urban science

MDPI

Article

User Preference Analysis for an Integrated System of Bus Rapid Transit and On-Demand Shared Mobility Services in Amman, Jordan

Farah Altarifi [1,*], Nawal Louzi [1], Dana Abudayyeh [2] and Tariq Alkhrissat [1]

[1] Faculty of Engineering, Al-Ahliyya Amman University, Amman 19328, Jordan; n.alouzi@ammanu.edu.jo (N.L.); t.khrissat@ammanu.edu.jo (T.A.)
[2] Faculty of Engineering, Al-Balqaa Applied University, Amman 19117, Jordan; dana.abudayyeh@bau.edu.jo
* Correspondence: f.tarifi@ammanu.edu.jo

Abstract: Amman, the capital of Jordan, has experienced significant traffic congestion due to the rise in private vehicle ownership and limited public transportation services. A Stated Preference (SP) survey was conducted to determine public transportation users' willingness to use the Bus Rapid Transit (BRT) service. Another survey assessed the demand for an on-demand transit bus service with flexible and moderate costs, particularly for individuals far from the main BRT stations who need to reach them. Two models, Multinomial Logit (MNL) and Mixed Logit (ML), were utilized to understand user preferences for work-related trips. The study findings indicate that the cost of the trip and the waiting time are the two primary factors influencing public transport users' choices. Furthermore, sociodemographic factors, such as age, income, household size, and current status, were found to have a significant impact. The results reveal that approximately 71% of participants would utilize an integrated public transportation system comprising BRT and on-demand services. The findings underscore the potential benefits of an integrated public transport system in addressing Amman's traffic congestion. By combining BRT and on-demand services, the city can offer residents comfortable, affordable, and efficient transportation options, thus effectively mitigating congestion.

Keywords: congestion; public transport service; bus rapid transit; on-demand mobility; stated preference survey; multinomial logit; mixed logit

Citation: Altarifi, F.; Louzi, N.; Abudayyeh, D.; Alkhrissat, T. User Preference Analysis for an Integrated System of Bus Rapid Transit and On-Demand Shared Mobility Services in Amman, Jordan. *Urban Sci.* **2023**, *7*, 111. https://doi.org/10.3390/urbansci7040111

Academic Editors: Panagiotis Georgakis, Babis Magoutas, Michiel de Bok, Suresh H. Renukappa and Subashini Suresh

Received: 6 September 2023
Revised: 10 October 2023
Accepted: 17 October 2023
Published: 25 October 2023

1. Introduction

Jordan has a population of approximately 11 million residents, with nearly half residing in the capital city, Amman [1]. This surge in population has led to a significant upsurge in the number of registered vehicles in the country. According to a study by the Jordanian Traffic Department, registered vehicles rose from 1,412,817 in 2015 to 1,677,061 in 2019. This represents an annual growth rate of approximately 5.5%. Consequently, this increase has resulted in traffic congestion, amplified levels of air pollution, and escalated emissions of greenhouse gases, such as carbon dioxide [2].

The issue of traffic congestion has emerged as a significant societal concern in large metropolitan areas globally. The adverse effects of this phenomenon are significant in terms of impeding efficient transportation, disrupting urban economic activities, and exacerbating environmental concerns. In the year 2014, the United States economy experienced a substantial loss of $160 billion, while in 2011, the environment was burdened with the emission of over 560 billion pounds of lethal carbon dioxide due to the issue of road traffic congestion [3,4]. In unpredictable scenarios like traffic congestion, bus vehicle scheduling must be considered [5]. Efficient transportation infrastructure is pivotal in urban areas, ensuring the smooth movement of people and goods [6]. Smart cities are becoming crucial to the progression of urbanization, known as the "next stage urbanization", due to their incorporation of comprehensive digital infrastructure and communication technologies that enhance the effectiveness of the urban movement [7].

In addition, several alternatives have been implemented to alleviate traffic congestion, such as the adoption of public transport services, including on-demand services and Bus Rapid Transit (BRT) systems. These alternatives have proven effective in reducing traffic jams. On-demand services refer to adaptive transportation services that utilize vehicles to offer flexible shared transport to passengers whenever and wherever they require it. For instance, on-demand services connect passengers with drivers using smartphone applications, known as ride-sourcing.

On-demand, shared mobility services reduce mode choice bias. The research conducted in Lahore, Pakistan, proposes that energy-efficient shared modes like car-sharing, bike-sharing, and ride-hailing may sometimes replace private car use [8]. When mode choice decisions are less biased, these shared mobility options can dramatically cut transport-related energy usage. Sharing options like car-sharing and bike-sharing may boost transport system energy efficiency. Shared modes may be more efficient in low-density locations than public transit [9]. This suggests that shared mobility services could supplement public transit and minimize automobile ownership.

