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Predicting satisfaction of railways users: the role of perceived evolution of the service and on-board activities.

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Key words: railways, public transportation, satisfaction, quality of service, on-board activities, machine learning, multitasking

JEL classification : L91, L92, L32, M31

Abstract

This study investigates the determinants of user satisfaction in railways by using both machine learning techniques and econometric models. In particular it assesses the impact of service quality attributes and the ability to conduct on-board activities on overall satisfaction. The analysis is based on data from a large-scale satisfaction survey with 4,286 respondents, administered by the French Court of Auditors and designed by academics. The results indicate that (1) users prioritize service performance over price, (2) perceived changes in service quality significantly affect satisfaction. Also, the ability to conduct activities (3), as well as the reasons for being unable to do so (4), influence satisfaction levels. This study is the first of its kind in France and contributes to a deeper understanding of railway user satisfaction.

1 Introduction

Transportation significantly impacts the environment and contributes to negative externalities such as congestion, accidents, and pollution in urban areas. Public transportation often faces stiff competition from cars, leading to a rapid decline in rail use during the 20th century (Brons et al., 2009). However, in recent years, there has been a growing interest in promoting public transport as a viable alternative due to its potential to reduce the environmental footprint. Fulton et al. (2014) found that carbon emissions could be reduced by 40% by 2050 with a significant increase in public transportation, walking, and bicycling. In France, according to the National Institute of Statistics and Economic Studies, only 16% of daily trips are made by public transport, while 74% are made by car. This share drops below 5% in suburban and rural areas. Rail-based transport is a viable solution, particularly in urban and interurban areas, as it presents a credible alternative to car travel. Increasing the use of public transportation, specifically rail-based systems, depends on understanding the determinants of user satisfaction (Eboli and Mazzulla, 2015; Allen et al., 2019 [a]; Chou et al., 2014; Cantwell et al., 2009; Aydin, 2017; Sañudo et al., 2019).

This paper aims to investigate one primary question: (1) What drives user satisfaction in railway transportation services? (1.2) how the ability to conduct activities during rail travel also impacts satisfaction? The question (1) is a common focus in satisfaction-related studies. The objective is to ascertain which quality attributes are most highly valued by users of railway services, for example, punctuality, price, cleanliness and so forth. This investigation of users' preferences has prompted some authors to examine heterogeneity among them (de Oña et al., 2015; Choi et al., 2021; Eboli et al., 2016; Grisé and El-Generidy, 2018; Dell'Olio, 2011; Monsuur et al., 2023). Such heterogeneity is frequently attributed to personal characteristics (gender, age, revenues etc.). While not directly addressed in this study, the personal characteristics-based heterogeneity can be completed by an unobserved heterogeneity (Monsuur et al., 2023). The unobserved heterogeneity leads to sub-question 1.2: To what extent does the ability to engage in activities such as reading or working influence overall satisfaction? Specifically, the capacity to perform activities while traveling may significantly contribute to variations in satisfaction levels. Although this ability is not a service quality attribute, it is complementary to understanding satisfaction. Ettema et al. (2012) demonstrated that the ability to engage in activities positively impacts satisfaction. Shaw et al. (2019) found that multitasking increases the likelihood of receiving benefits but also raises the probability of cognitive disadvantages. Additionally, Malokin et al. (2019) showed that the likelihood of conducting on-board activities affects modal choice, suggesting that public transit modes can increase ridership by catering to the productivity preferences and behaviours of commuters. Similar findings were reported by Choi et al. (2021). Lyons et al. (2016) observed that multitasking in railways has increased with the advent of digital alternatives, resulting in a larger proportion of passengers perceiving their travel time as worthwhile. For Frei et al. (2015), value of time is affected by multitasking and conducting activities should be recognized as productive. However, Axtel et al. (2008), demonstrated the strong impact of contextual factors on multitasking.

The data used for this paper come from a satisfaction survey administrated by the French Court of Auditors. The Court conducted a public policy evaluation of the strategy and quality of service of the Auvergne-Rhône-Alpes region's railways. In order to measure the user satisfaction, the Court sent an email to 27,000 users which resulted in 4,286 fully exploitable answers.

The method is based on a two-step analysis using two different models. First, we used a Random Forest model to identify the variables that most significantly contribute to satisfaction. Random forests, which are non-parametric tree-based algorithms, are particularly useful for survey analysis. Many authors have used such algorithms, in particular Classification and Regression Trees (CART) (Ona et al., 2015; Machado-Leóna et al., 2017; Vincente et al., 2020). If a single tree can be considered as a CART, an ensemble of CARTs is a random forest. Following the random forest analysis, an ordered logit regression was performed to assess the effect of activities, crowdedness and available space on overall satisfaction. Ruiz et al. (2024) used the combination of these two algorithms to predict the satisfaction of bus users. Machine learning techniques, especially random forests, are considered the most effective for analysing and predicting bus passenger satisfaction. However, the interest of the multivariate ordered logit regression is to perform a *ceteris paribus* analysis in order to measure the impact of one variable when the others are held constant.

Consistent with previous findings, our study reveals that users value service performance (regularity, punctuality, frequency) more than price (Machado-Leóna et al., 2017; de Ona et al., 2015; Brons et al., 2009; Shen et al., 2016; Gris  and El-Geneidy, 2018; Monsuur et al., 2023; Allen et al., 2020; Eboli and Mazzulla, 2015). Users primarily seek a reliable service, which is significant in the context of free transportation debates. Interestingly, one of the most important variables affecting satisfaction in Random Forests is the perceived evolution of the service (i.e., the answer to the question "Has the service a. improved, b. deteriorated, c. remained unchanged?")¹. This suggests that negative experiences with the service can impact long-term satisfaction, a finding supported by Gijzenberg et al. (2015) and the prospect theory (Kanheman and Tversky, 1979). Additionally, the ability to conduct activities during the trip, and the reasons for not doing so, impact satisfaction.

This paper is organized as follows. In section 2, we review the literature, both quantitatively and qualitatively, to assess what users value most and the main findings regarding railway user satisfaction in different countries and contexts. Section 3 presents our original database on railways users' satisfaction in the Auvergne-Rh ne-Alpes Region. Section 4 describes the methodology of our two-stage analysis based on machine learning techniques — random forests — and ordered logistic regression. We discuss our results in section 5 and provide policy recommendations in Section 6.

2 Literature review

The literature review proceeds to quantitatively analyse the findings of previous papers literature review to assess what quality attributes are valued by users. A two stages literature review was followed. The subsection 2.1 identifies the most relevant papers. The subsection 2.2 uncovers what service quality attributes items are more often asked in surveys, and which users value the most.

¹ The questions in the survey are discussed in depth in section 3.

2.1 Paper selection

We employed stringent criteria to select relevant papers for our systematic review. Studies needed to:

1. **Examine user satisfaction** : analyse how passengers perceive different attributes of service quality.
2. **Focus on railways**: exclusively examine railway systems or include them in a broader analysis of transport systems.

This selection resulted in 23 papers that were perfectly aligned with our research goals and provide valuable support for the validity of our findings. Table 1 summarizes these studies.

