

Development of an individualized multimodal trip planner for a MaaS system

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ABSTRACT

The increasing demand for sustainable transportation solutions necessitates advanced multimodal trip planning systems that can accommodate diverse travel needs and preferences. This paper presents an innovative approach to the development of an individualized, multimodal trip planner for the city of Thessaloniki, Greece. The proposed system integrates public buses alongside shared mobility options (e.g., bike-sharing) and walking, offering users a variety of transportation modes and combinations. A distinctive feature of this work is the inclusion of personalization, which tailors trip recommendations based on user-specific preferences. These preferences are captured through the historic trips of the users, with various shared modes. By incorporating user preferences into the trip planning process, the system prioritizes alternatives using a generalized cost function that balances travel cost, duration, and the number of mode changes. This individualized approach enhances user satisfaction and promotes the adoption of multimodal transportation solutions. The results of this research are relevant for both academic communities exploring advanced routing algorithms and practitioners in the field of Mobility as a Service (MaaS), who aim to deliver efficient and user-centered mobility services.

1. Introduction

During the last years, significant efforts have been directed towards promoting sustainable transportation modes as cities face increasing challenges related to congestion, pollution, and the environmental impacts of private car usage [1]. Urban mobility systems are increasingly becoming multimodal, driven by the emergence of new mobility services, a term that serves as an umbrella for various innovative transportation solutions [2]. Unlike traditional transport modes, these new mobility services are typically on-demand, leverage real-time location data, and are accessible via digital platforms and smart applications. Their distinctive features are reshaping urban mobility landscapes by offering flexible and efficient alternatives to private vehicle use [3,4]. Simultaneously, public transport serves as the backbone of urban transit networks, offering the core service that connects these shared and active modes, thereby enhancing the overall accessibility and coverage of the mobility system [5]. Importantly, having a variety of transport options available in the system adds value, even to individuals who may not use them frequently, much like lifeboats on a ship—rarely utilized, yet

essential to ensure when needed [6]. However, shifting traveler preferences away from the comfort and convenience of private cars necessitates the development of efficient, integrated, and user-friendly transportation systems. It is within this context that Mobility as a Service (MaaS) has emerged as a promising concept, aiming to facilitate seamless and flexible multimodal travel [7–9].

MaaS is a user-centric, data-driven approach to urban mobility that integrates various transportation services into a single, accessible platform [5]. By leveraging digital technologies and real-time information, MaaS platforms enable users to plan, book, and pay for multimodal journeys using a unified interface [10]. The MaaS concept first emerged in 2014 and has since considerable momentum, with numerous pilot projects and implementations worldwide [11]. The primary benefits of MaaS include enhanced convenience, improved accessibility, and the ability to provide seamless trip planning for multimodal journeys [12]. Users enjoy a streamlined experience, easily comparing different travel options based on criteria such as cost, travel time, and environmental impact [13]. Moreover, MaaS platforms are designed to dynamically adapt to evolving urban conditions, making them more resilient and

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responsive to the needs of users [14,15].

Despite the growing interest in MaaS and its emphasis on multimodality, achieving effective integration of diverse transportation modes into a single, optimized travel experience remains a significant challenge. The complexity of combining multiple modes—such as public transit, shared vehicles, walking, and cycling—within a single trip can create a disutility for users, which can be attributed to inconvenience and longer travel times [16]. To mitigate these issues, adequate infrastructure (e.g., multimodal hubs) and strong collaboration among mobility providers are essential [17]. The literature consistently highlights that effective partnerships between service operators are important for delivering integrated and multimodal transportation offerings [18].

In this context, multimodal trip planning is a critical component of successful MaaS systems [19,20]. Multimodal trip planning refers to the process of providing users with real-time, optimized travel itineraries that incorporate various transportation services [21]. While the development of routing algorithms for single-mode transportation (e.g., car navigation systems) has attracted a lot of research attention, research on algorithms capable of handling multimodal trip planning is still relatively limited [6]. The complexity of multimodal routing stems from the need to seamlessly connect disparate transportation networks while accounting for diverse user constraints and preferences [22].

Developing efficient multimodal trip planners is a challenging task, as these systems must integrate data from heterogeneous transport modes and consider various factors, including travel time, cost, mode changes, and user preferences. Unlike single-mode routing algorithms, such as Dijkstra's or A*, which focus on optimizing routes within one type of transport, multimodal trip planners face the additional challenge of managing mode transitions and coordinating between different types of services [23].

A prominent example is the VINTRA platform in Lithuania, a GIS-based solution designed to integrate multiple public transport services, such as buses, trains, and ferries. VINTRA utilizes General Transit Feed Specification (GTFS) data to provide real-time updates and employs optimization algorithms, including the Dijkstra method, to offer efficient route recommendations [24]. In the United States, a series of case studies from metropolitan areas like Boston, Dallas-Fort Worth, and San Francisco examine the integration of shared mobility services (e.g., bike-sharing and ride-sharing) into multimodal trip planning frameworks. For instance, Boston's integration of the Bluebikes program with the Massachusetts Bay Transportation Authority (MBTA) highlights how shared mobility can enhance first- and last-mile connectivity [25]. Another significant contribution is the Xerox Trip Planner (XTP), developed by Ulloa et al. (2017). XTP is a multimodal trip planning system that integrates various transportation modes, including public transit, walking, biking, and driving. The system utilizes a round-based algorithm for scheduled transport services alongside static graph-based planners for non-scheduled segments [22].

