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Evaluating fare evasion risk in bus transit networks

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ABSTRACT

In Proof-of-Payment Transit Systems (POP-TSs), fare evasion is a crucial issue for Transit Agencies (TAs) and/or Public Transport Companies (PTCs) worldwide. The related research background is based on the standard ratio between evaders and inspected passengers, whereas no research quantified the risk of fare evasion in POP-TSs. The objective of this study is the introduction of a framework covering this gap: it integrates fare evasion factors, prediction models, a risk-based method and returns the risk value on (parts of) routes as a function of the frequency of fare evasion, the related severity and exposure terms. Next, routes are ranked according to the risk value and classified by a 5-level scale, to show the (parts of) routes with the highest risk of evasion. Results show the capability of this framework on about 20,000 real-world data records gathered by a mid-sized Italian bus company through fare inspection logs and passenger surveys. To conclude, this framework is a support tool for TAs/PTCs to improve fare compliance and can be incorporated into any transit managerial system.

1. Introduction

Fare evasion (i.e., the circumstance in which a passenger is not provided with a ticket or owns an incorrect one) threatens the economic sustainability of Transit Authorities/Public Transport Companies (TAs/PTCs) and has an interdisciplinary nature (Barabino et al., 2020). In Proof-of-Payment Transit Systems (POP-TSs), passengers have to buy tickets before boarding vehicles; however, they are not automatically checked and may opportunistically decide to evade the fare. Many strategies can be adopted by TAs/PTCs to face fare evasion, the most relevant being passenger inspections and fine charging (Multisystems et al., 2002; Sasaki, 2014; Guarda et al., 2016; Dai et al., 2017; Alhassan et al., 2022; Wolfgram et al., 2022).

Inspections positively impact the revenues' protection and the reduction of aggressive behaviour and vandalism (Barabino et al., 2020). On the one hand, the optimal setting of inspection levels is empirically shown to reduce fare evasion (e.g., Barabino et al., 2015, Cools et al., 2018; Porath & Galilea, 2020). On the other hand, if inspection levels are suboptimal, the effectiveness in detecting evaders is low (Guzman et al., 2021).

The literature on deterrence has stressed that potential offenders pay greater attention to the certainty of being caught than to the severity of the punishment if caught (Smith and Clarke, 2000). Moreover, a suitable level of inspection can decrease 'criminal' issues and increase the security of passengers (Killias et al., 2009). The setting of the inspection level was theoretically discussed by simulated data (Boyd et al., 1989; Boyd, 2020) and formally addressed by analytical models supported by real data (Barabino et al., 2013, 2014; Barabino & Salis, 2019). Further research investigated the scheduling inspection patrols by optimisation methods to provide detailed inspection plans (Yin et al., 2012; Correa et al., 2017; Brotcorne et al., 2021).

In many TAs/PTCs, the inspections are based on the measure of the fare evasion ratio (FER)[1]. However, it is insufficient to draw conclusions, because low values of this ratio are observed due to both few evaders and low inspection rate. Therefore, this metric can be enhanced by the introduction of the fare evasion risk. This integrates components of frequency and/or probability, severity, and exposure (Aven, 2015). The risk definition requires linking the previous components to several factors (attributes, determinants, predictors, or variables). The effects of specific factors on the frequency and/or probability of fare evasion were already investigated in the literature by descriptive and inferential models, but they have some flaws (Barabino et al., 2020). Descriptive models could lack statistical significance, and inferential models were not integrated into a risk framework incorporating frequency, severity and exposure. Therefore, it is of interest to investigate the risk of fare evasion, while considering the characteristics of networks, policies and

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[1] The quotient between evaders and inspected travellers in a time period.

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practices of TAs/PTCs.

This study proposes a formal framework for evaluating the risk of fare evasion along each (part of a) transit network route. This framework builds on the risk concept adopted in the field of safety, introduced by Fine (1971) and revised by Barabino et al. (2021). First, it identifies the factors of fare evasion and risk exposure. Next, it defines the risk components in terms of frequency (or probability), severity (vulnerability or potential consequence) and exposure variables affecting fare evasion. The framework models the relationship among these components to build the fare evasion risk function for each (part of a) route. This is ranked and represented by easy-to-read dashboards to identify high-risk evasion routes requiring major attention.

The viability of this framework is proven out in a real-world experiment on data collected for three years by inspection reports (or fare inspection logs) and passenger surveys, to measure the frequency and the severity of fare evasion, respectively.

This framework makes both theoretical and practical contributions. From the theoretical viewpoint, the research on fare evasion risk was not yet investigated, as far as the authors know. As for the practical perspective, this framework provides a first-hand managerial tool for TAs/PTCs for evaluating the risk of fare evasion along routes. It can alert PTCs as to high-risk fare evasion routes and act as a decision support tool to improve the fare payment along routes.

The manuscript is structured as follows. Section 2 summarises existing models and methods for evaluating the frequency and the severity of fare evasion in the related literature. Section 3 presents the formal framework to estimate the risk of fare evasion. Section 4 shows the application of this framework in the real-word case of a mid-sized Italian PTC and discusses the results. Finally, Section 5 reports conclusions and provide future research perspectives.

2. Literature review

Since fare evasion in POP-TSs is a critical issue, it is an emerging topic capturing attention from academics (Barabino et al., 2020). In what follows, we review the main approaches to collect data as they affect fare evasion measures. Next, we switch to the main risk components and discuss their role in assessing the frequency, probability and severity. Finally, we report the gaps in the literature.

2.1. Data collection

Four main approaches are adopted for collecting data on fare evasion: (i) traditional fare inspection logs; (ii) surveys on passengers; (iii) unobtrusive observations; and (iv) electronic fare transaction data.

Approach (i) is based on checking the traveller's ticket. Notably, this approach is the most effective for ascertaining fare evaders, but TAs/PTCs often disagree on what *evaders* are (e.g., some operators consider both warnings and fines, others consider fines only, and some others also account for passengers who escaped when inspectors get on-board). Moreover, determining how many people are checked or not is tricky (e.g., Dauby and Kovacs, 2007; Multisystems, Inc. et al., 2002; Wolfgram et al., 2022).

Approach (ii) uses a stratified random survey on a representative group of passengers. Passengers fill out a questionnaire and/or are asked about their self-reported fare evasion frequency or their intent to evade fares. However, surveys suffer from limited spatial–temporal coverage, and, although anonymous surveys are performed, direct questions might not cover people's fears (e.g., Reddy et al., 2011; Egu and Bonnel, 2020; Barabino and Salis, 2023).

Approach (iii) uses an unobtrusive detection of fare evaders. For example, a checker may categorise passengers jumping over a gate as evaders, giving an already used but still valid ticket to another person, tailgating at the gates of a subway (Eddy, 2010; Reddy et al., 2011), or not validating their tickets on board (Cantillo et al., 2022). Nevertheless, this approach does not enable the collection of data on several features of fare evaders (e.g., scholastic level, employment, etc.), and some others are visually gathered with approximation (Cantillo et al., 2022).

The estimation of fare evasion could improve according to approach (iv), in which farebox transaction data and passenger counts are merged. Some models estimated fare noninteraction and evasion with and without automated passenger counting systems (e.g., Sánchez-Martínez, 2017; Egu and Bonnel, 2020). However, the effectiveness of approach (iv) strongly depends on the reliability of farebox data as well as passenger data, especially when they are automatically collected.

Therefore, all former approaches have drawbacks in the collection of fare evasion data. Hence, their combination is probably the most effective approach.

2.2. Determinants of fare evasion frequency

Fare evasion depends on many determinants, which were investigated by descriptive and inferential methods.

Relevant studies on descriptive methods were done in the US and Canada. In San Francisco, Lee (2011) showed that, in some POP-TSs, fare evasion depends on route, time, location, vehicle occupancy, level of inspection and entry door. Moreover, afternoon and evening hours have a higher FER than morning peak hours, as shown by Geographic Information System (GIS). Reddy et al. (2011) reported that rush times and attractors have higher evasions per hour but lower evasions per passenger, while more evasions occur in lower-income neighbourhoods in New York subways. In addition, the presence of staff is insufficient to reduce evasion.

In Montreal, Pourmonet et al. (2015) computed fare evasion as the ratio between validations and boardings using smart card transactions data and boarding data. A GIS-based map tool was developed to graphically illustrate the most critical points of the bus network to improve checks. However, the effectiveness of this tool is affected by the dependency of inspectors' travel time on routes, bus stops and intervention threshold.

In the area of inferential methods, some studies were done on the big transit system in Santiago (Chile) using (i) macroscopic and (ii) microscopic data. As for (i), Troncoso and de Grange (2017) showed a negative correlation between unemployment and evasion rates. Moreover, a 10% increase in the fare would raise the evasion rate by 2%, whereas a 10% increase in the inspection rate would decrease the evasion rate by 0.8%. As for (ii), Guarda et al. (2016) formulated a negative binomial count regression model and showed that the frequency of fare evasion is positively correlated with the number of boarding (and alighting) passengers, buses equipped with more doors, passengers boarding through the rear door, high occupancy levels and long headways. Other findings show that fare evasion is considerably stronger at bus stops in low-income areas and is more prevalent in the afternoon and evening.

Recently, Cantillo et al. (2022) calibrated a binomial logit model on one route. The results agree with Guarda et al. (2016) on the likelihood of fare evasion in low-income neighbourhoods during evening and night periods. Moreover, it increases in bus stops located more than 1 km away from metro stations and unequipped with off-board payment and ticket selling devices as well as on crowded buses without turnstiles. It is also more common in young men.

2.3. Determinants of fare evasion probability

Some studies aimed to understand motivations, behaviours, characteristics and attitudes of potential fare evaders to estimate the related probability. This research area mainly proposed: (i) crucial determinants to profile a one-size-fits-all fare evader and (ii) segments of evaders using *a priori* or *a posteriori* approaches.

In (i), data were processed by descriptive statistics, Probit models and logistic regressions. This research line showed that sociodemographic factors (e.g. gender, age, education level, engagement, nationality, car availability and motivations for travelling on the bus); travel

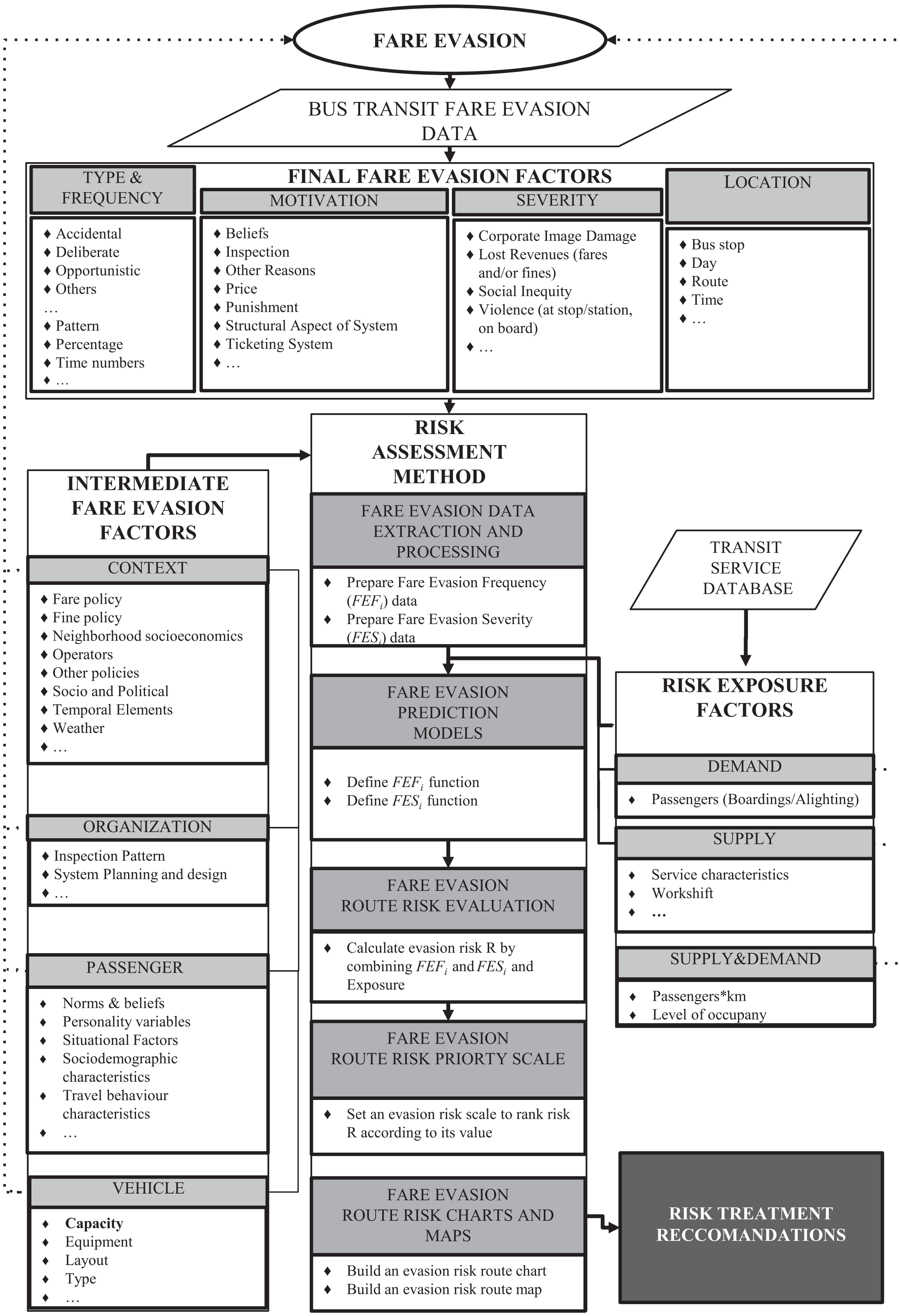

Fig. 1. Conceptual framework for fare evasion risk evaluation.

factors (e.g. trip motivation, hour of day, in-vehicle time, other transit system usage, transit usage frequency, trip origin and destination, travel frequency, travel options); and situational variables (e.g., former fare violations, awareness on the fine amount the likelihood of being discovered) may influence the probability of fare evasion (e.g., Eddy, 2010; Bucciol et al., 2013; Barabino et al., 2015; Dai et al., 2017; Cools et al., 2018). Moreover, the likelihood of inspection and sensitivity towards ticket fees affect the rate of evasion (Cools et al., 2018).

