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Best–Worst Method for Modelling Mobility Choice after COVID-19: Evidence from Italy

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Abstract: All countries have suffered from the COVID-19 crisis; the pandemic has adversely impacted all sectors. In this study, we examine the transport sector with a specific focus on the problem of commuting mode choice and propose a new decision-making approach for the alternative modes after synthesizing expert opinions. As a methodology, a customized model of the recently developed best–worst method (BWM) is used to evaluate mobility choice alternatives. The survey reflects citizens' opinions toward mobility choices in two Italian cities, Palermo and Catania, before and during the pandemic. BWM is a useful tool for examining mobility choice in big cities. The adopted model is easy to apply and capable of providing effective solutions for sustainable mode choice. The urban context is analyzed considering the importance of transport choices, evaluating the variation of resilience to the changing opinions of users.

Keywords: mobility choice; COVID-19; best–worst method; multi-criteria decision making

1. Introduction

The COVID-19 pandemic has produced several unprecedented effects around the world and has adversely affected the transport sector, which has experienced a drastic reduction in passenger traffic across all different modes of transport. With physical interaction being the key medium perpetuating the spread of the virus, government decisions have been pivotally centered on either discrete decisions or combinations of decisions to curtail or block mobility [1]. Therefore, during the outbreak, countries across the globe, including USA, Canada, Italy, and China, imposed different types of bans and restrictions on travel [2] and all types of mobility options that likely involve physical contact and implemented domestic emergency plans for medical response. According to the World Health Organization (WHO) [3], the virus is respiratory and spreads mainly through contact with an infected person. In particular, contact with droplets produced by infected subjects following sneezing or coughing is the key media spreading the virus. Transport modes are amongst the most critical platforms for the rapid spread of the infection in high-density and mixed-use urban environments. This aspect has manifested in the contemporary context where people move every day (on an average 2.5 journeys per day), covering an average distance of about 30 km, for various reasons (e.g., work, study, shopping, entertainment) with different modes of transport, including on foot, bicycle, public transport, and personal vehicle [4].

During the second stage of restrictions, many countries addressed the challenge associated with conventional travel, asking for requalification of the road infrastructure and acquisition of electric micro-mobility through political will and endorsement, while promoting walking [4] and cycling [5–7]. Design of road infrastructures and the enhancement of pedestrian and bicycle lanes are highly encouraging avenues for increasing mobility after the pandemic, promoting integrated infrastructure design and control through intelligent transport system (ITS) technologies [8], building information modeling for infrastructure (I-BIM) design, and the mobility as a service (MaaS) concept [9]. To contain the spread of COVID-19 and in anticipation of the gradual resumption of economic activities, people's mobility was restricted using local and domestic restrictive regulations in various domains of mobility, such as halting domestic and international flights, banning movement between communities, and self-isolation in homes. Production systems and work environments were also adapted to the necessary safety conditions through intelligent work environments or increased social distance.

Social media reports and the literature suggest that people will have to live with COVID at least until an effective vaccine is produced. During this time, the most effective strategy has proved to be social distancing, which has reduced the spread of the virus and significantly limited the contagion. Conversely, this seems to have negatively impacted the economy and societal relationships.

Having overcome the peak of contagion, we now enter a phase 2 of coexistence with the virus, which, considering the direct and indirect risks of contagion as the restrictions regarding the more radical social spacing of phase 1 are relaxed, emphasizes the issue of the mobility of people. This phase represents an essential opportunity to build an urban resilience strategy based on necessarily anti-fragile scenarios around mobility policies [10], taking the opportunity during the crisis to instigate an urban and social transformation that is able to strengthen the balance of the complex city system.

Some cities in Europe and in particular in Italy are facing the complex challenge of the reorganization of mobility, where the partial reopening on 4 May 2020 involved the resumption of some productive activities and the consequent increase in related mobility flows. In agreement with Renaud et al. [11], the different forms of mobility must ensure that global mobility can promote local mobility, encouraging solutions that can manage the entire territory.

The COVID-19 pandemic has raised some questions about the vision of infrastructure, changing everyone's viewpoint. Through long-term planning, the acquisition of public funds, and public–private partnerships, the economic system can be improved and the demand for transport can be increased. The long-term consequences of the COVID-19 pandemic may support the creation of more permanent changes related to smart working and other daily activities, thus reducing mobility needs and overall fossil energy consumption. These developments can promote research and new practices arising from the COVID-19 pandemic to accelerate sustainability transitions, improving understanding of the role of governance in transitions and bringing to attention the ethical and policy implications of the shock effect on the various landscapes [12].

In the literature, several studies examined resilience and sustainability in the transport sector. D'Adamo et al. [13] reported that the implementation of circular and green strategies is not explicitly aimed at improving resilience. Still, their impacts are significant in terms of response and recovery, and one benefit is their positive effect on the environment and climate change, reducing the likelihood of environmental disasters.

The main challenge is adapting transport systems to ensure safe mobility for people who return to work from May 2020 onward without losing efficiency. The efficiency of the transport system is linked to its ability to carry a large volume of passengers in a small number of vehicles to increase load factors while reducing mileage and the associated impacts (pollution, greenhouse gases, energy consumption, accidents, congestion). This principle has been adopted by most of the transport companies during the pre-pandemic era, particularly for the popular urban transport modes, i.e., subways/metros, trams/streetcars, and buses. The minimum physical distancing being critical during the pandemic, the conventional measurements for the efficiency of the transport system are being severely challenged [14]. In this critical juncture during this transition, we addressed the emerging problem of mobility choice for daily commuting during and after the pandemic in metropolitan cities. As a methodology, the best–worst method (BWM) was applied to evaluate the mobility choice alternatives. Urban residents were the evaluators of the possible mobility choices during the outbreak. The data were collected through an online survey in two metropolitan cities, Palermo and Catania, of the region of Sicily in Italy.

