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Do students, workers, and unemployed passengers respond differently to the intention to evade fares? An empirical research

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ABSTRACT

In *proof-of-payment* transit systems, fare evasion has recently captured increasing attention because of the relevant implications it produces. Research has investigated how sociodemographic, travel behaviour, and situational determinants affect the intention to evade fares for segments of passengers clustered according to 'Gender' and 'Age'. Conversely, no study has isolated these determinants in segments clustered according to 'Employment'. This paper fills this gap by analyzing students, workers, and unemployed passengers. Key determinants are isolated by logistic regression models. The findings show that gender, age, and having been fined are the common determinants that make all these segments more likely to evade fares. In addition, some specific determinants are identified for each segment. Hence, the overall findings may support transit operators by anticipating preventive and corrective strategies tailored to specific segments, which can positively impact other segments.

1. Introduction

1.1. Background

Nowadays, scarce subsidies are obliging public transport companies (PTCs) to operate under severe conditions and use resources efficiently. Thus, to preserve economic sustainability, PTCs aim to increase fare revenues by decreasing fare evasion problems through an in-depth marketing segmentation of passengers.

Marketing segmentation is pivotal in public transport because of the crucial differences in passenger demands and thus results in several benefits. A PTC's manager can adopt a marketing mix to target segments with relative accuracy and thus use resources more efficiently and effectively. Moreover, the knowledge of specific segments may result in a trust relationship between the PTC that delivers the service and the passenger who consumes it. In addition, findings from the segmentation may be employed to search for competitive strategies (e.g. to provide differentiation of the service with respect to the other).

Fare evasion results in lost fare revenues, damage to the corporate image, social inequity, and increased levels of violence that affect passenger security (e.g. Barabino et al., 2020; Bonfanti and Wagenknecht, 2010; Multisystems, Inc., et al., 2002; Reddy et al., 2011; Smith and Clarke, 2000). Moreover, fare evasion is more of a problem in open than closed transit systems (e.g. Dauby and Kovacs, 2007).

Thus, merging the concepts of marketing segmentation and fare evasion to analyse segments clustered according to the variable 'Employment' is of interest. This variable is essential in transit services to effectively reach all passengers by using tailored marketing strategies. More precisely, this variable may be used to select three large segments in the transit market that may be fare evaders: students, workers, and unemployed passengers. In addition, these segments are considered strategic when PTCs tailor fare structures, because they can differentiate fares by group. The interest in these segments is also strengthened by the following motivations. First, the variable 'Employment' is significant in explaining the self-reported fare evasion and intention to evade fares (Abrate et al., 2008; Barabino et al., 2015; Barabino and Salis, n.d.; Bucciol et al., 2013). Second, students and workers represent the largest quota of passengers in many transit systems, in small and large cities worldwide (e.g. Barabino et al., 2015; Delbosc and Currie, 2016b). Third, the managers of marketing and fare inspection departments of vanguard PTCs collect data on passenger characteristics and the number of evaders (e.g. Egu and Bonnel, 2020), respectively. Thus, these managers can merge these data to differentiate the types of passengers carried on each route and the corresponding fare evasion rate at different time periods; hence, as a possible strategy, they can send inspectors on those routes where the most students, workers, and unemployed passengers (potential fare evaders) are expected. Thus, inspectors may adopt tailored strategies to manage these passengers.

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This paper was motivated by the aforementioned background and the following literature review. In the subsequent sections, the gaps in the literature, the objective of this paper and the implications for research and practice are described.

1.2. Literature review

Recently, fare evasion has been receiving increasing attention and the approaches used are from several areas of research (Barabino et al., 2020) or the perspective of transit and passengers (Barabino et al., 2013, 2014, 2015; Delbosc and Currie, 2019).

Many studies have focused on the transit perspective. Recent studies have analysed strategies to protect PTCs against financial losses because of fare evasion, e.g., by evaluating changes to the system design (e.g. Guarda et al., 2016a; Sasaki, 2014), setting the level of inspection (e.g. Barabino et al., 2013, 2014; Barabino and Salis, 2019; Guarda et al., 2016) and establishing a scheduled programme of patrol inspection strategies (e.g. Borndörfer et al., 2012; Correa et al., 2017; Yin et al., 2012). Other studies have investigated the effectiveness of situation-specific measures against fare evasion such as enforcement and deterrence issues (e.g. Bijleveld, 2007; Clarke et al., 2010; Killias et al., 2009). These studies were mainly investigated within the context of situational crime prevention[1] (Smith and Clarke, 2000).

Conversely, studies have also examined the passenger's perspective, with a focus on the characteristics, attitudes, motivations, and behaviours of fare evaders. These studies have mostly provided: (i) key determinants (or attributes, or variables, or factors) to profile a 'one-size-fits-all' portrait (or model) of the fare evader and (ii) segments of fare-evader types.

More precisely, studies (i) have gathered and analysed data by using quantitative research methods and unobtrusive observations (Eddy, 2010), by directly checking the ticketholder (Abrate et al., 2008; Bucciol et al., 2013) or surveying passengers (Barabino et al., 2015; Cools et al., 2018; Dai et al., 2017; Mehlkop et al., 2007). Additionally, studies have used descriptive statistics (Eddy, 2010), logistic regression models (Abrate et al., 2008; Barabino et al., 2015; Cools et al., 2018; Mehlkop et al., 2007), and Probit models (Bucciol et al., 2013) to demonstrate that sociodemographic variables (e.g. gender, age, level of education, employment, nationality, car availability, and reasons for using the bus), travel determinants (e.g. trip purpose, time of day, in-vehicle time, other transit system use, transit use frequency, trip origin and destination, travel frequency, travel alternatives), situational factors (e.g. previous ticket violations, knowledge of the fine amount, the probability of being detected, attitude towards norms) may affect all forms of fare evasion (i.e. observed, measured, revealed, or stated – see Barabino and Salis, n.d.).