In (ii), other studies applied quantitative methods to understand the characteristics and patterns of fare evaders using intercept/on-board and web-based surveys. Data were mainly processed by descriptive statistics (Delbosc and Currie 2016b; Gonzalez et al., 2019; Busco et al., 2022), inferential statistics (Currie and Delbosc, 2017; Barabino and Salis, 2020; Barabino et al., 2022) and mixed statistics (Barabino and Salis, 2023).

In the area of a *priori segmentation* and logistic regressions, Barabino and Salis (2020) discovered that students are more likely to evade fare if they are male, younger, less educated, captive riders, frequent passengers, travel for less than 15 min and have a history of fare evasion. Workers evade more frequently if they are young males, middle school educated and have been fined in the past. Finally, unemployed passengers are likely to evade fares if they are young and captive males, are aware of the fine amount and were previously fined.

Barabino et al. (2022) showed that a past fine is the most frequent factor explaining whether a male, female, young, middle-aged or elderly passenger is more oriented towards fare evasion. Conversely, specific predictors characterise each segment. In Currie and Delbosc (2017), honesty and tolerance of evasion were shared critical factors explaining both unintentional and intentional evasion. Contrarywise, intentional and unintentional evasion were specifically determined by ticket competency and perceived ease of evasion, respectively.

In the area of *post hoc segmentation*, several works mined data on routes more affected by fare evasion through several clustering techniques and models. Delbosc and Currie (2016b) showed that the structural and operational elements of the system may have a significant impact on fare evasion (e.g., paid zone, empty smart cards, non-functional equipment, busy travelling conditions, short trips, low levels of inspection, etc.). Three segments were noticed: deliberate, unintentional and no history of evasion. Gonzalez et al. (2019) showed that several personality factors (e.g., values, attitudes, perceptions of the social acceptability of evasion, etc.) were motivators of whether passengers pay the fare. Other factors included the context (actions against fare evasion) and organisational issues. Several passenger segments were identified: paying (further divided into “proud”, “empathetic” and “circumstantial”) and non-paying passengers (who are further divided into “radical”, “strategic”, “ambivalent” and “accidental”).

Guzman et al. (2021) investigated the behaviour of evaders, including observable and latent factors by a hybrid discrete choice in Bogotà (Colombia). They showed that age and evasion records are the most important observable variables. Moreover, the greater the satisfaction, the lower the probability of fare evasion. Nevertheless, personality traits can moderate the effect of satisfaction on fare evasion. Salis et al. (2017) and Barabino and Salis (2023) discovered a minor portion of choice workers who rarely evade fares, a large number of captive students who frequently evade the fare and a medium segment of captive and chronic unemployed evaders. Finally, honesty is the common factor that considerably influences the likelihood to be a frequent fare evader among all clusters.

2.4. Fare evasion severity prediction models

The severity could be defined as the most likely consequence of a possible evader, comprising things like lost revenues and/or violence on-board. Few studies tried to quantify fare evasion according to the lost revenues by descriptive statistics. Cosby (1985) estimated the total revenues lost by measuring the average revenue on duties in which fraud was averted or not. Israel and Strathman (2002) assessed lost revenue covering passenger flows, evasion typology, average fare and evasion typology using data on 1,331 trips. Finally, Prokosch and Gartsman (2017) assessed a fare evasion rate of about 22% at the rear door on 110 trips with 1,532 passengers. All these methods were built *a posteriori*, i.e., they were based on circumstances that already occurred.

2.5. Gaps in the literature

All former works offered valuable elements to understand fare evasion from different corners. Nevertheless, several gaps remain.

First, although risk assessment methods are applied in specific fields (e.g., Andrews and Moss, 2002; ISO 31010, 2009; ISO 31000, 2018), there have been no related studies on the domain of fare evasion, according to the accepted concept integrating frequency (probability), severity and exposure measures.

Second, a handful of studies investigated the effects of TAs/PTCs-oriented variables on the frequency of fare evasion by descriptive and inferential models, respectively. Nevertheless, descriptive models could mask the understanding of these effects owing to their lack of statistical significance. Moreover, inferential models may report partial information, because they were not combined into a (bivariate) risk model integrating frequency and severity. For instance, Guarda et al. (2016) and Cantillo et al. (2022) investigated fare evasion including an exposure term, according to context and organisational factors. However, they considered only one aspect of the risk concept, because the severity is lacking. The remaining studies explored the effects of passenger-related factors on the probability or intention of fare evasion. No inferential study modelled the frequency of fare evasion by organisational factors on the inspection patterns.

Third, a handful of descriptive studies exist, but the severity of fare evasion was never investigated by an inferential approach.

Fourth, no research has reported a list of fare evasion factors, which could affect its frequency, severity and exposure variables.

Finally, although Cantillo et al. (2022) investigated the probability of fare evasion on a single route, all studies focused on an aggregate system level, whereas a more detailed analysis will be obtained by risk evaluation for each (part of a) a transit system route.

This study aims to cover these gaps.

3. Methodological framework

The framework for the assessment of fare evasion risk in transit networks is presented in this section. It defines the steps of fare evasion according to specific factors and incorporates them into a risk assessment methodology. Fig. 1 provides an illustration of this framework.

3.1. Conceptual construction and fare evasion factors

A fare evasion event or occurrence is due to the interaction of the context, the organisation, the passenger and the vehicle. They may indicate truthful planning, design and the deployment of the services along a transit network. In this study, they are referred to as *intermediate factors* of fare evasion, borrowing the well-accepted concept proposed by ISO 39001 (2012).

The context includes several factors affecting fare evasion occurrences, such as the political issue, the fare and fine policies (e.g., level of fare, the value of the fine, etc.); the temporal (e.g., day, time period, etc.) and spatial (e.g., operators) elements, as well as other attributes.

The organisation usually covers factors that can be managed by the TAs/PTCs. They can be clustered into system planning and design, as well as inspection pattern. As for system planning and design, the occurrence of fare evasion depends on the network configuration (e.g., the service type, operational characteristics, infrastructural design, the ticketing system in use, system entry, distance from/to main bus stops), type of fare media (e.g., multi-ride tickets) and marketing strategies (e.

g., setting up loyalty programs, communication system improvements, education users). The inspection pattern includes several attributes, such as type of inspection (e.g., random *vs* targeted or traditional *vs* embarrassing); level of enforcement (e.g., higher or lower than a threshold); type of inspectors (e.g., agency staff *vs* agency police) as well as the related budget.

Passenger-related factors contain classical socio-demographic characteristics (e.g., gender, age), travel behaviour (e.g., trip frequency and purpose) and situational factors (e.g., history of fare evasion, perceived inspection frequency), but other studies considered specific determinants of personalities (e.g., behaviour, risk attitude, values/principles) as well as norms and beliefs (e.g., moral, social and legal norms).

Finally, vehicle-related factors include type, equipment, design and capacity (e.g., buses with several doors, vehicles equipped with turnstiles or boarding allowed only through the front door). The interaction among these four intermediate factors helps characterise the event of fare evasion along a transit network (see the left-dotted arrow in Fig. 1).

Data on the service provided to passengers can be adopted to infer further factors accounting for people and services involved in the fare evasion occurrence. They are referred to as *risk exposure factors,* borrowing the well-accepted concept of risk exposure from safety analysis (ISO 39001, 2012). These factors can be separated into supply-oriented, demand-oriented and supply–demand-oriented. Supply-oriented factors involve route characteristics (e.g., station/stop spacing, frequency), service productions (e.g., the bus kilometres) and patrolling time-based features (e.g., the total inspector working hours). Demand-oriented factors consider the ridership along a route. Supply-demand-oriented factors include effectiveness attributes (e.g., passenger for km and level of occupancy). All these factors determine the relevance of each transit service to the fare evasion event (see the right-dotted arrow in Fig. 1).

Therefore, the interaction among the intermediate evasion factors and the risk exposure ones leads to the occurrence of fare evasion. Furthermore, these factors can influence the frequency (or the probability) and the severity of fare evasion. For instance, failures of the on-board validator machine can affect the vulnerability of the ticketing system and result in important lost revenues.

Several TAs/PTCs record fare evasion events in specific databanks with related factors. They largely reflect the frequency and severity of fare evasion and are referred to as *final fare evasion factors*, borrowing the same concept adopted for the safety analysis (ISO 39001, 2012). Specifically, many TAs/PTCs perform regular inspections of the passengers' tickets. During these activities, inspectors usually collect data (also called fare inspection logs), such as cited and escaped passengers (i.e., evaders), on-board passengers and evasion type (e.g., no tickets, unvalidated ticket). In addition, vanguard TAs/PTCs directly survey on-site passengers to improve the knowledge on fare evasion itself. In these cases, further data could be obtained on specific motivations for fare evasion (e.g., structural aspects of the systems, low punishment and others) and the related severity in terms of lost revenues (e.g., passengers without a ticket as opposed to passengers with an invalid ticket).

Tables A1-A3 in the Appendix list sources, several intermediate and final factors of fare evasion and risk exposure variables.

3.2. *Route evasion risk assessment method*

The fare evasion risk in POP-TSs could be evaluated in several ways. In this study, it integrates prediction models (or functions) of exposure frequency and the severity of fare evasion, while considering all intermediate and available factors, thus simplifying the interpretability of results.

The risk is computed for each route, both at an aggregate and disaggregate level. Specifically, each route is segmented in small and simple spatial units (or segments), in which the characteristics in a unit are very similar (homogeneous), but units differ from one other. In this study, a segment is at least the leg between two consecutive stops in a time window. Let:

- L be the set of routes.
- J be the set of homogeneous segments.
- T be the set of time windows.
- FEF_{jlt} be the Fare Evasion Frequency on homogeneous segment $j \in J$ of route $l \in L$ in time window $t \in T$ (note that FEF_{jlt} acts as a driver of probability).
- E_{jlt} be the exposure factor on homogeneous segment $j \in J$ on route $l \in L$ in time window $t \in T$.
- FES_{jlt} be the Fare Evasion Severity on homogeneous segment $j \in J$ of route $l \in L$ in time window $t \in T$ (note that FES_{jlt} acts as a driver of possible consequences or vulnerability).

Thus, for each route $l \in L$ and time window $t \in T$, the risk function R_{lt} is computed as follows:

$$R_{lt} = \sum_{j \in J} FEF_{jlt} * E_{jlt} * FES_{jlt} \quad \forall \ l \in L \quad \forall \ t \in T \tag{1}$$

Eqn. (1) is straightforward, but each term requires modelling and estimation. As detailed in the following subsections, some steps are required to build a bivariate (with both frequency and severity) risk model together with intermediate and exposure variables and return a comprehensive fare evasion risk assessment. The frequency of fare evasion is modelled as a function of exposure measures and site-specific intermediate factors on inspection activities. Conversely, the severity of fare evasion is estimated as a function of intermediate factors more related to passenger characteristics. Next, the findings of frequency and severity are multiplied to determine the overall fare evasion risk. Finally, three supplementary steps are provided to build a risk ranking scale, return some fare evasion risk charts and maps and offer recommendations on some risk actions.

Step 1 – Fare evasion data preparation

To evaluate FEF_{jlt}, individual fare evasion events must be merged considering common features. The new records contain the number of events in a specific circumstance (same values of context, organisation, passengers and vehicle as intermediate factors).

To evaluate FES_{jl}, individual fare evasion events need to be codified according to the related severity level (e.g., high, moderate, minor lost revenues or no lost revenues).

Step 2 – Fare evasion prediction models and refinements

Fare evasion frequency. It can be modelled as the number of events occurred in a fixed time interval (e.g., a month). In Guarda, et al. (2016), three modelling approaches are applied and compared: Multiple Linear Regression models, Poisson regression and Negative Binomial models. The Negative Binomial model is shown to be the best. Furthermore, when the exposure E_{jlt} is null, the evasion frequency must be zero. Therefore, the FEF_{jlt} prediction model can be formulated by a Generalised Linear Model (GLM) with a negative binomial regression error structure. Let:

- I be the set of intermediate frequency factors and i_{jlt} be a generic intermediate factor in set i for segment $j \in J$ of route $l \in L$ in time window $t \in T$.
- K be the set of risk exposure factors and k_{jlt} be a generic risk exposure factor in set K for segment $j \in J$ of route $l \in L$ in time window $t \in T$.
- α, β_k, γ_i be the coefficients to be estimated in the model, in which $k \in K$ and $i \in I$.

The functional form of the frequency prediction model is defined as follows:

Table 1
Definition of the ranking scale for the risk ranges of fare evasion.

Level	Ranges values Lower limit	Colour Upper limit
R_1	(Q3 + 1.5 IQR)	MAX
R_2	Q3	(Q3 + 1.5 IQR)
R_3	Q2	Q3
R_4	Q1	Q2
R_5	(Q1-1.5 IQR)	Q1

$$FEF_{jlt} = \alpha \prod_{k \in K} k_{jlt}{}^{\beta_k} \left(e^{\sum_{i \in I} \gamma_i * i_{jlt}} \right) \quad \forall j \in J; \forall l \in L; \forall t \in T \tag{2}$$

The model is evaluated by the quotient among the deviance of the regression and the degree of freedom (i.e., the deviance ratio - *d.r.*) and its statistical significance. Moreover, the signs of coefficients and the significance of each predictor are discussed.