Table 1: Papers used for the quantitative systematic literature review

Author	Year of publication	Title	Model
Allen et al.	2020	Effect of critical incidents on public transport satisfaction and loyalty: an Ordinal Probit SEM-MIMIC approach	SEM
Andreassen	1995	(Dis)satisfaction with public services: the case of public transportation	SEM
Aydin	2017	A fuzzy-based multi-dimensional and multi-period service quality evaluation outline for rail transit systems	Fuzzy
Brons and Rietveld	2009	Improving the Quality of the Door-to-Door Rail Journey: A Customer-Oriented Approach	PCA
Brons et al.	2009	Access to railway stations and its potential in increasing rail use	Regression
Cavana et al.	2007	Developing zones of tolerance for managing passenger rail service quality	SERVQUAL
Chou et al.	2011	Deploying effective service strategy in the operations stage of high-speed rail	SEM
de Oña et al.	2015	Heterogeneity in Perceptions of Service Quality among Groups of Railway Passengers	CART
de Oña et al.	2014	Key factors affecting rail service quality in the northern Italy: a decision tree approach	CART
Eboli and Mazzulla	2021	Assessing Perceptions of Railway Service Quality: A Compendium of Literature Studies	SEM & CART
Eboli and Mazzulla	2015	Relationships between rail passengers' satisfaction and service quality: a framework for identifying key service factors	SEM
Eboli and Mazzulla	2012	Structural equation modelling for analysing passengers' perceptions about railway services	SEM
Grisé and El-Geneidy	2018	Where is the happy transit rider? Evaluating satisfaction with regional rail service using a spatial segmentation approach	PCA - K-means
Machado-Leóna et al.	2017	Railway transit services in Algiers: priority improvement actions based on users' perceptions	CART

Miranda et al.	2018	Perceived service quality and customer satisfaction: A fuzzy set QCA approach in the railway sector	SERVQUAL
Monsuur et al.	2023	Investigating the role of preference variation in the perceptions of railway passengers in Great Britain	Regression
Mouwen	2015	Drivers of customer satisfaction with public transport services	Regression
Mouwen and Rietveld	2013	Does competitive tendering improve customer satisfaction with public transport? A case study for the Netherlands	Regression
Nathanail	2008	Measuring the quality of service for passengers on the Hellenic railways	Multicriteria
Sanudo et al.	2019	Addressing the Importance of Service Attributes in Railways	Regression
Shen et al.	2016	Passenger satisfaction evaluation model for Urban rail transit: A structural equation modeling based on partial least squares	SEM
Tyrinopoulos and Antoniou	2008	Public transit user satisfaction: Variability and policy implications	Regression
Vicente et al.	2020	Index of satisfaction with public transport: a fuzzy clustering approach	CART

Source: authors

Regression, structural equation modeling, and regression trees (CART) are the most commonly employed models. The prevalence of these tools likely stems from the interdisciplinary nature of satisfaction questions, which intersect the fields of economics and marketing.

2.2 Analysis process of the papers

This study adopted a comprehensive list of service quality attributes. Given the extensive nature of such lists, we have synthesized a concise and relevant set of attributes specific to our case study. To systematically analyse the attributes across the selected papers, we counted the number of times each attribute was mentioned. We grouped the attributes into different "family attributes," representing clusters of conceptually related attributes. A comprehensive list of family attributes can be found in Appendix 1.

Table 2: Mentioned attributes by category

Family attribute	Mentioned attribute
Service	120
Rolling stock attributes	88
Staff	81
Station attributes	80
On-board information	47
On-board safety - security	45
Cleanliness (rolling stocks)	35
Information at the station	30
Safety - security at the station	22
Other attributes	20
Cleanliness (station)	17

Source: authors

As shown in table 2, service quality attributes related to family “Service” are often asked. This family regroups attributes like punctuality, regularity, frequency and price. These attributes are used to estimate the perception of the service performance. Attributes related to stations are also often asked. This is not the case in our survey.

Table 3 delves deeper into the relative importance of service attributes from a user perspective. The first column ("First 10 items") indicates the frequency of an attribute's mention across the reviewed papers. Attributes like frequency, personal safety, punctuality, information, and price-quality fairness emerge as the most frequently mentioned. The second column ("Top 10 items in terms of importance") captures the number of times an attribute ranked within the top 5 most important factors based on user responses. Finally, the third column ("Ratio importance / mentioned") presents a ratio between the number of times an attribute appears in the top 5 and its total mentions. This ratio helps mitigate potential bias arising from attributes that are infrequently mentioned but highly impactful when addressed in surveys.

Table 3: Attribute importance

First 10 items in terms of mention in papers	First 10 items in terms of importance	Ratio importance / mentioned
Frequency	Punctuality	Regularity
Personal safety	Regularity	Punctuality
Punctuality	Frequency	Seat cleanliness
Information (station)	Information (station)	Crowding
On-board information	Crowding	Frequency
Personnal safety (station)	Seat comfort	Seat comfort
Quality-price ratio	Quality-price ratio	On-board space
Sympathy and competency	On-board information	Toilet cleanliness
Travel safe	On-board comfort	Substitute service
On-board comfort	Train cleanliness	Speed travel

Source: authors

Our analysis reveals service attributes, such as punctuality, regularity, and frequency, as the most frequently mentioned across the reviewed papers. This prominence is unsurprising, considering their consistent inclusion in railway passenger satisfaction surveys. Similarly, rolling stock attributes like comfort, temperature, and crowding are well-represented, reflecting their prevalence in passenger surveys. Likewise, attributes concerning staff competency, complaint handling, station facilities, and information provision frequently appear in these studies.

Our findings demonstrate that service performance attributes, encompassing punctuality, regularity, and frequency, are both frequently mentioned and highly valued by railway passengers. Crowding is another important aspect of the service according to passengers. Price is a service quality attribute often asked but not considered as important as service performance or crowding. Meaning that users are more attached to a reliable service than a cheap one.

These results resonate with the hierarchy of transit needs proposed by Allen et al. (2019 [b]) for bus and metro users in South American cities. Their research identified a Maslow based pyramid structure, prioritizing reliability (closely aligned with our service performance attributes) at the base, followed by safety, customer service, and lastly, comfort. While Allen et al. (2019 [b]) focused on different transportation modes, the observed alignment suggests a potentially hierarchy of needs applicable to railway passengers as well. Further research is needed to explore the generalizability of this framework across diverse contexts.

2.3 The effects of multitasking on satisfaction

There is a growing body of literature exploring the role of multitasking on satisfaction (Choi et al., 2021). Ettema et al. (2012) found that in-vehicle activities impact commuters' satisfaction, as does the nature of the commute itself. Lyons et al. (2016) discovered that activities involving digital technologies are associated with a better travel experience. However, the positive relationship between satisfaction and activities using digital tools is moderated by crowdedness. Frei et al. (2015) assert that service valuation is closely related to multitasking, emphasizing that the value of time while traveling should be recognized, given its productive use. Van Hagen et al. (2017) identified that the type of activities, whether useful or pleasant, affects satisfaction, with pleasant activities having a stronger impact. Choi et al. (2021) argue that using travel time productively positively influences commuters' satisfaction. Malokin et al. (2019) demonstrated that engaging in on-board activities affects both the utility and mode choice of transport. Shaw et al. (2019), using the same data, found that on-board activities enhance the benefits of travel but are also linked to cognitive disadvantages, such as unsafe distractions or fragmented attention. Krueger et al. (2019) highlighted that socio-demographic characteristics contribute to heterogeneity in time-use preferences. Axtell et al. (2008) found that mobile work on trains is hindered by a lack of reliable communication networks, limited access to co-workers, and insufficient privacy.

These studies collectively indicate that on-board multitasking impacts the utility of travel, with the extent of this impact varying according to user profiles. However, a deeper analysis is needed to understand why certain multitasking activities are not possible. There may be differences in users' appreciation of the inability to engage in productive activities, whether based on individual preferences (e.g., a reluctance to work on a train) or service-related factors (e.g., overcrowded trains).