The work focused on three steps related to (1) the selection of a random sample of inhabitants of two metropolises, (2) data processing using the BWM method, and (3) the evaluation of results for the assumption of future developments

We focused on the BWM methodology, which has been implemented in the literature in different sectors, as we considered it optimal for the analysis in the post-pandemic period in favor of the choice of optimal or strongly negative modes of transport in large cities. The data were directly derived from users of the different transport modes, which guarantees higher-accuracy data. The BWM is based on a systematic pairwise comparison of the decision criteria and lays the foundation for more in-depth studies.

2. Multi-Criteria Decision-Making (MCDM) Methods in Examining Mobility Choices

2.1. Specifics of Mobility Choices

Mobility is a natural part of human life. It is a result of lifestyles, infrastructure, climate, and multiple other factors widely presented in the literature [15]. Mobility can be described in many different dimensions, for example, as urban mobility (inter- and intra-urban mobility), for long and short distances, driving changes for a short or long term.

Mobility choices, even if a part of the mobility, are often capacious, and are mentioned in the scientific papers as travel behavior, transport choices, or mobility patterns [16]. They represent travel data and are defined by many socioeconomic attributes of travelers, enabling the identification of separable patterns [17], e.g., for younger and older cohorts, called generations, primarily mentioned only in the human resources literature, then adapted by transport- and mobility-related studies, among others [18]. Those criteria are not limited to age but also sex, family status, life stage, having a driving license, and access to a car [19,20]. Mobility choices involve decisions of passengers resulting from considering possible travel scenarios and priorities (criteria) [21]. Included in this set of criteria are, among others, accessibility, fares, travel time, comfort, safety, being on time, reliability, directness, and waiting time [22]. A strongly developing area of study is the multimodality of mobility, followed by choosing eco-friendly travel modes [23]. Usually, investigation is undertaken for policymakers [24] by evaluating the needs of different stakeholders [25]; these studies concern mobility management. The mentioned travel priorities and scenarios mainly result in the choice of means of transport (one or more, if a multimodal pattern). The most popular, comfortable, flexible, and convenient transport mode is a personal vehicle; although it is perceived as not eco-friendly, creating congestion and traffic, it decreases the popularity of public and active transport [26].

The car culture is still alive in many countries; in others, it is only in its infancy [27]. A number of studies focused on identifying the different aims of car users, e.g., by recommending the car-sharing initiatives [28]. The goal of many activities focused on evaluating the mobility patterns is promoting modes other than individual motorized transport, especially cars, e.g., by extensive use of park-and-ride stations or simply using a different mode of transport [29–31]. During the pandemic, a car can be perceived as one of the safest choices for mobility because of the low risk of being infected.

Mobility choices have been a popular area of studies over the last 10 years [32]. These choices can be measured and analyzed using surveys, interviews, travel diaries, and geographic information systems (GISs) [33]. Unfortunately, many results are biased [34] by evaluating the mobility choices of non-random samples or samples containing only chosen groups of respondents (usually students) [35].

Mobility management involves a set of rules for managing the travel demands of different users including residents and non-residents (e.g., guests, tourists, and workers living in other areas). Mobility management differs between weekdays and other dates (e.g., weekends, holidays, incidents). In urban areas, the primary tool for strategic mobility management should be a sustainable urban mobility plan [36], further implemented using forced and voluntary solutions [37], promoting the reduction of travel–trip substitution and travel distance, and promoting mode shift or low- and zero-emission mobility [29]. Solutions should influence changes in mobility choices, especially those of younger generations as they are more flexible than older adults [38]. The mobility patterns differ for the residents of big cities, smaller cities, and rural areas according to the characteristics of their surroundings and transport possibilities.

As a consequence, multiple studies analyzed mobility choices. The complexity of this issue and the wide range of significant criteria led to the dynamic development of multi-criteria decision-making (MCDM) methods for mobility investigation. The gaps appearing between strategic and operational levels in the decision-making process of travelers require further study [39], including:

- information gaps (differences in nature, kind, interpretation, and reliability of sources of information),
- methodological gaps (differences in complexity, transparency, and interpretation of approaches, and methods for choosing transport scenario),
- feedback/continuity gaps (gap resulting from the objective definition through solution selection to implementation),
- contextual gaps (differences in thinking models—rational and others—having some level of uncertainly of decision), and
- spatial vision gaps (differences in scales of decision and spatial dimension).

Therefore, multi-criteria approaches in the field of mobility choices indicate how to overcome these gaps and rationalize the assessment and decision-making processes.

2.2. Examining Mobility Choices by MCDM Methods

MCDM is defined as a set of different methods with various mathematical approaches used to identify the best solution among the proposed or possible group of solutions/scenarios. MCDM methods are used in research where a number of decision criteria are defined that they have different levels of importance for the decision-maker [40]. Sometimes they are also called multiple-attribute decision-making methods [41]. The number of these methods is extensive, as is that of customized MCDM approaches (e.g., fuzzy approaches). They differ from each other in terms of the aggregation, data (direct or indirect, like comparing the variables), kind of output, and ease of application by decision-makers less familiar with complex mathematical operations. A complex review of available MCDM methods was published [42,43]. In turn, the mode choice attributes were revised [21].