Fare evasion severity. It represents the degree of seriousness felt by the TAs/PTCs after the occurrence of a fare evasion event. As shown in Fig. 1, the severity could be defined in many ways. In this study, it is modelled by lost revenues to exploit the usual availability of these data among TAs/PTCs. Clearly, the more severe the evasion, the higher the lost revenues. The levels of severity may be measured by a response-ordered discrete variable and formulated by ordered logistic regressions as follows: no ticket ownership, unvalidated tickets or incorrectly validated (even if bought) and some minor irregularities (e.g., forgotten passes). Conversely, passengers with regularly validated tickets generate no evasion.

Nevertheless, since most TAs/PTCs could not have an accurate and refined databank to perform such a detailed analysis, in this study, the severity of fare evasion is modelled as a binary variable. That variable takes value 1 if the event of fare evasion occurs in the case of lacking or invalidated ticket or 0 if the fare evasion is minor or not committed at all. This is particularly suitable in the case of data collected by surveying passengers because of the possible uncertainties surrounding a self-reported event of fare evasion, if any. Hence, a binomial logistic regression model is implemented owing to the response factor in binary form. Results are stated in terms of Odds Ratio (OR), that indicates the number of successes (a severe evasion) versus every failure (not a severe evasion) and can be straightforwardly computed by taking the exponent of the estimated factor. Let:

- S be the set of intermediate severity factors and s_{jlt} be a generic intermediate factor in set S for segment $j \in J$ of route $l \in L$ in time window $t \in T$.
- δ, ϑ_i be the model coefficients to be estimated, in which $i \in I$;[2]

Hence, the probability that the response for the s^{th} observation takes value 1 can be computed as follows (Greene 1993):

$$FES_{jlt} = \frac{e^{\left(\delta + \sum_{s \in S} \theta_s * s_{jlt}\right)}}{1 + e^{\left(\delta + \sum_{s \in S} \theta_s * s_{jlt}\right)}} \quad \forall j \in J; \forall l \in L; \forall t \in T \tag{3}$$

Eqn. (3) provides the probability of a severe event of fare evasion along segment $j \in J$ of route $l \in L$ during time windows $t \in T$. Clearly, the logarithm of the odds – defined as *logit* (FES_{jlt}) – is the linear combination of predictors s_{jlt} and FES_{jlt} is in the interval [0–1] for every value taken by the predictors:

$$logit\left(FES_{jlt}\right) = log\left[\frac{\left(FES_{jlt}\right)}{1 - \left(FES_{jlt}\right)}\right] = log(odds) = \left(\delta + \sum_{s \in S} \theta_s * s_{jlt}\right) \quad \forall j \in J; \forall t \in T \tag{4}$$

[2] Note that intermediate factors in I may also belong to S and vice versa.

This model is evaluated by the deviance ratio (*d.r.*) and its statistical significance according to the chi-squared test. In addition, the sign of the regression coefficients, their significance and the OR are analysed.

Both full frequency and severity models (i.e., including all factors available from data) are estimated and refined by the stepwise method applied by forward selection and backward elimination strategies. Both techniques exclude all redundant variables from full regression to reach a trade-off among acceptable goodness-of-fit and simplicity. According to the highest deviance ratio and the overall statistical significance of the estimated model, the backward or forward technique is preferred. Thus, the list of the factors included in the final models is obtained.

Step 3 - Fare evasion risk calculation

After the estimation of functions FEF_{jlt} and FES_{jlt}, the fare evasion risk can be computed for each route segment $j \in J$. Next, it is computed for each route $l \in L$ as shown in eqn. (5):

$$R_l = \sum_{j \in J} \left[\left(\alpha \prod_{k \in K} k_{jlt}{}^{\beta_k} \left(e^{\sum_{i \in I} \gamma_i * i_{jlt}} \right) \right)_j * \left(\frac{e^{\left(\delta + \sum_{s \in S} \theta_s * s_{jlt}\right)}}{1 + e^{\left(\delta + \sum_{s \in S} \theta_s * s_{jlt}\right)}} \right)_j \right] \quad \forall l \in L; \forall t \in T \tag{5}$$

Step 4 - Fare evasion route risk priority scale

Next, routes can be ranked following a specific fare evasion risk scale, which can be built in several ways. In this study, a five-level scale is adopted. It is based on the distribution quartiles of the fare evasion risk index. Specifically, R_l is computed for each route, and its values are sorted in an increasing order. Next, we compute $Q_1 = 25$th percentile, $Q_2 = 50$th percentile, $Q_3 = 75$th percentile and the interquartile range (IQR), i.e., the difference between Q_3 and Q_1. Usually, the IQR is adopted to identify and remove outliers from a distribution as follows: Q_1 and Q_3 are adjusted by $\mp$ 1.5*IQR, respectively. Thus, a lower and upper threshold can be defined, and all the values beyond this range are outliers. Conversely, in this study, the IQR is used to better refine the ranking scale and emphasise these outliers. More precisely, the quantity $Q_3 + 1.5$*IQR defines a threshold, which enables identification of the routes with the highest risk of fare evasion. The quantity Q_1-1.5*IQR does not contribute to the definition of a new level of the ranking scale. However, as eqn. (5) returns a non-negative value, the previous quantity must be non-negative.

Table 1 shows the five-level ranking scale and reports the lower and upper limits for each risk level. The rank should be read as a fare evasion risk scale: the lower the risk value, the better the route. Therefore, according to the value returned by eqn. (5), levels R_1 and R_2 denote higher fare evasion routes than R_3, R_4 and R_5. Hence, R_1 and R_2 routes (segments) should be prioritised when defining strategies to address fare evasion.

Clearly, one does not have to obey the previous ranges, which can be built in different ways, to improve their acceptability.

Step 5 – Fare evasion route risk charts and maps

Once a ranking is computed, building comprehensible and usable performance reports is crucial for the effective analysis of data by experts (e.g., planners, managers, decision makers). Charts and maps can provide clear representations of the results. Charts provide a simple and clear dashboard of route rankings according to their fare evasion risk at an aggregate level. Hence, experts can have a clear picture of the fare evasion on the overall network. Maps show the fare evasion route ranking at a disaggregate level: each route segment is indicated by a colour associated with a fare evasion risk level. These maps are produced by a GIS and uploaded on a map to help detect the route portions deserving more attention.

Table 2
Original amount of data on final factors of fare evasion used in our databank.[1]

Use	Time windows	Year	Source	Collection location	Collection method	Record [#]
Frequency	October	2013	Inspection Logs	On-board	Direct measure	1889
	October	2014	Inspection Logs	On-board	Direct measure	1965
	October-November	2015	Inspection Logs	On-board	Direct measure	2906
Severity	March	2013	Passenger Survey	On-board	Personal interview	3791
	March	2014	Passenger Survey	On-board	Personal interview	4733
	March	2015	Passenger Survey	On-board	Personal interview	3808

[1] We are unable to analyse more current data due to the confidentiality policy of CTM.

Step 6 – Risk treatment recommendations

Once critical routes have been prioritised, implementing measures for contrasting the impact of fare evasion is required, particularly in routes with risk levels R_1 and R_2.

Prevention measures attempt to decrease FEF_{jlt}, while protection measures work to decrease FES_{jlt}. For example, consider a route with a high value of R_1 owing to captive riders, and assume that they evaded the fare owing to economic disadvantages. The implementation of an income-based fare is a preventive measure that is expected to lower the occurrence of fare evasion and, thus, the overall risk. Conversely, consider a route with a high value of R_1 owing to unvalidated tickets and assume that many passengers are (potential) evaders because they validate only when inspectors get on board; this could result in a high level of lost revenues (severity). Switching off the onboard validator machine a few moments before the boarding of inspectors could be a protection measure to lower the severity and the overall risk.

4. Experimentation in a real bus transit network

4.1. Research context

An experiment of the framework described in Section 3 was carried out in the metropolitan area of Cagliari (Italy). It has about 0.4 million residents spread among several communalities. The regional/local administrations in Cagliari own the transit systems, which are run by several PTCs. The biggest is CTM, which runs the transit service with 271 trolley/buses and carries 40.8+ million trips a year. Moreover, these vehicles travel 12.4+ million kilometres yearly along 34 routes (CTM, 2020). In Cagliari, several types of tickets exist (e.g., year, season, month, one-way, etc.) for all routes, and fare evasion could occur with any of these ticket types, even if it is expected to be more relevant for one way-tickets.

4.2. Data type and sources

The data on final, intermediate and risk-exposure factors in this study are gathered from various sources, as follows.

Final factors for the analysis of the fare evasion[3] frequency are collected by the fare inspection logs in use. These logs are generated during inspections, which are usually performed on-board to avoid service interruptions. Although few trips could be checked onboard, this policy is preferred because it makes inspections more unpredictable as opposed to checks at bus stops. Inspectors move in standard patrols with two people and fewer usual patrols with at least three people. Usually, for each route investigated in a time period, the inspectors fill up logs with data on checked and fined passengers. Information on escaped and eluded passengers is gathered; next, they are labelled as evaders and added into the databank. However, the collection of such data is subjective and must be supported by hunch and experience, as well as possible external checkers in plain clothes.

Final factors for the analysis of the fare evasion severity are collected by surveying onboard passengers. Specifically, surveyors ask passengers for their self-reported fare evasion as follows: '*How many times did you travel without a valid ticket in the last four months?*[4]' Note that a four-month period was felt to be adequate for this purpose (Barabino and Salis, 2023). Answers were clustered into five groups ranging from never to always. The severity was modelled in terms of lost revenues as follows: people admitting fare evasion in the three superior groups were generators of a severe evasion (e.g., the lacking or unvalidated ticket), whereas the others are not considered to be evaders. Some might argue the reliability of self-reported responses in the measure of fare evasion. However, several studies have shown that people can experience a psychological disutility, which holds them back from misreporting due to, e.g., intrinsic lying costs, honesty or conditional cooperation (e.g., Abeler et al., 2014; Traxler, 2010).

The amount of fare evasion data is shown in Table 2, along with the use, source, location and method of collection. Specifically, data for measuring the frequency and the severity of fare evasion were collected for at least two weeks on weekdays and weekends from 07:00 AM to 07:00 PM. Moreover, even if the months for each source differ, this is not a drawback, because the same service (i.e., routes and frequencies) is provided in March and October.

Data on **intermediate factors** related to context, organisation, vehicle and passengers were collected as follows.

Data on context, organisation and vehicle are considered for the estimation of the frequency of fare evasion. All these data were collected by the inspection log files kindly granted by the local PTC, according to the analysis of the contemporary literature in Appendix A. Specifically, the context data mainly include temporal elements, such as time period and weekday. Data on organisation considered both (i) system planning and design attributes strictly related to network configuration with the boarding and alighting bus stops of the fare inspectors and (ii) the inspection patterns, the type of inspection and the level of enforcement. For this study, two different inspection patterns are considered: random and targeted. In the former, inspectors board the vehicle at random bus stops. In the latter, inspectors move along both directions of planned routes between two crucial points, namely the bus stops where the daily (hourly) maximum passenger load is expected to occur. This choice depends on the fact that checks are done onboard. To clarify, fare inspectors move along the so-called target inspection paths shown in Fig. 2 (a) and 2(b) in the case of inspectors only or checkers and inspectors, respectively.

In the scenario of Fig. 2 (a), at first, the inspectors reach the boarding bus stop (i.e., the red border red square along the route direction y-z) and wait for the bus arrival. When the bus arrives, the inspectors board and check all passengers' tickets (the continuous line between the red-bordered square denoted by n and the red square denoted by n + 3). At the end of their travel, they alight the bus at the red square denoted by n + 3. Next, they cross the road (the dotted line between the red square

[3] According to CTM, a fare evasion occurs when a passenger did not intentionally buy, validate or obtain the travel ticket and/or pass for the travel.

[4] The Independent Ethical Board of the University of Cagliari was consulted on the entirety of this research project before it was submitted, which attested that this experiment did not require official ethical approval (Ref. PG/2018/13345).