On the other hand, the BRT system provides residents with frequent transportation services at affordable fares, covering a wide area. As a result, the BRT system is typically employed in major transportation corridors, while on-demand, shared mobility services are more suitable for areas with lower demand. In Amman, the Greater Amman Municipality (GAM) has proposed the implementation of a BRT system to address the issue of traffic congestion. The BRT system comprises three routes. The first route runs from Swuayleh to Al Mahattah, the second route spans the Sport City Circle to Al-Muhajereen, and the third route connects Zarqa to Amman. Each corridor covers a distance of twenty-five kilometers. The initial phase of the BRT system, which includes the first route, was inaugurated in 2021. The second route was inaugurated in August 2022, while the third route of the BRT system is expected to be operational by the end of 2023, with the goal of reducing traffic congestion. However, it is worth noting that these three corridors are currently not integrated with other modes of transportation. Therefore, the establishment of connections between these corridors would greatly enhance the efficiency and convenience of the transportation services, allowing passengers from surrounding low-demand areas to access the major corridors easily [10].

Several studies have inquired into how on-demand services could be included in the BRT system. The BRT system represents a transit bus service that provides efficient and rapid transportation in terms of travel time and cost. This mode of transportation encompasses various features, including dedicated lanes, traffic signal priority, and improved bus and passenger stations, all of which contribute to enhancing the overall experience for road users [11].

The current study aims to explore user preferences for Amman's BRT system and on-demand transit services in an urban setting. Initially, a Stated Preference (SP) survey was conducted to assess the willingness and acceptance of public transportation users towards utilizing the BRT service. Subsequently, an additional survey was conducted to investigate the demand for an on-demand transit bus service that operates with flexible hours and offers reasonable costs to facilitate access to the nearest BRT station for individuals far from the main BRT stations. The data obtained from the SP survey was subjected to rigorous analysis employing econometric models, such as the Multinomial Logit (MNL) and Mixed Logit (ML) models.

2. Literature Review

This section presents previous studies on preferences for using BRT, integrating on-demand and BRT services, and discrete choice modeling, as shown in Table 1.

Table 1. Previous studies on preferences for using BRT, integrating on-demand and BRT services, and discrete choice modeling.

Study	Approach	Location	Main Findings
[12]	RP	India	Students and 30 to 50-year-old men are more likely to switch to BRT. Increased travel time and cost contribute to modal shift.
[13]	RP	Netherlands	Micro-transit is not utilized due to inconvenience.
[14]	RP	Belleville, Canada	Travelers are unhappy with service waiting time and reliability.
[15]	SP	Khon Kaen City, Thailand	Psychological factors and social influence affect BRT choice.
[16]	SP	Riyadh, Saudi Arabia	Travel costs, walking time, and pricing policies influence sustainable transport choices.
[17]	SP	Pakistan	Students, low-income people, and non-drivers use BRT more.
[18]	SP	Hanoi, Vietnam	Private vehicle users stick with cars, even with longer travel distances.
[19]	MNL	Karachi, Pakistan	An inverse relationship between trip time and cost with BRT usage.
[20]	MNL	Multiple Locations	BRT service became less appealing with increased travel time and ticket prices.
[21]	MNL	Multiple Locations	Sociodemographic and trip information predict BRT usage.
[22]	SP–RP	Surabaya City, Indonesia	Elderly individuals, larger family incomes, and non-educated users were more likely to use BRT.
[23]	RP–SP	Madrid, Spain	Pure transfers have a penalty, and overcrowded transitions increase commuter dissatisfaction.
[24]	RP–SP	Multiple US Cities	Integration of ride-sourcing services with public transportation maximizes transit infrastructure utilization.
[25]	Various	Auckland, London, Canberra	Integration of BRT and micro-transit improves multimodal trips and travel time savings.
[26,27]	On-demand	Canberra, Australia; USA	On-demand micro-transit services improve transit services, reduce congestion and lower emissions.
[28]	DRT	Oberharz, Germany	Rural users prefer Demand Responsive Transport (DRT) over the bus.
[29]	Paratransit	Bangkok, Thailand	Integration of paratransit to reduce congestion.
[30]	On-demand	USA	Suggests tax-free or free on-demand transit services to encourage usage.
[31]	On-demand	USA	On-demand transit services attract young riders and increase satisfaction.
[32–34]	Logit	Various Locations	Logit models assume uniform preferences.
[35]	Logit	Quartier Latin district of Paris	Pedestrian behavior at crosswalks is influenced by crossing distances and traffic flow.

Table 1. *Cont.*

Study	Approach	Location	Main Findings
[36]	Logit	San Francisco	Micro-transit station distance affects preferences.
[37]	Logit	Detroit, Michigan	Male, highly educated travelers willing to use mobility on-demand (MoD) transit service.
[38]	MNL	Chicago	Public transport users are more likely to choose flexible transit services.
[39]	MNL	University of Michigan	Reducing waiting time and providing last-mile connections could increase transit use.
[40]	ML	North England	ML models compare present services to Demand Responsive Transport (DRT).
[41]	ML	New York City	ML models used to study mobility on-demand (MoD) service preferences.

2.1. Preferences for BRT

Preference surveys are commonly conducted to investigate how travelers will respond to an integrated system of on-demand and BRT. There are two types of preference surveys: the first one is Revealed Preference (RP), and the second is SP. The RP presents real data and takes into consideration observed variables (i.e., cost of trips), while the SP defines hypothetical data and includes existing and proposed various mode choice alternatives [42].