In the literature, multiple approaches were used, including both classical and customized as fuzzy-based methods, to explain the nature of mobility choices. Among the MCDM methods for describing the mobility choices are the multi-attribute utility technique [44]; spatial multi-criteria evaluation (SMCE) [25], which is a combination of spatial analysis and multi-criteria evaluation; analytic hierarchy process (AHP) [21,44,45]; preference ranking organization method for enrichment evaluation (PROMETHEE) [44,45] or a mix of previous methods (AHP-PROMETHEE) [46]; multi-actor multi-criteria Analysis (MAMCA) [47,48]; technique for order of preference by similarity to ideal solution (TOPSIS); complex proportional assessment (COPRAS), weighted aggregated sum product assessment (WASPAS) and evaluation based on distance from average solution EDAS [39]; best–worst Method (BWM) [38]; and maximum entropy multi-criteria user equilibrium (ME-MUE) [49]. For example, commuter mobility was evaluated using the TOPSIS method [28] for China (Beijing) using smart card data. BWM was found to be the best for the analysis of large amounts of data [45].

MCDM is the dominant method used for evaluating mobility choices in urban mobility studies [16,37], including those examining sustainable urban mobility plans [38,46–50]. Other researchers used MCDM in transport and mobility along with different approaches to compare public transport systems [51], to assess and add quality to transport nodes [32], to evaluate transport providers [34], and assess road projects [40]. Additionally, MCDM methods were used to evaluate scenarios in the fields similar to mobility, like neighborhood selection by the city newcomer (e.g., multi-attributive border approximation area comparison (MABAC) and Visekriterijumsko Kompromisno Rangiranje, (VIKOR), and combinative distance-based assessment (CODAS) [52].

2.3. Best–Worst Method (BWM) for Examining Mobility Choices

BWM was created by Rezaei [53] and is an element of an extensive set of MCDM methods. It is perceived as an efficient approach due to its data requirements, being well-structured, transparency, easy application, and reliable results [50]. It has attracted the attention of researchers from different fields. It has been used in research in business and non-business areas, like technological innovation [54], scientific activity assessment and relationships with industry [55,56], quality of life [39], consumer ethical beliefs [57], water resource management [58,59], and research and development performance [60]. A wide review of using BWM was published [38].

BWM has been applied to several transportation and logistics research areas like supplier selection [60,61], supply chain management (SCM) [62], and logistics performance [5]. BWM was also used to assess transport mode choice for freight transport [45], including combined transport [63]. BWM can be used as a stand-alone method and in a few derivative concepts, e.g., the new multiple-attribute decision-making method (MADM), which is a combination of BWM and multi-attributive ideal–real comparative analysis (MAIRCA) [52].

The usefulness of other MCDM methods is undeniable, but the main difference between the BWM method and the others based on pairwise comparisons is its main structure, which is based on the most and the least significant criteria [61,64]. The attractiveness of the BWM results from its advantages, including a number of features that facilitate calculations and their interpretation: a smaller number of pairwise comparisons than in other methods, higher reliability of calculated weight coefficients, consistency of output, and using only integer values when comparing criteria (in pairs) [33]. Additionally, BWM works well when comparing and considering many conflicting criteria and goals of decision-makers (tradeoffs). BWM by its nature—specific, structured pairwise comparison—solves the inconsistency issue with, e.g., in AHP. Compared to other methods, BWM requires fewer comparison data [60,65] and provides better consistency ratio and lower minimum violation, total deviation, and conformity; therefore, BWM generates more reliable results [45].

BWM has not been used in any situation with a best/worst choice. The best–worst approach is misleading, and the description of the BWM is unclear in the scientific literature. Sometimes the literature on, e.g., general or specific consumer values in mobility or transport mentions the best–worst choices being unequal to the best–worst method, but best–worst scaling (BWS) is only an approach used to support, e.g., logit or probit models [66,67] or cluster analysis [68]. The same applies to best/worst values used in multiple logistics regression [69] or a best/worst rank [70,71].

3. Changes in Mobility Choices during and after COVID-19

3.1. Impact of COVID-19 on Mobility Worldwide

The COVID-19 pandemic has affected the lives of almost all countries, even if they did not confirm any cases of infected residents or visitors. Three countries were perceived as most affected by the COVID-19 epidemic: China (as the first country with many deceased infected patients), Italy (most affected in Europe), and the USA (with the highest number of infected people). Although the situation in Europe has yet to stabilize, Italy is attempting to recover from this crisis as soon as possible [72].

Mobility was partly responsible for the rapid development of the epidemic. Both short- and long-distance travel caused the virus spread to increase dynamically. Therefore, among others, all the planned massive gatherings, rallies, and concerts were banned. The lockdown caused a sharp reduction in the number of trips and distance traveled. As the COVID-19 epidemic is still ongoing, some initial research results on mobility changes are now available. However, they are based mostly on Google data [73–75], which are non-random data, as the data are shared only by some groups of individuals who agreed to share the data about their localization. This generated the need to evaluate the mobility changes using data gathered separately for different countries.

The basic restrictions imposed by governments across the world are a group of solutions focusing on social distancing. They resulted in a number of changes in mobility as well as in short-term lifestyles [76]. Since the beginning of the epidemic, a number of techniques attempted to predict the possible scenarios associated with mobility [77,78]. Given the restrictions, long-distance travel, especially international travel, were sharply curtailed or banned. As a result, the spread of the new coronavirus through international mobility was controlled, given the limited possibility of traveling. Passengers were also under strict surveillance during and after the journey. A number of non-clinical strategies appeared to minimize the risk of infection [79]. After some time, short-distance travel was also strictly controlled as the epidemic continued to spread through urban areas [80]. Essentially, individual mobility decisions were the key medium to spreading the disease in local and international locations.

A set of changes were implemented regarding mobility during COVID-19 pandemic. Whereas mobility is purpose-driven, the change in the purpose (leisure, work, education, shopping, etc.) alters the nature of individual mobility. At the outset, with home-based work being an immediate response to contain the spread of COVID-19, many workers converted part of their homes into workstations; while many lost their jobs, others had to take care of children alongside their regular job [75]. Due to the need for stay-at-home and restricted mobility, the total number of trips to schools and offices drastically reduced almost to zero [72]. People started to display a higher propensity for recreation, especially the use of green spaces (which increased by 291% in Oslo) [81] and active transport (cycling, walking). This was especially observed in urban areas, which sparked discussion about the true needs during a pandemic and how the future cities will be reshaped to meet these transformational needs [82].