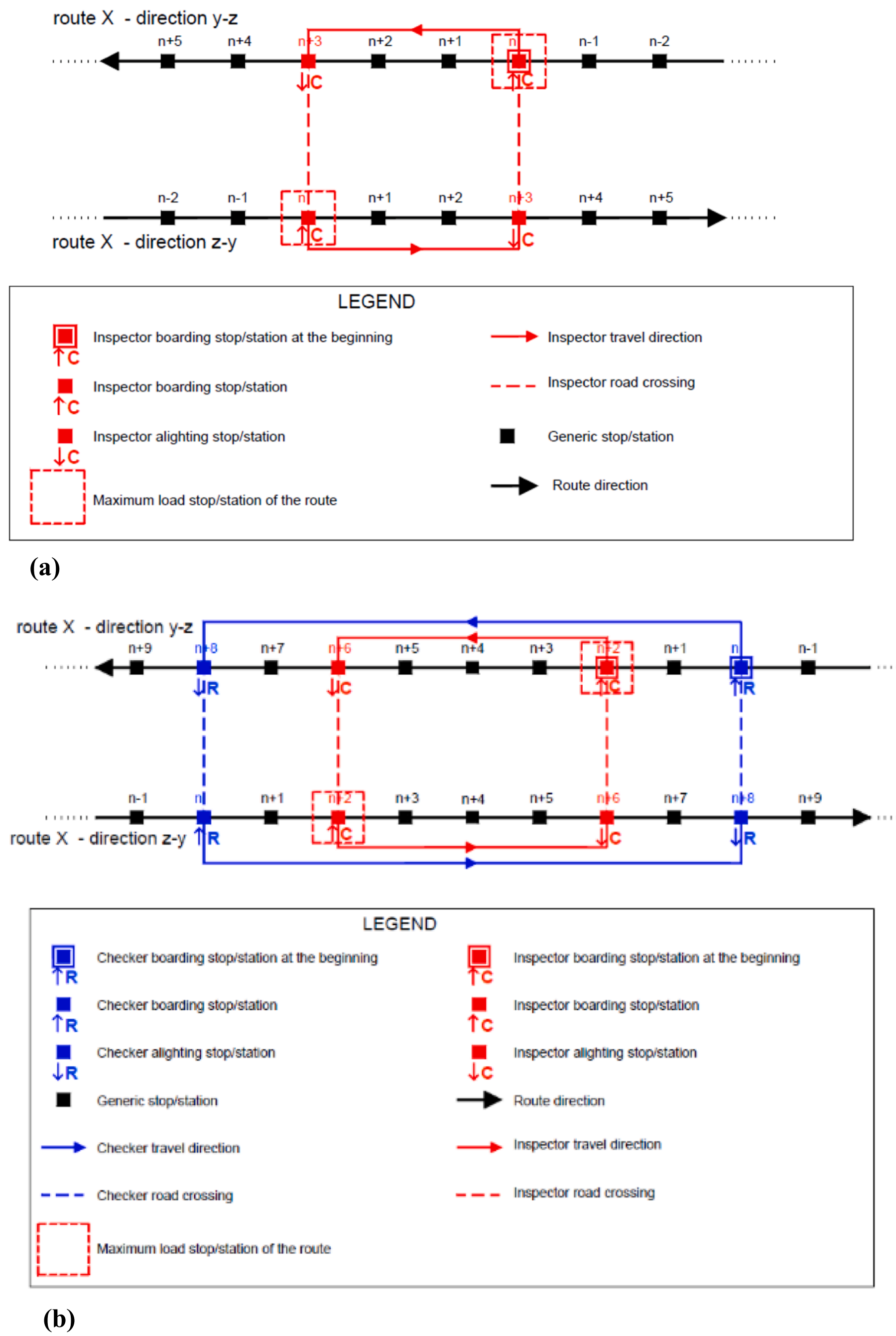

Fig. 2. Conceptual representation of a targeted inspection path by (a) inspectors only and (b) checkers and inspectors.

denoted by n + 3 and the red-bordered square denoted by n). The data collection continues for a new inspection round starting from the bus stop in the red-bordered square denoted by n, etc. In the scenario of Fig. 2 (b), checkers are employed along with inspectors. Checkers board and alight the vehicle two stops/stations before and after inspectors, respectively. The aim of such a scheme is twofold: 1) collecting additional data (e.g., number of passengers on the vehicle, number of passengers boarding and alighting at stops/stations) during each inspection round; 2) detecting whether a passenger validates her/his ticket only when s/he spots the inspectors, just immediately before they get on the vehicle.

Five types of inspection paths are considered for the experiment. Four of them represent targeted inspections and are labelled from A to D. The difference consists in the use of checkers and inspectors for paths A and B, respectively, where standard and longer buses are adopted, and the volume of passengers is relevant. Inspection paths C and D adopt only inspectors, medium and short buses and lower passenger volumes than A and B, respectively. Conversely, path E corresponds to a random inspection by inspectors only.

Data on passenger attributes are collected for estimating the severity of fare evasion by a four-section questionnaire, which was designed by mining from the list of factors provided in Appendix A, according to the analysis of the contemporary literature. It includes: (i) sociodemographic characteristics, such as gender, age, educational qualification, employment, car availability and reasons for using the bus; (ii) travel behaviour characteristics, such as the trip's purpose, time of day, in-vehicle time, use of other transit systems, travel frequency and overall satisfaction rate with the service; and (iii) situational factors, such as the

Table 3
Descriptive statistics of the original fare evasion databank for the computation of frequency.

Response variable		Abbreviation	Description	Min_Value	Max_Value	% Value
Number of evaders		Evaders	Total number of evaders [#]	0	76	-
Explanatory variables		**Abbreviation**	**Description**			
Context						
Temporal element	Time period	Rush_Morning	Rush morning hours from 7:30 to 9:30	0	1	15.54%
		Rush_Half-day	Rush half-day hours from 12:30 to 14:30	0	1	16.93%
		Rush_Evening	Rush evening hours from 17:30 to 19:30	0	1	11.41%
		Soft_During day	*The remaining hours of a day*	0	1	56.12%
	Type of Day	Weekday	Days from Monday to Friday	0	1	84.22%
		Weekend	*Saturday and Sunday*	*0*	1	15.78%
Organisation						
Inspection pattern	Type	A	Planned inspection path of Type A followed from inspectors centred on maximum load section	0	1	38.01%
		B	Planned inspection path of Type B followed from inspectors centred on maximum load section	0	1	30.77%
		C	Planned inspection path of Type C followed from inspectors centred on maximum load section	0	1	19.01%
		D	Planned inspection path of Type D followed from inspectors centred on maximum load section	0	1	9.96%
		E	Random inspection path followed from inspectors ignoring the maximum load section	0	1	2.25%
	Level of enforcement	Standard	The average number of inspectors (1 patrol inspection) is 2	0	1	43.35%
		No standard	The average number of inspectors (1 patrol inspection) is larger than 2	0	1	56.65%
System Planning and design	Network configuration	Path Length	Length of path [m]	100	14650	-
Vehicle						
Layout	Vehicle design	Bus	The vehicle is a bus	0	1	90.34%
		Trolleybus	*The vehicle is a trolleybus*	0	1	9.66%
	Capacity	Capacity	The capacity of the adopted vehicle [seats]	*9*	*179*	-
Type	Lenght	Medium	The vehicle is long 10.5 m	0	1	15.58%
		Standard	The vehicle is long 12 m	0	1	66.33%
		Long	The vehicle is long 18 m	0	1	6.09%
		Short	*The vehicle is long less than 10.5m*	0	1	12.00%

personal knowledge of fare evasion in general, the perception of the inspection frequency in a predefined time window, the knowledge of the fine amount, previous ticket violations (i.e., whether the passenger had already been fined) and the revealed fare evasion frequency; (iv) a personality trait, e.g., honesty, which is evaluated as follows: '*If no checks are performed, would you buy a ticket*?'

Finally, once the former data are merged, one obtains the descriptive statistics in Tables 3 and 4 on the intermediate and final factors of the fare evasion databanks considered for this research. All variables are categorised (or binarized, in some cases) for modelling purposes, except the path inspection length and bus capacity that are continuous and integer variables, respectively. In addition, Tables 3 and 4 provide the dummy variables in italics for comparison purposes.

The following **risk exposure factors** are considered: passenger volumes, the length of inspection path and the level of occupancy. These factors are chosen because they can be straightforwardly calculated and are generally accessible for most of TAs/PTCs. As for passenger volumes, these are manually collected route-by-route by ride checks. The length of inspection paths is inferred from the inspection logs by measuring the distance between the alighting and the boarding bus stops for each inspection run along a route direction. Finally, the level of occupancy was inferred by computing the ratio between the checked passengers and the vehicle capacity for each inspection run.

4.3. Results and discussion

As described in Step 1 of Section 3.2, data collected by log inspection files are merged as a function of common features. Specifically, every record reports the total number of fare evaders, which is the response variable modelling the frequency. Initial fare evasion data are merged according to intermediate factors (e.g., type of day, type of vehicles) associated with the boarding bus stops of inspectors. Conversely, each surveyed passenger is considered to model the severity of fare evasion, using a binary variable equal to 1 if the passengers state they evade the fare always, often and mildly (severe evasion) and 0 if passengers state to evade the fare seldom and/or never.

4.3.1. Frequency prediction model

As described in Step 2 of Section 3.2, the frequency of fare evasion is estimated by the software Genstat®. Two models are presented: the full and the final. Table 5 shows the best results, which are obtained through forward selection as opposed to backward elimination. Specifically, Table 5 reports for every factor the coefficients (*estimate*) and the related significance (*p-value*), which is bold when it is $<$0.001. The final section of Table 5 presents summary statistics. The positive sign indicates that more events of fare evasion occur as the factor increases. These models fit data very well, as χ^2 is consistently $<$0.001. Therefore, there is substantial proof for a regression effect (i.e., not all the β_k and γ_i are zero). Moreover, many variables are extremely significant. The final model contains all significant predictors, but it is simpler (the degree of freedom is reduced by 4 units = 17–13) and fits data better than the full model (d.r. 52.34 *vs* 40.07).

Notably, the final model overestimates about 3% of the amount of fare evasion events on the entire network. This is a satisfactory outcome, since it is compliant with the prudence principle, which would overestimate the fare evasion. The final model is discussed in what follows on the most significant factors.

As for the **risk exposure factor**, the coefficients for passengers and level of occupancy are positive, as expected. Therefore, the larger the exposure, the more frequent the fare evasion. This is particularly true for the level of occupancy, which provides the maximum effect to the increase in the fare evasion event. Besides, while the finding on passengers is a novelty of this study, the results on the level of occupancy confirm previous descriptive (Lee, 2011) and inferential research (Guarda et al., 2016; Cantillo et al., 2022). Nevertheless, unlike previous research, these results refer to a medium-sized European city.

As for the **intermediate context factors**, the results show more evasion during off-peak periods. This result looks counterintuitive,

Table 4
Descriptive statistics of the original Fare Evasion data bank for the computation of the severity.

	Variables	Abbreviation	Description	% Value
Passenger				
Sociodemographic characteristics	Gender	Gen_M	Male	61.47%
		Gen_F (D)	*Female*	*38.53%*
	Age	Above 65	Above 65 years old	5.10%
		51–65	Between 51 and 65 years old	10.66%
		36–50	Between 35 and 50 years old	*16.06%*
		26–35	Between 26 and 35 years old	16.11%
		18–25	Between 18 and 25 years old	37.39%
		Under_18 (D)	*Under 26 years old*	14.68%
	Educational qualification	Upper_sc	Upper school graduate	16.02%
		Middle_sc	Middle school graduate	45.48%
		Middle_sc_n	Middle school not graduate	35.60%
		Primary sc	Primary_school	2.68%
		No_Sc (D)	*No_school*	0.22%
	Employment	Work_y	Worker	30.45%
		Work_n (D)	*Not worker*	*69.55%*
		Stud_y	Student	49.32%
		Stud_n (D)	*Not student*	*50.68%*
		Unempl_y	Unemployed	20.23%
		Unempl_n (D)	*Employed*	*79.77%*
	Car availability	Car_y	Has a car	31.25%
		Car_n (D)	*Does not have a car*	*68.75%*
	Reason to use the bus	Other_use_bus	Use of the bus for other reasons (Not related to the lack of trip alternatives)	38.74%
		No_alter_use_bus (D)	*Use of the bus because there are no alternatives*	*61.26%*
Travel behaviour characteristics	Trip purpose	Work_trips	Trips for work	25.64%
		Study_trips	Trips for study	45.08%
		Other_trips (D)	*Other trips (shopping, sport, amusement, etc.)*	*29.28%*
	Time of the day	Rush_hour_y	Rush hours trips (7.30–9.30 and 12.30–13.30 and 17.30–19.30)	57.65%
		Rush_hour_n (D)	*Not rush hour trips*	*42.35%*
	In-vehicle time	In_vehicle_time_more15	Travel time more than 15 min	73.20%
		In_vehicle_time_less15 (D)	*Travel time less than 15 min*	*26.80%*
	Other transit systems use	Other_transit_y	Use of other transit systems	38.67%
		Other_transit_n (D)	*No use of other transit systems*	*61.33%*
	Bus use frequency	Freq_traveler_y	The user travels more than 3 days a week	87.24%
		Freq_traveler_n (D)	*The user travels less than 3 days a week*	*12.76%*
	Quality rating	Satisf_y	Satisfied user (grade on the overall service more than sufficient)	96.19%
		Satisf_n (D)	*Not satisfied user (vote on the overall service more than sufficient)*	*3.81%*
Situational factors	Perceived inspection frequency	Insp_freq_more5	User has seen the inspectors boarding the vehicle to perform control activities more than 10 times in 4 months.	3.67%
		Insp_freq_more5	User has seen the inspectors boarding the vehicle to perform control activities more than 5 times in 4 months.	13.12%
		Insp_freq_1_5	User has seen the inspectors boarding the vehicle to perform control activities a number of times between 1 and 5 in 4 months.	55.02%
		Insp_freq_null (D)	*User has never seen the inspectors boarding the vehicle to perform control activities in 4 months.*	*25.19%*
	Amount of the fine	Know_fine_y	User knows the amount of the fine	67.97%
		Know_fine_n (D)	*User does not know the amount of the fine*	*32.03%*
	Fines in the past	Fine_past_y	User has already been fined in the past	28.82%
		Fine past_n (D)	*User has not been fined in the past*	*71.18%*
	Severity	Fare_evasion_always	User evades the fare every time he travels (100% of trips)	1.49%
		Fare_evasion_often	User often evades the fare (more than 50% of trips)	3.34%
		Fare_evasion_mildly	User little evades the fare (between 10% and 50% of trips)	3.78%
		Fare_evasion_rarely (D)	*User evades the fare rarely (less than 10% of trips)*	*91.39 %*[1]
Personality var.	Value/Principles - Honesty	Honesty_y	User buys the ticket also if no checks are performed	77.70%
		Honesty_n (D)	*User does not buy the ticket if no checks are performed*	*22.30%*

[1] Owing to the uncertainties on self-reported fare evasion, note that this percentage also include people who admitted having never evaded the fare.

because fewer passengers are observed during off-peak periods, but it could be justified as follows. During peak hours, there could be many systematic passengers with a pass, and inspectors may not perform accurate checks, owing to expected crowds. This situation clearly could not occur during off-peak periods, during which time other passengers are expected to travel. Nevertheless, our results largely substantiate the previous research.

