	0.206	0.837
Severity of consequences	<—	E-scooter use (E-USE)	0.115	0.036	3.185	0.001
Worry	<—	Age (AGE)	−0.001	0.002	−0.582	0.561
Worry	<—	Female (GEN)	0.074	0.084	0.877	0.381
Worry	<—	Well educated (EDU)	−0.081	0.083	−0.971	0.332
Worry	<—	High Income (INC)	−0.002	0.094	−0.023	0.982
Worry	<—	Walking time to CBD (CBD)	0.001	0.001	0.638	0.524
Worry	<—	Car access (CAR)	0.052	0.101	0.515	0.606
Worry	<—	E-scooter use (E-USE)	0.132	0.036	3.678	0.000
Worry	<—	Probability assessment	0.300	0.077	3.906	0.000
Worry	<—	Severity of consequences	0.552	0.073	7.552	0.000
NAUS	<—	Age (AGE)	−0.017	0.004	−4.735	0.000
NAUS	<—	Female (GEN)	0.015	0.105	0.146	0.884
NAUS	<—	Well educated (EDU)	−0.225	0.106	−2.118	0.034
NAUS	<—	High Income (INC)	0.080	0.116	0.691	0.490
NAUS	<—	Walking time to CBD (CBD)	−0.003	0.002	−1.459	0.144
NAUS	<—	Car access (CAR)	−0.088	0.120	−0.731	0.464
NAUS	<—	E-scooter use (E-USE)	−0.131	0.032	−4.103	0.000
NAUS	<—	Probability assessment	−0.057	0.056	−1.017	0.309
NAUS	<—	Severity of consequences	−0.248	0.062	−4.005	0.000
NAUS	<—	Worry	−0.195	0.048	−4.033	0.000
Severity of consequences	<- ->	Probability assessment	0.277	0.050	5.555	0.000
Intercepts						
Probability assessment			3.577	0.213	16.795	0.000
Severity of consequences			3.073	0.196	15.691	0.000
Worry			−0.208	0.344	−0.604	0.546
NAUS			3.865	0.269	14.350	0.000
Residual Variances						
Probability assessment			0.614	0.084	7.334	0.000
Severity of consequences			0.678	0.060	11.222	0.000
Worry			0.611	0.068	8.998	0.000
Standardised Regression Weights						
Probability assessment	<—	Age (AGE)	0.121			
Probability assessment	<—	Female (GEN)	0.068			
Probability assessment	<—	Well educated (EDU)	−0.001			
Probability assessment	<—	High Income (INC)	−0.013			
Probability assessment	<—	Walking time to CBD (CBD)	0.007			
Probability assessment	<—	Car access (CAR)	0.069			
Probability assessment	<—	E-scooter use (E-USE)	0.218			
Severity of consequences	<—	Age (AGE)	0.235			
Severity of consequences	<—	Female (GEN)	0.017			
Severity of consequences	<—	Well educated (EDU)	−0.052			
Severity of consequences	<—	High Income (INC)	−0.008			
Severity of consequences	<—	Walking time to CBD (CBD)	0.048			
Severity of consequences	<—	Car access (CAR)	0.010			
Severity of consequences	<—	E-scooter use (E-USE)	0.213			
Worry	<—	Age (AGE)	−0.024			
Worry	<—	Female (GEN)	0.033			
Worry	<—	Well educated (EDU)	−0.036			
Worry	<—	High Income (INC)	−0.001			
Worry	<—	Walking time to CBD (CBD)	0.024			
Worry	<—	Car access (CAR)	0.020			
Worry	<—	E-scooter use (E-USE)	0.202			
Worry	<—	Probability assessment	0.226			
Worry	<—	Severity of consequences	0.455			
NAUS	<—	Age (AGE)	−0.344			
NAUS	<—	Female (GEN)	0.008			
NAUS	<—	Well educated (EDU)	−0.111			
NAUS	<—	High Income (INC)	0.033			
NAUS	<—	Walking time to CBD (CBD)	−0.082			
NAUS	<—	Car access (CAR)	−0.037			

(*continued on next page*)

Table 3 (*continued*)