Mane et al. (2015) used the RP approach to study the BRT service's influence on modal shift in India [12]. Demographic, socioeconomic, and trip-related factors were studied using a binary logistic model. Students and 30-to-50-year-old men are more likely to switch to BRT. Increased travel time and cost will contribute to this change.

The RP approach was used in the Netherlands to study older adults' preferences for micro-transit services (e.g., carrying small numbers of passengers at a time) [13]. Their investigation found that micro-transit is not utilized since it is inconvenient compared to other means of transport.

Zhang et al. (2021) used the RP approach to study Belleville, Canada's on-demand transport riders' happiness and activity engagement [14]. Results revealed that travelers were unhappy with service waiting time and reliability. Using the RP approach, these studies used real data to examine users' preferences for current services.

Multiple studies have used the SP survey to analyze users' mode choice behavior preferences. To assess these choices, the SP survey considers total cost, total time (from origin to destination), and travel time. Using a discrete choice model in Khon Kaen City, Thailand, the SP survey was used to study how psychological factors affect mode choice behavior [15]. The results showed that BRT choice behaviors were affected by service attribute factors (travel time and cost) and perceived social influence.

Youssef et al. (2021) conducted a study using the SP approach to sustainable transport in Riyadh, Saudi Arabia. The study highlights the importance of factors like travel costs, walking time, and pricing policies in influencing the shift towards more sustainable transportation choices, with socioeconomic factors having a lesser impact [16].

Another study used the SP survey to analyze what draws Pakistani private car users to BRT [17]. They examined vehicle ownership, driving license, demographics, travel purpose, and BRT use. They used descriptive analysis and MNL models. The data showed that students, low-income people, and non-drivers used BRT more.

Tuan (2015) used the SP approach to study the mode choice models for different population segments in Hanoi, Vietnam. Private vehicle users tend to stick with their cars, especially if they have trip chaining or young children in the family. Surprisingly, longer travel distances do not necessarily lead to a higher shift to public transport [18].

The BRT service became less appealing as travel time and ticket prices increased. The SP survey design aims to evaluate individuals who use private vehicles, public transport, and university shuttle services. This survey examines socioeconomic factors like age, gender, income, and travel behavior, with an emphasis on the BRT system.

In Karachi, Pakistan, the MNL model revealed an inverse relationship between trip time and cost parameters with utility [19]. The BRT service had minimal impact on shuttle riders, as their existing public transportation was fast and subsidized. The Binary Logit model revealed that consumers' preferences dropped with rising trip time and cost. BRT usage was higher among older motorbike riders, females, and those without driving permits [20]. In another study, linear hierarchical regression analysis revealed that 93% of users will utilize BRT in the future based on socio-demographic and trip information (e.g., gender, monthly income, current mode of transportation, and travel purposes) [21].

MNL models assessed the gender and income of Dhaka workers, which affect BRT use. The results showed that poor, female, and mature workers use BRT. Most bus riders who cannot afford higher bus prices will not switch to BRT [43].

An Indonesian BRT service in Surabaya City was assessed using the SP survey of individual characteristics, mode qualities, mode availability, and vehicle ownership. According to the MNL model, elderly individuals, larger family incomes, and non-educated users are more likely to use BRT, while automobile owners prefer their own vehicles [22].

Researchers use SP–RP approaches to examine BRT preferences to overcome SP and RP's drawbacks. For example, socioeconomic and travel data were used to evaluate interest in the proposed BRT service in Dhaka using RP of the real-time journey and SP of hypothetical scenarios. Only bus users, young passengers under 30, and low-income people were more interested in BRT. BRT ridership decreased as travel time increased [19].

Cascajo et al. (2017) used RP and SP approaches to estimate multinomial logit models in Madrid, Spain. The findings reveal that a pure transfer has a penalty regardless of in-vehicle duration, walking and waiting time, or congestion. This penalty rises with transfers. Commuter dissatisfaction rises when overcrowded transitions need more transfers for the whole route [23].

BRT examined the BRT's applicability in China utilizing SP–RP survey methodologies of personal and trip characteristics [20]. Their study used the MNL model and concluded that females are more likely to use the BRT, and public transit passengers will switch to the BRT due to bad service. BRT is inversely related to travel time and cost. The RP–SP survey was used to evaluate Quetta, Pakistan, BRT mode alterations. RP data came from recent public transit travels, while SP data represented hypothetical BRT travel behavior attributes. MNL and ML models indicated that trip time and cost are inversely related, while seat and air conditioning availability positively influence BRT choice [21].

2.2. Integrating Services

Transportation networks should offer well-integrated multimodal services, including on-demand mobility and micro-transit, to serve users efficiently from their starting point to their destination. These services combine traditional public transportation with intelligent applications like ride-sourcing. Micro-transit, utilizing flexible schedules with minibuses and shuttles, complements fixed public transit, reducing vehicle miles traveled (VMT) and private vehicle use while enhancing trip planning. Safety and income are crucial factors affecting implementation [43]. In Manhattan, integrating mobility-on-demand with other travel modes using MNL models showed that increasing ride-sourcing taxes without raising fares can boost ridership and reduce VMT [22].