Understanding COVID-19-induced changes in mobility is still developing as the epidemic continues. However, several studies only mentioned this topic in Japan [82], Canada [83], China [84], Italy [85], the USA [86], Bangladesh [87], India [88], Australia (but only a simulation) [89], France [90], and Sweden [91].

In Italy, the changes in mobility were mainly caused by government restrictions and society [92]; these changes intensified due to the rapid spread of the virus. The interventions regarding social distancing are a basic concept of regulating mobility. A simulation for Newcastle (Australia) showed that when 90% of people work from home, schools are closed, and social contact decreases by 70%, the infection rate decreased from 66% to 1%. Even when only 50% of the workers work from home and community interactions decrease by 30%, the infection ratio would be less than 10% [89]. This, however, would impact the mobility and change in travel distances, purposes, and numbers. All the needed restrictions are not possible to implement, so social distancing became the fundamental element of governmental decisions. It was challenging to implement in countries with low access to all the needed facilities including sanitation, especially in high-density societies and lower-middle-income economies [87].

The most comprehensive study on mobility during the COVID-19 epidemic was conducted by Chan et al. [93]. They examined the data for risk preferences for 60 countries (concerning the individuals) between 15 February and 11 April 2020 independent of government lockdown measures. They discovered that risk of infection caused people to be less willing to take risks, which reduced their travel to shops (even groceries and pharmacy), retail, and recreation locations. The decline in mobility to all local shops and other destinations was substantial for high-population-density countries. The larger percentage was the share of subpopulation of age 65 years old or older; this part of the population has a high risk of infection, so they additionally limited their visits to grocery stores, pharmacies, and parks. After the official WHO announcement about the COVID-19 pandemic, retail-, recreation-, transit-, and work-related trips decreased. For recreation and retail, the decrease was 7.47% [93].

Another study divided the COVID-19 epidemic period into two: before and after officially announcing the pandemic [93]. In the first period, people were starting to reduce work trips (especially the use of public transport) and non-essential retail shopping. The second period produced the next behavioral shifts, enhancing the previous changes. Social distancing was a more robust guideline than the lockdown (considering the people aged 65 years or older), which was intensified by shorter working hours in most of the shops. However, social distancing protocols and travel restrictions in many countries, were difficult to maintain. Sometimes, the controlling administration agencies were not prepared for such a large increase in tasks and people to be controlled [88]. In some cases, military force was used to enforce mobility restrictions. Leisure-centered mobility, including sports activities, was drastically limited. A noticeable change in mobility was observed from motorized to soft modes or active (cycling, walking etc.) transport due to companies, schools, and shopping centers being closed. Having more free time, people wanted to go walking, and many quarantine restrictions were violated.

To summarize, mobility choices were drastically disturbed by the COVID-19 outbreak. During this period, the choices mostly depended on government enforcements and optional recommendations. The many COVID-19 effects on mobility include: changing modes for both more active and non-motorized, from public to individual transport, more time spent playing sports, changes in travel purpose, and limiting travel aimed at shopping. This also caused changes in freight transport, e.g., for courier express parcels (CEP) and service providers for online shops. However, the studies are lacking on the changes in mobility choices during the COVID-19 epidemic. Therefore, the review of these studies provided limited empirical results.

3.2. Spread of COVID-19 in Italy and Effects on Mobility

Italy was the first country in Europe to be infected. According to Murgante et al. [94], COVID-19 hit Italy in February 2020 after its outbreak in China in early January. By comparing the spatial distribution and mortality model associated with COVID-19 in Italy with various geographical, environmental, and socioeconomic variables at the provincial level, a correlation was found between the number of COVID-19 cases and the associated pollutants nitrogen and soil, especially in the Po Valley area. Using a historical data series on air pollution, human mobility, winter temperature, housing concentration, health care density, population size, and age, the epidemic risk was assessed by identifying the most vulnerable areas [95].

They found that the highest risk occurred in some northern regions compared to central and southern Italy. Although the COVID-19 epidemic started almost simultaneously in both the north (Lombardy and Veneto) and in Lazio (central Italy) when the first cases were officially certified in early 2020, the disease spread more rapidly and with more serious consequences in regions with a higher epidemic risk.

Using various methodologies, the evolution of travel during the pandemic period has been monitored, with particular attention to the reasons for traveling and using public transport. Various technological tools made it possible to follow the development of passenger movements in various states. Some applications on smartphones and tablets enabled the geo-localization of people and the obtaining of information on the distances traveled [96].

The use of traffic meters, public transport ITS [97], and recordings from traffic control cameras and environmental sensors facilitated comparisons between travel flows and times before and during the lockdown. The impact on externalities, such as NO_2 emissions and road accidents, were also estimated [98]. Public transport users decreased by 93%, NO_2 concentration by 60%, and road accidents by 67%.

One out of four movements is provided by public transport in Italian cities with more than 250,000 inhabitants. A reduction or downsizing of the service provided was necessary

The decrease in the use of public transport compared to use on a working day, due to the COVID-19 emergency, is shown in Figure 1, considering the red zone where all travel was limited implemented from 12 to 25 March 2020 in various regions of Italy, comparing the South Italy data represented by Palermo and Trapani (for Sicily) and Naples and Province (for Campania) with the data of Milan and Lombardy, where the first deaths were recorded.