			Estimate	S.E.	Est./S.E.	p
NAUS	<—	E-scooter use (E-USE)	−0.222			
NAUS	<—	Probability assessment	−0.048			
NAUS	<—	Severity of consequences	−0.225			
NAUS	<—	Worry	−0.215			
Severity of consequences	<- ->	Probability assessment	0.429			
Intercepts						
Probability assessment			4.309			
Severity of consequences			3.383			
Worry			−0.188			
NAUS			3.865			
Residual Variances						
Probability assessment			0.891			
Severity of consequences			0.822			
Worry			0.503			
R-SQUARE						
Probability assessment			10 %			
Severity of consequences			17 %			
Worry			49 %			
Number of Free Parameters		42				
Loglikelihood						
	H0 Value	−1872.005				
	H0 Scaling Correction Factor for MLR	1.2182				
Information Criteria						
	Akaike (AIC)	3828.010				
	Bayesian (BIC)	3994.803				
	Sample-Size Adjusted BIC (n* = (n + 2) / 24)	3861.538				

likely to report higher NAUS before riding an e-scooter? And (iii) What is the level of risk perception in this transport domain? An integrated model combining path analysis and negative binomial regression was developed to predict NAUS by cross-sectional survey data collected in Trondheim, Norway.

On average, participants perceived that they safely could consume around 1.32 units (SD = 1.74) of alcohol before riding an e-scooter. Of note, a total of 56 % of participants reported that it is safe to consume one or more units of alcohol before riding an e-scooter. But (i) which groups in the sample report higher numbers? (ii) Who are more likely to request to be completely sober before riding an e-scooter? And (iii) how does risk perception relate to how many units of alcohol that are perceived to be safe? We addressed these research questions.

The findings show that older people are less likely to report that it is safe to consume a high number of units of alcohol before riding an e-scooter. According to the data, older individuals are more likely to perceive that being completely sober before riding an e-scooter is safer. This result is in line with the findings among e-scooter riders in Paris (Gioldasis et al., 2021) and Denmark (Blomberg et al., 2019). In other words, younger Norwegians also need to be carefully targeted in safety campaigns related to e-scooters. Some policy measures can be taken to reduce alcohol-influenced riding among young e-scooter users. For example, random alcohol testing can be implemented during weekends to deter people from riding under the influence of alcohol. Another option would be installing alcolocks in the rental e-scooters. Although Gioldasis et al. (2021) reported that males are the most likely to consume alcohol before riding e-scooter, we found no significant gender difference among participants in Trondheim when asked about the perceived amount of alcohol to safely operate an e-scooter. One plausible reason for this result may be the fact that there is a high degree of gender equality in Norway (Teigen and Wängnerud, 2009). This equality also seems to apply in alcohol consumption as Norwegian nightlife studies generally failed to reveal substantial gender differences in BAC levels (e.g., Nordfjærn et al., 2016). Our results also showed that people with high education are less likely to assume to be able to safely ride an e-scooter with more units of alcohol. One explanation for this could be that people with high education have a greater understanding and interest in safety and health issues. However, this variable was not found significant in past research. Policymakers could aim to increase awareness about consequences of riding under the influence of alcohol in Norway among individuals who do not have a high level of education.

Among situational and trip-related factors, we found no significant associations of car or e-scooter ownership and distance to the city centre with the number of units of alcohol assumed to be safe when riding an e-scooter. However, interestingly, the frequency of use of shared e-scooter was a significant variable. People who are frequent users of shared e-scooters report higher units of alcohol to be safe when riding an e-scooter. This result is in line with the finding in Paris (Gioldasis et al., 2021). Gioldasis et al. (2021) speculated that riders who are familiar with e-scooters are more likely to consume alcohol because this familiarisation can give confidence to riders and result in risk-taking behaviours. However, we expected that In Norway and other Nordic countries people tend to adapt to the rules and regulations of a particular phenomenon once they become frequent users. We expected that a high trust in governmental decisions in the Nordic countries could partly explain this psychological process (Andreasson, 2017). However, our results among Norwegians also showed that frequent users of e-scooters are more likely to take higher risks. We believe that further research is needed in other countries to investigate the relationship between frequency of use of e-scooters and NAUS. This relationship can play an important role for policy and implication. E-scooter operators or police may request alcohol tests from frequent users or distribute warning messages to such users specifically.

Structural relationships between risk perception, worry, and the perceived amount of alcohol to safely operate an e-scooter were examined through a path analysis. The model demonstrated that from three direct paths between risk factors (i.e., risk perception and worry) and the outcome variable (i.e., NAUS) two paths were found statistically significant. This result to a large extent supports our hypothesised modelling framework, showing a rather high level of risk perception in relation to this transport mode. Although the probability assessment of being involved in an accident under the influence of alcohol did not directly influence NAUS, it may indirectly impact NAUS through worry. Among the risk perception components, judgment of severity of consequences and worry were found to be significant and direct predictors of NAUS. Additionally, we found that there is a stronger association between the severity of the consequences and worry than between the probability assessment and worry.