In the context of smart cities, predictive analytics has been applied to enhance the efficiency of multimodal trip planning. Anagnostopoulos (2021) developed a predictive vehicle ride-sharing system that utilizes historical traffic data to forecast demand and optimize vehicle allocation [26]. Liu et al. (2019) introduced an extensible and personalized multimodal trip planner that allows users to upload auxiliary geographic data, such as crime rates, and specify temporal constraints and preferences over these data in combination with typical metrics like time and cost. The planner supports modes including walking, biking, driving, public transit, and taxi, using linear temporal logic to capture temporal constraints and preferential cost functions to represent preferences [27]. Similarly, Yang et al. (2023) developed an optimization framework integrating shared autonomous vehicles (SAVs) with metro systems. Using mixed-integer programming, the framework optimizes multimodal routes by balancing traditional fixed-schedule transit with flexible, on-demand services. [19].

Despite these advancements, there remains a need for incorporating

individualized user preferences in multimodal trip planners. Most current systems provide standardized route suggestions that fail to consider the specific preferences and unique needs of each user. However, it is well recognized that transportation choices are highly personal; for example, some users may prioritize active modes such as walking or cycling for health and environmental benefits, while others may prioritize comfort and convenience, choosing cars or public transport [28]. To address this gap, the focus of this paper is on the integration of personalized trip planning within a multimodal transportation framework. Personalization involves adjusting travel recommendations based on the specific preferences of individual users, considering factors such as accessibility requirements, sensitivity to travel costs, and preferences for environmentally friendly options [29]. In the case of the multimodal trip planner that the present paper proposes, historic trips that are captured by a MaaS app, are considered. The historic trips of each user are utilized for generating customized travel choices, enhancing user satisfaction and promoting sustainable transport alternatives. The proposed methodology aims to further contribute in the enhancement of multimodality in urban mobility and in the facilitation of the operation of MaaS systems.

2. Use case description

In the city of Thessaloniki, a pilot Mobility as a Service (MaaS) system was launched in 2023 with the aim of enhancing multimodal travel and reducing dependency on private cars, which have traditionally dominated the city's transportation landscape. Thessaloniki has long relied heavily on car-based transport, with high levels of vehicle ownership and a significant proportion of daily trips made by private vehicles. In contrast, active mobility options, such as cycling and walking, have consistently represented a minor share of the total modal split. This strong reliance on cars, coupled with limited cycling infrastructure, underscores the need for integrated and user-friendly multimodal solutions.

The implemented MaaS system incorporates five shared mobility hubs, strategically positioned across the city to offer a range of transportation options, including electric cars, e-bikes, and e-scooters (see Fig. 1). Due to the lack of a specific regulatory framework for the establishment of shared mobility hubs in the city of Thessaloniki, the five hubs were located in private areas based on specific agreements with their owners. To expand the reach of the service and accommodate additional trip origins and destinations, virtual stations exclusively providing e-bikes have been established. At the core of the MaaS platform is an enhanced multimodal trip planner, which offers a comprehensive range of transportation options. The trip planner integrates real-time data from three key modes: shared mobility (e-cars, e-bikes, e-scooters), public buses, and walking.

The public transportation component is powered by the extensive bus network managed by the Thessaloniki Urban Transport Organization (OASTH), which operates over 70 fixed routes that provide extensive coverage across the urban center, metropolitan zones, and surrounding suburbs. Recently, the fleet has been upgraded with the introduction of electric buses, aiming to modernize the service and reduce the environmental impact of public transport [30]. Additionally, a new metro line, currently in the final stages of construction, is projected to begin operations by the end of 2024. The metro will feature 13 stations, extending from the city center to the eastern districts, and is anticipated to play a significant role in reshaping the urban transport landscape by offering a reliable, fast alternative to road-based travel.

The trip planner's architecture is designed to interact seamlessly with the MaaS platform through direct application programming interface (API) connections, facilitating the real-time exchange of information on shared vehicle availability, user trip requests, and optimal travel recommendations. By utilizing General Transit Feed Specification (GTFS) data, the system integrates essential static data (routes, stops, schedules) from the public bus network into its routing algorithms. The