Studies (ii) have collected and analysed data by qualitative (Delbosc and Currie, 2016a; Perrotta, 2016; Suquet, 2010) or quantitative methods (Barabino and Salis, n.d.; Currie and Delbosc, 2017; Delbosc and Currie, 2016b; Hauber, 1980; Salis et al., 2017; Sterner and Sheng, 2013; González et al., 2019), and passengers were segmented and analysed by a priori (or profiling)[2] or a posteriori (or post hoc) approaches (Wedel and Kamakura, 2012).

By a priori segmentation, studies have aimed to learn more about the motivations and demographics of passengers to understand which strategies reduce fare evasion. The analysis included cross-tabulations, frequency distributions, and occasionally, regressions. Perrotta (2016) showed that low-income riders are often unable to pay for trips that satisfy their daily necessities; thus, they travel by evading fares, abusing free transfers, forgoing goods, and borrowing and using a free-fare card provided by welfare agents of the state. Sterner and Sheng (2013) showed an increase in the willingness to pay for using the subway if the ticket inspections were more embarrassing than the current procedure. However, among student fare evaders, almost no difference in social stigma was observed between the two types of inspections. Thus, social stigma may affect fare evasion but is unlikely a major factor in students' fare evasion. Barabino and Salis (n.d.) investigated the intention to evade fares for types of passengers—male, female, young, middle-aged, and older—and showed that having been fined is the most common determinant that makes all segments more oriented towards fare evasion. Moreover, specific determinants were identified for each segment, for example, females are more likely to evade fares if they are dissatisfied with the service and know the fine amount, whereas the orientation of males depends on whether they travel more than twice per day.

By post hoc segmentation, studies have aimed to discover segments more oriented towards fare evasion. Some clustering procedures and models have been adopted to identify segments within the data. Hauber (1980) showed that many individuals in some north European countries evade the fare because of economic, social (i.e. desire to emulate other evaders) and political reasons (i.e. public transport should be a free public service). Four groups of fare evaders were derived: 1) 'naïve,' not real offenders because they accidentally forgot to buy or validate a ticket, and no generalising effect was observed; 2) 'conscientious,' commit fraud only in some circumstances (e.g. when money is short at the end of the month); 3) 'regulars,' often practice fraud and usually include political fare evaders; and 4) 'cunnings,' commit the offence as often as possible and save money for their profit.

By approaching the problem of fare evasion from the inspector's perspective, Suquet (2010), in France, classified fare evaders into six categories: 1) users with no choice, 2) gamblers who are unlikely to see inspectors, 3) ideological opponents who challenge the inspectors, 4) users dissatisfied with service quality, 5) cheats who pretend to pay the fine but never pay, and 6) users who have difficulties understanding the fare structure. Delbosc and Currie (2016a) showed that fare evasion may depend largely on structural and operational aspects of the system (e.g. paid zone, empty smart card, malfunctioning equipment, crowded travelling conditions, short trips, low levels of inspection). They discovered four key segments of evaders: 1) the accidental evader with a strong view against fare evasion. 2) the 'it's not my fault' evader (i.e. the unintentional evader who would pay but sometimes evades, e.g., when the ticket validating machine is out of order; 3) the calculated risk-related evader who deliberately evades if s/he thinks s/he will not be caught; and 4) the career evader, who always evades. Delbosc and Currie (2016b) refined their previous segments by cluster analysis and merged fare evaders into just three segments: deliberate, unintentional, and never-evaders. Similar outcomes were obtained from Salis et al. (2017), who identified 1) the chronic, 2) the calculated risk, and 3) the accidental fare evader, by using an intercept survey of 850 fare evaders in Italy. González et al. (2019) categorised passengers into two main segments—paying or non-paying—according to their observed behaviour by using a sample of 457 bus travellers in Santiago (Chile). For the non-paying passengers, radical, strategic, ambivalent, and accidental evaders were discovered, for the paying passengers, proud, empathetic, and circumstantial evaders were observed.

Finally, Currie and Delbosc (2017) showed that honesty and permissiveness towards evasion were common key determinants in explaining intentional and unintentional evasion. Conversely, ticket competence and perceived ease of evasion were specific key determinants in explaining unintentional and intentional evasion, respectively.

1.3. Gaps in the related literature

These studies have provided relevant contributions to the field of fare evasion. However, some gaps persist.

First, the results of a literature review showed that many studies are limited to a 'one-size-fits-all' model of fare evaders. Recently, these studies have evolved to specific post hoc segmentations. Thus, further research is desirable regarding the a priori segmentations (Barabino et al., 2020).

[1] According to Freilich and Newman (2017) '*Situational crime prevention (SCP) is a criminological perspective that calls for expanding the crime-reduction role well beyond the justice system. SCP sees criminal law in a more restrictive sense, as only part of the anticrime effort in governance. It calls for minutely analyzing specific crime types (or problems) to uncover the situational factors that facilitate their commission.*'

[2] This could also be viewed as 'profiling in US'.

Although the a priori approach might not explore other opportunities to identify further segments without using sophisticated algorithms, this approach helps provide more straightforward results for interpretation among practitioners. Nevertheless, these segmentations may group potential evaders who share the same characteristics and may result in tailoring personalised strategies.

Second, Currie and Delbosc (2017) detected key determinants related to attitudes and behaviours in explaining unintentional and intentional fare evasion, by using post hoc segmentation. Thus, they disregarded the a priori segmentation of students, workers, and unemployed passengers, who may have presented different characteristics.

Third, Barabino and Salis (n.d.) investigated the intention to evade fares for demographic segments of passengers a priori selected but not for students, workers, and unemployed passengers.