2.4 Limitations of previous researches

Previous researches are flourish and give good insights about what users value in railways transportation. Although, this field is rich, we did not find any French case on regional railways satisfaction. To our knowledge, this paper represents the first French analysis. Secondly, for this paper we can rely on a unique source of data, since it comes from a large-scale satisfaction survey of 4,286 answers. In addition, this survey wasn't administrated by the public transport

authority or the operator and was designed by academics. Previous researches on multitasking are also flourishing. If the role of conducting activities on satisfaction is assessed, the reasons of not being able to conduct activities on satisfaction need more studies.

3 Survey

3.1 Design of the survey

The Court of Auditors conducted a public policy evaluation in the Region Auvergne Rhone Alpes, regional public transport authority (PTA). The purpose of this assessment was to reveal the links between quality of service and the PTA's strategy. The Court aimed to directly interview users and administrated its own survey. The purpose of this survey was to measure the satisfaction of railways users related to service performance and rolling stocks (space, comfort etc.). On behalf of the Court, the survey was designed by the authors with the support of two academics specialized in the field of satisfaction in railways².

The user survey comprised five sections (details in Appendix 2). The first section captured user profiles through questions on travel habits and subscription types.

The second section focused on service quality attributes, where users rated both their importance and their satisfaction with them (De Oña et al., 2015). Participants were also asked about the perceived evolution of service quality with the question, "Have you noticed evolutions in the service since you started using the TER?" The possible responses were: "I haven't noticed any improvements", "I noticed a deterioration", "I noticed a strong deterioration", "I noticed improvements", "I noticed great improvements" and "I don't know."

The third section explored users' ability to perform desired activities during their journey, along with reasons for any limitations. Participants were prompted to rate the feasibility of engaging in various activities while traveling (possible unique answers were: I can easily do this activity; I can do this activity but it's difficult; I would like to do this activity but I can't due to travel conditions; I don't want to do this activity). The proposed activities included working with a laptop, working with a cell phone, personal activities on a laptop, personal activities with a cell phone, reading a book, magazine, or engaging in playful activities such as crosswords, applying makeup, sleeping, resting or watching the scenery, and listening to music.

The fourth section employed images to facilitate user evaluation of train crowding density (Haywood et al., 2017). Finally, the fifth section collected respondents' socio-economic characteristics like income, gender, and age, which we do not consider in this study.

3.2 Survey administration

² Laura Eboli and Gabriella Mazzulla, University of Calabria, Italy.

The data source was a database provided by the railway operator, containing email addresses of 150,000 subscribers and discount card holders. Subscribers accounted for approximately 70% of total trips. In September 2023, the Court, not the Public Transport Authority (PTA) or the SNCF (French National Railway Company), emailed 27,000 randomly selected users to participate in the survey. A total of 6,200 responses were received, with 4,286 deemed usable for analysis. Notably, September 2023, based on the operator's open data, exhibited better performance than average regarding delayed and cancelled trains.

3.3 Data

For inclusion in the final database, respondents had to answer the overall satisfaction question, provide information on gender, age, and socio-professional category, and successfully complete at least 85% of the questionnaire. Subsequently, a statistical adjustment was implemented post hoc, taking into account age, gender, and socio-professional category. Participants were allowed to skip questions that did not apply to them. As a result, some data points were missing, with 2396 individuals (55%) responded to all 23 satisfaction questions. It's important to note that answers indicating "not concerned" were treated as missing values. Table 4 shows the descriptive statistics of our sample.

Table 4: Descriptive statistics of the sample characteristics

Characteristics	Total	Characteristics	Total	Characteristics	Total	Characteristics	Total
Gender		Professionnal condition		Frequency of use		Duration of use	
Male	42%	Full-time worker	51%	At least 4 time a week	48%	More than 3 years	40%
Female	56%	Part-time worker	7%	2-3 time a week	26%	1 to 3 years	40%
Other	2%	Student	32%	1 time a week	10%	6 m to 1 year	13%
Age		Unemployed	4%	Less than 1 time a week	17%	Less than 6 m	6%
Less than 18	9%		6%			Departure station	
18-26	33%	Retired		Day of trip		Lyon	12%
27-35	16%	Qualification		Weekdays	90%	Other	88%
36-45	16%	Master degree	34%	Week-end	29%	Arrival station	
46-59	17%	Bachelor degree	25%	Time of the trip (go)		Lyon	45%
60-	9%	Other higher education	19%	On-peak hour	51%	Other	55%
<i>Mean</i>	39	Upper secondary school	11%	Off-peak hour	49%	Trip purpose	
		Lower secondary school	5%	Time of the trip (return)		Work	54%
		No degree	2%	On-peak hour	52%	Studies	27%
		Don't want to answer	4%	Off-peak hour	48%	Leasure	12%
						Other	7%

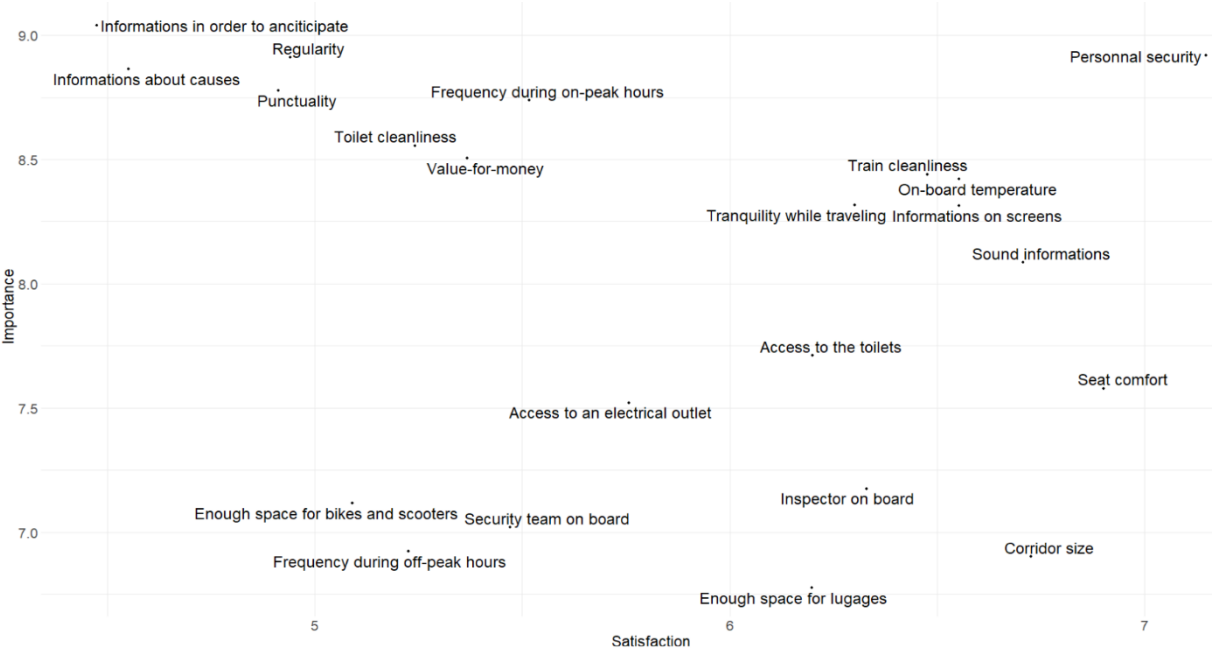
Our sample primarily consists of commuters traveling for work or study purposes, with the majority traveling to Lyon for their outbound journey. Notably, 48% of the sample travels at least four times per week, while 42% report working from home. This indicates that many railway service customers belong to professions that require less frequent travel due to remote work capabilities. According to SNCF data³, the total number of trip - kilometers traveled

³ https://www.laregionvoustransporte.fr/sites/aura_transport/files/2023-05/COTECH%20VDRN%20TRAME%20FINALISEE.pdf

increased by 14% between 2019 and 2022. However, the frequency of trips by subscribers decreased by 2%, whereas occasional users increased their usage by 33%. These trends suggest a shift in the customer base.