Ride-sourcing apps like Uber have expanded study areas. Several researchers examined the effects of using Uber instead of public transportation to avoid fixed schedules. High-income users may use Uber [44]. Additionally, California Uber adoption characteristics were examined. They used Logit models to discuss how Uber could minimize private vehicle use and improve public transportation in terms of travel time, cost, comfort, safety, and convenience. Users were willing to use Uber, reducing private automobile utilization [45].

Ride-sourcing and public transportation must be integrated. For efficiency and last-mile connections, the University of Michigan preferred integration [39]. The Discrete Choice Model was used to examine the data, which revealed that the integration would improve last-mile transit services. The use of ride-sourcing services with public transportation in the US was studied to minimize private vehicle use and VMT [46]. About 37% of respondents struggle to locate parking due to its high cost.

In order to decrease the use of private vehicles, increase mobility, and develop collaboration between the private and public sectors, research examined the opportunities and challenges of integrating ride-sourcing services with public transportation in seven cities: Austin, Boston, Chicago, Los Angeles, San Francisco, Seattle, and Washington, DC. The utilization of transit infrastructure will be maximized by this integration [24].

Micro-transit services are new and gaining popularity. For instance, a study examined BRT and micro-transit integration at the University of Auckland and University College London [25]. This study found that integrating these services will improve multimodal trips, first-mile-last-mile services, and travel time. Canberra investigated integrating high-frequency buses with hubs or shuttles. The analysis found that this integration might save travel time by two units without raising cost [25]. Additionally, some studies have suggested adding on-demand micro-transit services to current transportation systems to improve transit services. These solutions provide first- and last-mile services, reduce congestion, and lower emissions [26,27]. Oberharz, Sörensen et al. (2021) examined Demand Responsive Transport (DRT) to feed the public transportation system. The study indicated that rural users liked the DRT service better than the bus [28].

The integration of paratransit into Bangkok's public transportation system has been discussed to reduce congestion [29]. In the USA, it is suggested that integrating on-demand transit services with public transportation should be tax-free or offered as a free service [30]. On-demand transit services have shown positive impacts on transportation systems, attracting young riders, with 72% using them for work. Users express high satisfaction due to readily available information and the ease of nighttime travel, potentially leading to increased income [31].

2.3. Discrete Choice Modeling

Discrete choice models describe and predict travel mode choices (e.g., private cars, public transportation, taxis) for reaching destinations.

Discrete choice models use travel demand models with quantitative parameters like time, cost, and socioeconomics. These models focus on sociodemographic data without incorporating people's attitudes, opinions, and decision-making [47]. On the other hand, Random Utility Maximization (RUM) models like Logit models use observable variables. RUM is a fundamental concept in discrete choice modeling, which is used to analyze and predict individuals' choices among different alternatives when faced with decision-making situations. RUM models are commonly used in various fields, including transportation, economics, and marketing. The basic idea behind RUM is that individuals make choices by maximizing their utility or satisfaction, but this utility is not entirely deterministic. Instead, it has a random component that reflects the variability in individual preferences and decision-making processes. Utility, randomness, maximization, and probability of choice are the key components of the RUM [48,49]. Thus, such models showed that everyone has the same preference [32–34]. To avoid evaluating the same choice preference for all users without addressing their attitudes in decision-making, choice models needed observable values [33].

The logit model uses observable variables without addressing decision-making attitude. This model examined pedestrian behavior at crosswalks by analyzing crossing distances, traffic flow, and the presence of crossing control devices. It concluded that the risk of accidents at crosswalks is affected by pedestrians' decisions in their prior crossings [35]. Another study examined San Francisco users' opinions on a new micro-transit service. Logit models showed that micro-transit station distance inversely affects preferences [36].

Logit models also indicated that male, highly educated travelers are willing to use the proposed mobility on-demand (MoD) transit service in Detroit and Ypsilanti, Michigan [37]. This study will determine BRT and MoD mode choice preferences using logit models.

Logit models are extended to focus on relationships between more than two categories in MNL models. MNL was utilized in several studies to examine service preferences. For instance, an SP study in Chicago using MNL models indicated that public transport users are more likely to choose flexible transit services than car users [38]. Another study studied University of Michigan RP and SP surveys using MNL models to uncover consumers' opinions on the proposed integrated transit system and concluded that reducing waiting time and providing convenient last-mile connections could increase transit use [39].

This study will use the MNL model to identify service preference factors. MNL models have limitations. They are still used in studies when their assumptions align with the research objectives and when data availability and simplicity are important considerations. Researchers may use them as a practical starting point for understanding choice behavior before exploring more complex models that can better capture preference heterogeneity and interactions among attributes. Since the MNL model assumes the same preference structure across people, ML models explain taste variation since heterogeneous preferences would lead to biased estimates and inaccurate predictions. An SP survey in North England compared present services to DRT, a new service utilizing ML models [40]. Another study employed an SP survey to understand New Yorkers' MoD service preferences. MoD ride-hailing, ride-sourcing pooling, and micro-transit services with capacities 1, 4, and 10 were used. For example, agencies could raise fares if capacity is 1 and offer discounts if the service is shared to boost transit ridership [41].

MNL models are used to study generic user preferences on the assumption that all users are identical. Instead of being identical, ML models utilize users' preference heterogeneity to determine responders' choices.

