Travel Behaviour and Society 37 (2024) 100847

Contents lists available at ScienceDirect

Travel Behaviour and Society

journal homepage: www.elsevier.com/locate/tbs

Analysis of user behavior in urban parking under different level of information scenarios provided by smart devices or connected cars

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ARTICLE INFO

Keywords:
Parking choice
Parking policies evaluation
Parking simulation model
Smart parking information system

ABSTRACT

Due to the issues of land redevelopment and changes of use within urban areas, many cities must adopt measures to reorganise and optimise parking space. This paper proposes a methodology to study one of them by implementing parking information systems (PIS). This solution offers users a competitive advantage by allowing them to know about the free parking spaces at the moment of decision-making. To achieve this goal, microscopic simulations are conducted to analyse the effects of various scenarios involving the implementation of PIS. The data used in these simulations is obtained from the Santander area in Spain. For the evaluation of results, a methodology has been developed that combines the evaluation of social factors for citizens and operational impacts for decision-makers. The results show significant improvements with increasing user information rate, e.g., the number of unsuccessful parking attempts before finding a final parking space is reduced by 55%, and 37% less particulate pollutants are emitted into the atmosphere.

1. Introduction

Urban growth has augmented the demand for private vehicle transportation and parking in cities (Egidi et al., 2020) in spite of governmental efforts advocating for alternative means of transport (Dadashzadeh & Ergun, 2018; Lin et al., 2021). Current trends, such as the rising use of autonomous vehicles, aren't appearing to encourage greater public transport use (Soteropoulos et al., 2019).

These dynamics are affecting public parking management policies, which aim to curtail reliance on private cars and endorse non-motorized transportation, thereby fostering more sustainable, safer urban environments (Arnott & Inci, 2006). The availability of urban parking spaces is being limited, elevating the significance of efficient parking space management in devising effective transportation systems (Newman & Kenworthy, 1999). On-street parking in urban environments has a spectrum of adverse impacts, including increased traffic from parking space searches and the associated greenhouse gas emissions (Shoup, 2006; Van Ommeren et al., 2012); as such, parking policies form a critical part of efforts to reduce these emissions and achieve the Sustainable Development Goals set by the United Nations (Wenz et al., 2020). Implemented parking management policies, like pay parking, have been shown to influence transportation decisions and user behaviour, delivering benefits such as reduced parking search, increased parking turnover, and improved spatial parking distribution among users (Ball, 2013; Vickrey, 1954).

Despite these benefits, authorities have not fully integrated the use of advanced information and forecasting systems into parking management (Chen et al., 2012; Nawaz et al., 2013; Pazos et al., 2016; Pérez González & Díaz Díaz, 2015). Based on big data, collaborative applications, and installed sensors, these systems aim to provide real-time information on available parking spaces.

In this study, a new approach is presented to explore the potential benefits of innovative parking management policies that provide different levels of information to users. The paper begins with a comprehensive literature review to provide the theoretical basis and existing research context. It then sets out a new methodological strategy for the testing and calibrating Parking Information Systems (PIS) models, which encompasses the factors considered. The process includes a crucial stage of model development and calibration, where model parameters are adjusted to observed data in a stated preferences survey (SP). After calibration, the model is applied to various scenarios, examining its performance under different circumstances and policy options, thereby demonstrating its robustness and utility for decision-making. Subsequently, the model is validated by comparing predictions with observed data to ensure credibility and provide confidence in its applicability to future scenarios. The study concludes by presenting

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https://doi.org/10.1016/j.tbs.2024.100847
Received 14 July 2023; Received in revised form 5 June 2024; Accepted 7 June 2024
Available online 12 June 2024

detailed results for a specific case study, including occupancy rates, parking-induced traffic, and pollutant emissions, offering a practical perspective on the model's usage and potential implications for urban parking management.

2. Literature review

On the basis of Litman (2016) classification, it can be stated that there are four main types of congested parking management policies As one of them, the use of intelligent transport systems as a parking management tool will be evaluated. There are then 3 other approaches, the first approach to address parking problems in densely populated areas is to introduce in-city road tolls. While this may not be a traditional parking policy, it can significantly influence parking demand. Tolling fees can be established based on a schedule, with rates that fluctuate depending on the time of day, such as higher fees during peak periods. Alternatively, tolling fees can be dynamic and adjusted in real time. For instance, in 2003, London introduced a daily congestion charge of £5 for driving on the Inner Ring Road, resulting in a reduction of traffic volume by approximately 15 % (Blow et al., 2003).

The "Park and Ride" method reduces city congestion by placing parking lots on city edges linked to public transport. Barcelona is a notable example of this method, which alleviates traffic and lowers emissions (Vila Serrano, 2019).

The third strategy, parking time limitations, aims to enhance turnover and discourage long-term use. They set duration constraints, with shorter limits for general users and longer ones for locals. Implementing 10–30 % short-term parking can boost business in commercial areas. (Institute, 2020). Boosting parking turnover can enhance business customer flow. However, enforcing time limits can be difficult as users often move their cars after reaching the limit. (Simićević et al., 2013).

Another set of commonly employed parking regulation strategies, as identified by Litman (2016) parking strategies focused on operators, can include reserving spots for authorised users, limiting parking during peak hours for traffic flow, and imposing time-based parking limitations.

As a complementary element to the fourth of the above-mentioned branches of parking policy management and focusing on providing information directly to the user, some options have been explored in the literature. There are authors Teng et al. (2008) who emphasise the significance of incorporating new technologies to mitigate parking search traffic or the unfair rate distribution (Fulman & Benenson, 2018). For example, from the infrastructure approach, Idris et al. (2009) explore some Intelligent Transportation Systems (ITS) use technologies to manage parking issues. These include infrared, induction, magnetic, pneumatic, microwave, acoustic, and ultrasonic sensors, as well as methods like video, laser, and wireless detection, especially for off-street parking. From this, authors began to emerge who studied how to quantify their effect as Caicedo et al. (2012) who aimed to demonstrate that there are benefits to presenting detailed information to users, and one of their objectives was to quantify these benefits.

Subsequently, ITS infrastructure evolves using sensors for parking management, such as monitoring individual spaces. In addition, it was identified that smartphone applications can provide users with information on parking location and prices and facilitate reservation and prepayment services (Lotlikar et al., 2016; Vlahogianni et al., 2016) Guidance of vehicles to free spaces using apps has already been tested (Caliskan et al., 2006) with no results extrapolable to other cases. All of these systems have, however, high deployment costs, high maintenance costs and a high failure rate in case of e.g. illegal parking (Tasseron et al., 2016).