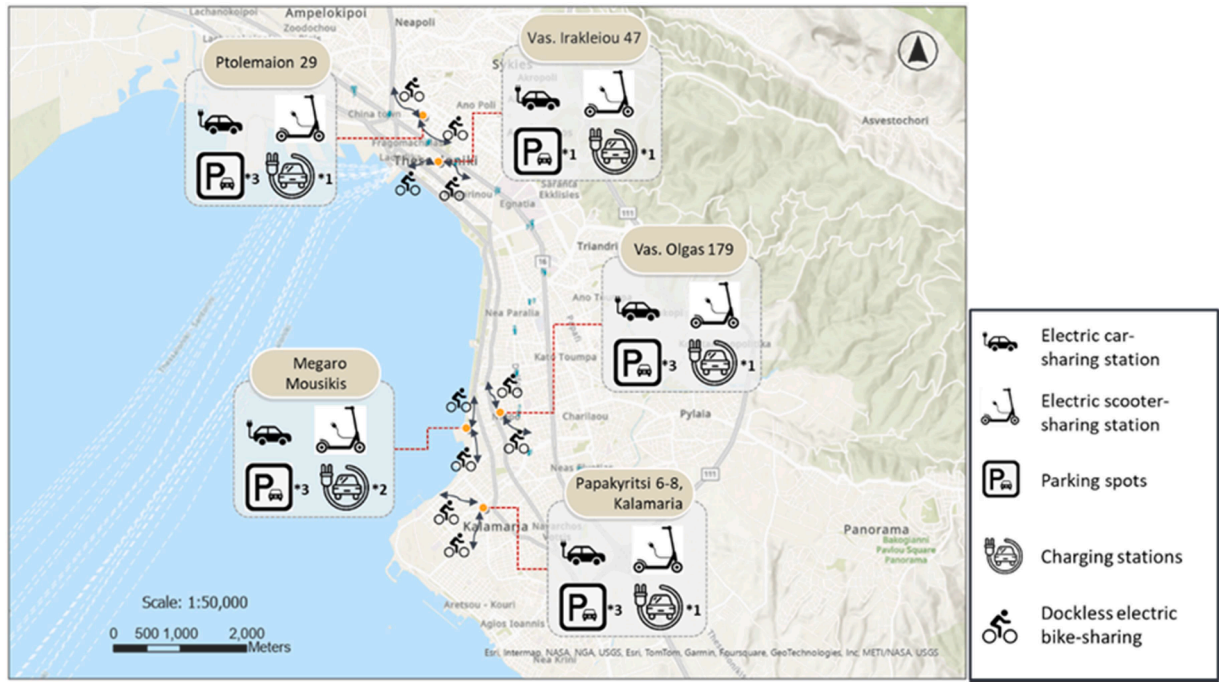


Fig. 1. Overview of shared mobility hubs in Thessaloniki.

planner provides personalized travel suggestions, considering factors such as time, cost, and user preferences, thereby offering tailored and efficient multimodal solutions. By combining these various transport modes seamlessly, the system aims to boost the attractiveness of shared mobility and public transit, reduce traffic congestion in the city, and support the broader transition towards more sustainable urban transportation in Thessaloniki.

3. Methodology

The steps that were followed for developing and testing the individualized multimodal trip planner are presented in Fig. 2.

For solving the multimodal trip planning problem, the first step was to identify the various alternative unimodal and multimodal solutions that can be reasonable from users' perspective. Considering the spatial allocation of the shared mobility hubs and the bike-sharing stations, 23 alternative solutions were identified, as presented in Fig. 3.

The second step was to define the criteria, based on which the various alternatives will be assessed for providing to the user the optimal one or a ranking of the alternatives. For this prioritization task, 3 criteria were defined, namely travel time, travel cost and number of transfers between different transport modes. The calculation of travel time was made with the aid of the OpenTripPlanner [31], which is an open source software capable for providing passenger information and transportation network analysis. Travel cost was calculated considering the travel times and the cost of using the various modes in Thessaloniki's MaaS system.

Since the different criteria are measured in different units, a way to combine the different criteria in a single utility function is needed. For doing so, a stated preference (SP) approach was followed. A short survey was designed, consisting of very specific socioeconomic characteristics (i.e. gender, age, occupation, monthly income) and four SP scenarios. In each scenario, the respondents had to select between two different trips. The trips were different with regards to the travel cost, the travel time with the different modes and consequently the number of transfers between the modes. An example of the SP scenarios is presented in Table 1. It should be noted that public transport options were not included in these SP scenarios, since at a first stage public transport information

(GTFS) was not available in the MaaS system and a first multimodal trip planner version was developed without including public transport suggestions.

The survey was distributed, in electronic form via communication channels of authors and their affiliated organizations, within March 2023. During this period 200 valid responses were collected. The 52.5 % of the respondents are male, while the majority of the respondents is aged between 18 and 39. More specifically, 31.5 % are aged between 18 and 24 and 41 % are aged between 25 and 39, while the rest are shared approximately equally between the classes "40–54" and ">54". With regards to the monthly income, a sufficient number of responses for all income classes is being observed, with a slight tendency towards more responses in the higher income classes (1601–2000€ and >2000€). The aforementioned figures largely coincide with the profile of participants in previous published studies with the city of Thessaloniki as the study area. Based on the responses a binary logistic regression model was developed, using the R programming language [32] and the aod package [33]. The aim of the model was to estimate the impact that the various criteria have on the choice of respondents. The developed model can explain about 18 % of the variance of the respondents' choices (McFadden's $R^2 = 18.2\%$). The results of the binary logistic regression model led to the following generalized cost equation.

$$GC = -0.18 \times ttc - 0.236 \times ttb - 0.37 \times tts - 0.275 \times ttw - 1.073 \times c - 3.925 \times nt \quad (1)$$

where:

- ttc , ttb , tts , ttw is the travel time with shared car, bike, scooter and walk respectively,
- c is the total cost of trip,
- nt is the number of transfers between different modes.