For instance, Lee (2011) observed that *"fare evasion was more prevalent on certain routes and during the afternoon and evening hours."* Conversely, the inspectors are deployed in the morning when most of them had a regular day off. Similar results on afternoon peaks are reported by Guarda et al. (2016) and Cantillo et al. (2022). Reddy et al. (2011) observed that "*evasion rate peaks at 3 pm due to students' dismissal, otherwise hovers around 0.9% peak, 1.9% off-peak.*" However, they showed that rush times and locations "*have higher evasions per hour but lower evasions per passenger.*" Finally, Prokosch and Gartsman (2017) also estimated more evasion in the afternoon.

As for the **intermediate organisational factors**, the findings show

Table 5
Results of the frequency prediction model of fare evaders.

Factor	Full Model		Final model	
	Coefficient estimate	P-value	Coefficient estimate	P-value
Natural Log of constant (i.e., α)	0.1889	**<0.001**	0.2034	**<0.001**
Exponent of Passengers (i.e., β_1)	0.3932	**<0.001**	0.3915	**<0.001**
Exponent of Level of occupancy (i.e., β_2)	0.6434	**<0.001**	0.638	**<0.001**
Exponent of Path Length (i.e., β_3)	−0.0034	0.940		
Time period				
Rush_Morning	−0.4735	**<0.001**	−0.4744	**<0.001**
Rush_Half-day	−0.4032	**<0.001**	−0.4051	**<0.001**
Rush_Evening	−0.1980	0.041	−0.1988	0.040
Type of Day				
Weekday	0.0725	0.77		
Inspection Type				
A	0.572	0.001	0.593	**<0.001**
B	0.619	**< 0.001**	0.635	**<0.001**
C	0.602	0.001	0.616	**<0.001**
D	0.576	0.004	0.582	0.003
Level of enforcement (staff)				
Standard	−0.3951	**<0.001**	−0.4103	**<0.001**
Type				
Bus	0.014	0.920		
Length				
Medium	0.194	0.325	0.2315	0.015
Standard	−0.044	0.857		
Long	−0.667	0.179	− 0.586	0.002
Capacity	0.01089	0,009	0.01043	**<0.001**

Summary Statistics						
Source	Degree of freedom	Deviance	Mean deviance	Degree of freedom	Deviance	Mean deviance
Regression	17	681	40.0655	13	680	52.3429
Residual	1106	1019	0.9214	1110	1020	0.9186
Total	1123	1700	1.5139	1123	1700	1.5139
d.r		40.07		*d.r*	52.34	
$\chi 2$		<0.001		$\chi 2$	<0.001	

that there is more evasion when inspectors are assigned to targeted paths. Indeed, all inspection paths from A to D produce more evasion than a random inspection. Moreover, the use of checkers (A and B) is expected to generate more evasion than inspectors only (C and D). This result could appear counterintuitive, because targeted inspection (especially on high evasion routes) is expected to produce a relevant quota of evaders. However, if the inspections are deterministically targeted along inspection paths, the most cunning evaders can search for solutions to defraud the ticketing system by moving on other paths where the inspection is not yet targeted. In fact, these evaders are always alert and prepared to take advantage of ticketing system shortcomings to elude inspectors (e.g., virtual communities of fare evaders - Assaf and Van den Broeck, 2022). Nevertheless, our results contrast several studies assuming that targeted inspections would reduce fare evasion (e.g., Multisystem 2002; Boyd, 2020). Finally, these results confirm a lab-in-the-field experiment by Dai et al. (2018): they showed that random inspections are more effective than concentrated crackdowns in terms of reduction of fare evasion. Nevertheless, more research is needed, because the findings are different, and our percentage of random inspection is low as opposed to targeted inspection. Interestingly, a standard patrol of two inspectors is more beneficial for addressing fare evasion than a team of three or more inspectors. These results seem unexpected, because more inspectors should catch more evaders owing to a more accurate inspection. However, past research noticed that, if many inspectors are simultaneously on-board, a crowding of inspectors could occur and increase fare evasion (Barabino et al., 2014). Nevertheless, adopting more than two inspectors for patrolling could be justified by security reasons on specific routes.

As for **intermediate vehicle factors**, the findings indicate that more evasion is originated in the case of medium-sized vehicles as opposed to short ones. This is an expected result because short vehicles have only one door to enter and exit; therefore, passengers could be checked more easily and fined if caught evading. Conversely, long vehicles generated less evasion than shorter ones. This is an unexpected result that contradicts the findings of Guarda et al. (2016), who observed a higher evasion rate in longer vehicles with multiple doors. However, in the city of Cagliari, long vehicles are adopted in the morning on heavily congested routes where less evasion is observed (as shown before). Finally, the increase in the vehicle capacity increases the frequency of fare evasion, as expected.

4.3.2. Severity prediction model

As described in Step 2 of Section 3.2, the severity of fare evasion was estimated using Genstat®. Even in this case, two models are presented: the full and the final. Table 6 shows the best results, which are obtained by forward selection instead of backward elimination. Table 6 also reports the coefficients (*estimate*), the p-value and the OR, which quantifies how much each factor affects the fare evasion severity. In Table 6, when OR < 1 (>1), a decrease (increase) in the odds of the severity of fare evasion is reported. Therefore, each unitary increase in predictor results in the decrease (increase) of severity. Moreover, a positive (negative) sign implies an increase (decrease) in the severity of fare evasion if a predictor increases. For the sake of clarity, we examine the inverse of OR when it is lower than 1.

The final portion of Table 6 shows the statistical fit of each severity model. Both models fitted the data very well, as χ^2 is consistently <0.001. Nevertheless, the final model contains all significant predictors, but it is simpler (degree of freedom reduced by 7 units = 27–20) and fits the data better (d.r. 93.42 *vs* 69.30). Notably, the final model returns 92.33% as a percentage of right, highlighting very good performances in prediction on the overall network. For the sake of ease, only the final model is discussed.

As for the intermediate socio-demographic factors, males practice 1.482 times more severe evasion than females. Although we investigated the severity as opposed to the likelihood or the intention to evade the fare, this result is consistent with past research (e.g., Bucciol et al., 2013;

Table 6
Results of the severity prediction model of fare evaders.

Variable	Full Model			Final Model		
	Estimate	*p value*	*OR*	*Estimate*	*p value*	*OR*
Constant	1.560	0.110	4.758	0.613	0.099	1.846
Gen_M	0.3996	**<0.001**	1.491	0.3936	**<0.001**	1.482
Age						
Above_65	−2.224	**<0.001**	0.1082	−2.172	**<0.001**	0.1140
51_65	−1.932	**<0.001**	0.1449	−1.893	**<0.001**	0.1506
36_50	−1.101	**<0.001**	0.3327	−1.075	**<0.001**	0.3413
26_35	−0.741	**<0.001**	0.4765	−0.714	**<0.001**	0.4895
18–25	0.155	0.261	1.167	0.177	0.185	1.193
Educational qualification						
Upper_sc	−3.133	**<0.001**	0.04361	−2.236	**<0.001**	0.1069
Middle_sc	−2.626	**0.005**	0.07234	−1.733	**<0.001**	0.1767
Middle_sc_n	−2.023	**0.029**	0.1322	−1.119	**<0.001**	0.3267
Primary sc	−0.962	0.309	0.3819			
Employment						
Work_y	0.301	0.181	1.351	0.348	0.101	1.417
Stud_y	−0.112	0.542	0.8944			
Car_y	−0.121	0.539	0.8865			
Other_use_bus	−0.113	0.508	0.8936	−0.192	0.104	0.8249
Trip purpose						
Work_trips	−0.477	**0.036**	0.6208	−0.500	0.025	0.6068
Study_trips	−0.973	**<0.001**	0.3779	−1.033	**<0.001**	0.3560
Rush_hour_y	0.0079	0.925	1.008			
In-vehicle time_more15	−0.4306	**<0.001**	0.6501	−0.4297	**<0.001**	0.6507
Other_transit_y	0.0863	0.363	1.090			
Bus use frequency						
Freq_traveler_y	−0.026	0.869	0.9748			
Satisf_y	−0.353	**0.063**	0.7028	−0.360	0.056	0.6976
Perceived inspection frequency						
Insp_freq_more10	−0.046	0.852	0.9548			
Insp_freq_6_10	−0.341	0.027	0.7112	−0.334	0.024	0.7164
Insp_freq_1_5	−0.167	0.139	0.8465	−0.161	0.127	0.8512
Know_fine_y	0.598	<0.001	1.819	0.602	<0.001	1.825
Fine_past_y	1.2836	<0.001	3.610	1.2831	<0.001	3.608
Honesty_y	−2.234	<0.001	0.1071	−2.228	<0.001	0.1078
Summary Statistics	Degree of freedom	Deviance	Mean deviance	Degree of freedom	Deviance	Mean deviance
Regression	27	1871	69.2996	20	1868	93.4236
Residual	8654	3264	0.3771	8661	3266	0.3731
Total	8681	5135	0.5915	8681	5135	0.5915
d.r	*69.30*			*93.42*		
χ2	***<0.001***			*<0.001*		

Barabino et al., 2015; Barabino and Salis, 2020; Barabino et al., 2022; Barabino and Salis, 2023; Cools et al. 2018; Cantillo et al., 2022).

The severity of fare evasion is a crucial issue in those younger than 26 years of age. Indeed, being over 26 decreases the severity of fare evasion to different extents: the higher the age, the less the severity. For instance, being older than 65 years of age reduces the severity 8.77 times (i.e., OR = 1/0.1140) than being younger than 18 years of age. In addition, being between 18 and 26 years of age generates the largest contribution to the severity of fare evasion. This result confirms almost all previous research (Bucciol et al., 2013; Barabino et al., 2015; Delbosc and Currie, 2016b; Cools et al. 2018; Barabino and Salis, 2020; 2022; Barabino et al., 2022; Cantillo et al., 2022) but not always (Eddy, 2010).

As for the education level, less educated passengers increase the severity of fare evasion to a different extent: the higher the education level, the lower the severity. For instance, a passenger with an upper school diploma - *Upper_sc* - generates a severe evasion of 9.35 (OR = 1/0.1069) times lower than travellers with lower school levels. This result confirms a previous study (Barabino et al., 2015), but it contrasts with past research. Indeed, according to Bucciol et al. (2013), education level does not play a significant role. According to Delbosc and Currie (2016b), more educated passengers could evade the fare more and generate a more severe evasion than less educated ones. Moreover, in some ways, this result contrasts with Barabino and Salis (2020), who showed that middle-school employees evaded more often than upper-school students. Nevertheless, these differences could be explained as follows: a certain social "stigma" could be perceived by people with high-level education, because they may be more aware of fare evasion consequences. Moreover, survey methods could also explain this difference: the web surveys of Delbosc and Currie (2016b) did not include a sizable percentage of low-income users or new immigrants without internet access. Finally, middle-school workers could be considered a low-income segment because of the lower education level.

Workers practiced more severe evasion than unemployed passengers. Indeed, being a worker increases the likelihood of a severe evasion by 1.417. Nevertheless, this result confirms the findings by Delbosc and Currie (2016b); however, it differs from those of Bucciol et al. (2013), Barabino et al. (2015), Barabino et al. (2022). Although this result looks counterintuitive, it could be justified because workers travelling on a bus could be a low-income segment, which should be investigated further.

Finally, captive riders originated an evasion 1.21 times (i.e., = 1/0.8249) more severe than choice riders. While confirming previous studies (Barabino et al., 2015; Barabino and Salis, 2020; Barabino et al., 2022), this result contrasts with Bucciol et al. (2013), who detected an opposite trend. However, our results could be justified because choice riders could exploit the bus service in certain circumstances (e.g., car breakdown) and accept to pay the fare for the sake of tranquillity; hence, they do not originate (a severe) evasion.

In terms of travel behaviour characteristics, three factors help explain the severity of fare evasion. Specifically, if passengers travel for study or work trips (i.e., systematic trips), the severity of fare evasion is shown to decrease. For instance, travelling for work or study trips

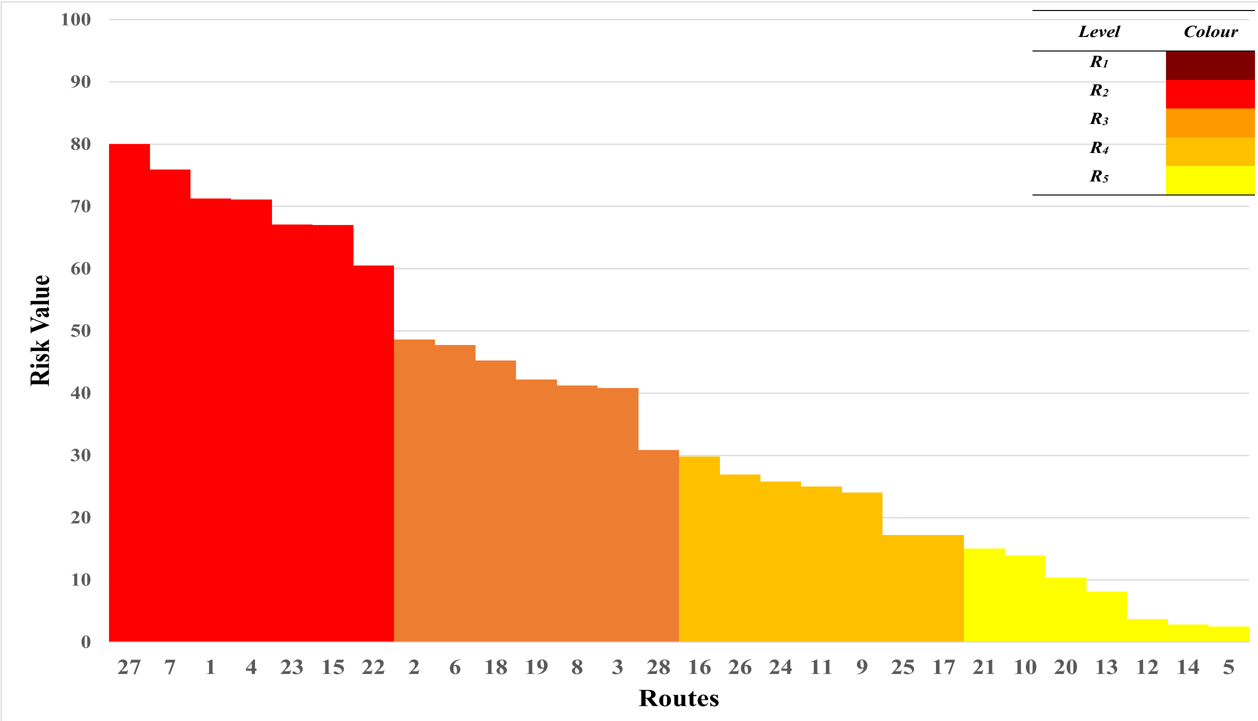

Fig. 3. Fare evasion risk for each route. High-risk routes are reported on the left. According to the risk scale in Table 1, red colours denoted R_2 risk routes.

decreases the severity of fare evasion by 1.645 (i.e., 1/0.6068) and 2.80 (1/0.3560) times as opposed to travelling for other reasons, respectively. Therefore, fare evasion is more severe when passengers travel for occasional trips. These trips usually do not occur during rush hour, and this evidence also confirms the result of the frequency model, where there is more evasion during off-peak periods. Although our results differ from previous research, it is not surprising: passengers travelling for work or study are likely to have regular passes and, thus, do not generate (a severe) evasion.