Another approach to manage information use using augmented reality traffic simulators was later tested, and one of the most obvious extrapolated conclusions is the limiting factor of the age of the users of the different information sources (Ahangari et al., 2018). Or earlier games such as the study by Kaspi et al. (2014) demonstrates that time constraints and available parking information significantly influence users' choice of parking. All these previous parking information systems have mainly focused on the study of the improvement in search times without establishing relationships with other indicators such as distance to destination, parking attempts or reallocation of users to other facilities (Ahangari et al., 2018; Liu et al., 2018).

Finally, in relation to the traffic effects of such systems, numerous survey-based studies have been carried out to measure them, firstly McCahill et al. (2016) established a clear association between the availability of parking offered to users and car mode share in cities, indicating the impact of parking provision on driving behaviour. In this line Tasseron and Martens (2017) investigated through a survey of Antwerp citizens the influence of parking information provision by testing its effects together with a reservation system. The most comprehensive study was carried out by Yang and Lam (2019) a Hong Kong SP study of 800 samples introduced by Intelligent Parking Information Systems (IPIS). Findings showed downloading habits, parking time, and app usage influenced user behaviour, but practical implementation failed. And finally more recently, Hess and Flowers (2023) examined developers' responses to the removal of minimum parking requirements for certain users by providing them with information, suggesting that alternative approaches to parking provision could reduce driving tendencies. The problem is that none of these studies opted for effects similar to those previously suggested in the literature (Chaniotakis & Pel, 2015), all being survey studies or simulations of theoretical scenarios.

After analysing the main studies on the impact of user information on mobile devices on parking, it has been identified that these findings need to be more fully integrated into widely used microsimulation software and a common standard established to evaluate results obtained in similar studies. This is the rationale behind the development of the proposed model and evaluation methodology. Such integration and standardisation could enable managers and decision-makers to acquire detailed and quantified information regarding the extent of the impact of introducing an information system in real-world environments.

3. Methodology

To carry out the experiment and to be able to establish a comparative of the different scenarios, a methodology must be developed that covers, on the one hand, the microsimulation of the different scenarios to be developed and, on the other hand, to establish the basis of the indicators to be compared to measure the effectiveness of the introduction of PIS to the user. For the first of these tasks, this research is completely in line with what has been defined by Rodríguez et al. (2022) those who developed the DYNAPARK model that allows the simulation of users when parking in a zone by combining on-street, off-street parking and different static or dynamic pricing policies depending on occupancy. The model is similar to other models that consider the network, traffic and parking patterns such as PARKANALYS, PARKAGENT or PARKFIT (Levy & Benenson, 2015; Levy et al., 2013) but in this case, the model includes the possibility of changing utility function in order to introduce specific information scenarios.

3.1. Dynapark model

The Dynapark model is built to run on the Aimsun traffic microsimulation software (Casas et al., 2010). The Python-based model was created in compliance with the Aimsun API, utilising Python versions 3.7 and 2.7 as per the requirements. After selecting the appropriate detection technology, it was integrated into Aimsun, a traffic modelling software, using the provided software API (Application Programming Interface). This integration allows for more detailed and realistic modelling of user behaviour in the traffic network, taking into account factors such as vehicle interactions, lane changes, and gap acceptance, which can affect the overall performance of the parking management system. In this study, the model was utilised for microscopic simulations to analyse the impact of different scenarios, allowing the authors to establish and analyse the effects of various PIS penetration scenarios.

The DYNAPARK model simulates car parking behaviour using spatially explicit parameters derived from Santander City Council data and user preferences. It considers various conditions, such as pricing policies and occupancy rates, and focuses specifically on car parking scenarios.

It is important to mention that Dynapark employs two distinct submodels, namely the parking selection submodel and the parking search submodel. Fig. 1 shows how the model works with the entry of each vehicle into the study area; it is worth mentioning that, in this specific case, several modifications to the model have been made to introduce the effects of user information into the system shown in Fig. 2.

In order to carry out the methodological development proposed in Fig. 2, a specific Multinomial logit MNL model was derived from the model developed by Rodríguez et al. (2022) for the DYNAPARK model. This model was developed based on a survey. In addition, a specific parameter has been introduced that is activated or deactivated depending on the degree of information of the users (eq 3).

$$V(on-street) = \beta_0 + \beta_{TD}TD_{onstreet} + \gamma_{info}\beta_{TB}TB_{on-street} + \beta_{OCU}OCU_{on-street} + \beta_{TAR}TAR_{on-street} + \beta_{TMAX}TMAX_{on-street} \quad (1)$$

$$V(off-street) = \beta_0 + \beta_{TD}TD_{off-street} + \gamma_{info}\beta_{TB}TB_{off-street} + \beta_{OCU}OCU_{off-street} + \beta_{TAR}TAR_{off-street} \quad (2)$$

where:

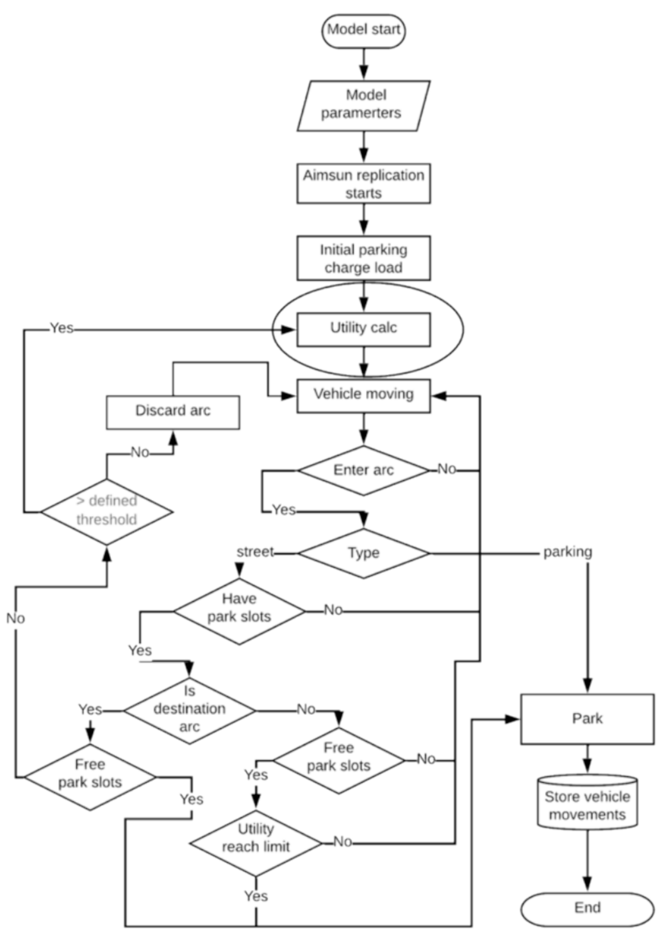

Fig. 1. Original Dynapark model methodology (Rodriguez et al., 2022).