From the coefficients derives that the users are more willing to use a shared car and less willing to use a shared e-scooter. This outcome probably reflects on the one hand the car-oriented culture in Thessaloniki and on the other hand the unsafe built environment for riding an e-

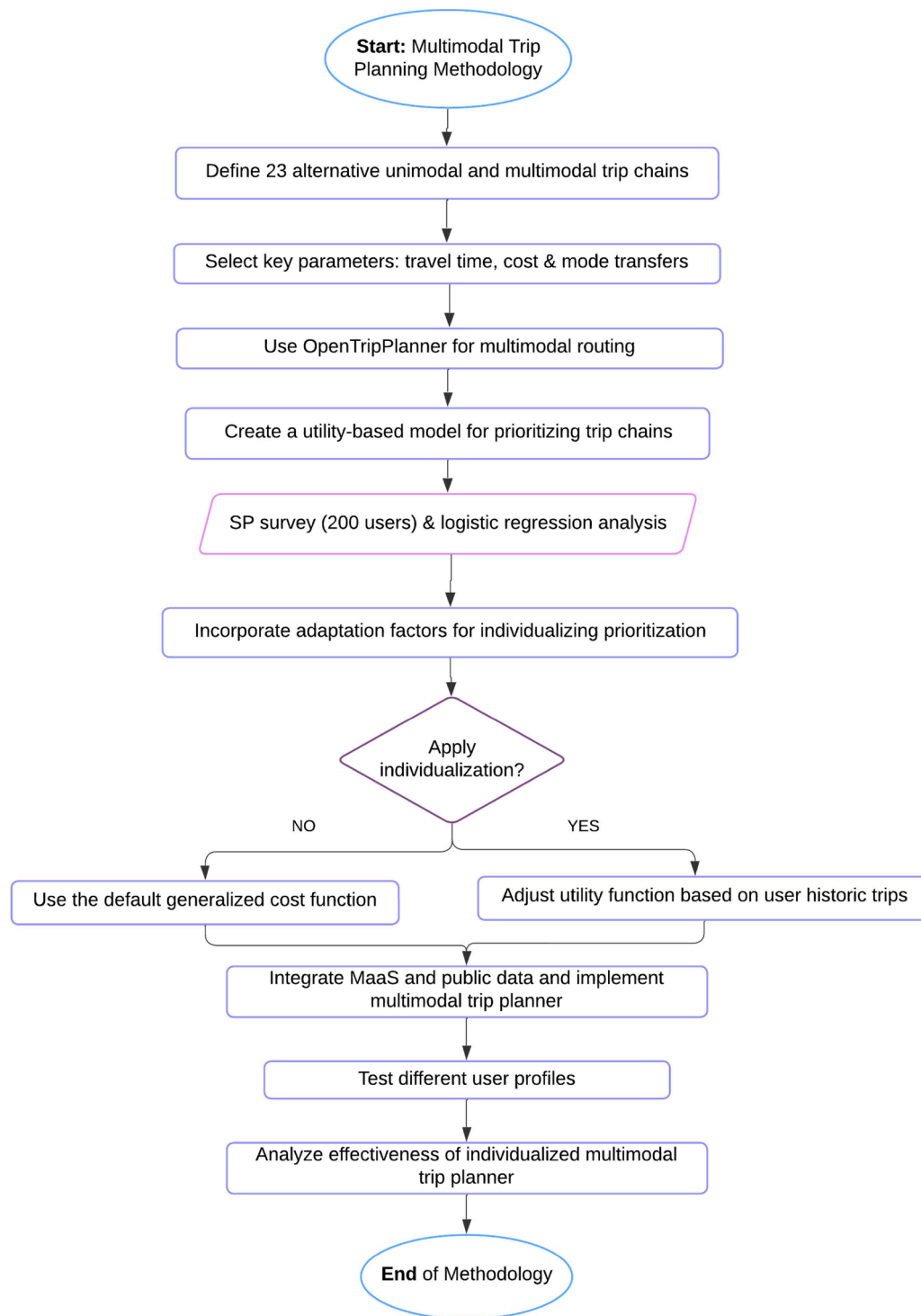


Fig. 2. Research methodology flowchart.

scooter. Moreover, from the coefficients can be acknowledged that the number of transfers between different modes creates an important additional burden to the users, especially in the city of Thessaloniki, where travelers are not used to multimodality.

Once the public transport information (GTFS) became available to the MaaS system, the need for incorporating public transport options in the multimodal trip planner appeared. Therefore, it was required to properly modify the generalized cost function for accounting also for public transport trip-legs. Based on the findings of a recent study that conducted in the city of Thessaloniki and models the willingness to use a

shared scooter instead of public transport, the parameter of the “travel time with public transport” variable can be derived [34]. More specifically, the parameters identified by the referenced study, along with the already identified parameter for the “travel time with scooter” variable, are being used to estimate the parameter for the “travel time with public transport” variable. As such, the utility function now takes the following form:

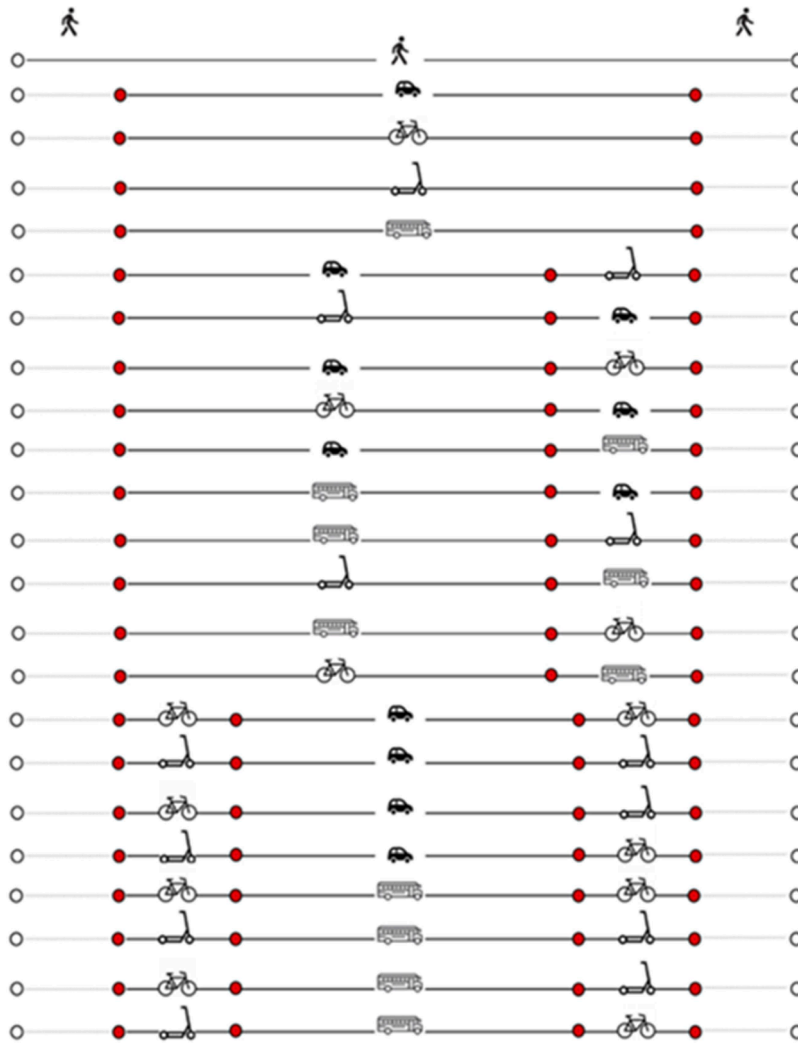


Fig. 3. Representation of the 23 alternative solutions.

Table 1
Stated preference scenario for defining a generic utility function.

Trip 1	Trip 2
Trip duration with shared car: 35 min + Trip duration with shared bike: 8 min	Trip duration with shared car: 15 min + Trip duration with shared bike: 8 min + Trip duration with shared scooter: 8 min
Trip total cost: 3.5 €	Trip total cost: 3.5 €
☐	☐

$$GC = -0.18 \times tt_c - 0.236 \times tt_b - 0.37 \times tt_s - 0.275 \times tt_w - 0.314 \times tt_{pt} - 1.073 \times c - 3.925 \times nt \quad (2)$$

where tt_{pt} is the travel time with public transport.

The new form of the utility function, as well as the initial one, is generic (i.e. the same for all users). For incorporating individual preferences in the utility function, a mechanism is being proposed that will consider for each user his/her historic trips, as they are gathered by the MaaS app. Considering that the MaaS app records only the trips that the user made through shared car, bike and scooter, the adaptation of the utility function can only be made with regards to the specific modes. As a result, an adaptation factor is being added in the function of each one of the three modes and the final form of the utility function is the following.

$$GCI = -0.18 \times f_{ci} \times tt_c - 0.236 \times f_{bi} \times tt_b - 0.37 \times f_{si} \times tt_s - 0.275 \times tt_w - 0.314 \times tt_{pt} - 1.073 \times c - 3.925 \times nt \quad (3)$$

The adaptation factors (f_c , f_b , f_s) are being computed separately for each user i and they are dynamically changing as the user makes new trips. The three adaptation factors are computed using the following steps.

Step 1: calculate adaptation factors for each separate historic trip

i) if it is a car trip:

$$f_{c1} = \frac{t_b}{t_c}, \text{ if } \frac{t_b}{t_c} > 1 \text{ then cap } f_{c1} \text{ to } 1 \quad (4)$$

$$f_{c2} = \frac{t_s}{t_c}, \text{ if } \frac{t_s}{t_c} > 1 \text{ then cap } f_{c2} \text{ to } 1 \quad (5)$$

$$f_{b1} = 1, f_{b2} = 1, f_{s1} = 1, f_{s2} = 1$$

ii) if it is a bike trip:

$$f_{b1} = \frac{t_c}{t_b}, \text{ if } \frac{t_c}{t_b} > 1 \text{ then cap } f_{b1} \text{ to } 1 \quad (6)$$

$$f_{b2} = \frac{t_s}{t_b}, \text{ if } \frac{t_s}{t_b} > 1 \text{ then cap } f_{b2} \text{ to } 1 \quad (7)$$

$$f_{c1} = 1, f_{c2} = 1, f_{s1} = 1, f_{s2} = 1$$

iii) if it is a scooter trip:

$$f_{s1} = \frac{t_c}{t_s}, \text{ if } \frac{t_c}{t_s} > 1 \text{ then cap } f_{s1} \text{ to } 1 \quad (8)$$

$$f_{s2} = \frac{t_b}{t_s}, \text{ if } \frac{t_b}{t_s} > 1 \text{ then cap } f_{s2} \text{ to } 1 \quad (9)$$

$$f_{c1} = 1, f_{c2} = 1, f_{b1} = 1, f_{b2} = 1$$

where t_c , t_b , t_s correspond to the travel time that is needed with car, bike and scooter for a trip from the origin to the destination of the specific historic trip.

Step 2: calculate adaptation factors for each user

$$f_{ci} = \frac{\sum_{j=1}^n (fc1j + fc2j)}{n} \quad (10)$$

$$f_{bi} = \frac{\sum_{j=1}^n (fb1j + fb2j)}{n} \quad (11)$$

$$f_{si} = \frac{\sum_{j=1}^n (fs1j + fs2j)}{n} \quad (12)$$

where n is the number of trips that the user i carried out with the specific mode.