Fourth, Perrotta (2016) and Sterner and Sheng (2013) have analysed, a priori, low-income passengers and students, respectively, and provided insights into the economic reasons and social stigma associated with fare evasion. However, they did not evaluate the effect of sociodemographic, travel behaviour and situational factors on the intention to evade fares.

1.4. Objective of this study

These gaps resulted in the following research question: What are the sociodemographic, travel behaviour, and situational factors that affect the intention of students, workers, and unemployed passengers to evade fares?

To answer to this question, we used a two-step approach. First, we used the 'Employment' variable to segment a priori students, workers, and unemployed passengers, and second, we estimated the intention to evade fares for each segment; in doing so, 4404 interviews were collected among public transport passengers in Cagliari (Italy) and then processed through logistic regression models.

1.5. Implications for theory and practice

This paper is expected to contribute to theory and practice.

From a theoretical perspective, the modelling of students, workers, and unemployed passengers can refine models and methods addressing topics such as (1) the optimal choice among ticketing systems in public transport (e.g. Sasaki, 2014), (2) setting the number of fare inspectors (e.g. Barabino et al., 2013, 2014; Barabino and Salis, 2019), and (3) scheduling inspectors along routes (e.g. Borndörfer et al., 2012; Correa et al., 2017; Yin et al., 2012). For instance, in the third field, much more research is necessary on segmenting passengers along routes. This research would help refine the optimisation models, usually based on the 'one-size-fits-all' demand model (Barabino et al., 2020).

On the practical side, recognising and differentiating among these segments on specific routes may help PTC managers tailor strategies accordingly. For instance, if a route is almost exclusively used by students staying on board for a few stops, inspectors can enforce inspections by remaining on board for a longer time. In addition, this segmentation may be useful in the marketing of transport services by addressing education campaigns for demographic segments. In our opinion, to be effective against fare evaders, these campaigns should emphasise the motivations behind why it is crucial to pay the fare when using public transport.

1.6. Paper outline

The remainder of this paper is organised as follows: Section 2 reports the methods and data used to profile students, workers, and unemployed passengers, who are the most likely to evade fares; Section 3 presents the results; Section 4 discusses the results in the context of the literature and provides an overview of policy recommendations for these segments; and Section 5 presents our conclusions and recommends for further research.

2. Methodology and data

We used the same dataset as Barabino and Salis (n.d.); however, we aimed to investigate different demographic segments of passengers within the same methodological framework.

2.1. Research context

This study was conducted in the metropolitan area of Cagliari, Island of Sardinia (Italy). This area has 0.4 million inhabitants distributed among several municipalities and represents the highest demographic density on the island; in addition, it represents the island's central commercial and administrative hub, attracting thousands of commuters daily. The bus system, used by approximately 16% of the residents, is managed by CTM, has 271 vehicles (i.e. buses and trolleybuses), and provides approximately 38.9 million journeys per year on 32 routes (CTM, 2018). The *proof-of-payment* ticketing system is provided by magnetic and contactless tickets. Buses have ticket validators at entrances and exits, and drivers are not responsible for this task. Cagliari has one fare zone and fares are established by the regional government and mainly include ordinary tickets and passes. The price of an ordinary ticket is €1.30 for 90 min.

Conversely, passes allow an unlimited number of trips in the considered time interval (e.g. 1 month, 1 year). The price of an ordinary monthly pass is €34.50. Therefore, the fare policy adopted in Cagliari aims to retain regular passengers rather than occasional passengers: Approximately 70% of passengers buy passes. The fine for fare evasion ranges from €24 to €72: The lower bound represents the amount reduced by two-thirds if paid within 60 days after notification (CTM, 2017). This *modus operandi* may represent a favoured condition for individuals who intend to evade fares.

2.2. Survey method

For this study, the on-board intercept survey of Barabino and Salis (n.d.) was adopted. It was preferred over other surveying techniques (e.g. mail, telephone, web) because of the possibility to cover all the routes of interest, the higher response rates, and the ability to collect the information from the surveyed sample experiencing the service (TCRP Synthesis 63, 2005; TCRP, 2017). The relative complexity of the survey results in the opportunity to adopt a paper-and-pencil interview (compared with a self-administered one) to boost the accuracy and quality of the answers provided. An argument could be that individuals are more likely to lie in an interview than in a self-administered survey for some questions (e.g. admitting the intention to evade the fare). However, surveys conducted among passengers in Cagliari have suggested a high likelihood that a self-administered survey could have resulted in the misinterpretation of some questions and low response rates (Barabino et al., 2012). In addition, a paper-and-pencil interview is more convenient for passengers because they do not have to write.

A preliminary survey was developed based on the literature published up to 2015 (e.g. Abrate et al., 2008; Eddy, 2010; Barabino et al., 2015; Bucciol et al., 2013). Next, after a pre-test and pilot test, the final questionnaire contained four main sections: general, sociodemographic, trip-related, and situational attributes. Finally, unlike most other studies of the revealed (or self-reported) fare evasion, this study aimed to analyse the intention to evade fares (stated fare evasion). This research field is less explored but useful on a strategic level, especially if the PTC aims to remove or reduce fare inspectors. In this regard, the variable explaining the intention of evade fares was evaluated by 'If no checks are performed, would you buy a ticket?' Some passengers might cheat in their answers. However, recent economic studies have noted that individuals could experience a psychological disutility, which prevents them from misreporting because of, for example, intrinsic lying costs, honesty, and conditional cooperation (e.g. Abeler et al., 2014; Traxler, 2010).