2.4. Current Situation in Amman, Jordan

Amman faces significant challenges due to its inadequate infrastructure and lack of efficient and convenient transit systems. According to a study, these issues can be summarized as follows: during peak hours, the waiting time for public transportation was reported to be between 12 and 23 min, primarily due to the high volume of traffic [50]. Additionally, there was a shortage of public transport coverage in certain areas and limited routes. Furthermore, the operating systems of public transport were not properly scheduled, causing further inconvenience to commuters. Another perspective, highlighted by Hurr & Tashman (2019), emphasized that the VMT for private vehicles exceeded that of public transport, leading to increased fuel consumption and environmental problems [51]. This highlights the importance of improving public transit, such as expanding services to suburban regions, to encourage travelers to switch from private vehicles to public transportation.

2.5. Remarks

Previous studies have indicated that users are inclined to shift towards the BRT service when the cost and travel time are moderate. However, no studies have been conducted in Jordan to explore user preferences towards the BRT and Origin-Destination Surveys (ODS). This study aims to address these gaps by conducting SP surveys to investigate users' preferences for using the BRT service, particularly when integrating it with shared mobility options as feeder services to the nearest BRT station. It is important to note that the BRT is now working on the first two routes, shown in Figure 1.

The findings of this study will provide valuable insights for decision-makers to enhance the BRT services in Amman.

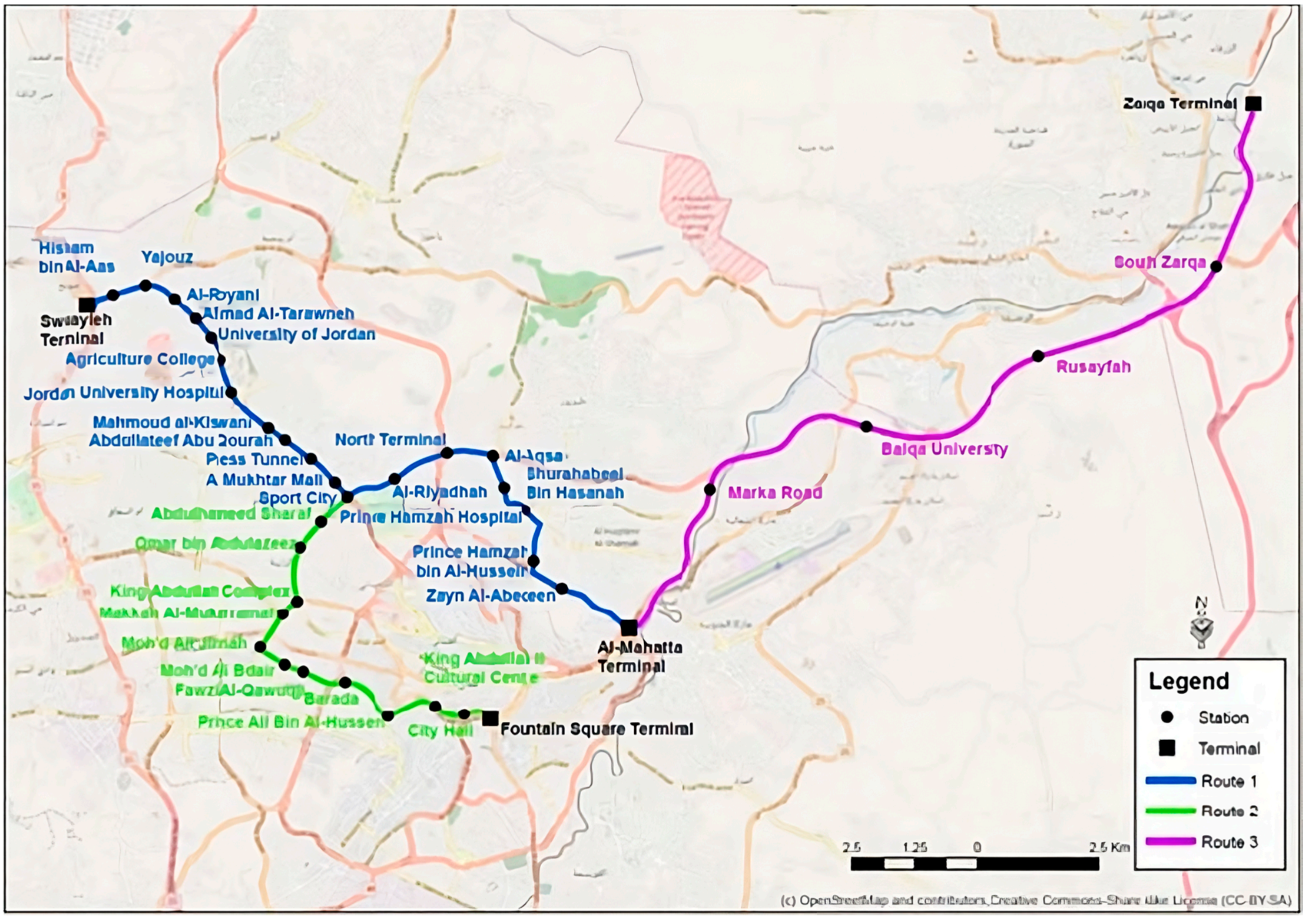

Figure 1. The BRT network.