We found that both risk as analysis and risk as feelings can explain fewer number of alcohol units perceived to be safe before riding an e-scooter. In other words, there is room for safety experts to employ interventions to discourage riding e-scooter under the influence of alcohol. The findings demonstrate that people with stronger judgment of the severity of consequences, and worry are less likely to consider more units of alcohol as safe. A further analysis on demographic, socioeconomic and travel attributes showed that risk campaigns could be targeted to younger citizens and those who are frequent users of e-scooters.

5. Conclusions

Our first research aim was to estimate the number of alcohol units perceived to be safe (NAUS) before riding an e-scooter. Around 56 % of participants reported that it is safe to consume one or more units of alcohol prior to riding an e-scooter. The average units of alcohol that respondents in the study sample thought can be safe to consume before riding an e-scooter was 1.32 (SD = 1.74) units. Our findings show that there is considerable variance in the number of alcohol units perceived as safe. Secondly, we sought to find out who was more likely to report higher NAUS. We found that younger people, frequent users of shared e-scooters, individuals with low education, and people with lower perceived risks of accidents are more likely to assume more units of alcohol before riding e-scooter to be safe. Therefore, alcohol health warnings and tests can be prioritised among these segments of the population. The third aim of our study was to determine the extent to which risk perception contributes to NAUS. We also conclude that there is a high level of risk perception in relation to this transport mode. Our study showed that there are strong connections between risk perception, worry and considering fewer units of alcohol to be safe before riding e-scooters. Policymakers could also devise prevention measures to highlight risks of accident by e-scooters under the influence of alcohol.

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CRediT authorship contribution statement

Milad Mehdizadeh: Writing – original draft, Conceptualization, Methodology, Investigation, Formal analysis, Resources, Data curation, Visualization, Funding acquisition, Project administration, Supervision. **Trond Nordfjaern:** Validation, Conceptualization, Writing – review & editing. **Christian A. Klöckner:** Validation, Formal analysis, Conceptualization, Writing – review & editing.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Milad Mehdizadeh reports financial support was provided by Norwegian Centre for Energy Transition Strategies (NTRANS).

Data availability

Data will be made available on request.

Appendix A

The Poisson distribution approximates counts of rare events such as accidents, manufacturing failures, and vehicles waiting in line. Among its requirements, the Poisson distribution demands that the mean and variance of the count process are equal. Overdispersed data are those in which the variance is significantly larger than the mean. It is possible to model overdispersed count data using a negative binomial model in many cases.

In a Poisson model, the probability of individual i having y_i unit of alcohol is given by

$$P(y_i) = \frac{EXP(-\lambda_i)\lambda_i^{y_i}}{y_i!} \tag{1}$$

where $P(y_i)$ is the probability of individual i having y_i unit of alcohol before riding e-scooter and λ_i is the Poisson parameter for individual i, which is equal to individual i's expected unit of alcohol can safely drink before riding e-scooter, E[y_i]. By specifying the Poisson parameter λ_i (the expected units of alcohol) as a function of explanatory variables, Poisson regression models can be estimated. In most cases, the Poisson parameter is correlated with explanatory variables via a log-linear model,

$$\lambda_i = EXP(\beta X_i) or, LN(\lambda_i) = \beta X_i \tag{2}$$

where X_i represents a vector of explanatory variables and b represents a vector of estimable parameters. Maximal likelihood methods can be used to estimate this model, with the likelihood function given as

$$L(\beta) = \prod_i \frac{EXP[-\mathrm{EXP}(\beta X_i)][\mathrm{EXP}(\beta X_i)]}{y_i!} \tag{3}$$

Logarithms of likelihood function are simpler to manipulate for estimation, and are represented as

$$LL(\beta) = \sum_{i=1}^{n} -\mathrm{EXP}(\beta X_i) + y_i \beta X_i - LN(y_i!) \tag{4}$$

As a result of either under- or overdispersion (E[y_i] $\neq$ VAR[y_i]), the negative binomial model can be a solution and is derived by rewriting Eq. (2) such that for each individual i,

$$\lambda_i = EXP(\beta X_i + \varepsilon_i) \tag{5}$$

Adding $EXP(\varepsilon_i)$ term (being a Gamma-distributed disturbance term) with a mean of 1 and a variance of α. As a result, the variance can differ from the mean. According to the negative binomial distribution, the likelihood function can result in the following formulation:

Table A1
Decision guidelines for count data model selection (Washington et al., 2020).

		t-Statistic of the NB Overdispersion Parameter α	
		< |1.96|	> |1.96|
Vuong statistic	< –1.96	ZIP or Poisson as alternative to NB	NB
	> 1.96	ZIP	ZINB

$$L(\lambda_i) = \prod_i \frac{\Gamma\left(\left(\frac{1}{\alpha}\right) + y_i\right)}{\Gamma\left(\frac{1}{\alpha}\right) y_i!} \left(\frac{\frac{1}{\alpha}}{\frac{1}{\alpha} + \lambda_i}\right)^{\frac{1}{\alpha}} \left(\frac{\lambda_i}{\frac{1}{\alpha} + \lambda_i}\right)^{y_i} \tag{6}$$

where $\Gamma(\cdot)$ is a gamma function.

Regression models with zero-inflated Poisson (ZIP) and zero-inflated negative binomial (ZINB) address phenomena involving zero-inflated counting processes.

In the ZIP model, it is assumed that the events, $Y = (y_i, y_i, \cdots, y_i)$, are independent and the model is

$$\begin{aligned} y_i &= 0 \ \textit{with probability} \ p_i + (1 - p_i)EXP(-\lambda_i) \\ y_i &= y \ \textit{with probability} \ \frac{(1 - p_i)EXP(-\lambda_i)\lambda_i^{\ y}}{y_i!} \end{aligned} \tag{7}$$

As for the ZINB model, a similar formulation is assumed as follows

$$\begin{aligned} y_i &= 0 \ \textit{with probability} \ p_i + (1 - p_i)\left(\frac{\frac{1}{\alpha}}{\frac{1}{\alpha} + \lambda_i}\right)^{\frac{1}{\alpha}} \\ y_i &= y \ \textit{with probability} \ (1 - p_i)\left[\frac{\Gamma\left(\left(\frac{1}{\alpha}\right) + y\right)\left(\frac{\frac{1}{\alpha}}{\frac{1}{\alpha} + \lambda_i}\right)^{\frac{1}{\alpha}}\left(1 - \left(\left(\frac{\frac{1}{\alpha}}{\frac{1}{\alpha} + \lambda_i}\right)^{\frac{1}{\alpha}}\right)\right)^{y}}{\Gamma\left(\frac{1}{\alpha}\right) y!}\right], y = 1, 2, 3, \cdots \end{aligned} \tag{8}$$

Rather than relying on a traditional model to test the appropriateness of zero-inflated models, Vuong (1989) suggested a test statistic for non-nested models that can be used when the distribution of the data (Poisson or negative binomial) is known. For each observation i, the statistic is calculated as follows:

$$m_i = LN = \left(\frac{f_1(y_i|X_i)}{f_2(y_i|X_i)}\right) \tag{9}$$

where the probability density function of model 1 is $f_1(y_i|X_i)$, whereas the probability density function of model 2 is $f_2(y_i|X_i)$.

The statistic used by Vuong to test non-nested hypotheses of model 1 versus model 2 is

$$V = \frac{\sqrt{n}(\overline{m})}{S_m} \tag{10}$$

where m is the mean $((1/n)\sum_{i=1}^{n} m_i)$, S_m is standard deviation, and n is a sample size. According to Table A1, Shankar et al. (1997) provided useful guidelines on model selection, where they consider possible values of Vuong-tests and overdispersion parameters (α).

In addition, the likelihood ratio test and McFadden ρ^2 statistic were used to assess two competing models and the overall fit of the models as goodness-of-fit statistics. As expressed in Eq. (11), the ρ^2 statistic is

$$\rho^2 = 1 - \frac{LL(\beta)}{LL(0)} \tag{11}$$

where $LL(\beta)$is the log-likelihood at convergence with parameter vector β and $LL(0)$ is the initial log-likelihood (with all parameters set to zero). The χ^2statistic evaluates potential improvement of a new model by the likelihood ratio test as follows.

$$\chi^2 = -2[LL(\beta_R) - LL(\beta_U))] \tag{12}$$

where $LL(\beta_R)$ is the log-likelihood at convergence of the "restricted" model and $LL(\beta_U)$ is the log-likelihood at convergence of the unrestricted model. Mplus software was used to test the models.

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