Sixteen qualified interviewers were recruited from an ISO 9001:2015-accredited recruitment agency to administer the survey and instructed on

Table 1

Response variable	Abbreviation	Description	%
Intention to evade fares	EV_SP = 1	Stated probability of being a fare evader: the passenger would not buy the ticket without ticket inspection activities	*29.81%*
	EV_SP = 0	*Stated probability of not being a fare evader: the passenger would buy the ticket without ticket inspection activities*	70.19%
Explanatory variables	**Abbreviation**	**Description**	
Socio-demographic characteristics			
Gender	Gen_F	Female	60.61%
	Gen_M	*Male*	*39.39%*
Age	Above_50	Above 50 years old	16.60%
	26_50	Between 26 and 50 years old	33.26%
	Under_26	*Under 26 years old*	*50.14%*
Educational qualification	Upper_sc	Upper school graduated	56.38%
	Middle_sc	Middle school graduated	40.52%
	Middle_sc_n	*Middle school not graduated*	*3.10%*
	Stud	Student	41.99%
	Work	Worker	29.85%
Employment	*Unemp*	*Unemployed*	*28.16%*
	Car_y	Has a car	30.05%
Car availability	*Car_n*	*Does not have a car*	*69.95%*
Reason for use bus	Other_use_bus	Use of the bus for other reasons (not related to the lack of trip alternatives)	36.05%
	No_alter_use_bus	*Use of the bus because there are no alternatives*	*63.95%*
Travel behaviour characteristics			
	Syst_trips_y	Systematic trips for work or study	48.30%
	Syst_trips_n	*Non- systematic trips (for purposes other than work or study)*	*51.70%*
	Leis_trips_y	Leisure trips for shopping, sport, amusement, *etc.*	22.50%
Trip purpose	*Leis_trips_n*	*Non-leisure trips (for purposes other than shopping, sport, amusement)*	*77.50%*
	Rush_hour_y	Rush hours trips (7.00-9.00 and 13.00-14.00)	17.05%
Time of the day	*Rush_hour_n*	*Non-rush hour trips*	*82.95%*
	In_vehicle_time_more_15	Travel time more than 15 minutes	70.60%
In-vehicle time	*In_vehicle_time_less_15*	*Travel time less than 15 minutes*	*29.40%*
	Other_transit_y	Use of other transit systems	33.42%
Other transit systems use	*Other_transit_n*	*No use of other transit systems*	*66.58%*
	Freq_traveler_y	The user travels more than 3 days a week	75.67%
Bus use frequency	*Freq_traveler_n*	*The user travels less than 3 days a week*	*24.33%*
	Daily_trips_over_2	*Number of daily trips over 2*	33.11%
	Daily_trips_under_2	Number of daily trips under 2	*66.89%*
	Satisf_y	Satisfied user (grade on the overall service larger or equal to sufficient)	96.02%
Quality rating	*Satisf_n*	*Non-satisfied user (grade on the overall service less than sufficient)*	*3.98%*
Personal knowledge of fare evasion			
	Know_fine_y	The user knows the amount of the fine	73.70%
Amount of the fine	*Know_fine_n*	*The user does not know the amount of the fine*	*26.30%*
	Fine_past_y	The user has already been fined in the past	36.18%
Fines in the past	*Fine past_n*	*The user has not been fined in the past*	*63.82%*

how to conduct the interview during classroom lessons to stimulate the voluntary participation of passengers. Next, according to a statistical route-based plan, interviewers administered the survey to a sample of randomly approached passengers travelling along routes of the overall network. The interviews were administered for 8 weeks, from 0700 AM to 0700 PM in March and July of 2015 and 2016, respectively. We collected 4404 questionnaires (75% response rate), without using incentives. Completed surveys were entered into a database created in Tanagra.[3] Table 1[4] presents the variables and provides the self-explanatory, descriptive statistics. For modelling, the response variable is binary: It takes value 1 if the passenger does not buy the ticket, and 0 otherwise. Except for the variables of 'Age' and 'Educational Qualification,' which are categorical, the remaining explanatory variables are coded as binary for ease. The dummy variables (in italics in Table 1) are used as a base case to compare the outcomes of models.

2.3. Data analysis

Two main steps were adopted for data analysis: the preliminary evaluation of segments and the application of inferential analysis on those segments.

The first step avoids overlapping segments. This analysis was performed as follows. First, a Kruskal–Wallis test was applied to the variable EV_SP to determine that at least one segment is from a different population than the others (i.e. alternative hypothesis). Second, a pairwise comparison was performed among segments to ensure that they differ significantly from the others, by comparing the difference between the rank means with a calculated value according to the sample size and a fixed significant level. Segments are assumed to be different if the previous difference is larger than the calculated value. Third, to foster the evaluation, the confidence interval (CI) was calculated for the mean and the variance of EV_SP of each segment. Segments are assumed to be different if CIs do not overlap.

The second step isolated crucial determinants of the intention to evade fares by inferential models for each segment. A binomial logistic regression model was used both because of the binary nature of the dependent variable and for the ease of reading the results. Indeed, the results may be interpreted by using the odds ratio (OR), which returns the number of successes (to evade the fare) against each failure (to not evade the fare) and can be easily calculated by taking the exponent of the parameter estimated. In this paper, when OR > 1 (< 1), an increase (decrease) in the odds of the

[3] Tanagra is a free data mining software for academic and research purposes. It proposes several data mining methods from exploratory data analysis, statistical learning, machine learning, and databases' area. The main purpose of Tanagra is to give researchers and students an easy-to-use data mining software, conforming to the present norms of the software development in this domain, and allowing to the analysis of either real or synthetic data. More information is available at http://eric.univ-lyon2.fr/~ricco/tanagra/en/tanagra.html

[4] The same dataset was adopted in Barabino and Salis (n.d.).

Table 2
References, variables, and statistics to evaluate the differences between segments.

Reference variables and segments	Sample size segments	Rank sum	Rank mean
Employment			
'Stud'	1856	4,570,594.0	2462.60
'Work'	1311	2,537,014.5	1935.17
'Unemp'	1237	2,592,201.5	2095.55

Segment Employment – KW = 144.37 – KW (with corr. tiers) = 229.88, p value < 0.0001.