In our survey, users were asked to rate their satisfaction with and the importance of various aspects of the service on a 1 to 10 Likert scale. Figure 1 presents the average importance and average satisfaction as reported by users. Attributes in the top-left quadrant are considered important but unsatisfactory; those in the top-right quadrant are both important and satisfactory; attributes in the bottom-right quadrant are not important but satisfactory; and those in the bottom-left quadrant are neither important nor satisfactory. To ensure accurate descriptive statistics, post-stratification (marginal calibration) was applied, adjusting for gender, socio-professional category, and age.

Figure 1: Average satisfaction and importance by service quality attributes according passengers



Source: authors

Attributes related to performance and information are regarded as the most important yet least satisfying by users. In contrast, attributes concerning security and comfort (such as temperature, cleanliness, and tranquillity) are considered both important and satisfying. This declared hierarchy closely aligns with the findings of de Oña et al. (2015), where attributes related to security, performance, and cleanliness were identified as the most important.

Allen et al. (2020), in their study on the effects of critical incidents, provide crucial insights for our methodological approach. Typically, customer satisfaction surveys employ a Likert-type scale ranging from 1 (very dissatisfied) to 10 (very satisfied). However, ordinal scales present significant limitations: a rating of 4 does not necessarily represent twice the satisfaction of a

rating of 2, and the difference between ratings such as 1 and 2 is not equivalent to the difference between 4 and 5. This non-linearity can introduce bias into numerical analyses. Despite the inherent ordinality of survey responses and the potential biases affecting reproducibility (e.g., variations in scales used by different individuals), an effective strategy is to aggregate multiple items for each latent construct, thereby enhancing measurement accuracy and mitigating bias. To avoid bias and align with the operator's standard analytical practices, we recoded the Likert scale according to the Net Promoter Score (Reichheld, 2004) metrics. Satisfaction scores from 1 to 6 were classified as "poor," scores from 7 to 8 as "fair," and scores from 9 to 10 as "good." In our sample, 63% (2,702 respondents) fell into the "poor" category, 32% (1,385 respondents) into the "fair" category, and 5% (197 respondents) into the "good" category.

4 Method

We conducted a two-step analysis utilizing a Random Forest algorithm and an ordered logit regression to identify the effects of service attributes on overall satisfaction. The objectives of this analysis were to determine what users value the most and to assess the impact of multitasking on satisfaction.

Both models aim to predict satisfaction, categorized as "poor," "fair," or "good." This classification is based on explanatory variables such as service quality attributes and other service indicators (e.g., ability to conduct activities, crowdedness, and standing frequency). The rationale for employing these two distinct models lies in their interpretability and the use of different explanatory variables for each model.

4.1 Random Forests

Random Forest models are extensions of Classification and Regression Trees (CART) models, which have been extensively utilized in the analysis of transport surveys (De Oña et al., 2015; Eboli and Mazzulla in Mitra et al., 2021; De Oña et al., 2014; Machado-León et al., 2017; Vicente et al., 2020). The rationale behind their widespread use includes several factors: CART models yield easily interpretable outputs and provide insights into the importance of independent variables in predicting outcomes. Moreover, CART models are nonparametric, making them particularly effective in handling multicollinearity, which is advantageous in satisfaction surveys where scores for attributes like punctuality and frequency may be correlated.

Random Forests, introduced by Breiman (2001), enhance predictive performance by aggregating multiple decision trees, each constructed from a random sample of the dataset. This method mitigates the risk of overfitting, a common limitation of individual decision trees. Formally, Random Forests are algorithms based on decision trees to predict a variable. Considering a variable to predict Y , and a vector of variables $X = (X_1, \dots, X_i)$, the object of the regression is to estimate the function $f(x) = \mathbb{E}[Y|X = x]$ with Y the overall satisfaction and X the service quality attributes. Data are recursively split based on a feature that maximizes the purity of each child node. This purity is measured by the Gini Index:

$$G = \sum_{i=1}^K p(i) \times (1-p(i)), \quad (1)$$

where K is the total number of classes, and $p(i)$ is the probability of an instance being classified into class i . The Gini Index measures variance, and higher variance indicates more misclassification. To reduce variance and improve model accuracy, a bootstrap aggregating (bagging) method is used. From the original data D_1 , a new dataset D_2 of the same size n is created by randomly sampling with replacement from D_1 . Bootstrap samples are then aggregated by majority voting in classification problems.

One of the key outputs of a Random Forests model is feature importance, which indicates the significance of each variable in predicting the model's outcome (Molnar, 2022). Mean Decrease Gini measures how each variable contributes to the homogeneity within the decision trees. To assess the importance of a feature X_m for predicting Y , impurity decreases ΔG are summed up and averaged over all trees N_T in the forest (Breiman, 2001; Louppe et al., 2013):

$$\text{Imp}(X_m) = \frac{1}{N_T} \sum_T \sum_{t \in T: v(S_t) = X_m} p(t) \Delta G(t), \quad (2)$$

where $p(t)$ is the proportion of samples reaching node t and $v(S_t)$ is the variable used in split S_t .

Higher Mean Decrease Gini scores signify that a feature is the most common one when it comes to split the data. In simpler terms, the most important features reduce the impurity of all trees, so increase the prediction.

4.2 Ordered logit regression

The nature of the data determined the regression model used to analyse the links between overall satisfaction and the various indicators of service quality i.e. ability to conduct activities, crowdedness, and standing up frequency. Ordered logit regression measures the effect of individual variables relative to others, making it suitable for mutually exclusive responses such as reasons for not performing activities and perceptions of crowdedness.

Given that our dependent variable (overall satisfaction) is categorical with three modalities (poor, fair, good) and is naturally ordered, we opted for an ordered logistic regression:

$$\text{satisfaction}_i = \begin{cases} 0 & \text{if } s_i^* < \mu_1 \text{ (poor satisfaction)} \\ 1 & \text{if } \mu_1 \leq s_i^* < \mu_2 \text{ (fair satisfaction)}, \\ 2 & \text{if } s_i^* \geq \mu_2 \text{ (good satisfaction)} \end{cases} \quad (3)$$

with $s_i^* = X_i \beta + u_i$,

where satisfaction_i is the overall satisfaction level of the individual i , s_i^* is the latent variable associated with the satisfaction variable, X_i is the matrix of covariates that contains the indicators of service quality, β the associated parameters to be estimated, and μ the threshold

parameters for which $\mu_1 < \mu_2$. u_i is a random term *iid* distributed by the standard logistic distribution.

The coefficients associated with the covariates were estimated by maximizing the standard following likelihood:

$$L(\beta|X_i) = \prod_{i=1}^N \prod_{j=0}^2 \left[\frac{\exp(\mu_{j+1} - X_i\beta)}{1 + \exp(\mu_{j+1} - X_i\beta)} - \frac{\exp(\mu_j - X_i\beta)}{1 + \exp(\mu_j - X_i\beta)} \right]^{y_{ij}}, \quad (4)$$

where μ_0 is defined as $-\infty$ and μ_3 as $+\infty$, and y_{ij} is a binary variable, equals to 1 if $satisfaction_i=j$ and 0 otherwise.