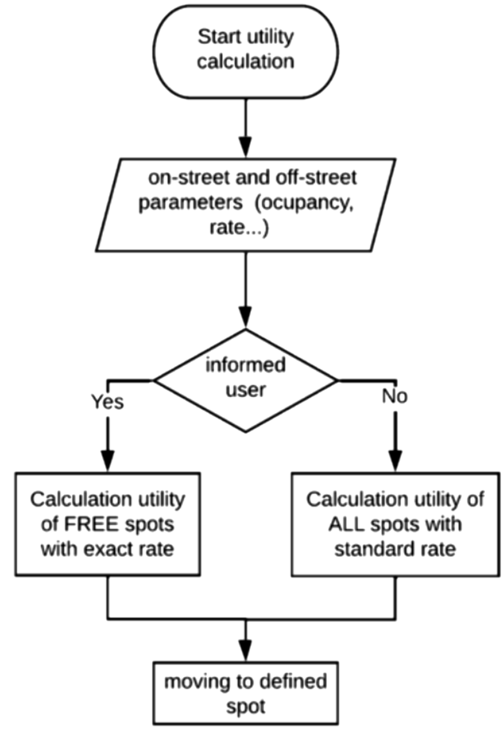

Fig. 2. Specific submodel in utility calculation step developed to consider user information.

$$\gamma_{info} = \begin{cases} 0\forall no-info \\ 1\forall info \end{cases} \quad (3)$$

The variables on which the parking decision depends are, therefore, the choice of paid on-street parking depends on the fare charged (*TAR*), the time to final destination (*TD*), the search time (*TB*), the occupancy of the spaces (*OCU*) and the maximum length of stay allowed (*TMAX*). The choice of free parking depends on the search time (*TB*), the time to destination (*TD*) and the occupancy of the spaces (*OCU*). In the case of choosing off-street private parking (underground car park), the choice will depend on the fare charged (*TAR*), the time to final destination (*TD*), the search time (*TB*) and the occupancy of the spaces (*OCU*). All these variables are consistent with the research (Chaniotakis & Pel, 2015). In the case of the γ_{info} parameter referring to the availability of information of a PIS provided by a phone or connected car, it is activated when an informed user enters the network and is aware of free places. When this option is activated, affecting the search time, which is evidently reduced by the availability of the parking space. This information was supposed to be offered via a mobile application to the users, informing them about the existence or absence of free parking spaces at the destination. They knew which parking spaces were available before entering the area, which was considered for the utility calculation. However, the parking supply is the same for both types of users, who can opt for all available parking spaces. It is therefore considered that informed users obtain an advantage due to the knowledge of free spaces and this is quantified by activating this parameter γ_{info}.

To run the model, traffic demand data must be inputted, including data on transit traffic and vehicles searching for parking within the analysis area. The demand data used in the model is unimodal and is represented as an Origin-Destination matrix. The matrix provided is a subset of the larger multimodal Origin-Destination matrix for the city of Santander. This subset has been extracted and reorganised from the original matrix, which was obtained from a household survey conducted in 2015 by the University of Cantabria transport research group, which was described within the studio Krishnakumari et al. (2020). It has also been recalibrated using traffic data from the traffic vehicle counting loops installed by the Santander City Council (Ayuntamiento de Santander, 2023) in the area with data from the year 2023. In addition to demand data, parking supply data is also required for the model. The analysis area is subdivided into multiple sections, with each Origin/Destination pair considered as a distinct section. In total, there are 11 origin sections from which users can access the area and travel to their respective destinations.

In addition, the model relies on input data related to parking supply, which includes information on the number of parking spaces and businesses available in each section. The number of shops and businesses present in each section determines the distribution of vehicles searching for parking across sections. This approach helps to reflect the parking demand generated by the commercial activities in each section. Data for validation are obtained from the Santander smart parking system, which is available at the city council's open data portal.

The Aimsun application is used to perform simulations. Each vehicle's stopping point along the section is randomised, introducing realistic variability in parking choices. This allows for a more accurate representation of real-world parking behaviour, where drivers may choose different parking spots within a section based on various factors such as availability, proximity to their destination, and personal preferences.

3.2. Establishment of the methodology and criteria for PIS penetration scenarios evaluation

As described at the beginning of this section, the methodology of this study needs to be developed in two ways. The second oversees defining the set of indicators to establish the basis for comparing the different scenarios that will be evaluated. Furthermore, this methodological framework can provide a foundation for implementing a new PIS provided through mobile phones or connected cars that can influence the dynamics of cities. Therefore, administrators should carefully analyse the impacts of new parking policies on various aspects such as the environment, traffic, revenues, and more. Various methodologies are available for comparing and quantifying the effects of different parking policy alternatives, which can be based on factors identified in existing literature and aligned with the specific goals of each administration. To establish the evaluation criteria, the following significant parameters have been defined according to the existing literature, resulting in the following (Litman, 2016; Najmi et al., 2021). Specifically, indicators have been described to quantify the social and operational impact. Local administrations have more required social indicators in their search for citizen welfare. On the other hand, operational indicators are more appreciated by parking infrastructure managers who seek to maximise their management and operational benefits. All of them are described below. Fig. 3 resumes indicators and their relationship with the evaluation model defined.

3.2.1. Social indicators

Research indicates that the presence of vehicles actively searching for parking can have a notable impact on traffic congestion in cities. Studies have shown that approximately 30 % of urban traffic consists of vehicles that are cruising or circling around in search of an available parking space (Assemi et al., 2020). Parking policies have the potential to influence parking demand, which in turn can impact various factors such as the number of vehicles searching for parking, occupancy rates, searching times, and more. Therefore, it is essential for administrators to carefully forecast and analyse the potential repercussions of implementing new parking policies on traffic. Usually, the impact on traffic is assessed by measuring factors such as travel speed, the volume of vehicles searching for parking, traffic density, and other indicators. In this research, quantitative data will be collected to analyse the number of vehicles engaged in parking searches and the time spent on this activity. This data will be used to compare the impacts of different parking policy options. By collecting and analysing this data, researchers can assess the effectiveness of various parking policies in reducing the number of vehicles searching for parking and minimising the time spent on this activity. This information can inform decision-making and policy recommendations to optimise parking management strategies and improve urban mobility. The most favourable parking policy would be