Table 3
Multiple comparisons between segments.

Segment A	Segment B	Difference between rank mean	Comparison value
Employment			
'Stud'	'Work'	527.43	109.81
'Work'	'Unemp'	160.38	120.65
'Unemp'	'Stud'	367.05	111.72

Table 4
Overlapping analysis.

Variable and segments	Mean	Variance	95%-confidence interval for mean	95%-confidence interval for variance
Employment				
'Stud'	0.417	0.243	0.394–0.439	0.221–0.266
'Work'	0.177	0.145	0.156–0.197	0.125–0.166
'Unemp'	0.250	0.187	0.226–0.274	0.163–0.211

intention to evade fares is observed. The sign of parameters is also important. A negative sign implies a reduction in the likelihood of the intention to evade fares for each increase in the corresponding explanatory variable and vice versa.

For each segment, the maximum likelihood procedure estimates a logistic regression with all the candidate variables (full model). Next, some procedures may be applied to the careful selection of variables to obtain an improved and reduced model. Forward selection and backward selection were considered to search for significant variables for these segments to achieve a balance between reduced complexity and a good model.

In this paper, the deviance ratio (*d.r.)*, the ratio between the regression deviance and degree of freedom, and the check of the statistical significance provide goodness-of-fit statistics for each model. In addition, the sign and the significance of the coefficient and the OR are evaluated for each model.

3. Results

The findings for Students ('Stud'), Workers ('Work'), and Unemployed Passengers ('Unemp') are briefly presented.

3.1. Segment analysis

In this section, the segments were proved to be different and not overlapping. Computed with and without correction tiers, the outcomes of the Kruskal–Wallis test clearly showed that the intention to evade the fare is different for at least one segment at a 5% significance level (Table 2).

The second test provided further evidence that segments are statistically different: The absolute value of the difference between the rank means is higher than the comparison value (Table 3).

In addition, 95% of CIs for means and variances demonstrated that segments do not overlap within the reference variables (e.g. segments of students do not overlap with workers), whereas a very negligible overlap is observed among variances between the segment of 'Work' and 'Unemp' (Table 4). According to these results, separate logistic models can be applied to each segment.

3.2. Logistic regression analysis

3.2.1. Overall model fit

Table 5 reports the values and signs of the coefficients (i.e. *Estimate*) and the OR, which quantify the influence of each significant determinant on the intention to evade fares for each segment. These results were obtained by backward selection,[5] which provided better fits than the forward selection.

Each segment is inside quotes (e.g. 'Stud'), the entries of significant specific variables are in bold, and a dash indicates the reference variable excluded from the explanatory variables for that segment. Furthermore, for the sake of ease, the inverse of OR is discussed when it is lower than 1. Finally, the last part of Table 5 reports the statistical fit of each segment.

Overall, all models fit the data quite well. Indeed, a large *d.r.* coupled with a small *p value* indicates a 'good' goodness-of-fit of the logistic model: the χ^2 is consistently <0.001, showing a good fit of the data for each model and strong evidence of a regression effect (i.e. not all the coefficients are zero). The best model is 'Unemp' because it is characterised by the highest *d.r.* By contrast, 'Stud' is the worst model. According to Barabino and Salis (n.d.), owning a car, travelling at peak time and being a frequent traveller do not influence the intention to evade fares for any segment. Conversely, unlike Barabino and Salis (n.d.), travelling for systematic reasons or for leisure, using a variety of transit systems, and quality satisfaction do not influence this intention either. A possible reason for this contrast is the correlation among similar variables in the same category. For instance, Freq_traveler_y is correlated with Daily_trips_over_2. Thus, a frequent traveller probably makes more than two trips per day. Conversely, for Rush_hour_y*,* no variable is related to the same category, even if passengers will probably travel systematically during rush hours; thus, a possible correlation with other variables in other categories could result. Moreover, Car_y is correlated with Other_use_bus because car owners will probably travel by bus for reasons other than no travel alternatives. In addition, the insignificance of related trip-purpose variables may be justified as follows: The trip purpose may be assumed to be implicitly included in the segments. For instance, students and workers may be assumed to travel systematically, and the assumption for the unemployed would be leisure.

Gender, Age, and Past_Fine_y variables are always significant and influence the intention to evade fares for each segment, even if to a different extent. For instance, all models showed that male students, male workers, and/or unemployed males are more likely to evade fares than females are: This intention is stronger in the 'Unemp' model being 1.751 (= 1/0.571) times than in the 'Work' model being 1.545 (= 1/0.647) times, and the 'Student' model being 1.309 (= 1/0.764) times, respectively. Moreover, passengers younger than 26 years old are more likely to be oriented towards evading fares than older passengers, and this intention is stronger in the 'Student' model than in the 'Unemp' and the 'Work' models, respectively. In addition, the effect of Past_Fine_y on the intention to evade fares is strongest for the segment of unemployed passengers and confirms previous findings, even when different segments were investigated (Barabino and Salis, n.d.).

3.2.2. Effect of Sociodemographic, travel behaviour, and situational determinants on students

The 'Stud' model explains the intention to evade fares by seven variables. Moreover, it presents significant variables in all the categories related to sociodemographic, travel behaviour, and situational determinants.

According to the sociodemographic determinants, the intention to evade fares could be explained as follows. For instance, for a male student, the findings indicate that he is 1.309 (= 1/0.764) times more likely to be oriented towards evading fares than a female student is. Moreover, being

[5] This procedure allows us to eliminate all unnecessary variables from the full regression to achieve a balance between reduced complexity and an adequate goodness-of-fit of the model.

Table 5
Logistic model results estimating the intention to evade fares by employment.