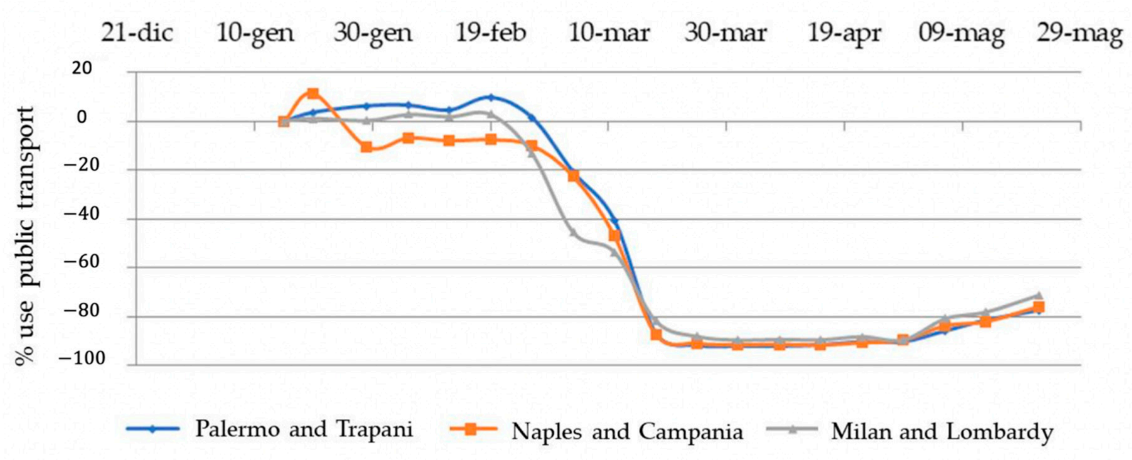

Figure 1. Public transport trend in South Italy

4. Methodology

For evaluating mobility choices, we adopted one of the most recently created MCDM techniques. BWM is similar to many other MCDM techniques, consisting of pairwise comparisons of the decision elements [53]. The main difference of BWM from the other techniques is that not all comparisons are completed; only the pairs with the previously selected best and worst alternatives are evaluated. In modelling and application, the following phases were followed (Figure 2).

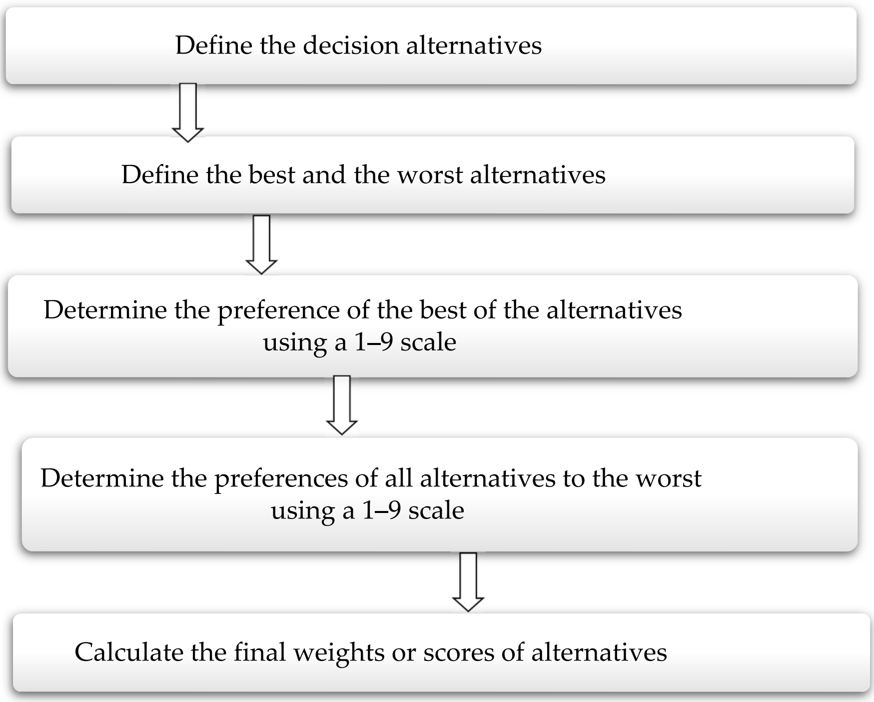

Figure 2. The main steps of the best–worst method to derive the weights of the alternatives.

The first step was identifying the best and worst alternatives determined by the evaluators. Secondly, the pairwise comparisons were applied between the best and other alternatives, then between the worst alternative and other alternatives. After, the weights of all alternatives were calculated. The consistency ratio was used to test the reliability of the pairwise comparisons.

To provide an overview of all stages for the survey, we completed the phases in the following order:

- Step 1: Identifying the mobility types.
- Step 2: Defining the best and worst mobility types using simple scoring by expert participants.
- Step 3: Evaluating the pairwise comparisons between the best mobility type with the other types using a (1–9) scale, where 1 denotes equal importance and 9 means extremely important. The following set represents the results of the best to other types (V_B):

$$V_B = (v_{B1}, v_{B2}, \ldots, v_{Bn}), \tag{1}$$

  where v_{Bj} is the preference of criterion B (the most important or the best) over all *criteria* j, and $v_{BB} = 1$. In our model, $n = 6$, as we have six alternatives to compare, $j = (1, 2, \ldots, n)$.
- Step 4: Making the pairwise comparisons between the worst mobility type and all other types by using a (1–9) scale. The result of other to worst type (V_W) is represented by the following set:

$$V_W = (v_{1W}, v_{2W}, \ldots, v_{nW}) \tag{2}$$

  where v_{jD} is the preference of criteria j (the most important or the best) over the criteria D and $v_{DD} = 1$. n = 6, as we have six alternatives to compare in our model, $j = (1, 2, \ldots, 6)$.
- Step 5: Calculating the final optimal weights $(D_1^*, D_2^*, \ldots, D_n^*)$ of the mobility types, and the indicator of the optimal consistency of comparisons, ξ^*.