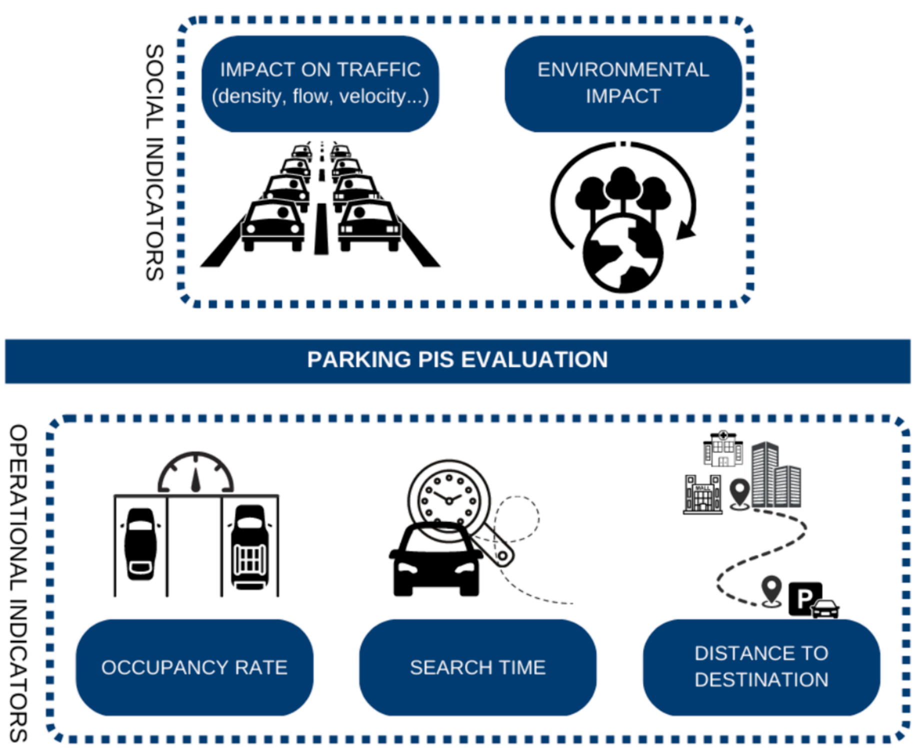

Fig. 3. Indicators for PIS evaluation.

the one that minimises the impact on these indicators as much as possible.

Parking policies impact traffic and have repercussions on environmental factors, such as emissions and fuel consumption (Aloi et al., 2020; Shoup, 2017). As a result, administrators may need to consider this aspect when evaluating different parking policies. Therefore, this study will analyse the effects of each policy on fuel consumption and emissions. The ideal parking policy would result in lower emissions and fuel consumption, making it the most environmentally friendly option.

3.2.2. Operational indicators

The occupancy rate, which is the proportion of occupied parking spaces to the total number of parking spaces, is a widely used metric for evaluating parking policies. Research indicates that an optimal parking occupancy rate is typically around 85 % (Shoup, 2005). As a result, parking administrators may establish 85 % as a benchmark criterion for parking regulations. In this study, the effectiveness of various parking policies will be evaluated based on their ability to attain and sustain an occupancy rate of 85 %. The assessment will concentrate on the adjustment of parking prices and the information provided to users to gauge their impact on the occupancy rate.

Search time: Another of the main factors to be analysed is the determination of search time. This factor affects users and operators negatively since it represents a high percentage of users' total travel time and, in some cases, its duration exceeds 5 min on average (Assemi et al., 2020). This indicator allows to measure the overall system's effectiveness as more user information data is added since it should show a reduction as the share of informed users increases.

Distance travel from parking to destination: Users usually want to park as close as possible to their destination. The introduction of a PIS-based guidance system will likely assign higher utilities to spaces located further away but available in longer search times. Therefore, this indicator is chosen to be shown in combination with the previous one, which will give useful information to future managers implementing this methodology.

The current study aims to analyse various PIS penetration scenarios based on established parking policy evaluation methodologies, as indicated in Fig. 3. Quantitative data for evaluating the effects of different parking policies will be obtained through simulation of various scenarios. The comparison of policies will be based on three key criteria: (i) minimising parking search times and the number of vehicles engaged in parking search, (ii) minimising search time while considering a secondary criterion, and (iii) mitigating emissions and fuel consumption. By analysing the simulation results based on these criteria, researchers can assess the effectiveness of different parking policies in reducing parking search times, minimising the number of vehicles searching for parking and addressing environmental concerns such as emissions and fuel consumption. This analysis can provide valuable insights for decision-makers in optimising parking policies to improve urban mobility and sustainability.

4. Experiment real case (Santander)

4.1. Area of analysis

The DYNAPARK model is being implemented in Santander, Spain. The city centre is a densely populated area with high economic activity and parking demand. According to ICANE (Instituto Cantabro de Estadastica - ICANE, 2022) data, in 2022, there were 102,069 employed workers in Santander, and the total number of registered vehicles was reported to be 112,267.

Currently, there are three types of public parking facilities in the city, as mentioned in reference (Antolín, 2019): (i) free on-street parking, (ii) paid on-street parking, and (iii) paid off-street parking, which includes underground parking. Fig. 4 shows the entries, exits, and vehicles having the area as the final destination of the vehicles intervening in the area during the study period. As shown, the peak cruising time should occur at 14.00. It also coincides with the peak of parking manoeuvres obtained from the parking smart sensors installed that also occur at that time, which is the time chosen for the studio, reinforcing the need to reduce this traffic.

4.1.1. Free on-street parking

Free on-street parking, without charges or time limits, is often in low-demand areas, such as the city outskirts or residential zones. However, its proximity to paid off-street facilities may cause increased cruising for parking, leading to traffic congestion. The location and management of these parking spaces need careful consideration to balance drivers' needs, reduce congestion, and improve urban mobility.

4.1.2. Paying on-street parking

Santander's paid on-street parking is concentrated in the city centre and active during peak economic hours. A fixed fare is applied with a maximum parking duration of two hours. Enforcement happens on weekdays between 10 AM and 2 PM and 4 PM and 8 PM and on Saturdays between 10 AM and 2 PM. Outside these hours, parking is free. Understanding these regulations aids in evaluating the impact and dynamics of parking usage patterns. Which are considered in this model together with the free and paid off-street option.

The current study is in the regulated parking area highlighted in Fig. 5.

The study area encompasses local roads and two major arteries, all having regulated on-street parking. Local roads are single or dual carriageways with one lane in each direction, some offering car or motorcycle parking. These road configurations and parking arrangements significantly influence parking policies' impacts on traffic and parking demand. Special lanes for buses, taxis, and motorcycles on Paseo de Pereda also affect traffic flow and parking demand. Thus, understanding these settings is key in assessing parking policies' effectiveness, informing strategies to alleviate congestion, optimise parking use, and enhance urban mobility.