Variable	Employment					
	'Stud'		'Work'		'Unemp'	
	Estimate	*OR*	*Estimate*	*OR*	*Estimate*	*OR*
Constant	−0.211		−0.904		−1.217	
Gen_F	−0.269*	0.764	−0.435*	0.647	−0.560**	0.571
Age						
Above_50			−2.995**	0.050	−1.405**	0.245
26_50	−0.503*	0.605	−1.204**	0.300	−0.513*	0.598
Educational qualification						
Upper_sc	**−0.417****	**0.659**				
Middle_sc			**0.748****	**2.112**		
Employment						
Work	–	–	–	–	–	–
Stud	–	–	–	–	–	–
Unemp	–	–	–	–	–	–
Car_y						
Other_use_bus	−0.500**	0.607			−0.553*	0.575
Trip purpose						
Syst_trips_y						
Leis_trips_n						
Rush_hour_y						
In_vehicle_time_more_15	**−0.289***	**0.749**				
Other_transit_y						
Bus use frequency						
Freq_traveler_y						
Daily_trips_over_2	**0.318***	**1.374**				
Satisf_y						
Know_fine_y					**0.771****	**2.162**
Past_fine_y	1.063**	2.896	1.027**	2.791	1.352**	3.864

Segment 1 – Stud: d.r. = 31.557, $\chi 2 < 0.001$ Segment 2 –Work: d.r. = 43.783, $\chi 2 < 0.001$ Segment 3 – Unemp: d.r. = 56.100, $\chi 2 < 0.001$
* p value < 0.001.
** $0.001 < p$ value < 0.01.

aged between 26 and 50 years results in a student being 1.652 (1/0.605) times more likely to be honest, compared with a student who is younger than that. This latter result might be explained as follows: Students younger than 26 years old are systematic travellers and might have good knowledge of the criticalities of ticket inspection; thus, they may think they will evade detection while travelling without a ticket. The educational qualification affects the intention to evade fares, because students with a high school diploma are less likely to be fare evaders by 1.517 (=1/0.659) times compared with students without a high school diploma. The variable Other_use_bus showed that choice students are more likely not to evade the fare by 1.647 (=1/0.607) times compared with captive students.

According to the travel determinants, the variables In-vehicle_time_more_15 and Daily_trips_over_2 affect the intention to evade fares only for students: Travelling for more than 15 min reduces the intention to evade fares by 1.335 (= 1/0.749) times compared with the opposite case; conversely, making more than two trips per day increases the intention to evade fares by 1.374 times compared with those who make fewer than two trips.

Finally, according to situational factors, the Past_fine_y variable showed that students who have been fined are 2.896 times more likely to evade fares than in the opposite case.

3.2.3. Effect of sociodemographic, travel behaviour, and situational determinants on workers

The 'Work' model explains the intention to evade fares by five variables, four of which are related to the sociodemographic category. More precisely, results showed that a female worker will probably be 1.543 (=1/0.647) times more honest than a man. The variables Age and Educational Qualification are more relevant than gender in explaining the intention to evade fares for workers.

As age increases, the intention to evade fares decreases. Indeed, the results showed that a worker between 26 and 50 years old is less likely to evade the fare by 3.333 times (1/0.300) compared with a younger passenger aged under 26 years. This intention is more evident if a worker is aged older than 50 years: 20 (= 1/0.050) times.

Regarding education, only a middle school diploma increases the intention to evade fares by 2.112 times. According to this result, improving the educational level may increase the intention to evade fares. However, the nonsignificance of higher education does not allow the generalisation of this result.

Finally, Past_fine_y is the only significant variable affecting the intention to evade fares related to the situational category.

3.2.4. Effect of sociodemographic, travel behaviour, and situational determinants on unemployed passengers

The 'Unemp' model presents six significant variables that explain the intention to evade fares and includes all the variables related to the situational category.

Gender, Age, and Other_use_bus affect the intention to evade fares for this segment. More precisely, an unemployed female is less likely to evade the fare by 1.7513 (1/0.571) times more than an unemployed male. As for the segment 'Work', as Age increases, the intention to evade fares decreases. For instance, an unemployed middle-aged (i.e. aged 26–50 years) passenger is less likely to evade the fare by 1.672 (1/0.598) times than a younger passenger aged under 26 years. This intention is approximately 2.5 times stronger in the case of passengers older than 50. Other_use_bus affects the intention to evade fares for this segment as follows: choice unemployed passengers are 1.739 times (=1/0.575) more likely to be honest than captive passengers, as expected. This intention is stronger than that explained by the 'Stud' model.

According to the travel behaviour category, no determinants were significant.

Finally, according to situational determinants, knowing the amount of the fine and having been fined increases the intention to evade fares by 2.162 and 3.864, respectively, compared with the opposite cases: although the latter result might seem bizarre, the policy of discounted fines may support it (Section 2.1).

Table 6
Comparison with the literature on key determinants of the fare evader.

Variable type	Segments of our study	Abrate et al., 2008	Barabino and Salis (n.d.)	Barabino et al., 2015	Bucciol et al., 2013	Currie and Delbosc, 2017	Dai et al., 2017	Cools et al., 2018	Delbosc and Currie, 2016b	Eddy, 2010	González et al., 2019
Gender	1,2,3	+	+	+	+			+		+	
Age	1,2,3	+	+	+	+			+	+	−	
Fines in the past	1,2,3		+	+	*n.s.*		−				
Educational qualification	1,2		+,-	+,-	*n.s.*				−		
Other use bus	1,3		+		−						
In_ vehicle_time_more15	1		+	+	+		+				
Bus use frequency-Daily_trips_over_2	1		+	+	−				+		
Fine amount knowledge	3		+	+	+						
Bus use frequency-Frequent Traveller	*n.s*		*n.s.*	−	−				−		
Quality rating	*n.s.*		−	−	−	*n.s.*			−		−
Trip purpose – Systematic trips	*n.s.*		*n.s.*	*n.s.*	*n.s.*						
Trip purpose – Leisure trips	*n.s.*		*n.s.*	*n.s.*	*n.s.*						
Time of day	*n.s.*	*n.s.*	*n.s.*	*n.s.*	*n.s.*						
Car availability	*n.s.*		*n.s.*	*n.s.*							
Other transit systems use	*n.s.*		−	*n.s.*							