To quantify the own effect of each covariate, we referred to the average marginal effects. Table 5 shows those calculated for the probability of having a good level of overall satisfaction ($\Pr(satisfaction=2)$).

5 Results

In the context of Random Forests, our objective is to assess the importance of various service quality attributes, perceived crowdedness, perceived evolution of the service, and the ability to conduct activities on overall satisfaction. While crowdedness, perceived evolution, and the ability to conduct activities are not inherent attributes of the service, nor are they personal characteristics that can be used to split the data in the traditional manner, their impact on satisfaction and interactions with other variables make their inclusion in the model highly pertinent.

The ordered logit regression is used to assess the particular effect of perceived crowdedness and reasons of not being able to conduct activities on satisfaction. The three most important service quality attributes derived by the random forests were included in the model in order to avoid omission bias.

This two-step has been done using R software.⁴

5.1 Results from the Random Forests

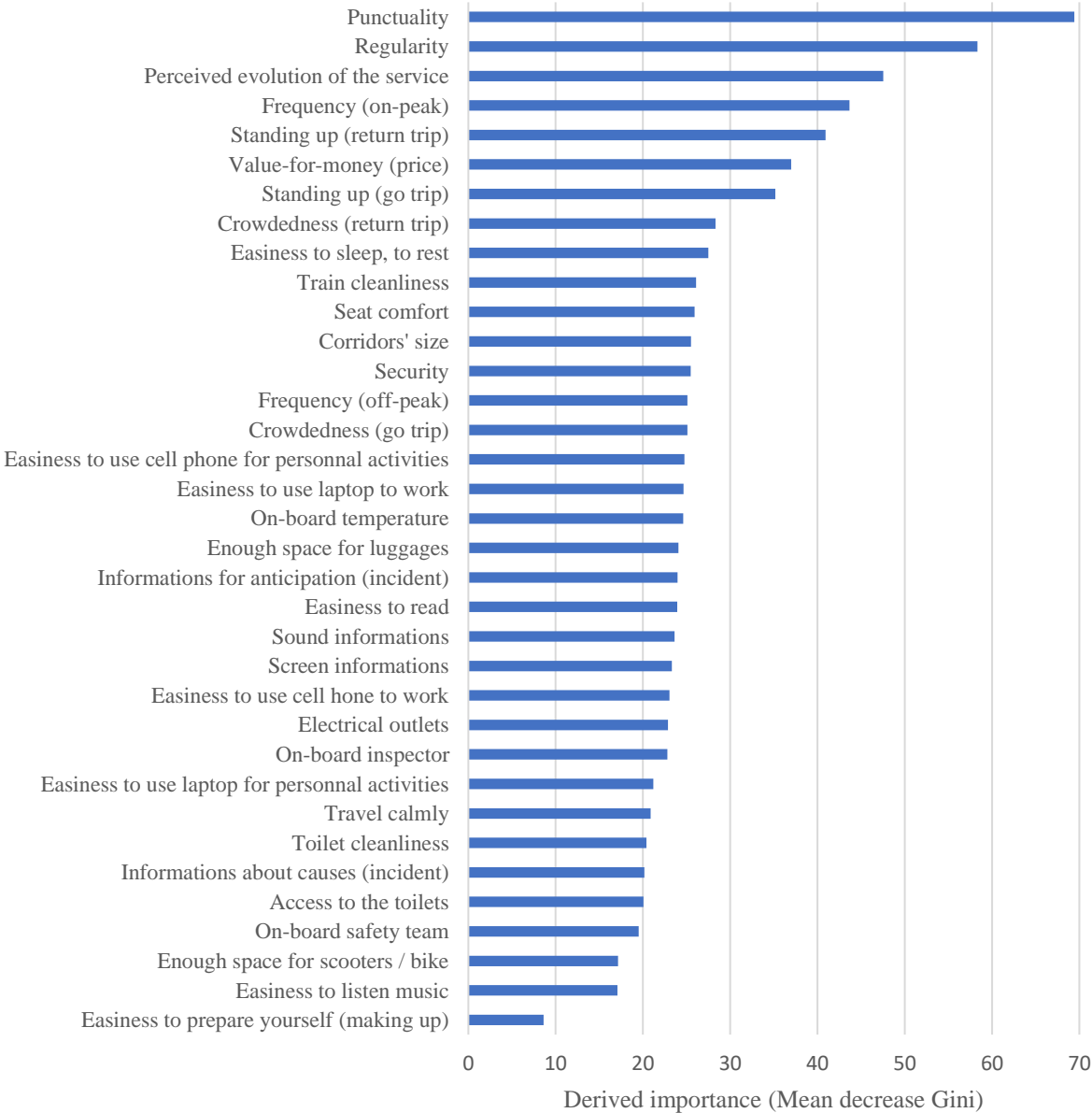
Figure 2 presents the output of the Random Forests model, illustrating the importance of each variable. Variables that significantly reduce impurity are deemed more critical in predicting overall satisfaction. The Random Forests model identified punctuality, regularity, frequency during peak hours, and perceived evolution of the service as the most influential features. These findings align closely with user-declared importance ratings from the survey, with the notable exception of security, which ranked 13th in importance within the model. This discrepancy

⁴ These results were obtained using R software and the following libraries: "randomForest" for the Random Forests model (Liaw and Wiener, 2002), "hstats" for the calculation of the H-statistic (Mayer, 2024), "MASS" for the ordered logit regression (Venables and Ripley, 2002), and "erer" for the calculation of marginal effects (Sun, 2022).

mirrors the findings of de Oña et al. (2015), who observed that while users considered security important, it was not prioritized by the model.

Our “Out of Bag” estimate of error rate is set at 27% (i.e., in 73% of case, our algorithm predicted the output, bad, fair, good, correctly). The overall error rate on the test data (20% of the sample) is set to 30%.

Figure 2: Most impactful features on overall satisfaction derived by the Random Forests



5.1.1 Perceived evolution of the service has an impact on users' satisfaction

As observed in figure 2, our model identified perceived evolution of the service as one of the most important variables. This feature corresponds to the question: "Have you noticed evolutions in the service since you started using the TER?"

This finding suggests a potentially strong influence of perceived service evolution on overall satisfaction. However, the causal direction remains unclear: does current satisfaction influence the perception of service evolution, or vice versa?

To our knowledge, no study directly investigated the link between satisfaction and perceived evolution. Allen et al. (2020) however, found that added-value service, which perceived evolution is part of, contributes the most to overall satisfaction, followed by operator's performance.

Limited research in railway transportation directly mirrors this finding. However, Gijzenberg et al. (2015) analyzed time series data and observed that service quality declines have a greater impact on user perception, both in the short and long term, compared to service quality improvements. This aligns with the notion that perceived quality suffers more significantly from deterioration. This finding resonates with the work of Monsuur et al. (2021), in which they found that passenger satisfaction is influenced by "true" performance (delays, cancellations). Users who experienced strong delays (> 30 minutes) or cancellations increase heavily the probability of dissatisfaction. These studies and our finding could be interpreted as (1) a greater elasticity concerning performance losses than improvements in user satisfaction and (2) a strong persistence of performance losses on the satisfaction. In other words, users continue to be sensible to performance losses even after a long time. This finding aligns with Prospect Theory developed by Kahneman and Tversky (1979), which predicts that a loss in performance has a greater impact on satisfaction than a gain of the same scale. Smith and Bolton (1998) found the existence of a service recovery paradox, when a high recovery will maintain or increase satisfaction. However, the recovery is challenging since every customer must be satisfied with every service failure.