4.1.3. Paying off-street parking

In the bustling commercial centre of Santander, 11 paid underground parking facilities accommodate 4,500 spaces. They charge a fixed fee of 1.7€ per hour in 2023, with capacities ranging from 900 spaces in Parking 1 to 350 in Parking 3. The analysis zeroes in on a highly demanded, centrally located, regulated, on-street parking area equipped with the Smart Santander project's smart sensors for validation and real-time monitoring. This region has approximately 600 parking spaces, with a 36 % share for on-street and paid parking and 64 % for off-street parking. Its boundaries encompass unique dynamics to the east and west, free on-street parking to the north, and the sea to the south.

In building a model using Aimsun software, diverse inputs like road geometry, junctions, speed limits, and traffic light timings are critical. This rich data set enables accurate simulations of the area and robust evaluations of parking policies' impacts on traffic flow and urban congestion. Aimsun can also simulate complex traffic behaviour such as car following, lane changing, and gap acceptance. Moreover, it integrates parking simulation, which is crucial in assessing the effect of various parking strategies.

In the defined analysis area, Fig. 4 shows two main types of parking choices: (i) paid on-street parking and (ii) private parking. The study area is also equipped with parking sensors, provided by the city council, that convey information about the availability of parking spaces in the area.

4.2. Questionnaire design

A survey was elaborated on so that the model would work properly as described in the methodology. This survey, distributed online among regular parking lot users, was developed in 2 parts. The first part aimed

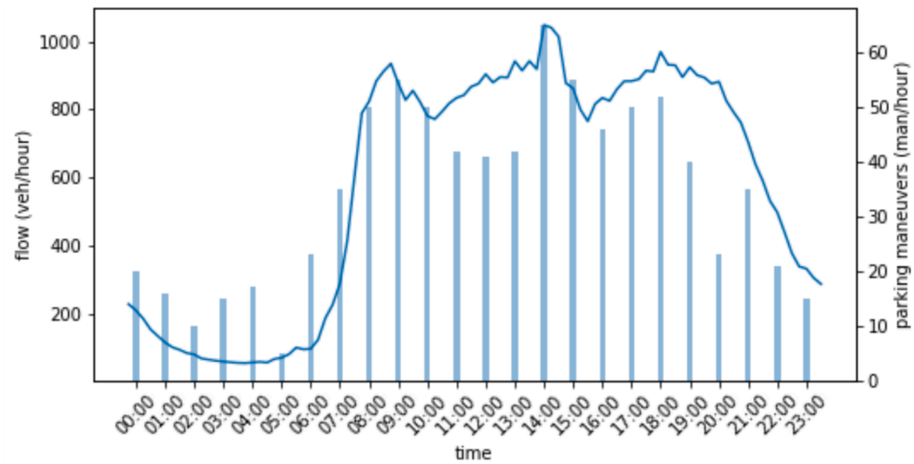

Fig. 4. Average weekday vehicle flow at the zone and parking manoeuvres (Source or the data: Santander open data portal).

Fig. 5. Study area and off-street parking locations.

to collect the socioeconomic characteristics of the participants, such as age, gender, income level, residence, and other related information about parking, the degree of use of private or public parking, or the recurrent reason for using parking. The second part consisted of a stated preference (SP) experiment, designed efficiently using the NGENE software (ChoiceMetrics, 2012). This 6-scenario SP questionnaire had three parking choice options(option 1 on-street, option 2 on-street with other characteristics or off-street parking. For each of the three options, one of three possible levels was offered for each of the attributes considered in the survey. These attributes were fare, search time, distance to destination, expected car park occupancy and maximum length of stay.

From the questionnaire's initial design, a pilot test of the measurement instrument was conducted to calibrate the final parameters and to find the sample needed to obtain significance in the parameters for subsequent modelling. In this case, the estimated sample size needed to obtain this significance (s-optimum) (Rose & Bliemer, 2009) was at least 56 completed questionnaires.

4.3. Survey results and model parameters

With the design developed and tested, the questionnaire was launched, and a total of 576 observations were obtained, exceeding by 69 % the necessary number of observations to obtain a sufficiently robust model. With this data, a multinomial logit model was calibrated that granted different utilities to the street sections where users could park and to the subway parking available to them with the formulation of equations (1), (2) and (3). Table 1 shows the parameters of the model and their statistical significance (above 99 % in all cases). The model was also validated using the NLOGIT software (Greene, 2016), obtaining the data in Table 1. Which, as shown, offers parameters consistent in sign and highly significant. This significance is demonstrated by checking basically two aspects of the results: on the one hand, the signs shown by the variables and, on the other, the values of the t-statistics. The signs are consistent with what would be expected since an increase in the rates or times associated with parking causes a decrease in utility, so its parameter must be negative. On the other hand, the maximum length of stay brings utility to a parking option, so it's positive sign is also consistent. In the case of the t-statistics (which are represented by the robust *t*-test), they are above the value of 1.96, which provides a significance greater than 95 % for the parameter estimate. Therefore, after verifying the sign and statistical significance, the values of the coefficients in Table 1 are validated for the modelling of parking preferences.

Table 1
User behaviour model parameters (***, **, * indicate the confidence level of 99%, 95% and 90%).

Variable	Parameter		Z (robust *t*-test)
Fare (€/h)	−0.49092		−11.67***
Search time (min)	−0.06744		−2.80***
Time to destination (min)	−0.06881		−2.53***
Occupancy (%)	−0.00880		−3.17***
Max. allowed t. of stay (h)	0.26111		4.70***
Underground constant	1. 3322		6.85***
Log-Likelihood		−503.608	
Log-Likelihood (Null)		−632.801	
Log-Likelihood (Constants only)		−621.219	
McFadden Pseudo R-squared		0.189	

As can be seen in Table 2, where the Row indicator is present, a column is predicted, and columns are the predicted results, the model presents a validation of about 88%, which validates the model's ability to replicate users' parking behaviour in all cases.

5. Analysis of results

The following section presents an impact analysis of the application of different PIS penetration degrees on the system. It focuses on the percentage of users who are informed about parking availability and rates through parking applications. These informed users can access real-time information about available parking spaces and associated fares, which they take into consideration when choosing a parking spot, as shown in Fig. 1. Various indicators, including delay time, vehicle density, distance travelled, fuel consumption, and emissions of CO2 and PM, have been obtained and analysed for conducting the sensitivity analysis. These indicators have been estimated for all types of vehicles, including transit vehicles (passing vehicles with no intention to park) and vehicles searching for parking in the designated analysis area. However, some metrics, such as delay and density, are presented regarding the total number of vehicles. Similar to the previous section, to ensure accuracy, each scenario representing a different percentage of informed users was simulated 15 times, and the average results from the 15 simulations were calculated (Lu et al., 2014).