• + According to authors' findings 1 = Stud; 2 = Work; 3 = Unemp
• - Contrasting to authors' findings
• *n.s.* Variable not significant for authors

4. Discussion

4.1. Comparison with past research

All segments show the intention towards fare evasion, even if with specificity. Table 6 compares the key determinants isolated in this study and those of the literature.[6] Moreover, Table 6 shows that the findings from the literature are largely confirmed; however, some differences exist and are discussed in this section.

First, **younger passengers** are more likely to evade fares than older passengers. Unlike Eddy (2010), we conclude that older individuals are more compliant with laws and perhaps more apprehensive of being caught without a ticket, revealing a more relevant social stigma. Moreover, a different method of data collection could explain this difference.

Second**, having a history of fare evasion** significantly influences the intention to evade fares. This result contrasts that of Dai et al. (2017), who compared individuals who had just been fined in the field and other fare dodgers. However, our result confirms that individuals who have been fined attempt to recover their loss (i.e. fine), because they continue to have the intention to evade fares. In addition, our result shows that some individuals who declared the intention to evade fares may be immune to the actions to curb fare evasion and are thus more likely to continuously evade the fare (Barabino et al., 2020; Delbosc and Currie, 2016a; Salis et al., 2017).

Third, middle school-educated **workers** are oriented towards evading fares; conversely, high school-educated students are not as oriented towards this intention. This result is partially in accordance with Barabino et al. (2015) and Barabino and Salis (n.d.): In this study, we detect an opposite trend in the case of the worker-passenger segment that had a middle school diploma. However, this might be a low-income segment because of the lower education level, resulting in a higher intention to evade fares. Thus, even if the income was not directly investigated in our study, we might consider the recent research showing that the increase in fare evasion is also because of a low income (Guarda et al., 2016a; Schwerdtfeger, 2016 and Perrotta, 2016). Conversely, Delbosc and Currie (2016b) showed that the deliberate fare evader is more likely to have a degree. However, this difference may partially depend on the adopted survey method, which is web-based as opposed to our intercept survey. Indeed, web surveys are confined to passengers who have internet access and might not include low-income users or recent immigrants, who represent a relevant group of passengers in many countries. More research is necessary to confirm this hypothesis.

Fourth, **students and unemployed captive passengers** are more likely to evade fares than choice passengers. This result differs from Bucciol et al. (2013): Choice passengers could probably use the bus in special situations (i.e. car breakdown). Thus, they ignore where and when a frequent inspection occurs, which are keys factors in fare evasion. Therefore, these passengers would accept paying the ticket and travel in a more relaxed state because they would have the ticket if they were asked by inspectors. Usually, fare evaders are more 'careful' than honest passengers regarding inspection activities (e.g. Salis et al., 2017).

Fifth, **travelling a lot during the day** affects the intention to evade the fare only for students. Unlike Bucciol et al. (2013), our result is reasonable, because passengers who make many trips learn when and where they are likely to be caught and can emulate others who evade the fare. Furthermore, according to Garrett et al. (2016), several passengers may experience a psychological utility to evade the fare over time, and with a high frequency, they may be insensible to evading fares. Conversely, being a frequent traveller does not affect the probability of the intention to evade fares for any segment. Moreover, this outcome differs from Barabino et al. (2015) and Delbosc and Currie (2016b), who showed that passengers using buses frequently are most prone to evade fares, and from Bucciol et al. (2013), who showed an opposite trend. Therefore, a more in-depth investigation of Freq_traveler_y and its effect on the intention to evade fares is necessary.

[6] This comparison is a bit forced because1) it considers all variables for the three segments, even if the literature considered only the variables that affect the choice of evading without distinguishing among demographic segments; Barabino and Salis (under review) investigated different demographics segments; 2) it considers variables concerning the intention to evade fares as opposed to the literature in which the variables concern the observed, measured, and revealed fare evasion. Moreover, this comparison 3) shows variables in decreasing order according to the number of demographic segments in which the variable is significant and 4) reports the most comparable studies alphabetically ordered, even if for some of them just one variable could be compared.

The remaining variables do not influence the intention to evade fares for any segment, even if the influence of the quality rating produced mixed results. Being satisfied with the transit system has a negative effect on the intention to evade fares in Barabino et al. (2015), Delbosc and Currie (2016b), and Barabino and Salis (n.d.)—only in the case of the female segment—and González et al. (2019) for radical and strategic groups of evaders, respectively. Conversely, perceiving a low-quality bus service seems to be a deterrent against fare evasion (Bucciol et al., 2013). Finally, using other transit systems seems to be a significant determinant of the intention to evade fares only for the segment of elderly individuals (Barabino and Salis, n.d.). Further research is required to confirm these contradictory effects.

4.2. Policy recommendations

This segmentation disclosed stimulating situations for setting suitable strategies. Moreover, strategies addressing a specific segment can positively impact other segments. For the three segments, two types of strategies are suggested: preventive and corrective, which include the related sub-strategies in Table 7.