3. Survey Design and Data Collection

The BRT system in Amman is regarded as a recent addition to the public transportation network. However, it is currently operating on the first two routes. Conversely, on-demand shared mobility services are not yet accessible in Amman. A survey was conducted using SP methodology to assess the acceptance and willingness to utilize the BRT system, and on-demand shared mobility services in Amman. In this regard, choice experiments were employed to evaluate various hypothetical scenarios associated with the utilization of the BRT system and on-demand shared mobility services.

3.1. Survey Design

An SP survey was designed to obtain respondents' perceptions of using BRT and on-demand shared mobility services. This survey consists of five sections: socioeconomic characteristics, daily trip information, public transport, shareability with intelligent transportation applications, BRT, and hypothetical scenarios related to merging more than one mode of transport and linking them together.

The Jordan University BRT station holds significant importance within the BRT system due to its proximity to the University of Jordan, resulting in high user demand. This selection makes it an ideal station for designing hypothetical scenarios. To analyze the travel patterns in Amman, the average travel distance from the origin to the destination was determined to be 9 km [52]. To gather data on private vehicles, Google Maps applications were used by inputting the origin and destination points, allowing for the measurement of distance, In-Vehicle Travel Time (IVTT), Waiting Time (WT), and fuel consumption and maintenance costs. Ride-sourcing services data were collected from the Ride-Sourcing (e.g., Uber) application by entering the origin and destination points and measuring the distance, IVTT, WT, and cost. The BRT data used in the analysis were obtained from GAM (Greater Amman Municipality). Lastly, the bus on-demand data were calculated based on previous studies. On-demand shared mobility service trips, also known as Micro-transit, took approximately 2–4 min longer than private vehicle trips [53]. The cost for these trips was assumed to be 0.55 JD, the same as the BRT cost, and the waiting time for this service was estimated to be 9 min based on available data.

The five modes are categorized into upper, middle, and lower levels. Three are considered hybrid services: Private Vehicle (PV) when integrated with BRT, Ride-Sourcing when integrated with BRT, and Bus on-Demand (BoD) when integrated with BRT. This design aims to determine users' preferences for work and study trips. Five sets of choices were presented to each respondent, e.g., Private Vehicle (PV), Ride sourcing (RS), Private Vehicle (PV) + BRT, Ride sourcing (RS) + BRT, and Bus on demand (BoD) + BRT. Each choice set consists of five alternatives based on the following attributes: distance, IVTT, WT, and cost.

The choice sets were based on key attributes essential for understanding mode preferences. The values (levels) for these attributes in the choice sets were determined using a carefully calculated approach. The attribute levels were calculated based on an average distance of 9 km. The lower distance was multiplied by 0.5, resulting in 4.5 km, and the upper distance was multiplied by 1.5, resulting in 13.5 km. The IVTT, WT, and cost were calculated using the same procedure as the JU calculation but with the lower and upper distances. The final data obtained from designing the survey are summarized in Table 2, and Figure 2 represents an example of a choice set presented to the survey respondents.

Table 2. Survey modes, attributes, and attributes levels.

	PV	Ride-Sourcing	PV + BRT	Ride-Sourcing + BRT	BoD + BRT
Distance (km)	4.5, 9, 13.5	4.5, 9, 13.5	4.5, 9, 13.5	4.5, 9, 13.5	4.5, 9, 13.5
IVTT (min)	9, 21.5, 22.5	10, 21.5, 27.5	11.4, 19.3, 22.8	11.4, 21.8, 24.3	15.4, 23.3, 26.8
WT (min)	-	2, 3, 4.5	2.5, 2.5, 2.5	4.5, 5.5, 8	7, 9.3, 11.5
Cost (JD)	1.3, 1.6, 1.9	1.63, 3, 3.34	1.77, 1.8, 1.86	1.8, 2.4, 3	0.83, 0.96, 1.1