The following indicators are analysed to reflect the impacts of promoting the use of parking applications with the aim of increasing the proportion of informed users in the system.

For the correct interpretation of Table 3, important data that needs to be provided is the ratio of parking vehicles to transit vehicles in the study area. The data was collected from the Santander open data portal for a typical day and combined with the estimated parking demand from the survey conducted. The percentage of parking destination vehicles is around 12.6 % of the total number of vehicles entering the area during the peak hour.

Firstly, the delay will be analysed in terms of the indicators that directly affect traffic (delay, density, and distance travelled). This indicator of the additional time each driver takes in the zone shows the first

Table 2
Model cross validation.

		PREDICTED			
		on street (info)	on street (no-info)	off street	sum
OBSERVED	on street (info)	147	9	13	169
	on street (no-info)	7	155	9	171
	off street	15	16	205	236
	sum	169	180	227	576

results in increasing the degree of information. The decrease with each 20 % decrease in the test is remarkable but analysed globally. The decrease is 4.8 s on average for vehicles, which is about a 10 % improvement. The data on vehicle density on the network again shows the positive effects of introducing informed users into the system. In this case, the effect is not linear but shows significant steps between 20 % and 40 % of informed users and between 60 % and 80 %. It remains more stable in the intervals 0–20, 40–60 and 80–100. In terms of overall improvement in the network, the reduction in density is more than two vehicles per kilometre, about a 20 % reduction. This figure is evidently related to a reduction with respect to the last of the network's traffic indicators, the total distance travelled by vehicles in the area. Due to its typology, this data could be disaggregated between the two types of users considered for traffic purposes (parking and transit users). The results again improve as the degree of information increases. The improvement in the information on available parking spaces leads to a decrease of about 2.5 % for every 20 % increase in the information rate as the share of users with this information increases. If the three data are studied together, a correlation of around 85 % can be established between them so that the results of improvement in the network at a global level can be validated.

Respect the other three parameters studied in Table 1. These refer to environmental parameters. These parameters have been calculated using the method developed by (Panis et al., 2006). Firstly, the fuel consumption data shows results that are in line with the decrease in the distance travelled by users searching for parking on the network. The expected fuel savings for one hour of simulation amount to 14 % of the total, whether it is differentiated between transit and search users. In the latter case, the decrease is more than 30 %. This decrease in consumption, which is directly related to the decrease in distance travelled, has a positive impact not only on search users but also on users travelling to or from outside the area. This type of user has a positive impact of 3 %. Likewise, the emissions data provided by the microsimulation software in the area show a reduction of 8 kg of CO2 and 37 % less emission of particulate pollutants.

The table provided below presents the outcomes of various models for each percentage of informed users that was previously examined. The table includes results for both informed and uninformed users at different levels of user information. These findings are valuable for examining the differences in parameters among various user types. The table likely includes the following variables: (i) Distance covered by users until they find an available parking space: This refers to the total distance travelled by a vehicle from its origin to the location where it finds an available parking space. It may include the distance travelled while cruising for parking, as well as any detours or extra distance covered in search of an available parking space. (ii) Distance walked by users from the parking space to their intended destination: This refers to the distance pedestrians need to walk from the parking space where they have parked their vehicle to their intended destination, such as a shop, office, or another point of interest. This variable is relevant in assessing the convenience and accessibility of parking options for users. (iv) Number of attempts made to find parking: This refers to the number of times a vehicle makes attempts to find a parking space before successfully finding one. It may reflect the level of parking availability and the difficulty in finding parking in the study area and can provide insights into the efficiency of parking policies in meeting the parking demand. (v) Time spent searching for a parking space: This refers to the total time spent by a vehicle searching for an available parking space, including the time spent cruising for parking, waiting for a parking space to become available, and making attempts to find parking. To properly understand cruising time in this particular study, it should be noted that cruising time is calculated as the time from when vehicles enter the area until they either park or leave the area without having achieved their objective. For this purpose, the area chosen as the study area can be considered the same area of influence as the car park to be studied. It is an important indicator of the efficiency of parking policies and their

Table 3
Indicators based on percentage PIS users.

Variable	Vehicle Type	% informed users					
		0	20	40	60	80	100
Avg Delay respect to free-flow travel (sec/vehicle)	All	57	56.7	55	54.6	52.6	52.2
Avg Density (veh/km)	All	9.31	9.19	8.42	8.34	7.66	7.26
Total Distance Travelled (including searching distance) (km)	All	2084.16	2073.3	1997.05	1975.7	1881.38	1847.43
	travelling	1391.3	1395	1387.5	1389.7	1386.3	1395.1
	searching	692.86	678.30	609.55	586.00	495.08	452.33
Total fuel consumption (l)	All	467.3	466	445.5	441.3	412	401.3
	travelling	275	275.4	271.1	271.1	267.1	267
	searching	192.3	190.6	174.4	170.2	144.9	134.3
Total CO2 emissions (kg)**	All	50.92	50.34	47.66	47.00	43.65	42.33
	travelling	28.42	28.49	28.03	27.99	27.60	27.48
	searching	22.50	21.85	19.62	19.00	16.05	14.84
Total PM emissions (g)**	All	16.9	16.4	15.4	15.4	14	13.7
	travelling	9	9	8.7	8.8	8.5	8.7
	searching	7.9	7.5	6.7	6,6	5.4	5.1

**Emissions are calculated using the Panis model (Panis et al., 2006).

impact on travel time and congestion in the study area. In addition, Fig. 6 compares the initial state of the installed sensors with the simulations with 0 % informed users (baseline situation) and with 100 % informed users, demonstrating the dispersion of parking spaces, which reinforces the usefulness of the solution introduced to redistribute the cruising.

Some figures are shown in the next lines for the correct interpretation of the data provided in Table 4. These graphs describe all the variables splitting between info users, no info users and average values resulting from both user types combined.

Analysing the data on the distance travelled by users shown in Fig. 7, it can be seen that not informed users drive approximately 1700 m to find a parking space. This contrasts with informed users whose distance is considerably less, on average about 700 m less. If the data are considered together, the advantages of introducing information are linear to the advantages of introducing the information. As more informed users are introduced, the reduction in distance travelled by users is not influenced by introducing more informed users. An 80 % increase in the number of informed users only increases the distance travelled by users to get a slot by 10 %.