Preventive strategies aim to induce changes in a passenger's behaviour by reducing his/her intention to evade fares and the level of social acceptance towards such behaviour. These changes may be pursued by introducing high-level actions into the design of the fare structure and enforcement. The analysis disclosed that **all segments** might have a specific intention to evade the fare if they are aged under 26 years and captive riders (apart from the workers' segment). This might suggest economic or social disadvantages, because younger and captive passengers may be perceived as having an insufficient income. Therefore, introducing an income and/or age-based fare for these segments may be a successful strategy to prevent the intention to evade fares. In addition, the opportunity to implement transit loyalty programmes may be particularly effective for the segment of **students.** Indeed, these programmes aim to establish a relationship between passengers and the company to trigger an additional incentive to pay for the service. Thus, they can reward paying passengers by offering superior services and offer additional benefits for those who make multi-ride trips a day. For instance, these programmes could track the number of trips a registered student makes and offer reward points that accrue towards prizes, retail discounts, or savings on future trips.

Specific enforcement actions are also recommended. For instance, the opportunity to increase the amount of the fine is suggested for the **unemployed segments**. Indeed, the current amount of the fine seems to be perceived as low. In addition, punishing evaders with a tangible penalty may push them to comply with the law. For instance, **all segments** that have been fined are more likely to evade fares. This finding may suggest that these individuals appear unaffected by the certainty of being fined because the current penalty fare system is unable to prevent future attitudes towards evading fares. These passengers usually do not pay for bus tickets and do not appear deterred by tougher actions, because most of them might have an extensive rap sheet and be 'criminals'. Moreover, they might make no effort to escape detection because they do not incur losses. Moreover, there are groups of 'artful' evaders who are clever and well informed of the mazes in the system and '*have become experienced, in that no harm will come if they simply keep quiet*' (Bijleveld, 2007). Therefore, the adoption of a fast-judicial procedure for this violation and an increase in the fine or penalty in case of reiteration of the evader's behaviour could prove to be a high-level strategy if the legislative framework can be changed.

Unlike preventive strategies, **corrective strategies** aim to immediately punish fare evaders. Nevertheless, corrective actions contain an element of a preventive nature because their application should help discourage recidivism in the behaviour of punished individuals. Notably, these strategies seem to fit better in the segments of **students** rather than the remaining segments. Indeed, **students** are more likely to evade the fare if they travel for less than 15 min. In this case, scheduling and targeting the on-board inspection might limit the intention to evade fares. This objective may be pursued by 1) allocating inspectors to critical routes and periods in which many passengers are students, 2) keeping inspectors on board for a time sufficient to discourage student fare evasion, and 3) investing in conductors along critical routes (regardless of the expense). Moreover, these actions will be significantly benefitted by inspectors with the authority to take legal action against evaders. This power may be pursued through the development or outsourcing of a training and certification process for inspectors to have the authority to request proof of identity. According to Torres-Montoya (2014) and practical experience, this strategy may also be useful when this request is performed only on passengers caught in the act of evading fares.

Table 7
Proposed strategies for the three segments.

Strategy types	Sub-strategy	'Stud'	'Work'	'Unemp'
Preventive	Introduce an age-based fare	•	•	•
	Introduce an income-based fare	•		•
	Set loyalty programmes	•		
	Increase the fine			•
	Increase repeat offender fine or penalty	•	•	•
	Introduce a fast-track justice procedure for repeat offenders	•	•	•
Corrective	Schedule and target inspections in terms of quantity and quality	•		
	Allow qualified inspectors to perform an identity check	•		
	Use conductors if necessary	•		

5. Conclusions and research perspectives

Over the past decade, much research on fare evasion has been performed from the transit perspective. However, less attention has been devoted to the passenger perspective to understand determinants, attitudes, reasons, and behaviours useful to profile 'a one-size-fits-all' model or discover post hoc segments of fare evaders. Only one study investigated a priori segments of males, females, young, middle-aged, and old passengers. Conversely, no study explored a priori segments of students, workers, and unemployed passengers to discover the influence of key sociodemographic, travel behaviour and situational factors on the intention to evade fares and whether they vary among these segments. To that end, this paper filled this gap.

The results show that only gender, age, and having been fined affect the intention to evade fares for each segment. Conversely, some specific variables are isolated. This research is not very large in scale compared with the population who uses public transport daily in our context. In addition, the implementation of the results might depend on the country and legal setting for fare inspections; thus, further studies are recommended. However, this study is sufficiently large to contribute to the research evidence base on this topic, because we provide a more explicit indication of key determinants on the intention of students, workers, and unemployed passengers to evade fares.

The findings can also be applied to similar contexts with comparable elements, for example, a transit system (e.g. number of routes and their frequencies), carried passengers, fare structure, and level of fines. Conversely, the research methodology is straightforward and has general validity. Thus, we provide new input data on the studied system, and this methodology can be applied to any urban context in the case of *proof-of-payment* ticketing schemes.

To conclude, this study is an additional step in the authors' research agenda and raises a relevant topic for further research from the passenger's perspective. Segmenting passengers according to travel behaviour characteristics may reveal new insights into the intention to evade fares. Moreover, although segmentation is illegal in some countries (Harris, 1999), it is a relevant topic because of the many studies on deception (e.g. Dreber and Johannesson, 2008). In the field of fare evasion, profiling is poorly developed and should be addressed within the legal framework of geographic contexts where PTCs operate. Finally, the moral acceptability of passenger profiling to guide inspection strategies results in a challenge on ethical concerns regarding that practice (Barabino et al., 2020; Delbosc and Currie, 2019). Therefore, PTCs should ensure that their inspection strategies are equitable and do not profile or target some individuals over others. Further research must be conducted to evaluate how to conduct equitable profiling.

CRediT authorship contribution statement

Category 1

Conception and design of study: B. Barabino, S. Salis;

Acquisition of data: B. Barabino, S. Salis;

Analysis and/or interpretation of data: B. Barabino, S. Salis.

Category 2

Drafting the manuscript: B. Barabino, S. Salis;

Revising the manuscript critically for important intellectual content: B. Barabino, S. Salis.

Category 3

Approval of the version of the manuscript to be published (the names of all authors must be listed):

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