The severity of fare evasion also germinates from dissatisfaction. Indeed, being satisfied reduces the probability of a severe evasion of 1.43 (i.e., 1/0.6976) times as opposed to being unsatisfied. Similar results are obtained in the literature, even if the probability of evasion was estimated instead (Barabino et al., 2015; Delbosc and Currie, 2016b; Barabino et al., 2022). As a result, on the one hand, our findings may advise TAs/PTCs to reduce fare evasion by enhancing user satisfaction through quality improvement procedures (e.g., Nocera, 2010; Nocera, 2011; Bruzzone et al, 2020). On the other hand, our finding contrasts with some others: for example, Bucciol et al. (2013) discovered that dissatisfaction reduces fare evasion. Satisfaction was not significant for unintentional and deliberate fare evaders (Currie and Delbosc, 2017), workers, students, unemployed passengers (Barabino and Salis, 2020) and several clusters of evaders (Barabino and Salis, 2023). Hence, further research is required to confirm these results.

Finally, all situational factors affect the severity of fare evasion. It depends on the perceived frequency of inspection: the higher this perception, the lower the tendency to evade. This is an expected result. Particularly, a passenger checked by inspectors from 6 and 10 times (in 4 months) could produce a severe evasion of 1.40 (i.e., = 1/0.7164) times lower than passengers, who never met the inspectors in the same temporal frame. Therefore, passengers practice more severe evasion if they have a low perception of the inspections. This result confirms previous studies (Barabino et al., 2015; Cools et al., 2018; Porath and Galilea, 2020) and agrees with studies focused on deterrence (e.g., Beyleveld, 1980; Von Hirsch et al., 1999; Clarke et al., 2010). However, it contrasts other studies reporting an opposite trend for specific clusters of passengers (Barabino and Salis, 2023) or a one-size-fits-all model of passengers (Bucciol et al., 2013). Thus, no clear trends are observed, and further studies are recommended.

If a traveller is aware of the amount of the fine if discovered evading the fare, s/he is 1.825 times more likely to produce a severe evasion as opposed to the case of no knowledge of the fine. This result confirms all previous research on the same Italian context by the one-size-fits-all model of passengers (Barabino et al., 2015; Bucciol et al., 2013), *a priori* cluster of passengers (Barabino and Salis, 2020; Barabino et al., 2022) and *post hoc* segmentation (Barabino and Salis, 2023).

Having a history of fare evasion is the largest factor affecting the severity. Indeed, a passenger already fined in the past could generate further severe evasions. Particularly, being previously fined raises the probability of a serious evasion by 3.608 times compared to not having been previously fined. This result confirms past works in the same context (Barabino et al., 2015; Barabino and Salis, 2020; Barabino et al., 2022; Barabino and Salis, 2023). However, Bucciol et al. (2013) demonstrated that prior fines were not significant. Moreover, unlike Dai et al. (2017), our research reveals that already-fined passengers attempt to regain their loss evading fares again. This finding suggests that, in Cagliari, passengers may perceive a situation in which administrative enforcements do not sufficiently counteract fare evasion. Therefore, even if found, the fined evader may choose to skip paying the penalty since once an established time-period has passed, the infringement will probably not be pursued. Additionally, rather than focusing on the value of the fine, the PTC might concentrate its efforts on lessening the severity of fare evasion through improved inspections. Finally, the personality variables work as expected: being honest reduces the severity 9.28 (i.e., =1/0.1078) times as opposed to being dishonest and confirms previous *post hoc* segmentation studies (Delbosc and Currie, 2016b; Currie and Delbosc, 2017; Barabino and Salis, 2023).

4.3.3. Risk prediction model

Next, according to Step 3 of Section 3.2, the risk R_l values are computed for each route segment and aggregated for the overall route $l \in L$ by eqn. (5). A typical travel condition (e.g., morning rush hour,

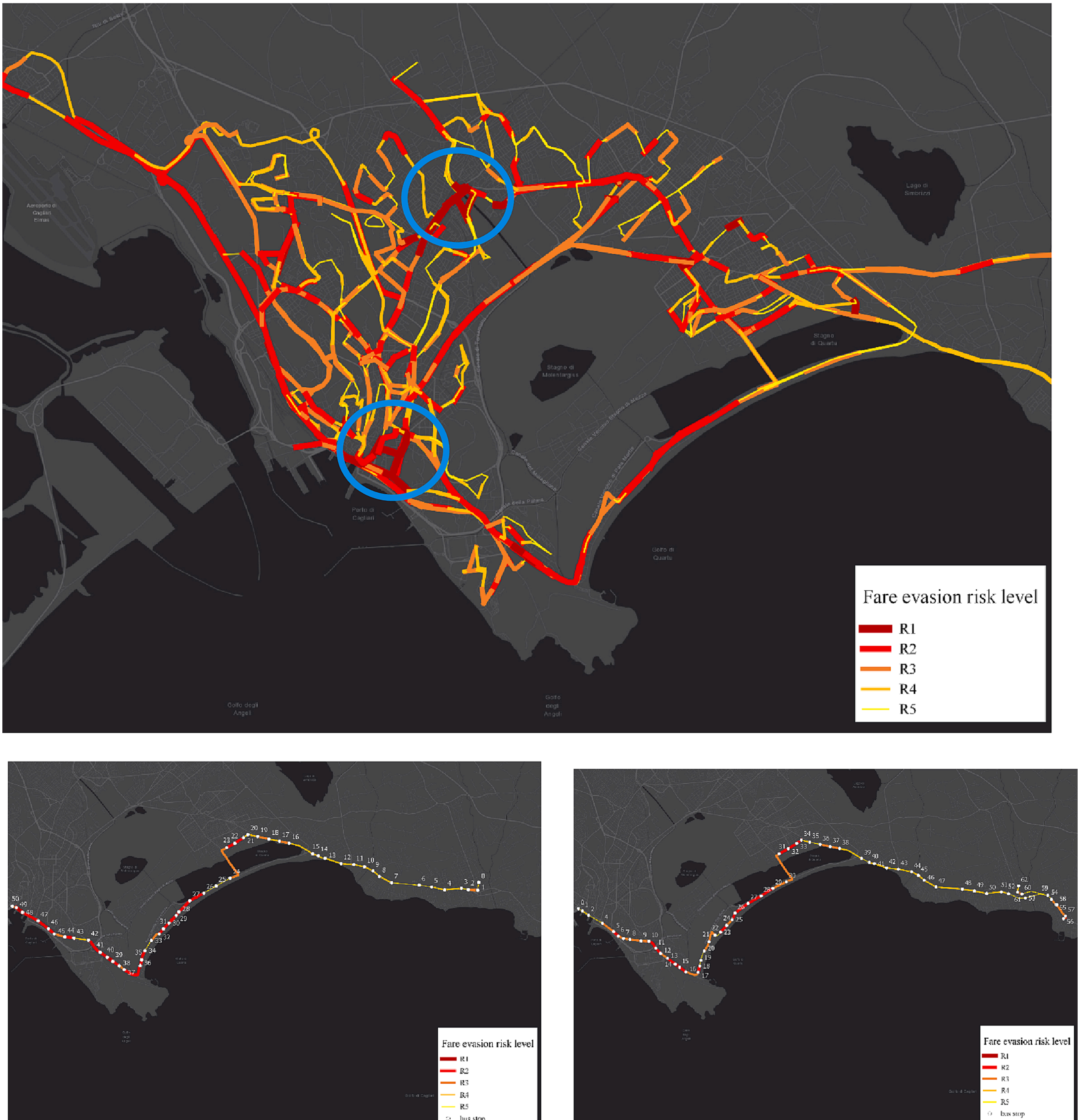

Fig. 4. Fare evasion risk maps. (a) Overall network of routes. (b) Route 27 Westbound. (c) Route 27 Eastbound.

inspection path A, standard staff and vehicles, an average level of occupancy up to 30%) and a typical passenger profile for each bus route $l \in L$ are considered. Next, every route is classified by the risk scale described in Step 4 of Section 3.2.

According to Step 5 of Section 3.2, charts and maps are built. Specifically, charts help PTC recognise the highest evasion risk routes that require priority measures. The computed risks are indicated for the overall network of routes in Fig. 3. All values are scaled in such a way as to assign 80 points to the maximum measure taken of risk, as no route belongs to the risk R_1 type at aggregated level. Fig. 3 shows that the most critical routes are 27, 7 and 1 and corroborates the PTC's concerns on these routes.

4.3.4. Risk network and route maps

Finally, fare evasion risk maps for both the overall network and each route are built as a visualisation tool for experts. For instance, Fig. 4(a), 4(b) and 4(c) highlight the risk of fare evasion of each segment $j \in J$ of each bus route $l \in L$.

Fig. 4 (a) shows that the most critical segments with level risk R_1 are clustered in two areas, which are emphasised by blue circles. The bottom circle corresponds to the Central Business District (CBD), whereas the other indicates a peripherical area (Pirri) of Cagliari. These high risks may depend on the concentration of bus routes like 27 and 1. Conversely, level risks R_2 and R_3 are spread along the main traffic corridors.

It is also possible to provide a more detailed representation on the different segments of each route as shown in Fig. 4(b) and 4(c), where both directions of route 27 are reported. One can observe that some critical areas in these directions overlap, and PTC could exploit this fact to schedule the paths of inspectors. Moreover, the framework provides insights on which preventive and protective actions can be taken by the PTC on this route. According to the frequency model, the risk could be reduced by the scheduling of random inspections of a standard patrol in off-peak hours. Moreover, long buses are recommended on this route. According to the severity model, the risk could be reduced by inspecting many times for more than 15 min.

5. Conclusions and research perspectives

Fare evasion is an emerging research area, and the determination of rigorous solutions is a challenging issue. This study improves the current knowledge on fare evasion as follows:

- It introduces a new metric for evaluating fare evasion and the fare evasion risk, as opposed to the standard fare evasion rate, which is adopted by most Transit Agencies (TAs) and/or Public Transport Companies (PTCs) worldwide.
- It proposes a framework to evaluate the risk of fare evasion on transit routes. First, this framework identifies the fare evasion factors as well as the risk exposure ones. Next, it specifies, calibrates and validates mixed frequency exposure and severity prediction models to measure the impact of fare evasion on each route. Then, the framework formulates a fare evasion risk function for each route by combining the outcomes of the previous models. Finally, a fare evasion performance ranking for each route segment is built, and each route is classified accordingly.
- It illustrates in a real-world experiment the effectiveness of this framework. Easy-to-read control dashboards based on charts and maps help diagnosticate the fare evasion performance on each route and drive for prioritising interventions on the high-risk evasion routes.

This framework results in the following implications. It can be adopted to:

- Assess the risk of fare evasion on each route for possible scheduling of randomised inspection paths. Indeed, the belief that a passenger might encounter an inspector anywhere or anytime could be underestimated. This study showed that the measure of fare evasion risk could help develop a program against fare evasion for TAs/PTCs.
- Predict the risk of fare evasion in the case of a new (planned) route on the network. A planner can calculate this risk adopting the previous frequency and severity models once spatial and temporal characteristics are set up. Consequently, preventive actions could be conceived even before the planned line will be operative.

This study indicates several research developments. First, the fare evasion databank can be updated with new intermediate factors. The inspection log file and the passenger survey can be integrated by several factors (e.g., type of evasion), also including the accurate locations (i.e., the boarding bus stop of the surveyed passenger), to improve the quality of fare evasion databank in new studies. Second, new studies should more carefully evaluate the severity by specific measurement of the type of evasion. Third, this research can enhance the state-of-the-art evaluation of the fare evasion risk because the framework is applicable to any PTC. Therefore, if new data is available, this framework can be implemented in every urban environment to investigate the consequences that many factors have on the risk of fare evasion.

Fourth, the exposure factors were integrated into the frequency model, but their explicit modelling would provide a more careful assessment of the fare evasion risk, according to specific predictors.

Fifth, this study provided TAs/PTCs with a risk prediction framework recommending effective management actions to reduce fare evasion. Consequently, econometric models (i.e., Negative Binomial and Logistic Regression) were employed due to the straightforward interpretability of the effect each explanatory factor has on fare evasion risk. Nevertheless, Machine Learning methods (e.g., Artificial Neural Networks and Clustering Analysis) present promising performances and will be tested as done in other transportation engineering fields (e.g., Sun et al., 2018; Ventura et al., 2023).