Another indicator in Table 4 assessed individually is the distance users travelled from the parking space to their destination Fig. 8. This is one of the most controversial indicators as the distance increases for informed users compared to not-informed users. This is because these users know the network beforehand, and the search time and distance travelled weigh more heavily in the utility function of the model. Although a priori, this may be presented as an adverse effect, it supports the introduction of information for another reason. On the one hand, as shown in Table 1, pollutants are drastically reduced in favour of the environment, and the distance travelled is slightly increased (25 %). This favours the physical activity of the users. In terms of the effect of the degree of information, there is hardly any influence of the increase in the % of the information, only a 12 % increase. Another effect observed is shown in users without information since they place a high priority on the usefulness of finding a place close to the destination and find less competition as their share decreases, reducing the distance to the destination by more than 15 %.

The number of unsuccessful parking attempts before finding a final parking space has also been studied in detail as an indicator of the effectiveness of the information entry measure. The result shown in Fig. 9 also demonstrates once again that the more users with information, the lower the overall average number of attempts. This is a positive

Fig. 6. Initial situation of the area with the sensors (top) versus the simulated states 0% informed (left) and 100% (right).

Table 4
Model results based on the percentage of PIS users considered.

%info users Parking user type	0 No info	 Info	20 No Info	 Info	40 No Info	 Info	60 No Info	80 Info	 No Info	100 Info
Avg Distance travelled including searching (m/veh)	1834	1086	1890	1132	1899	1224	1827	1213	1687	1173
Avg Distance between parking node and activity node (m/veh)	167	212,3	171,9	211,4	169,8	204,2	168,5	205,5	153,3	193,7
Avg Parking attempts per vehicle	5,8	2,2	5,9	2,4	6	2,7	5,8	2,7	5,3	2,6
Avg Search time including searching (min/veh)	5,9	3,7	6	3,7	5,8	4	5,6	4	5,2	3,9

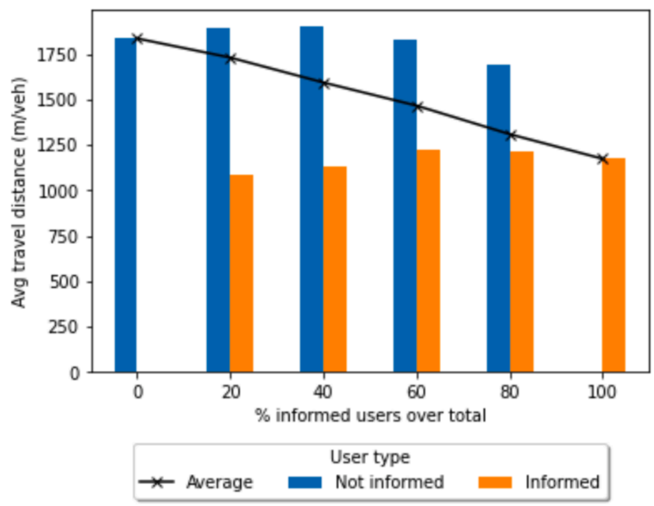

Fig. 7. Average travel distance per parking vehicle in the analysis area over different penetrations of PIS.

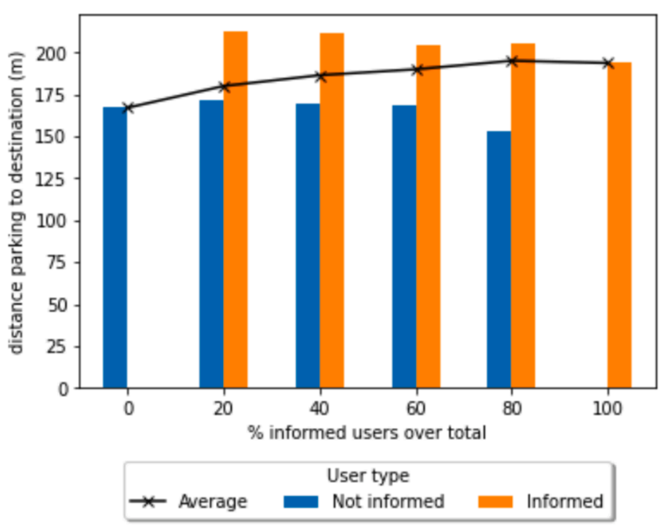

Fig. 8. Average distance to be walking from parking to destination per parking vehicle in the analysis area over different penetrations of PIS.

indicator and is closely related to the distance travelled. Combined, they show a correlation of 94 % for each type of user. Also, as has been shown with other indicators, a higher percentage of users with information does not negatively affect those with a competitive advantage when the share is low. Between 20 % and 100 %, there is only a 5 % increase, which is insignificant compared to the overall 45 % decrease for both types of users combined.

The last of the indicators in Table 4 refers to the average search time shown in Fig. 10. Here, the differences between the different levels of information.

Ion show an improvement of about 8 % compared to the previous gap

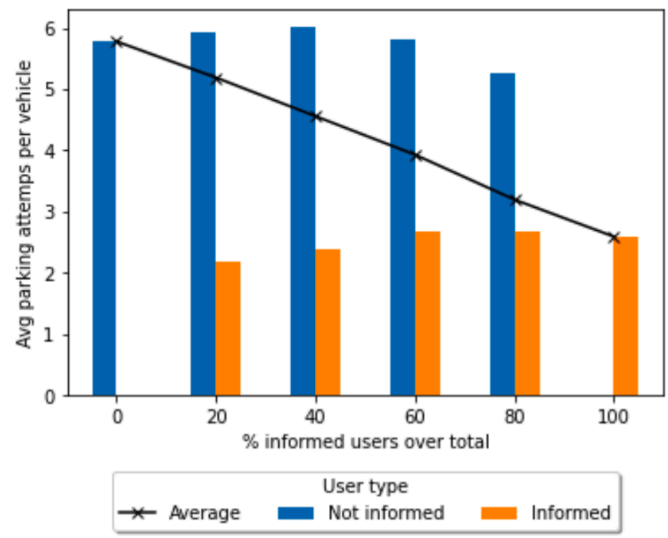

Fig. 9. Average parking attempts per parking vehicle in the analysis area over different penetrations of PIS.

time. This indicator shows an overall decrease unaffected by the increased proportion of informed users. This causes the average time spent by the two types of users to decrease overall. On average, users take almost 6 min for the worst-case scenario versus 4 min for the most information available. These times are in line with user data from the PD survey carried out. They are also similar to those observed for similar sectors under congested circumstances such as the development carried out (Fulman & Benenson, 2021; Mannini et al., 2017).