5.1.2 Users value service performance over price

Another finding is the importance of service quality attributes related to performance (punctuality, frequency and regularity) derived by users. It shows an attachment to an efficient service to rely on, as we saw in our literature review where punctuality, regularity and frequency were the most important items for users (table 3). These attributes, related to performance, are considered as "basic" by Eboli and Mazzulla (2008) in opposition with "non-basic" attributes.

Satisfaction with price comes after performance of the service features, showing less attention for price than performance. In France all companies have to refund half of public transport subscription paid by their employees since 2008. Any subscriber who is also employed in a company pays in reality half of the subscription price. Since it's km-based fees, it is not possible to define precisely the gain for subscribers. For a trip of 26km (Villefranche-sur-Saône – Lyon) the total cost per month is 84.90€ and 42.45€ for the user. The data used for the analysis come from subscribers' answers, who, by definition, pay less than other users. This could be an explanation of these results: commuters need an efficient service on which they can rely on to go to work. A lower price paid, since the employer pays the half, contributes also to limit the value for money importance.

5.1.3 Perceived frequency of standing up and on-board crowdedness impact satisfaction.

Participants were prompted to indicate the frequency of standing during both their outbound and return journeys, selecting from the following options: every trip, one trip out of two, one trip out of three, rarely, or never. The level of crowdedness was estimated using an image-based approach, following the methodology of Haywood et al. (2017). Both standing and crowdedness are critical factors that impact travel comfort, with higher levels of crowding resulting in more passengers standing rather than sitting. This can be particularly discomforting for passengers, given that over 57% of respondents reported travel times exceeding 30 minutes. According to the model, users seem to less value available space than performance. Several studies showed the effect of crowding on satisfaction, such as Cantwell et al. (2009), Haywood et al. (2017).

5.1.4 Possibility to easily conduct activities is another driver of satisfaction.

In the survey, participants were prompted to rate the feasibility of engaging in various activities while traveling (possible unique answers are in appendix 2). The proposed activities included working with a laptop, working with a cell phone, personal activities on a laptop, personal activities with a cell phone, reading a book, magazine, or engaging in playful activities such as crosswords, applying makeup, sleeping, resting or watching the scenery, and listening to music.

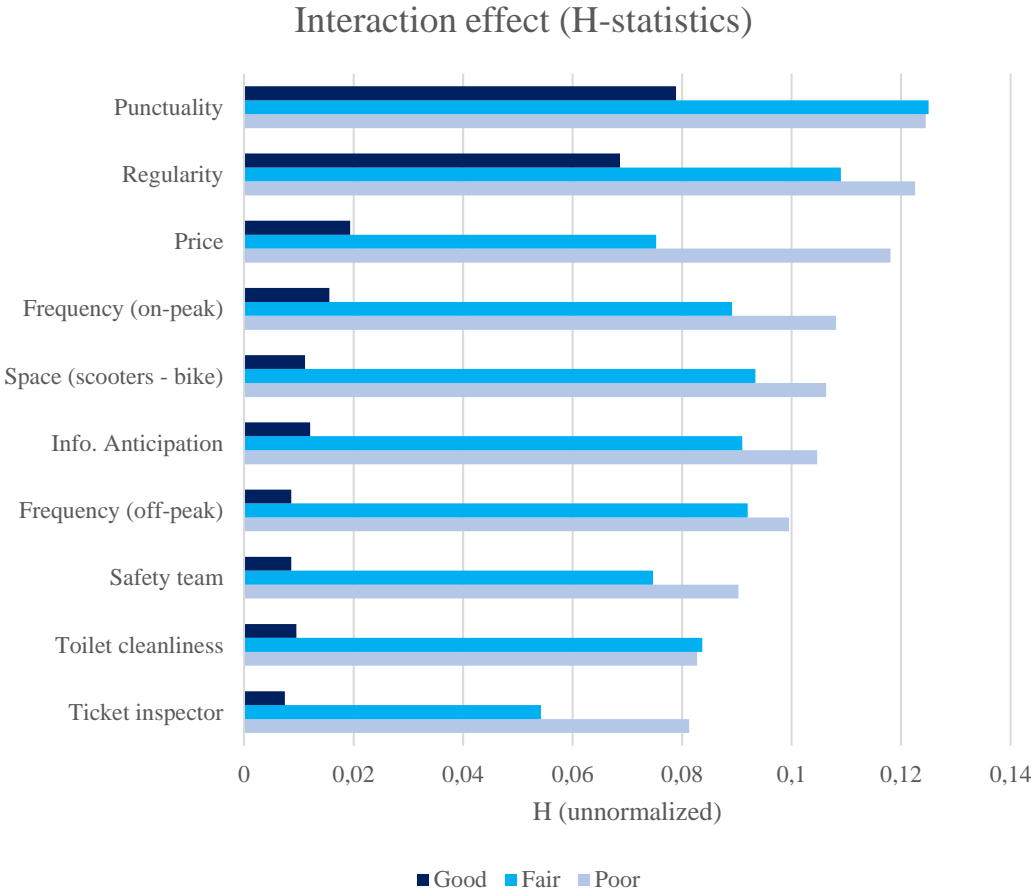
In terms of importance, the ease of sleeping or resting was ranked ninth, followed by the ease of using a cell phone for personal activities (16th position) and the ease of using a laptop for work (17th position). The feasibility of engaging in activities is considered another proxy for travel comfort, as overcrowded trains can make it difficult for passengers to conduct activities, potentially affecting their perceived waiting time and value of time. Ettema et al. (2012) found that in-vehicle activities affect users' satisfaction with public transport, while Molin et al. (2020) reported that conducting activities reduces commuters' value of time by 30%, aligning with our results. The frequency of standing up during travel is also significant and may be linked to the ability to conduct activities, as it is generally easier to do so while seated. The following section 5.2 is meant to dive deeper on the role of activities on users' satisfaction.

5.1.5 Interactions between variables

The Friedman's H statistic evaluates the interaction between features within a model (Friedman et Popescu, 2008; Molnar, 2022; Oh, 2019). This statistic increases as feature interactions become more pronounced. It represents the proportion of variance explained by interactions, making interpretation straightforward.

Considering the inherent interconnectedness of our variables (e.g., users prioritizing punctuality likely value regularity), Friedman's H appears suitable for our analysis. A value of 0 indicates no interaction, while 1 signifies that all variance is explained by the sum of partial dependence functions. H statistics is unnormalized in order to prevent overinterpretation, when the total effect of a features is weak but interacts a lot. It results in a reduction of spurious interactions identification (Inglis et al., 2021). Labels “Good”, “Fair”, “Poor”, represents the modalities taken by the dependent variable i.e. overall satisfaction. In other words, figure 3 shows the impact of features' interaction on overall satisfaction, depending on the modality.

Figure 3: Interaction effect using Friedman H statistic



The provided plot suggests a relatively strong interaction effect between features. The most impactful interactions on the “poor” outcome, are information about causes, punctuality, regularity, price and frequency. On the “good” outcome, punctuality, regularity and price are the most impactful variables. Considering the “fair” outcome, punctuality, regularity and information about causes are strong interaction variables.

Following the H-statistic, the strongest variability of the overall satisfaction can be attributed to the interaction of punctuality, following by regularity. Comparatively to other features, punctuality and regularity strongly interacts with other variables, especially when a user has a good opinion about the service.

We can also see that price feature interacts a lot with other variables when a user has a bad opinion about the service.

5.2 Identifying the key role of activities in users’ satisfaction

To gain a deeper understanding of the impact of the ability to conduct activities during trips, descriptive statistics to questions related to activities can be found in figure 4 and 5.