4. Results

The proposed individualized multimodal trip planner was evaluated through a series of test scenarios tailored for the urban environment of Thessaloniki. The testing includes two phases: a) the modification of the adaptation factors based on the historic trips of different test users, b) the differentiation in the proposed multimodal trip plans based on the different adaptation factors.

As a first step, four different user profiles were created, where each user had a different set of historic trips. It was hypothesized that the first user is more inclined in car-sharing trips, the second one in bike-sharing trips, the third one in scooter-sharing trips and the last one balances between these three shared mobility services. For each trip that was assumed, the travel time was computed, using the OpenTripPlanner. As such, the adaptation factors can derive for each trip and consequently for each user. Table 2 summarizes the results of this process.

For the first test user, despite the fact that most of his/her trips are with a shared car, the adaptation factors for the three modes are approximately the same, meaning that trips with shared car were not significantly prioritized for the specific user. This result is attributed to the calculation of lower travel times for the shared car comparing with the other two modes, which justify the selection of the specific mode for the specific trip and do not indicate any special preference of the user for this mode. For the second test user, the adaptation factor for the shared bike is significantly lower comparing with those of the other two modes, meaning that for this user multimodal trips that include bike-sharing will be prioritized, because he/she chooses to ride a bike despite that it has higher trip durations comparing with the alternatives. Similarly,

Table 2

Calculation of adaptation factors based on different sets of historic trips.

User	Trip	Used mode	Trip duration with selected mode	% difference in trip duration with the two non-selected modes	f_c	f_b	f_s
1	1	Shared car	46	−38.1 %	0.985	0.993	0.986
				−67.15 %			
	2	Shared car	25	−42.5 %			
	3	Shared car	26	+15.9 %			
				−41.6 %			
	4	Shared bike	16	−64.6 %			
				+6.9 %			
	5	Shared scooter	12	−21.7 %			
				−14.2 %			
				+23.7 %			
2	1	Shared bike	27	−14.2 %	1.000	0.888	0.968
				+37.6 %			
	2	Shared bike	22	+23.7 %			
				+6.9 %			
				−21.7 %			
	3	Shared bike	16	−37.6 %			
				+23.7 %			
	4	Shared car	22	−41.6 %			
				−64.6 %			
	5	Shared scooter	24	+38.0 %			
				−23.1 %	1.000	0.947	0.920
	1	Shared scooter	13	+38.1 %			
				−31.0 %			
	2	Shared scooter	12	+14.2 %			
				−23.7 %			
	3	Shared scooter	17	+41.6 %			
				−24.7 %			
	4	Shared car	27	−14.2 %			
				−37.6 %			
	5	Shared bike	24	+37.6 %			
				−23.7 %	0.988	0.893	0.960
	1	Shared car	44	−38.1 %			
				−67.1 %			
	2	Shared car	32	−42.5 %			
				+15.9 %			
	3	Shared bike	14	+65.4 %			
				+30.3 %			
	4	Shared bike	19	+37.6 %			
				+23.7 %			
	5	Shared scooter	21	+41.6 %			
				−24.7 %			
	6	Shared scooter	13	+14.2 %			
				−23.7 %			

for the third test user multimodal trips that include scooter-sharing will be prioritized. For the fourth test user, despite the fact that his/her history shows a balance between the three modes, the shared bike will be prioritized.

Overall, these results reveal the tendency of the algorithm to promote the usage of micromobility and especially the usage of active mobility (bike-sharing), which is in-line with the sustainable urban mobility goals. The tendency of the algorithm to promote the usage of micromobility instead of car-sharing is attributed to the way that the adaptation factors are being computed. More specifically, the adaptation factors (as presented in Eqs. (4)–(12)) are calculated based on the travel time needed for each transport mode to connect a specific OD. As such, those modes that are typically faster (i.e. car-sharing) are considered in most cases a reasonable choice. On the other hand, the selection of a slower mode expresses a preference of the individual to this mode.

Although, Table 2 showed that there is a tendency for promoting micromobility trips, for holistically evaluating the results of the multimodal trip planner it is crucial to explore the effect that these changes in the adaptation factors have in the proposed multimodal trip plans. For this purpose, for specific origins-destinations, Figs. 4–5 compare the results of the multimodal trip planner between different test users, as well as the generic utility function (Eq. (2)) which applies for someone