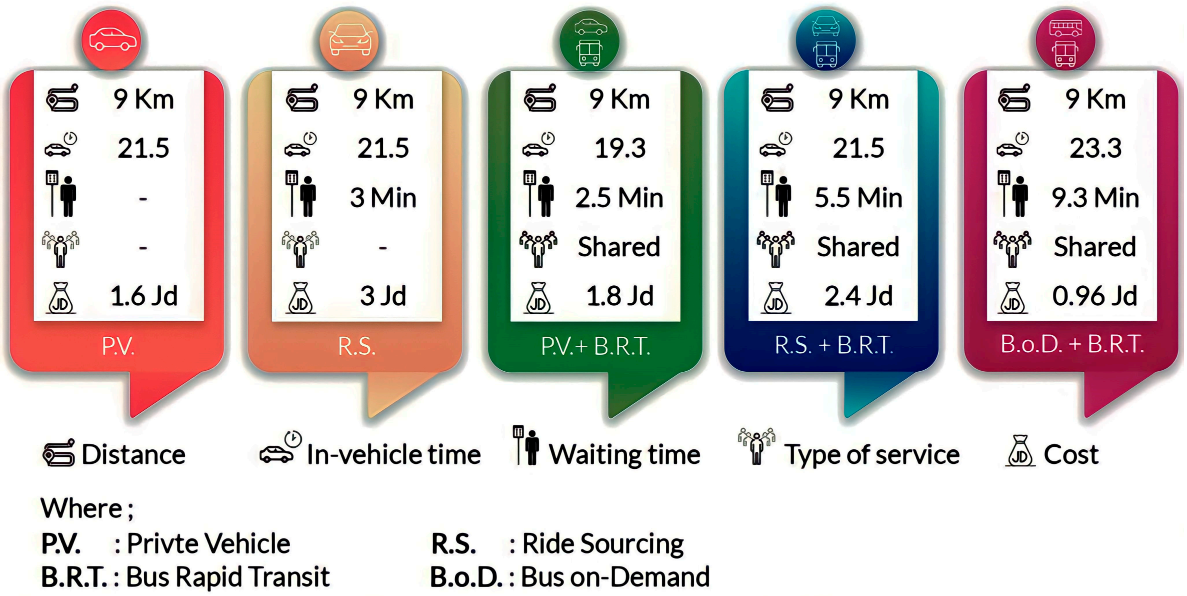

Figure 2. Example of 5 choice sets presented to respondents.

3.2. Sample Size

Based on the rule-of-thumb Equation of

$$n = (500\ c)/ta = 125 \quad (1)$$

where

n: Minimum sample size required
c: Number of analysis cells
t: number of tasks
a: number of alternatives per task

However, the rule of thumb justifies the sample size of 125, that are too small, so the sample sizes used for discrete choice modeling obtained from previous studies generally range from about 150 to 1200 respondents [54]. In our study, 708 respondents completed the survey within the range of a suitable sample size for modeling.

3.3. Data Description

To obtain a deeper understanding of the perceptions held by respondents regarding BRT in its current state and the potential integration of on-demand mobility services, we collected the following data from the participants:

Sociodemographic and socioeconomic characteristics: gender, age, household size, education, driving license ownership, car ownership, income, current status, and disability are included if they exist.

Travel history information: trip duration, trip purpose, modes of transportation, parking availability, and parking fees are included in travel history information.

Public transportation information includes the citizen's opinions on the current public transportation.

BRT information includes the citizen's knowledge about the BRT if they can use it or not, the main mode to reach BRT stations (e.g., feeders), the main determinants of not using the BRT, and scenarios to be chosen based on the current situation for these attributes, i.e., WT, IVTT, and cost.

Scenarios related to merging more than one mode of transport and linking them to each other.

Attitudinal statements questions about public transportation. Respondents were asked about their attitude to five statements using a five-point Likert scale ranging from strongly agree to not strongly agree, as shown in the Questionaire S1.

3.4. Data Collection

The survey was distributed online to the participants of Jordan between 7 December 2021 and 15 January 2022. Responsive sampling was used. This method involves deliberately selecting participants based on specific criteria that are relevant to the research objectives. Researchers choose respondents who are likely to provide valuable insights into the stated preferences being studied.

The survey was conducted utilizing the QuestionPro platform, with an average time of 15 min. It was found that some of the respondents completed the survey in remarkably short time. For example, there were respondents reported to have taken as short a time as three minutes. In contrast to this, there were other respondents who took over 200 min to complete the survey.

On the other hand processing and cleaning the raw data is an important thing in order to have a relatively precise data, data were filtered by removing the following (Geržinič et al., 2023):

- Respondents with in-completed tasks;
- Respondents who answer the survey much faster than the average time required to complete the survey;
- Responses with patterns like a straight line or zig-zag in answer options.

A total of 1232 respondents participated in the initial survey, which was subsequently refined to 708 participants after the application of data filtering techniques.

4. Methodology

The SP survey was analyzed to investigate the user service preferences and perceptions toward integrating BRT and on-demand mobility services. All models were estimated using the PandasBiogeme package in Python, which used the maximum likelihood estimation technique [55]. Two discrete choice models analyze the user's preferences toward mode choice. The first is to have an overview of the current mode of transportation used, and the other is to understand the preferences toward integrated public modes. Two models used were MNL and Mixed Logit (ML). The variables used in these models are defined and summarized in Table 3.

Table 3. Description of model variables.