Figure 5: answers to question “In general, are you able to conduct these activities while traveling?”

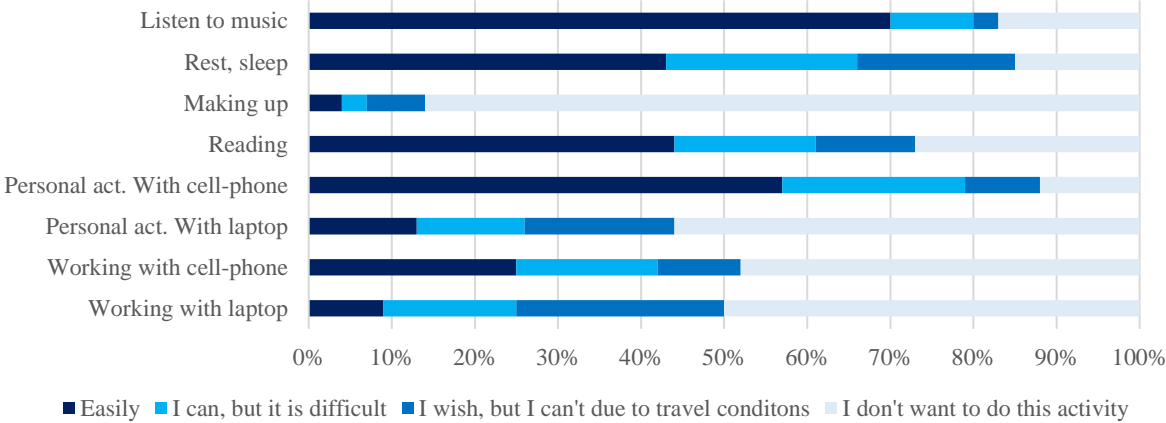
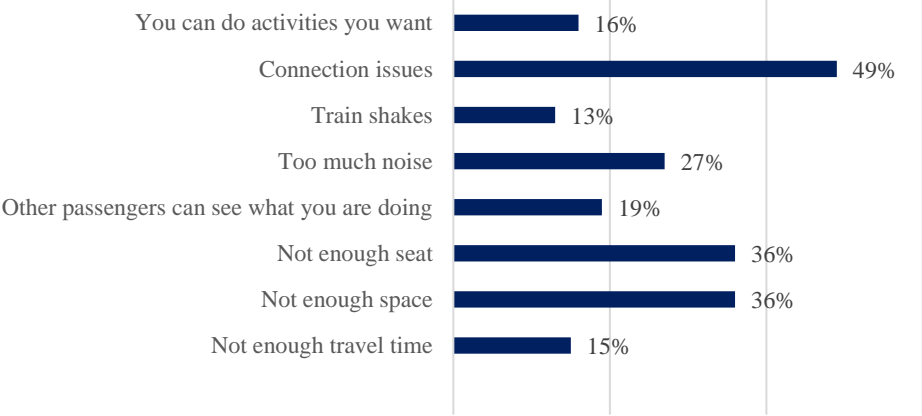


Figure 4: answers to question “What are the reasons for you to not conduct activities you'd like?”



Listening to music and personal activities on cell phones are considered the easiest tasks to conduct on trains. In contrast, activities such as applying makeup, working, and personal tasks on laptops are those users are most reluctant to perform. Notably, one in two users does not want to work on trains. However, the largest group of users impeded by travel conditions comprises those who wish to work on laptops. Specifically, 25% of users would like to work on their laptops but are unable to due to service constraints.

Regarding the reasons for not conducting activities, connection issues is the most important one, following by available space and noise. These findings aligning with Axtell et al. (2008), who found that contextual factors constrain work tasks. advocated for integrating the value of

conducting activities into the transit value of time, many of the impediments are contextual factors beyond users' control.

In addition to descriptive statistics, an ordered logit model was employed to examine the impact of the ease of conducting activities. The model also incorporated features related to space and comfort, such as the frequency of standing up and feelings of crowdedness. In order to avoid omission variable bias, the top 3 service quality attributes in the Random Forests model were added.

The results of the model are presented in table 5. According to the results, connection issues, noise, and shaky trains were found to be the most important features affecting overall satisfaction. In terms of available space, feelings of crowdedness during both go and return trips were found to have the most significant impact on satisfaction. Haywood et al. (2017) found similar results. Interestingly, the feature 'standing up one trip out of two' was found to have a greater impact on satisfaction than 'standing up always,' suggesting that passengers who are accustomed to standing may be more resigned to their situation. Finally, the results indicate that return trips have a stronger impact on overall satisfaction than go trips.

Table 5: Ordered logit output

<i>Dependent variable: overall satisfaction</i>					
Level of reference	Feature	Coef.	Std. Err.	P>z	Average marginal effect (good)
Poor	Punctuality (good)	1.43318	.1679642	0.000	.0886791
	Punctuality (fair)	.9934016	.0992142	0.000	.0460086
	Regularity (good)	1.066386	.1699067	0.000	.0606782
	Regularity (fair)	1.062672	.1014366	0.000	.0505901
	Frequency (good)	1.08215	.1362794	0.000	.0609933
	Frequency (fair)	.8337992	.086165	0.000	.0383984
Never	Standing-up (go trip - one trip out of three)	-.2396837	.1692513	0.157	ns
	Standing-up (go trip - one trip out of two)	-.428113	.2034393	0.035	-.0166937
	Standing-up (go trip - rarely)	-.2268203	.1098588	0.039	-.0098626
	Standing-up (go trip - always)	-.603615	.2614773	0.021	-.0220629
	Standing-up (return trip - one trip out of three)	-.3061594	.166563	0.066	-.0125083
	Standing-up (return trip - one trip out of two)	-.6030743	.1977382	0.002	-.0224196
	Standing-up (return trip - rarely)	-.2714385	.1174447	0.021	-.0119366
	Standing-up (return trip - always)	-.8756517	.2875171	0.002	-.0292168
Empty	Crowdedness (return trip - crowded)	-.1821776	.1126506	0.106	ns
	Crowdedness (return trip - overcrowded)	-.4605567	.1794206	0.010	-.0171207
	Crowdedness (go trip - crowded)	-.2579627	.0994909	0.010	-.0114408
	Crowdedness (go trip - overcrowded)	-.3324654	.1989569	0.095	-.0164721
I can easily do what I want	Can't conduct activity - not enough place (seat)	-.098212	.1190119	0.409	-.0041821
	Can't conduct activity - not enough space	-.3904295	.1438676	0.007	-.0167412
	Can't conduct activity - too much noise	-.2653809	.0999249	0.008	-.0110392
	Can't conduct activity - travel time too short	.2425446	.1053906	0.021	.01125
	Can't conduct activity - train shakes	-.4460806	.1431393	0.002	-.0173283
	Can't conduct activity - other passengers can see what you are doing	.0883252	.1124902	0.432	ns
	Can't conduct activity - connection issues	-.2959441	.0822996	0.000	-.0128173
Interaction effects					
	Crowdedness (go trip - overcrowded) * Can't conduct activity - not enough space	-.51591	.2427445	0.034	-.0309356
	Crowdedness (return trip - overcrowded) * Can't conduct activity - not enough space	.3022505	.2101447	0.150	ns
	Crowdedness (go trip - overcrowded) * Can't conduct activity - not enough space (seat)	-.028828	.2480832	0.907	ns
	Crowdedness (return trip - overcrowded) * Can't conduct activity - not enough space (seat)	-.1624	.2168329	0.454	ns

According to the regression outputs, high satisfaction with punctuality is associated with an increase in overall satisfaction by 9 points. Similarly, high satisfaction with regularity and frequency is associated with increases of 6 and 5 points, respectively. Conversely, consistently standing during both go and return trips results in decreases in satisfaction by 2 and 3 points, respectively, aligning with Monsuur et al. (2021) results. Crowdedness negatively impacts satisfaction for both trips, with a 2-point decrease when users perceive the train to be overcrowded.