  The maximum absolute difference has to be minimized by:

$$\min max_j \left\{ \left| \frac{D_B}{D_j} - v_{Bj} \right|, \left| \frac{D_j}{D_W} - v_{jW} \right| \right\}, \sum_j^{s.t.} D_j = 1, \; D_j \geq 0, \text{ for all } j. \tag{3}$$

  Then, the solution can be obtained by solving the following Linear programing (LP):

$$\min \xi^* \text{s.t.} \left| \frac{D_j}{D_W} - v_{jW} \right| \leq \xi^*, \text{ for all j}, \sum_j D_j = 1, D_j \geq 0, \text{ for all } j. \tag{4}$$

The following formula computes the consistency ratio (CR) to check the consistency of the comparisons [65]:

$$\text{Consistency Ratio} = \frac{\xi^*}{\text{Consistency Index}} \tag{5}$$

where the consistency index (CI) is presented in Table 1 [70], which was determined by random experiments for a different number of comparisons.

Table 1. The consistency index (CI) values for computing the consistency ratio.

v_{BD}	1	2	3	4	5	6	7	8	9
CI	0	0.44	1	1.63	2.3	3	3.73	4.47	5.23

The CR is acceptable for the BWM methodology if its value is between 0 and 1.

This ratio can be calculated for individual evaluators or group-wise when aggregating the scores of the group by creating the geometric mean of the scores and then conducting the consistency check. In our case, the CR was checked individually. The survey was based on the BWM method and collected general information about participants' characteristics.

5. Results

We defined the area of investigation to Sicily in southernmost Italy, including the metropolitan areas of Palermo and Catania. These cities are located in the north (Palermo), with approximately 674,000 inhabitants, and in the east (Catania), with approximately 314,000 inhabitants, respectively. The areas presented different forms of mobility, including shared and multimodal types.

We collected 400 surveys before the crisis (November and December 2019); we analyzed the data and did not publish the results.

However, the same sample size was used to collect data during the crisis (March and April 2020) to highlight the main differences in public preference toward mobility usage. The participants' characteristics are presented in Table 2.

Table 2. Participants' characteristics.

	n = 400	
Gender	Male	43%
	Female	47%
Marital Status	Married/in a relationship	27%
	Single	73%
Age	18–30 years	69%
	31–50 years	17%
	>50 years	14%

Before the pandemic, although the online survey was sent to 4000 respondents, only 487 responded, which were selected for analysis. However, during the pandemic, the survey was sent again to the 487 respondents, of which 400 surveys were received and selected for evaluation. The users who responded were controlled through identification by email address. Before the pandemic, 10% of the sample responded.

To conduct a longitudinal analysis and compare the responses of the users, we decided to limit the sample. This type of study design is mostly suitable for research regarding existing resources and constraints. We chose one longitudinal study (e.g., a panel survey), in which measurements over time were foreseen for each detection unit (repeated measurements) and specifically the variations in the choice of mobility.

The number of users, although small, was acquired randomly, guaranteeing the heterogeneity of the sample as hypothesized during the planning phase of the research. This approach enables estimates with variations over time and reduces related distortions of remembrance, especially for time intervals of the order used (a few months). We chose the variables to be investigated and administered an in-person questionnaire.

The transport choices are described in Figure 3. All the transport modes were available in the two cities except for the tram/streetcar, which was only available in Palermo.

Having selected the commuting alternatives (Figure 4), the following questions were created according to the BWM logic:

- Please select the most- and the least-used transport mode for commuting to work before COVID-19.
- Please select the most- and the least-used mobility option for commuting to work during COVID-19.
- Please evaluate the other types of transport with respect to the most used using a 1–9 scale.
- Please evaluate the least-used using a 1–9 scale.

where 1 represents equal importance between two alternatives, 9 represents the extreme importance of one alternative over another, and 2–8 are intermediate values [65].

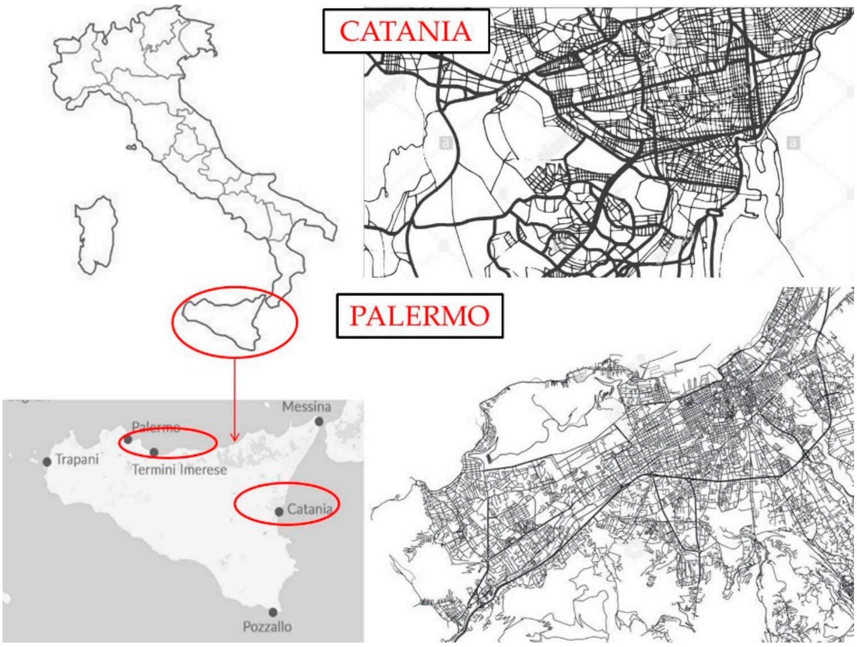

Figure 3. Location of case study.