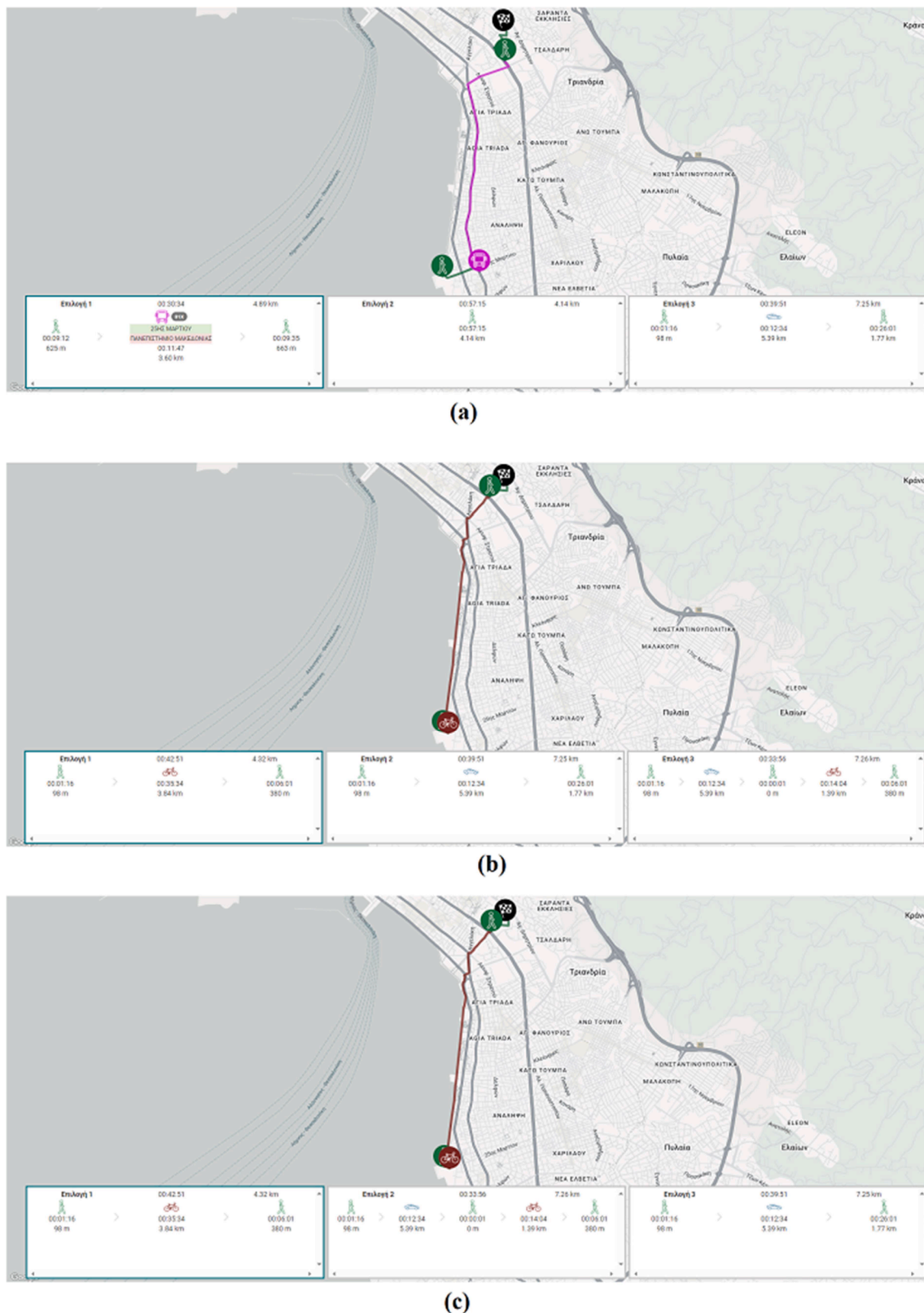


Fig. 4. First example of multimodal trip planner results; a) generic utility function, b) test user 1, c) test user 2.

that has not previously conducted any trip with a shared car, bike or scooter. It is noted that Figs. 4 and 5 are snapshots from an application where the individualized multimodal trip planner has been integrated (the application is available at: <https://play.google.com/store/apps/details?id=gr.brainbox.emaas&hl=el>).

In the case of Fig. 4, it is observed that using the generic utility function, the multimodal trip planner proposes as an ideal option a trip that combines public transport with walking, while the second-best option is a walking-only trip. For test user 1, who has mostly used shared car in the past (as shown in Table 2), the multimodal trip planner



Fig. 5. Second example of multimodal trip planner results; a) generic utility function, b) test user 1, c) test user 2.

proposes as an ideal option the combination of bike-sharing with walking. This change in the ideal option is attributed to a historic bike-sharing trip that test user 1 had made and resulted in an f_b value lower than 1 (i.e. 0.993). Also, the second-best option has changed for test user 1. More specifically, a trip that combines car-sharing with walking is

identified as the second-best option, due to the preference that this test user showed in the past for car-sharing. Finally, for test user 2, who has mostly used bike-sharing in the past (as shown in Table 2), the multimodal trip planner maintains the same ideal option (i.e. combination of bike-sharing with walking), but changes the second-best option. More

specifically, due to the preference of this user for bike-sharing, the second-best option in this case replaces one part of the car-sharing trip with bike sharing; thus, in this case the second-best option combines car-sharing, bike-sharing and walking.

Fig. 5 presents the results of the multimodal trip planner for a different origin-destination pair. For this origin-destination pair, in all presented cases, the combination of car-sharing with walking is identified as the ideal trip option, since there is a car-sharing station in a close proximity both to the origin and the destination. However, some changes are identified in the second-best trip option. Using the generic utility function, the multimodal trip planner identifies the combination of two different bus lines with walking as the second-best option. For test user 1 and test user 2, who have both used shared mobility services in the past, the combination of bike-sharing with walking is identified as a better option comparing with the combination of two different bus lines.

The methodology effectively integrated real-time data from shared mobility services, public buses, and walking routes, providing tailored travel recommendations that adapted to user preferences. The results indicate that the trip planner reliably suggested optimal routes based on travel time, cost, and mode transfers, showing promising potential in delivering efficient and user-centered travel solutions.

5. Discussion

Multimodal trip planners are a growing area of research in transportation and urban mobility, aiming to provide seamless and efficient travel experiences. The development of multimodal trip planners is crucial for improving urban mobility by integrating various transportation modes such as public transport, cycling, walking, and vehicle-sharing. These planners enhance efficiency, reduce congestion, and promote sustainable travel by optimizing routes based on specific criteria. However, significant challenges remain, including real-time data integration, interoperability between transport networks, and accurately modeling user preferences. Despite these challenges, multimodal trip planners play a key role in smart mobility solutions, improving accessibility and encouraging more sustainable travel choices.