Additionally, the inability to conduct activities due to specific reasons further decreases satisfaction: shaky trains lead to a 2-point decrease, insufficient space results in a 2-point decrease. Connection issues and noise cause a 1-point decrease, aligning with Axtell et al. (2008).

Only the interaction effect between over crowdedness during go trips and insufficient space to conduct activities was significant. This finding suggests a complex interplay between the purpose of the trip and passenger resignation; when space is limited, attempting to conduct activities becomes more futile. Lyons et al. (2016), found that multitasking affects positively travel time usage, but crowding limits the worthwhileness of time use in trains. Ettema et al. (2012) found similar results, although the effects varied depending on whether commuters were traveling to or from work. Their study posits that the trip's purpose influences the traveller's mindset, a hypothesis supported by our findings. Furthermore, the authors argue that engaging in activities alone is insufficient to create a positive travel experience.

6 Conclusion: the role of perceived evolution and on-board activities on users' satisfaction

This study employed a combined approach utilizing both Random Forests and logistic regression models to investigate passenger satisfaction in the railway industry. The findings reveal a consistent emphasis on a specific set of variables – perceived service quality evolution, service performance and ability to conduct activities – as significantly impacting overall satisfaction. These variables act as "splitters" in the Random Forests model, indicating their ability to divide the data based on class homogeneity and exert a strong influence on overall satisfaction. This implies that passengers prioritize these service attributes, and their satisfaction with them heavily influences their overall evaluation of the service. With an ordered logit model, we found that reason of not being able to conduct an activity has also an impact. When a user can't conduct an activity, issues with space and shaky trains have the strongest importance on satisfaction.

This study reveals that "perceived service quality evolution" and the ability to conduct activities with underlying reasons are significant variables in predicting user satisfaction. These findings have several implications for operators and policymakers:

- **Perceived evolution of service interacts with current satisfaction:** Our results align with Gijzenberg et al. (2015) and Monsuur et al. (2021), indicating that perceived evolution of service quality is more negatively impacted by declines than improvements in both the short and long term. Therefore, operators should avoid train cancellations or significant delays to prevent dissatisfaction. Policymakers could consider implementing

regulations based on satisfaction measures to identify affected passengers for specific compensation, such as discounts or gift cards.

- **Emphasis on industrial performance:** Our findings show that users highly value service performance. Moreover, users prioritize performance over value-for-money, indicating that they expect reliable and efficient train systems. Therefore, operators and policymakers should prioritize service attributes such as punctuality, frequency, and connectivity.
- **Ability to conduct activities while traveling has an impact on satisfaction:** The ability to conduct activities while traveling impacts user satisfaction. When users cannot conduct their desired activities, it leads to dissatisfaction. This finding could also explain the significance of the impact of seating availability and train crowdedness. Operators should ensure adequate train capacity to meet user demand.
- **Reasons of not conducting activities do not have an equal impact on satisfaction:** Shaky trains, insufficient space, connection issues and noise are significant drivers of dissatisfaction. This indicates that the reasons for not engaging in activities do not impact satisfaction to the same extent.

According to the Random Forests model, users prioritize service performance over available space. This finding suggests that passengers may tolerate discomfort if they arrive on time. However, space and performance are interrelated: increasing frequency can enhance available space. Therefore, operators and policymakers should consider both factors to improve user satisfaction.

While not directly addressed in this study, data from the Auvergne-Rhône-Alpes region indicates a 91% punctuality rate since 2018, exceeding the national average of 90%. However, train cancellations remain an issue, with 763 cancellations recorded compared to the average of 674 cancellations per month since 2018. Future research could explore the specific impact of cancellations on user perception and satisfaction.

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APPENDIX

Appendix 1: family attributes

Services	Rolling stock attributes	Staff	Station attributes	On-board information	On-board safety	Cleanliness (rolling stocks)	Information at the station	Safety - security at the station	Cleanliness (station)	Other attributes
Connection with other PT services	On-board comfort	Communication	Station maintenance	On-board information	Personnal security	Seat cleanliness	Information at the station	Personnal security at the station	Station cleanliness	On-board bike
Frequency	Seat comfort	Ticket inspection	Location	On-board information about other PT connection	Travel safe	Toilet cleanliness	Fast information			Disabled access
Punctuality	Temperature	Complaints and competency (on-board and at the station)	Access to the station	Fast information		Train cleanliness				Company green policy
Quality-price ratio	Crowding		Parking							First and second class
Substitute services	Doors and windows		Bike parking							
Network coverage	Light		Functionnality of ticket machines							
Operating hours	On-board space		Waiting conditions							

Travel speed Noise
Strikes

(including
queue)
Station
equipment

Appendix 2: Survey

Section 1: user profile

Subscriber or discount card holder

Type of subscription or discount card

Using more than one transport mode

Ease of doing without the train service

Driving licence holder

Number of cars

Disability

Day of travel

Hour of travel (go and return)

Departure station

Arrival station

Reason of the travel

Frequency of travel

Travel time

Duration of use

Possibility of working from home

Number of day of home-working

Estimation of the number of standing trips (go and return)

Travel with bike, scooter or luggages

Section 2: service attribute	Importance	Satisfaction
Many trains during on-peak hours	X	X
Many trains during off-peak hours	X	X
Value-for-money	X	X
Punctuality	X	X
Regularity (i.e cancellations)	X	X
Enough space to travel with luggages	X	X
Enough space to travel with bike or scooter	X	X
Seat comfort	X	X
Corridor size	X	X
Availability of working electrical outlet	X	X
Ease of access to the toilets	X	X
Cleanliness of the toilets	X	X
Cleanliness of trains interior	X	X
Temperature on-board	X	X
Calm during travel	X	X
Security on-board	X	X
Sound information	X	X
Displayed screen information	X	X
Information on the cause of an incident	X	X
Information to help you to anticipate	X	X
Ticket inspector	X	X
Security team	X	X
Video surveillance	X	
Overall satisfaction		
Recommendation to a friend		

Activities

Section 3: activities

In general, do travel conditions allow you to do these activities during your journey?

	I easily can	I do, but it's difficult	I would like, but I can't	I don't want to do this activity
Work with your laptop	X	X	X	X
Work with your cellphone	X	X	X	X
Personal activities with your laptop	X	X	X	X
Personal activities with your cellphone	X	X	X	X
Read a book or other recreational activities	X	X	X	X
Get ready (makeup, comb your hair)	X	X	X	X
Sleep, rest watch landscape	X	X	X	X
Listening music	X	X	X	X

Why don't you do some of the things you'd like to do?

- Travel time is insufficient
- There is not enough space
- There is not enough seat
- Other passengers can see what you do
- Too noisy
- Train shakes
- Connection issues (wifi, cellphone)
- You can conduct all the activities you want
- Other reason

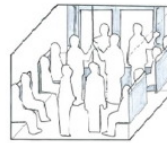
Crowdedness



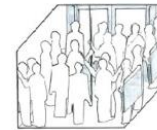
Empty



Almost empty



Crowded



Overcrowded

Socio-economics characteristics

- Gender
- Age
- Number of person in the household
- Professionnal situation
- Social category
- Qualification (degree)
- Income per month