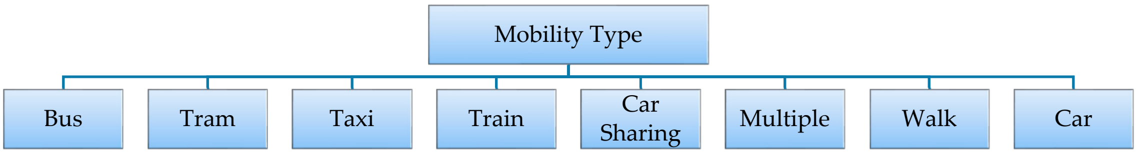

Figure 4. Transport modes in Sicily.

The example in Table 3 illustrates how the survey was conducted.

Table 3. Example of evaluating all mobility types compared to the most-used mobility type.

Mobility Type	Bus	Tram	Taxi	Train	Car Sharing	Multiple	Walk	Car
Most used mobility choice: Tram	2	1	5	4	6	6	7	3

Table 3 shows the weights of an evaluator of the best mobility type, which, in this case, was tram. The lower the number, the closer a certain alternative to the best choice.

Table 4 shows the weights of an evaluator of the least-used mobility type, which was sharing. Lower numbers indicate closeness of a certain alternative to the least-used type.

Table 4. Example of evaluating the least used mobility type to all other mobility types.

Mobility Type	Bus	Tram	Taxi	Train	Car Sharing	Multiple	Walk	Car
Least-used mobility choice: sharing	3	6	2	5	1	4	7	6

The consistency ratio (CR) was acceptable for all individual responses, as its value was between (0–1) in all cases. CR values were computed using Equation (5).

The final results before COVID-19 are presented in Table 5. The most-used mobility type was car, followed by walking; the least-used was car sharing, followed by multiple modes (Figure 5).

Table 5. Final scores of the mobility types before COVID-19.

	Bus	Tram	Taxi	Train	Car Sharing	Multiple	Walk	Car
Weight Score	0.1319	0.079	0.0659	0.0989	0.0312	0.0565	0.1979	0.3385

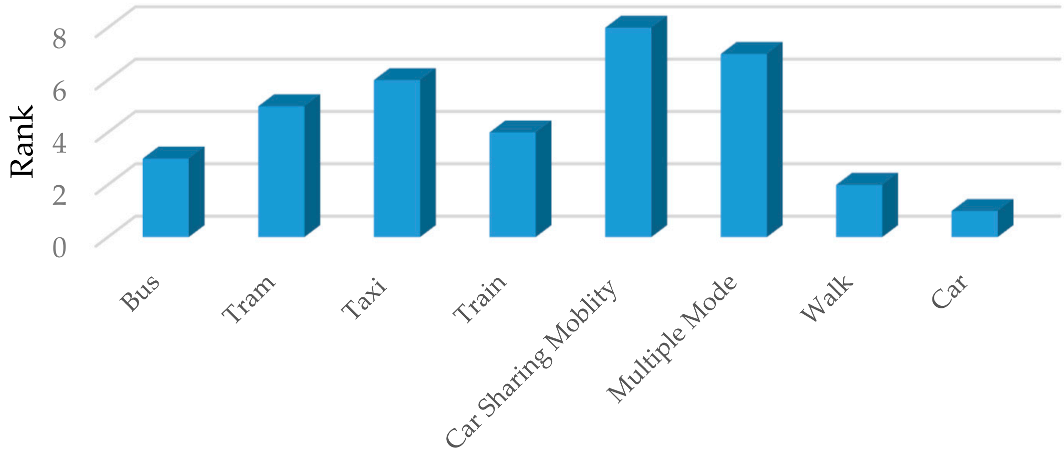

Figure 5. The final rank of the most used mobility types before COVID-19.

The final results of the surveys during the crisis are presented in Table 6. The most-used mobility type was walking, followed by car. The least-used mobility type was tram, followed by taxi (Figure 6).

Table 6. Final scores of mobility types during COVID-19.

	Bus	Tram	Taxi	Train	Car Sharing	Multiple	Walk	Car
Weight Score	0.1184	0.0338	0.0592	0.0789	0.0677	0.0947	0.3892	0.1579

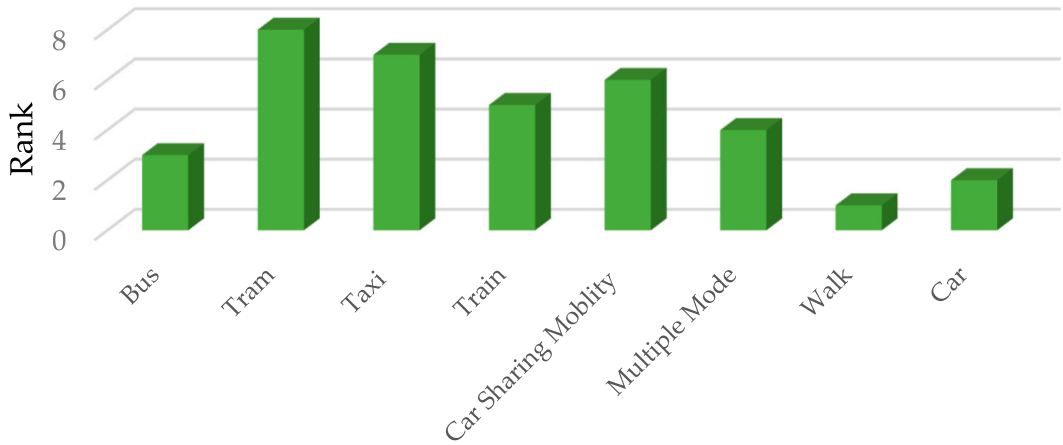

Figure 6. The final rank of the most used mobility types during COVID-19.