Tailored travel solutions are offered by individualized multimodal trip planners through the consideration of user-specific preferences and constraints across various transportation modes. This individualization enhances user satisfaction and promotes the adoption of sustainable transport options. Several studies have focused on developing such planners using diverse methodologies. Campigotto et al. [35] introduced the FAVOUR algorithm, which provides personalized, situation-aware multimodal route recommendations, by involving an initial user profile setup, followed by a Bayesian learning approach that refines recommendations based on user feedback and situational context, such as weather conditions. Liu et al. [27] developed a hypergraph-based multimodal trip planner that allows users to upload auxiliary geographic data, like crime rates, and specify temporal constraints and preferences; this approach enables the planner to generate routes that align with individual user needs and safety considerations. Yatskiv et al. [36] also developed an individualized multimodal trip planner for the city of Riga, that considers the feedback of users for assigning weights to the examined criteria. These studies employ techniques such as machine learning to create individualized multimodal trip planners that cater to user preferences and situational factors, thereby enhancing the overall travel experience.

The multimodal trip planner presented in this paper employs a utility-based approach to assess the impact of various criteria on ranking alternative trip chains. By leveraging passively collected historic trip data from the MaaS app, it personalizes route recommendations without requiring user feedback. This enables adaptive trip planning based on past mode choices, enhancing the travel experience while minimizing user effort.

The multimodal trip planner has the potential to significantly

promote sustainable urban mobility, particularly by encouraging multimodal travel. However, maximizing its benefits requires additional measures. Integrating ticketing systems and real-time data sharing among transport providers can enhance seamless transitions between modes while improving the overall efficiency of multimodal trip planners and MaaS apps. Additionally, incentivization mechanisms, such as discounts, loyalty points, or cashback for sustainable transport use, can influence traveler behavior. Personalized incentives based on user preferences and travel history further boost adoption. By implementing these strategies, MaaS platforms can drive a shift toward more sustainable and efficient mobility, reducing congestion and environmental impact.

6. Conclusions

This paper outlines the development of an individualized multimodal trip planner for the city of Thessaloniki, integrating public transport options, shared mobility services, and walking routes within a comprehensive MaaS framework. The proposed planner is designed to be scalable and requires only real-time data on vehicle availability and station locations, making it adaptable for various urban contexts. One of the key contributions of this work is the implementation of a prioritization mechanism that evaluates and ranks unimodal and multimodal travel options based on a utility function tailored to user preferences.

A significant focus of this research was the incorporation of user-specific preferences into the trip planning process, moving beyond standardized routing solutions. By integrating revealed preferences of users, captured automatically through the MaaS app, the planner can dynamically adjust the utility function, offering route suggestions that better align with individual travel preferences and attitudes.

The findings of the testing of the individualized multimodal trip planner highlight a distinct tendency of the algorithm to prioritize micromobility modes, particularly active options, like bike-sharing. This tendency aligns closely with sustainable urban mobility goals, emphasizing reduced car dependency and increased use of environmentally friendly transportation options. The adaptation factors computed for different user profiles demonstrated that the algorithm tends to prioritize modes like bike and scooter sharing, especially when users consistently choose these modes despite longer travel times. The adaptation factor for cars, on the other hand, shows limited variation, reflecting the rationale that car usage is often justified by its generally shorter travel times. The outcome reflects a logical prioritization of cars in situations where they offer significant travel time advantages, showing that their selection is often based on practical reasoning.

Although the planner emphasizes promoting micromobility and active travel, the suggested solutions have commonalities with those produced by the generic algorithm, which does not account for individualization. The outcome is determined by the availability of shared mobility options near specific origins and destinations, shaping the practicality of the proposed routes. As depicted in the maps and outputs generated in the test cases, deviations from the generalized algorithm's recommendations are specific and reasonable. As such it is ensured that the planner achieves a balance between integrating sustainability goals and remaining adaptable to real-world conditions, offering realistic and user-focused travel suggestions.

The focus of the present paper is on presenting specific methodological steps for developing an individualized trip planner; these steps are applicable on various contexts. Yet, the present paper does not emphasize on the modeling task for defining the generalized cost function, since this is highly dependent on the context (i.e. characteristics of the MaaS system, the city and the population). Thus, the suitability of the presented generalized cost function is limited in the case of Thessaloniki. Even for the case of Thessaloniki, future research can emphasize more in the definition of a more robust generalized cost function, which except of the travel time of each trip-leg, the total travel cost and the number of transfers between modes, would also consider

user-attributes, like gender and age. Another limitation of this paper is that the adaptation factors are only applied on the three shared mobility modes, since only for these three modes historic trips are being gathered. In the case of having historic trips for other modes (and mainly for public transport), for each user, the incorporation of the adaptation factors can be extended to the other transportation modes too. Future research should also focus on real-world testing to validate the system's performance in live settings and further explore the dynamic adjustment of the generalized cost function to accommodate the diverse needs of urban travelers.

CRedit authorship contribution statement

Josep Maria Salanova Grau: Validation, Methodology, Conceptualization. **Andreas Nikiforiadis:** Writing – original draft, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Panagiotis Tzenos:** Validation, Software, Methodology. **Despoina Tsavdari:** Writing – original draft, Data curation. **Georgia Ayfantopoulou:** Supervision, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

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Data availability

The authors do not have permission to share data.

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