Finally, in this study, the fare evasion risk assessment is adopted as a driver to show the level of fare evasion along the network. Challenging research will be the development of optimisation methods for randomised patrols, inspection planning and scheduling on complex (real) POP-TS route segments according to the risk value.

CRediT authorship contribution statement

Benedetto Barabino: Conceptualization, Methodology, Data curation, Investigation, Software, Supervision, Funding acquisition, Writing – original draft, Writing – review & editing. **Massimo Di Francesco:** Conceptualization, Funding acquisition, Methodology, Writing – original draft, Writing – review & editing. **Roberto Ventura:** Conceptualization, Visualization, Methodology, Writing – original draft.

Declaration of Competing Interest

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

Data availability

The authors do not have permission to share data.

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Any opinions, findings, conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the CTM and MUR Any remaining errors are the authors’ responsibility alone.

Appendix A. List of factors

Table A1
Intermediate outcome factors.

Level 0	Level 1	Level 2	Source	Effect*
Context	Fare policy	Fare level	Busco, González, Jaqueih, Jiménez, 2022	*n.a.*
			Cools, Fabbro and Bellemansd, 2018	*n.s.*
			Lee 2011	+
			Milioti, Panoutsopoulos, Kepaptsoglou, Tyrinopoulosd 2020	+
			Porath and Galilea, 2020	+
			Wolfgram, L., C. Pollan, K. Hostetter, A. Martin, T. Spencer, S. Rodda, and A. Amey, 2022	*n.a.*
	Neighbourhood socioeconomics	Location	Cantillo, Raveau and Muñoz, 2022	+ *(if low-income neighbourhood)*
				+ *(If middle-income neighbourhood)*
				+ *(If higher Social Priority Index)*
			Cools, Fabbro and Bellemansd, 2018	*n.s.*
			Dai, Galeotti, Villeval, 2018	- *(If upper class neighbourhood)*
	Operators	Type	Guarda, Galilea, Paget-Seekins, Ortuzar, 2016	+; -
	Socio and Political	Employment (Macroeconomic)	Porath and Galilea, 2020	*n.s.*
		Image of the public transport service	Busco, González, Jaqueih, Jiménez, 2022	*n.a.*
			Porath and Galilea, 2020	*n.s.*
		Political issue	Porath and Galilea, 2020	- *(If higher government approval rate)*
				- *(If higher general Trust/Confidence experimented at social level)*
		Type of service contract	Porath and Galilea, 2020	*n.s.*
	Temporal Elements	Seasonality	Guarda, Galilea, Paget-Seekins, Ortuzar, 2016	- *(If winter)*
			Porath and Galilea, 2020	*n.s.*
			Reddy, Kuhls, Lu, 2011	+ *(If summer)*
		Time period	Barabino and Salis, 2020	*n.s.*
			Barabino and Salis, 2023	*n.s.*
			Barabino, Salis, Useli 2015	*n.s.*
			Barabino, Salis, Useli 2022	*n.s.*
			Bucciol, Landini, Piovesan 2013	*n.s.*
			Busco, González, Jaqueih, Jiménez, 2022	*n.a.*
			Cantillo, Raveau and Muñoz, 2022	+ *(If weekday evening peak: 17:00–21:00)*
				+ *(If weekday off-peak: 9:30–17:00)*
				+ *(If weekend noon: 11:00–17:00)*
				+ *(If weekend afternoon: 17:00–21:00)*
				+ *(If night: 21:00–00:30)*
			Dai, Galeotti, Villeval, 2018	*n.s.*
			Guarda, Galilea, Paget-Seekins, Ortuzar, 2016	*n.s.*
				- *(If morning off-peak: 8:30–12:29)*
				+ *(If afternoon off-peak: 14:00–17:29)*
				+ *(If afternoon peak: 14:00–17:29)*
				+ *(If evening: 20:30–21:29)*
			Lee 2011	- - - *(If weekday Morning peak: 7 am.-9 am)*
				- - *(If weekday Midday: 9 am-2 pm)*
				- *(If weekday School: 2 pm-4 pm)*
				+ *(If weekday Afternoon Peak: 4 pm-7 pm)*
				+++ *(If weekday Evening: 7 pm-10 pm)*
				++ *(If weekend: all day)*
			Reddy, Kuhls, Lu, 2011	- *(If weekday morning peak: 7 am.-9 am)*
				+ *(If weekday Off-peak)*
				- *(If weekday Afternoon Peak: 4 pm-7 pm)*
		Type of Day	Bucciol, Landini, Piovesan 2013	+ *(If weekend)*
			Guarda, Galilea, Paget-Seekins, Ortuzar, 2016	*n.s.*
	Wheater	Conditions	Bucciol, Landini, Piovesan 2013	+ *(If warm day)*
	Fine Policy	Penalty	Bijleveld, 2007	*n.a.*
			Busco, González, Jaqueih, Jiménez, 2022	*n.a.*
			Mehlkop et al., 2007	- *(If higher fine amount)*
			Torres-Montoya 2014	*n.a.*
	Other policies	Punishment	Guzman, Arellana, Camargo, 2021	*n.a.*

(*continued on next page*)

Table A1 (*continued*)

Level 0	Level 1	Level 2	Source	Effect*
Organisation	Inspection Pattern	Budget	Mutisystem et al. 2002	*n.a.*
		Level of Enforcement	Guzman, Arellana, Camargo, 2021	*n.a.*
			Lee 2011	*- (If heavy)* *+ (If light)*
			Mutisystem et al. 2002	*n.a.*
			Porath and Galilea, 2020	–
			Sterner and Sheng, 2013	–
		Type of Inspection	Busco, González, Jaqueih, Jiménez, 2022	*n.a.*
			Dai, Galeotti, Villeval, 2017	– +
			Guzman, Arellana, Camargo, 2021	*n.a.*
			Mutisystem et al. 2002	*n.a.*
			Sterner and Sheng, 2013	*- (If embarrassing controls)*
			Torres-Montoya 2014	*n.a.*
		Type of Inspectors	Mutisystem et al. 2002	*n.a.*
	System Planning and design	Marketing Strategies	Torres-Montoya 2014	*n.a.*
		Network Configuration	Busco, González, Jaqueih, Jiménez, 2022	*n.a.*
			Cantillo, Raveau and Muñoz, 2022	*- (If Off-board payment station)* *+ (If Bus stop immediately upstream from an OBPS)* *- (If metro station located less than 1000 m from the bus stop)* *- (If number of fares vending machine less than 500 m from bus stop)*
			Guarda, Galilea, Paget-Seekins, Ortuzar, 2016	*n.s.* *+ (If greeter headway)*
			Mutisystem et al. 2002	*n.a.*
			Porath and Galilea, 2020	*n.s.*
			Reddy, Kuhls, Lu, 2011	*+ (If entered in quieter stations)*
			Torres-Montoya 2014	*n.a.*
			Wolfgram, L., C. Pollan, K. Hostetter, A. Martin, T. Spencer, S. Rodda, and A. Amey, 2022	*n.a.*
			Wolfgram, L., C. Pollan, K. Hostetter, A. Martin, T. Spencer, S. Rodda, and A. Amey, 2022	*n.a.*
		Type of Media	Busco, González, Jaqueih, Jiménez, 2022	*n.a.*
			Milioti, Panoutsopoulos, Kepaptsoglou, Tyrinopoulosd 2020	*+ (If single type fares)*
			Torres-Montoya 2014	*n.a.*
Passenger	Personality variables	Behaviour	Currie & Delbosc 2017	*n.s.*
			Delbosc & Currie, 2016a	*n.a.*
			Delbosc & Currie 2016b	– *n.a.*
			Mehlkop et al., 2007	*+ (If higher utility)*
			Sterner and Sheng, 2013	*n.s.* *+ (If has fare evaded more than once last month and inspections are embrassing)*
		Risk Attitude	Bucciol, Landini, Piovesan 2013	*- (If concerned)*
			Busco, González, Jaqueih, Jiménez, 2022	*n.a.*
			Currie & Delbosc 2017	+ *n.s.*
			Dai, Galeotti, Villeval, 2018	+ *n.s.*
			Delbosc & Currie 2016b	+; -
			Mehlkop et al., 2007	+ *n.s.*
			Sterner and Sheng, 2013	+
		Values/Principles	Barabino and Salis, 2023	–
			Busco, González, Jaqueih, Jiménez, 2022	*n.a.*
			Currie & Delbosc 2017	– *n.s.*
			Delbosc & Currie, 2016b	+
			Wolfgram, L., C. Pollan, K. Hostetter, A. Martin, T. Spencer, S. Rodda, and A. Amey, 2022	*n.a.*
	Situational Factors	Amount of the fine	Barabino and Salis, 2020	*+ (If there is knowledge about the amount)*
			Barabino and Salis, 2023	+
			Barabino, Salis, Useli 2015	+
			Barabino, Salis, Useli 2022	+
			Bucciol, Landini, Piovesan 2013	+
			Dai, Galeotti, Villeval, 2018	*n.s.*
			Guzman, Arellana, Camargo, 2021	*n.a.*
		Fines in the past	Barabino and Salis, 2020	+
			Barabino and Salis, 2023	+
			Barabino, Salis, Useli 2015	+
			Barabino, Salis, Useli 2022	+
			Bucciol, Landini, Piovesan 2013	*n.s.*

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Table A1 (*continued*)

Level 0	Level 1	Level 2	Source	Effect*
			Dai, Galeotti, Villeval, 2017	*n.s.*
			Guzman, Arellana, Camargo, 2021	*n.a.*
		Perceived certainty of Punishment	Cools, Fabbro and Bellemansd, 2018	+
			Currie & Delbosc 2017	*n.s.*
			Guzman, Arellana, Camargo, 2021	*n.a.*
		Perceived inspection frequency	Barabino and Salis, 2023	+
			Barabino, Salis, Useli 2015	–
			Bucciol, Landini, Piovesan 2013	+
			Cools, Fabbro and Bellemansd, 2018	–
			Currie & Delbosc 2017	–
			Milioti, Panoutsopoulos, Kepaptsoglou, Tyrinopoulosd 2020	*n.a.*
			Wolfgram, L., C. Pollan, K. Hostetter, A. Martin, T. Spencer, S. Rodda, and A. Amey, 2022	*n.a.*
		Perceptions of actions against fare evasion	Milioti, Panoutsopoulos, Kepaptsoglou, Tyrinopoulosd 2020	*n.a.*
	Norms & beliefs	Moral norms	Barabino and Salis, 2023	–
				+
			Busco, González, Jaqueih, Jiménez, 2022	*n.a.*
			Dai, Galeotti, Villeval, 2018	+
			Guzman, Arellana, Camargo, 2021	*n.a.*
			Mehlkop et al., 2007	*- (If higher attitude towards Norms)*
			Milioti, Panoutsopoulos, Kepaptsoglou, Tyrinopoulosd 2020	*n.a.*
		Social norms	Busco, González, Jaqueih, Jiménez, 2022	*n.a.*
			Currie & Delbosc 2017	*n.s.*
			Milioti, Panoutsopoulos, Kepaptsoglou, Tyrinopoulosd 2020	*n.a.*
		Beliefs	Delbosc & Currie 2016b	*n.s*
			Currie & Delbosc 2017	*n.s.*
			Dai, Galeotti, Villeval, 2018	–
				+
			Milioti, Panoutsopoulos, Kepaptsoglou, Tyrinopoulosd 2020	*n.a.*
		Legal norms	Milioti, Panoutsopoulos, Kepaptsoglou, Tyrinopoulosd 2020	*n.a.*
	Sociodemographic characteristics	(Dis)ability	Wolfgram, L., C. Pollan, K. Hostetter, A. Martin, T. Spencer, S. Rodda, and A. Amey, 2022	*n.a.*
		Age	Abrate, Fraquelli, Meko, Rodia, 2008	–
			Barabino and Salis, 2020	–
			Barabino and Salis, 2023	–
			Barabino, Salis, Useli 2015	–
			Barabino, Salis, Useli 2022	–
			Bucciol, Landini, Piovesan 2013	–
			Busco, González, Jaqueih, Jiménez, 2022	*n.a.*
			Cantillo, Raveau and Muñoz, 2022	–
			Cools, Fabbro and Bellemansd, 2018	–
			Dai, Galeotti, Villeval, 2018	*n.s.*
			Delbosc & Currie 2016a	*n.a.*
			Delbosc & Currie 2016b	–
			Eddy,2010	+
			Guzman, Arellana, Camargo, 2021	*n.a.*
			Milioti, Panoutsopoulos, Kepaptsoglou, Tyrinopoulosd 2020	–
		Car availability	Barabino and Salis, 2020	*n.s.*
			Barabino and Salis, 2023	+
			Barabino, Salis, Useli 2015	*n.s.*
			Barabino, Salis, Useli 2022	*n.s.*
			Cools, Fabbro and Bellemansd, 2018	*n.s.*
			Milioti, Panoutsopoulos, Kepaptsoglou, Tyrinopoulosd 2020	–
		Clothing	Bucciol, Landini, Piovesan 2013	+ *(If poor dressed)*
		District	Busco, González, Jaqueih, Jiménez, 2022	*n.a.*
		Driving licence	Barabino, Salis, Useli 2015	*n.s.*
		Educational qualification	Barabino and Salis, 2020	–
			Barabino and Salis, 2023	+; -
			Barabino, Salis, Useli 2015	–
			Barabino, Salis, Useli 2022	–
			Bucciol, Landini, Piovesan 2013	*n.s.*
			Busco, González, Jaqueih, Jiménez, 2022	*n.a.*
			Cools, Fabbro and Bellemansd, 2018	*n.s.*
			Dai, Galeotti, Villeval, 2018	+
			Delbosc & Currie 2016b	+
			Guzman, Arellana, Camargo, 2021	*n.a.*

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Table A1 (*continued*)