Table 7 illustrates the differences in preference before and during COVID-19 crisis based on the citizens' point of view.

Table 7. Final scores and ranks of the mobility types before and during COVID-19.

Mobility Type	Score before COVID-19	Rank	Score during COVID-19	Rank
Bus	0.1319	3	0.1184	3
Tram	0.0791	5	0.0338	8
Taxi	0.0659	6	0.0592	7
Train	0.0989	4	0.0789	5
Car Sharing	0.0312	8	0.0677	6
Multiple Modes	0.0565	7	0.0947	4
Walk	0.1979	2	0.3892	1
Car	0.3384	1	0.1579	2

The results showed that the transport mode split for Italians significantly changed during the pandemic. Especially observable was the shift from public into individual transport (including walking, car travel, and ride sharing). Bus remained the third choice of Italians, but the multimodality increased, which may influence the mobility choices even if the epidemic ends.

The variation in choice by users regarding mobility is linked to the reduction in the use of public transport and an increase in the number of individuals both in shared vehicles, which indicates some considerations in terms of the vulnerability and resilience of the city.

The increase in individual mobility will have to be supported by local and domestic strategies to encourage soft or shared mobility at the expense of private mobility, which could lead to high pollution rates as well as traffic congestion. The new transport choices should influence planners to rethink the use of open public spaces and roads, providing more services to the citizens and creating a resilient transformation of the city, i.e., by redesigning or adapting an urban system to climate change as well as social (including distance), cultural, economic, and structural changes.

6. Discussion

The study results suggested a greater tendency to walk for shorter journeys, in compliance with social distancing and other safety precautions during COVID-19. We identified differences in the transport mode split in Italy, similar to those observed in other countries, especially the increasing share of walking and car transport and the decreasing percentage of public transport use. As Italy was the country most affected by the pandemic in Europe, the changes in modal split were obvious, but the characteristics of those changes were unknown. The dynamic situation in many countries and the dynamics of the pandemic, combined with regulatory issues (restrictions), determined the changes in mobility choices.

A reduction in the use of public transport, a change in the reasons for moving due to confinement, and social distancing led to a sharp decrease in the use of some forms of mobility such as public transport, but also to a strong reduction in pollution. This finding brings into question the sustainability of urban mobility. Mass transit and shared transport might need to be re-designed in a way that respects the need for social distancing [98].

Mobility studies during the COVID-19 outbreak are scarce. Most of the published papers [72,79,82] were based on Google or Apple sources, where data were gathered from mobile phones. However, they do not reflect the real opinions of the citizens of particular regions, but instead offer valuable insights into the changes in mobility (mode and pattern) and demand.

In this study, we addressed the necessity of comparing mobility choices before and after the outbreak in Italy.

The government decisions on mobility restrictions aimed to reduce the risk of spreading COVID-19 consisted of multiple actions. However, the change in the mobility choices in Italy may be an effect of the temporary closure of schools and companies and therefore the lower travel demand [72]. This was especially observed in March and April 2020 (the worst periods for Italy in terms of coronavirus spread), when the primary survey of this study was conducted.

During that peak time, public transport was justifiably perceived to be a potentially risky mode of transport in terms of infection spread [79]. Therefore, walking was found to be the first choice of transport mode [82]. The results of this study were similar to those previously reported for Italy [72], but those results were less complex and needed some more in-depth insight. Some additional information should be obtained about the socioeconomic characteristics of respondents to conduct a profound analysis of mobility choices [78]. The share of the real impact of government restrictions and personal decisions should be analyzed for Italy [92,93]. Although future studies are warranted to examine the changing nature of mode choices, our findings provide new insights into the current dynamics of mobility choices in the selected Italian regions. We identified a transformation not only resulting from governmental restrictions, but also from the choices of the individual residents [96].

We found that before COVID-19, the preferred form of movement was the car, followed by walking. This was due to the moderate frequencies of public transport and the relative delays, which prevent users from reaching their destination on time. Therefore, multiple modes were the least-used type due to the difficulty of synchronization and the lack of guarantees among the various modes of transport of delays of less than 5–10 min in the context examined. The development of mobility as a service (MaaS) could guarantee and manage this complex issue, but it requires further investigations.

7. Conclusions

The survey results presented in this paper suggest that the BWM method can act as a reference point and base for future studies. Firstly, our results can be compared with those for other countries. The simplicity of the BWM method combined with the usefulness of the results indicates that BWM could be perceived by other researchers as a valuable method for data analysis and an attractive alternative for the well-known multi-criteria decision-making methods used in mobility studies. The public stakeholders (public transportation companies, local authorities) can use the method for their own research and managerial purposes to strengthen the already-used methods. Secondly, the results provide a starting point for more in-depth analyses of mobility choices during the COVID-19 outbreak and the changes in mode choices after the epidemic, e.g., examining the long-term results in the mobility area, like walking or using active transport modes more than before the outbreak.

Despite the strengths of this study (including research about mobility changes not based on Google data [73–75]), it has a few limitations. Firstly, the sample size was small. The survey was simple and contained only a few questions, which prevented deep analysis of the causes of mobility choices of the respondents. Secondly, we included only two Italian cities, so the results from this limited area may not be necessarily extended to other areas. Thirdly, most of the outcomes resulted from obligatory changes. Many changes in the observed mobility resulted from the government restrictions and were not facultative for Italians. Fourthly, comparing the results with the studies for other countries with similar or different pandemic characteristics is difficult, because the results for those countries are not known. Regardless, this study contributes to mobility studies, especially those about the changes during the COVID-19 outbreak. We plan to conduct further studies focusing on passenger mobility.

The sample will be extended by implementing predictive market models based on the idea of crowdsourcing, i.e., on what collective information should be based to support the forecasting of transport demand [99,100].

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