Finally, a combined analysis of all the variables studied above has been carried out to understand their impact as a whole. Fig. 11,

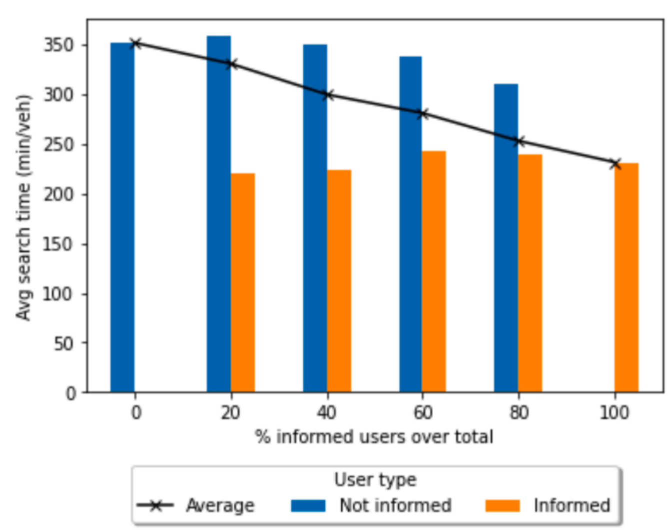

Fig. 10. Average search time per parking vehicle in the analysis area over different penetrations of PIS.

therefore, shows three of the four indicators studied. The search time has been omitted due to the aforementioned correlation with the distance travelled to avoid showing redundant information. For the actual comparison, the data have been normalised by taking the highest value in each case as 100 % and showing the data as a relative percentage of the latter value. Thus, the distance travelled between the destination and the parking space increases by less than 15 %, which is much less significant than the improvement represented by the other two indicators. Firstly, the distance travelled by each vehicle improves by about 35 %, and the number of parking attempts improves much more severely by more than 50 %. This improvement is therefore much more important than the distance to the destination. In addition, the perception of overall time wasted improves, so user satisfaction will also improve, as overall time is one of the variables most appreciated by citizens (Dell'Olio et al., 2010; Fulman & Benenson, 2021; Mannini et al., 2017). In addition, Fig. 12 shows a comparison of cruising times and distances travelled, comparing the measurements with 100 % of informed users with respect to the baseline situation. These images further clarify the effects of the introduction of the simulation. On the one hand, there is a redistribution of traffic towards the more peripheral areas, and on the other hand, the times are adjusted and equalised for all users in the area without generating large differences between sectors.

6. Conclusions

This work has modelled user behaviour in response to the introduction of different degrees of information in the parking search process. Microsimulation simulations of various scenarios have been carried out using the developed model to verify this. As a result, the study reveals the significant impact of parking search and payment applications in optimising traffic flow and reducing emissions. The findings, as expected, point to a decrease in search time of up to 35 %, offsetting the usual value of search traffic (Shoup, 2006), correlated with an increase in informed users and linked to a decrease in vehicle density. In parallel, a 35 % reduction in emissions was detected compared to uninformed user scenarios, reiterating the effectiveness of these applications in terms of sustainability.

Contrary to the initial hypothesis, the walking distance from the parking space to the destination increased in scenarios with high penetration of informed users. This phenomenon could be a result of increased competition for available parking spaces. However, the improved spatial distribution of parking spaces and the reduction in emissions seem to outweigh the potential increase in walking distance.

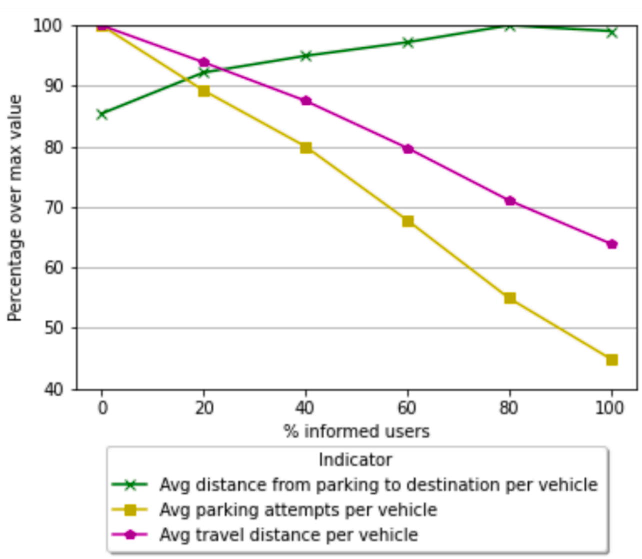

Fig. 11. Evolution of indicators over different information penetration scenarios. Show as % over the max value of each indicator.

Fig. 12. Comparison of search distance (top) and time (bottom) during cruising for 0% reported and 100% reported cases.

The reported users' preference for underground parking, evidenced in the sensitivity analysis, is attributable to their prior knowledge of the situation and a higher value of time. Additionally, a 30 % decrease in travel time for transit users was revealed in scenarios of high penetration of informed users, suggesting that the implementation of these applications generates collective benefits for all users of the information systems.

Finally, the combined interpretation of all variables examined shows that the introduction of information leads to significant improvements in system efficiency despite the marginal increase in walking distance. A reorganisation of the parking space is also achieved, leading to a more optimal use of the spatially available parking spaces. In summary, the study supports the promotion of parking search and booking applications as a viable strategy to improve transport system efficiency and environmental sustainability.

Although parking apps have been proven to enhance system efficiency by promoting equitable distribution of parking spaces, it should be acknowledged that informed users tend to park farther from their destinations compared to uninformed users. Therefore, when evaluating total travel costs, it is essential to consider the increased distance travelled and walking time from the parking spot to the destination in order to assess the impact of parking apps accurately. However, it is crucial also to consider the implementation levels of such systems to avoid potential adverse effects on mobility, as mentioned in references, caused by the use of developed systems (Eboli & Mazzulla, 2011; Echaniz et al., 2022).

7. Funding sources

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

The work was supported in part by: Grant PLEC2021-007824 funded by MICIU/AEI/10.13039/501100011033 and, by the European Union NextGenerationEU/PRTR. Also by the Spanish Ministerio de Ciencia e Innovación under grants TRA2017-85853-C2-1-R, PID2019- 110355RB-I00 and in part was supported by Universidad de Cantabria under grant Ayudas Predoctorares Concepción Arenal (2019).

CRediT authorship contribution statement

Andrés Rodríguez: Conceptualization, Methodology, Investigation, Data curation, Visualization, Writing – original draft. **Borja Alonso:** Writing – review & editing, Investigation, Data curation, Conceptualization. **Jose Luis Moura:** Writing – review & editing, Resources, Project administration, Funding acquisition. **Luigi dell'Olio:** Writing – review & editing, Validation, Supervision, Resources, Project administration.

Declaration of competing interest

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

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