Level 0	Level 1	Level 2	Source	Effect*
			Milioti, Panoutsopoulos, Kepaptsoglou, Tyrinopoulosd 2020	*n.s.*
			Wolfgram, L., C. Pollan, K. Hostetter, A. Martin, T. Spencer, S. Rodda, and A. Amey, 2022	*n.a.*
		Employment	Abrate, Fraquelli, Meko, Rodia, 2008	+ *(If worker or unemployed)* - *(If housewife)*
			Barabino and Salis, 2020	*n.s.*
			Barabino and Salis, 2023	*n.s.*
			Barabino, Salis, Useli 2015	+ *(If do not have money)*
			Barabino, Salis, Useli 2022	+ *(If do not have money)*
			Bucciol, Landini, Piovesan 2013	+ *(If do not have money)*
			Busco, González, Jaqueih, Jiménez, 2022	*n.a.*
			Delbosc & Currie, 2016b	+ *(If full time worker)* - *(If retired)*
			Dai, Galeotti, Villeval, 2018	*n.s.*
			Guzman, Arellana, Camargo, 2021	*n.a.*
			Sterner and Sheng, 2013	*n.s.*
			Wolfgram, L., C. Pollan, K. Hostetter, A. Martin, T. Spencer, S. Rodda, and A. Amey, 2022	*n.a.*
		Gender	Abrate, Fraquelli, Meko, Rodia, 2008	+ *(If male)*
			Barabino and Salis, 2020	+ *(If male)*
			Barabino and Salis, 2023	+ *(If male)*
			Barabino, Salis, Useli 2015	+ *(If male)*
			Barabino, Salis, Useli 2022	+ *(If male)*
			Bucciol, Landini, Piovesan 2013	+ *(If male)*
			Busco, González, Jaqueih, Jiménez, 2022	*n.a.*
			Cantillo, Raveau and Muñoz, 2022	+ *(If male)*
			Cools, Fabbro and Bellemansd, 2018	+ *(If male)*
			Dai, Galeotti, Villeval, 2018	+ *(If male)*
			Delbosc & Currie, 2016a	*n.a.*
			Delbosc & Currie, 2016b	*n.s*
			Eddy,2010	*n.s.*
			Guzman, Arellana, Camargo, 2021	*n.a.*
			Milioti, Panoutsopoulos, Kepaptsoglou, Tyrinopoulosd 2020	+ *(If male)*
			Wolfgram, L., C. Pollan, K. Hostetter, A. Martin, T. Spencer, S. Rodda, and A. Amey, 2022	*n.a.*
		Income	Bucciol, Landini, Piovesan 2013	–
			Cools, Fabbro and Bellemansd, 2018	+
			Dai, Galeotti, Villeval, 2018	–
			Delbosc & Currie, 2016b	*n.s.*
			Guarda, Galilea, Paget-Seekins, Ortuzar, 2016	–
			Guzman, Arellana, Camargo, 2021	*n.a.*
			Milioti, Panoutsopoulos, Kepaptsoglou, Tyrinopoulosd 2020	+ *(If unemployed, employees of the private sector, retired)*
			Reddy, Kuhls, Lu, 2011	+
			Wolfgram, L., C. Pollan, K. Hostetter, A. Martin, T. Spencer, S. Rodda, and A. Amey, 2022	–
		Living situation	Cools, Fabbro and Bellemansd, 2018	*n.s.*
		Marital Status	Guzman, Arellana, Camargo, 2021	*n.a.*
		Nationality	Abrate, Fraquelli, Meko, Rodia, 2008	+ *(If stranger)*
			Bucciol, Landini, Piovesan 2013	+ *(If non-European immigrants)*
			Busco, González, Jaqueih, Jiménez, 2022	*n.a.*
			Wolfgram, L., C. Pollan, K. Hostetter, A. Martin, T. Spencer, S. Rodda, and A. Amey, 2022	*n.a.*
		Reason for using the bus	Barabino and Salis, 2020	+ *(If no alternatives are available)*
			Barabino and Salis, 2023	*n.s.*
			Barabino, Salis, Useli 2015	+ *(If no alternatives are available)*
			Barabino, Salis, Useli 2022	+ *(If there are not alternative)*
			Bucciol, Landini, Piovesan 2013	*n.s.*
		Size of the family	Busco, González, Jaqueih, Jiménez, 2022	*n.a.*
		Type of contract	Busco, González, Jaqueih, Jiménez, 2022	*n.a.*
	Travel behaviour characteristics	In-vehicle time	Barabino and Salis, 2020	–
			Barabino and Salis, 2023	*n.s.*
			Barabino, Salis, Useli 2015	–
			Barabino, Salis, Useli 2022	–
			Bucciol, Landini, Piovesan 2013	–
			Busco, González, Jaqueih, Jiménez, 2022	*n.a.*
			Dai, Galeotti, Villeval, 2018	*n.s.*
			Milioti, Panoutsopoulos, Kepaptsoglou, Tyrinopoulosd 2020	*n.a.*

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Table A1 (*continued*)

Level 0	Level 1	Level 2	Source	Effect*
		Quality rating	Barabino and Salis, 2020	*n.s.*
			Barabino, Salis, Useli 2015	–
			Barabino, Salis, Useli 2022	–
			Bucciol, Landini, Piovesan 2013	+
			Busco, González, Jaqueih, Jiménez, 2022	*n.a.*
			Currie & Delbosc 2017	*n.s.*
			Delbosc & Currie, 2016b	–
			Guzman, Arellana, Camargo, 2021	*n.a.*
			Milioti, Panoutsopoulos, Kepaptsoglou, Tyrinopoulosd 2020	–
			Porath and Galilea, 2020	*n.s.*
			Wolfgram, L., C. Pollan, K. Hostetter, A. Martin, T. Spencer, S. Rodda, and A. Amey, 2022	*n.a.*
		Transit use frequency	Barabino and Salis, 2020	+
			Barabino and Salis, 2023	*n.s.*
			Barabino, Salis, Useli 2015	+
			Barabino, Salis, Useli 2022	+
			Bucciol, Landini, Piovesan 2013	+
			Busco, González, Jaqueih, Jiménez, 2022	*n.a.*
			Delbosc & Currie, 2016a	*n.a.*
			Delbosc & Currie, 2016b	+
			Dai, Galeotti, Villeval, 2018	*n.s.* + *(If only using tram wrt metro)*
			Guzman, Arellana, Camargo, 2021	*n.a.*
			Milioti, Panoutsopoulos, Kepaptsoglou, Tyrinopoulosd 2020	+
		Travel alternatives	Barabino and Salis, 2020	*n.s.*
			Barabino and Salis, 2023	*n.s.*
			Barabino, Salis, Useli 2015	*n.s.*
			Barabino, Salis, Useli 2022	+ *(If other transit systems are used)*
			Busco, González, Jaqueih, Jiménez, 2022	*n.a.*
		Trip origin/destination	Barabino, Salis, Useli 2015	+ *(If the city is the origin)*
			Bucciol, Landini, Piovesan 2013	+ *(If stop at train station)*
			Busco, González, Jaqueih, Jiménez, 2022	*n.a.*
		Trip purpose	Abrate, Fraquelli, Meko, Rodia, 2008	- *(If work)*
			Barabino and Salis, 2020	*n.s.*
			Barabino and Salis, 2023	*n.s.*
			Barabino, Salis, Useli 2015	*n.s.*
			Barabino, Salis, Useli 2022	*n.s.*
			Bucciol, Landini, Piovesan 2013	*n.s.*
			Busco, González, Jaqueih, Jiménez, 2022	*n.a.*
			Cools, Fabbro and Bellemansd, 2018	*n.s.*
			Guzman, Arellana, Camargo, 2021	*n.a.*
			Milioti, Panoutsopoulos, Kepaptsoglou, Tyrinopoulosd 2020	*n.s.*
		Travelling Pattern	Bucciol, Landini, Piovesan 2013	- *(If provided with luggage)* - *(If travel with relative)* + *(If travel with friends)*
			Dai, Galeotti, Villeval, 2018	*n.s.*
Vehicle	Layout	Vehicle design	Wolfgram, L., C. Pollan, K. Hostetter, A. Martin, T. Spencer, S. Rodda, and A. Amey, 2022	*n.a.*
	Equipment	Boarding door	Guarda, Galilea, Paget-Seekins, Ortuzar, 2016	- *(If front door)* *n.s. (If back door)*
		Devices	Cantillo, Raveau and Muñoz, 2022	–
	Type	Number of doors	Busco, González, Jaqueih, Jiménez, 2022	*n.a.*
			Guarda, Galilea, Paget-Seekins, Ortuzar, 2016	+

+ indicates that fare evasion increases as the factor increases.
- indicates that fare evasion decreases as the factor increases.
-;+ indicates that the factor has a contrasting effect on fare evasion.
n.s. indicates that the factor is not significant at 0.05 level in explaining fare evasion.
n.a. indicates that the effect of the factor on fare evasion has not been directly evaluated (e.g., only descriptive statistic has been provided).
() contains useful information to correctly understand the effect of the factor on fare evasion.

Table A2
Risk Exposure factors.

Level 0	Level 1	Level 2	Source	Effect *
Demand	Alighting	Daily system ridership	Guarda, Galilea, Paget-Seekins, Ortuzar, 2016	+
	Boarding	Daily system ridership	Mutisystem et al. 2002	*n.a.*
		Back door boarding	Lee 2011	*n.s.*
		Daily system ridership	Guarda, Galilea, Paget-Seekins, Ortuzar, 2016	+
Supply-Demand	Space on board	Level of Occupancy	Cantillo, Raveau and Muñoz, 2022	+
			Delbosc & Currie, 2016a	*n.a.*
			Guarda, Galilea, Paget-Seekins, Ortuzar, 2016	*- (If low)* *n.s. (If high)*
			Lee 2011	*- - (If ridership less than 50% of seats)* *- (If ridership 50–100% of seats)* *+ (If ridership 100–125% of seats)* *++ (If ridership more than 125% of seats)*

+ indicates that fare evasion increases as the factor increases.
- indicates that fare evasion decreases as the factor increases.
-;+ indicates that the factor has a contrasting effect on fare evasion.
n.s. indicates that the factor is not significant at 0.05 level in explaining fare evasion.
n.a. indicates that the effect of the factor on fare evasion has not been directly evaluated (e.g., only descriptive statistic has been provided).
() contains useful information to correctly understand the effect of the factor on fare evasion.

Table A3
Final outcome factors.

Level 1	Level 2	Source	Effect *
Type of Fare evasion	Deliberate	Lee 2011	*n.a.*
		Reddy, Kuhls, Lu, 2011	*n.a.*
	Accidental	Lee 2011	*n.a.*
	Opportunistic	Lee 2011	*n.a.*
		Reddy, Kuhls, Lu, 2011	*n.a.*
Frequency of Fare evasion	Percentage/times	Barabino and Salis, 2023	*n.s.*
		Bucciol, Landini, Piovesan 2013	*n.a.*
		Delbosc & Currie, 2016a	*n.a.*
		Guzman, Arellana, Camargo, 2021	*n.a.*
		Milioti, Panoutsopoulos, Kepaptsoglou, Tyrinopoulosd 2020	*n.a.*
	Pattern	Cools, Fabbro and Bellemansd, 2018	*+ (If experience with free public transport)*
		Milioti, Panoutsopoulos, Kepaptsoglou, Tyrinopoulosd 2020	*n.a.*
Motivation of Fare evasion	Beliefs	Currie & Delbosc 2017	*+ (If it as a commercial service)*
		Delbosc & Currie, 2016b	*+; - (Commercial service vs. social service)*
	Price	Cools, Fabbro and Bellemansd, 2018	*+ (Perception w.r.t. PT price)* *- (If high price of PT)*
	Inspection	Cools, Fabbro and Bellemansd, 2018	*n.a.*
	Punishment	Cools, Fabbro and Bellemansd, 2018	*n.a.*
	Other reasons	Cools, Fabbro and Bellemansd, 2018	*n.a.* *- (If forgotten to pay)*
	Ticketing System	Cools, Fabbro and Bellemansd, 2018	*n.a.*
		Currie & Delbosc 2017	*- (Significant only for unintentional evasion)*
	Structural aspect of System	Currie & Delbosc 2017	*n.s.*
		Delbosc & Currie, 2016a	*n.a.*
Severity	Lost revenues and/or Fines	Abrate, Fraquelli, Meko, Rodia, 2008	*n.a.*
		Barabino,Lai and Olivo, 2020	*n.a.*
		Bonfanti and Wagenknecht, 2010	*n.a.*
		Lee 2011	*n.a.*
		Mutisystem et al. 2002	*n.a.*
		Reddy, Kuhls, Lu, 2011	*n.a.*
		Smith and Clarke, 2000	*n.a.*
	Social inequity	Abrate, Fraquelli, Meko, Rodia, 2008	*n.a.*
		Barabino,Lai and Olivo, 2020	*n.a.*
		Lee 2011	*n.a.*
	Violence on Board	Barabino,Lai and Olivo, 2020	*n.a.*
		Bonfanti and Wagenknecht, 2010	*n.a.*
		Mutisystem et al. 2002	*n.a.*
		Reddy, Kuhls, Lu, 2011	*n.a.*
		Smith and Clarke, 2000	*n.a.*
	Corporate Image Damage	Abrate, Fraquelli, Meko, Rodia, 2008	*n.a.*
		Barabino,Lai and Olivo, 2020	*n.a.*

+ indicates that fare evasion increases as the factor increases.
- indicates that fare evasion decreases as the factor increases.
-;+ indicates that the factor has a contrasting effect on fare evasion.
n.s. indicates that the factor is not significant at 0.05 level in explaining fare evasion.
n.a. indicates that the effect of the factor on fare evasion has not been directly evaluated (e.g., only descriptive statistic has been provided) or that the field cannot be applied.
() contains useful information to correctly understand the effect of the factor on fare evasion.

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