Variable	Definition	Variable	Definition
Choices for the current situation scenario	1. if the preference for Private Vehicles 2. for Ride-Sourcing 3. for Ride-Sourcing and BRT	Driv. lic.	1. if the user has a driver's license 2. if the user does not have a driver's license
Choices for the integration situation scenario	1. if the preference for Private Vehicles and BRT 2. for Ride-Sourcing and BRT 3. for Bus on-demand and BRT 4. for Private vehicle	Number Veh.	1. if the user does not have a vehicle 2. if the user has one vehicle 3. if the user has two vehicles 4. if the user has three or more vehicles
Gender	1. male user 2. female user	Income	1. if the user's income is low (<499 JOD) 2. if the user's income is medium (500–1499 JOD) 3. if the user's income is high (1500 JOD or more)
Age	1. for young users (18–24) 2. adult users (25–44) 3. middle-aged users (45–64) 4. senior users (65 and above)	Education Lev.	1. if the user has a high school certificate 2. if the user has a Diploma certificate 3. if the user has a Bachelor's certificate 4. if the user has a Postgraduate certificate
Household size	1. two or fewer family members 2. three or four family members 3. five or six family members 4. six or more family members	Current Status	1. if the user is a student 2. if the user is an employee 3. if the user is a housewife 4. if the user is retired
Disabilities	1. user with a disability 2. user without disability	Average Daily Trips	1. if the average daily trips are low 2. if the average daily trips are medium 3. if the average daily trips are high
Travel Time	1. for less than 10 min travel time 2. for 10–20 min travel time 3. 21 min to 39 min 4. for 40–60 min travel time 5. larger than 60 min travel time	Major	1. if the trip is for work 2. if the trip is for studying 3. if the trip is for recreation 4. if the trip is for other purposes
Trans Mode	1. if one mode is used 2. if two modes are used 3. if three or more modes are used	Main Modes	1. if the user travels by walking 2. if the user travels by private vehicle 3. if the user travels by public transportation 4. if the user travels by Ride-sourcing services 5. if the users travel by taxi. 6. if the users need more than one mode

Table 3. *Cont.*

Variable	Definition	Variable	Definition
Parking	1. if the parking available with fees 2. if the parking is available without fees 3. if the parking is not available	IVTT	IVTT_PV IVTT_Ride-Sourcing IVTT_BRT IVTT_PvBRT IVTT_Ride-Sourcing_BRT IVTT_BoDBRT IVTT_PV
WT	WT_PV WT_Ride-Sourcing WT_BRT WT_PvBRT WT_Ride-Sourcing_BRT WT_BoDBRT WT_PV	Cost	Cost_PV Cost_Ride-Sourcing Cost_BRT Cost_PvBRT Cost_Ride-Sourcing_BRT Cost_BoDBRT Cost_PV

4.1. Multinomial Logit Model (MNL)

The MNL model estimates the coefficients in the utility functions and identifies the user's and trip characteristics in mode choice [56]. In this study, MNL is used to investigate the factors affecting the service's preference for the given alternatives of transportation modes. However, although MNL gives the basic parameters of the mode choice, it is weak in assuming an identical population, and the estimation does not account for heterogeneity and correlation among individuals.

4.1.1. MNL for the Current Transportation Conditions

This study presents the results of the Multinomial Logit (MNL) model, which analyzes transportation choices based on various parameters. Table 4 summarizes the MNL model specifications under the current transportation conditions, including parameters related to different transportation modes. The parameters include ASCpv, ASCRide-Sourcing, βAge, βIncome, βCurrent_Status, βNumber_Veh, βMain_Mode, βParking, βIVTT, and βCost, each with corresponding variables. This table outlines the variables: private vehicle (PV), ride-sourcing, and bus rapid transit (BRT) options.

Table 4. MNL model specifications based on current transportation conditions.

Parameter	Variables		
	Private Vehicle	Ride-Sourcing	BRT
ASC_{pv}	1	-	-
$ASC_{Ride\text{-}Sourcing}$	-	1	-
β_{Age}	2	1	1
β_{Income}	3	2	1
$\beta_{Current\_Status}$	2	1	1
β_{Number_Veh}	-	1	1
β_{Main_Mode}	-	-	3
$\beta_{Parking}$	1	-	3
β_{IVTT}	IVTT_PV	IVTT_Ride-Sourcing	IVTT_BRT
β_{Cost}	Cost_PV	Cost_Ride-Sourcing	Cost_BRT

4.1.2. MNL for the Proposed Scenarios of Integrating Modes

This section presents the MNL model specification for the proposed scenarios, as shown in Table 5. The table outlines various parameters and their corresponding variables, crucial for the study analysis.

Table 5. MNL model specification for the proposed scenarios.

Parameter	**Variables**			
	Public Modes			**Private Mode**
	PV_BRT	**Ride-Sourcing_BRT**	**BoD_BRT**	**PV**
ASC_{PV_BRT}	1	-	-	-
$ASC_{Ride\text{-}Sourcing\_BRT}$	-	1	-	-
ASC_{BoD_BRT}	-	-	1	-
β_{Gender}	-	-	-	1
β_{Age}	3	1	1	2
β_{Income}	3	1	2	3
$\beta_{Education\_Lev}$	2	4	1	1
$\beta_{Current\_Status}$	2	3	1	3
β_{Number_Veh}	2	1	1	2
β_{Main_Mode}	- -	4	3	2
β_{WT}	WT_PvBRT	WT_Ride-SourcingBRT	WT_BoDBRT	WT_PV
β_{Cost}	Cost_PvBRT	Cost_Ride-SourcingBRT	Cost_BoDBRT	Cost_PV

4.2. Mixed Logit Model (ML)

The ML model is used to find the random taste variation of choices provided to respondents by taking into account the preference heterogeneity of users in which the coefficients of the attributes varied randomly rather than being identical for all users [57]. The ML model used two additional coefficients in addition to the coefficients used in the MNL model, which are the standard deviation of the distribution of the two random parameters.

The choice of modeling approach depends on the specific research questions, the nature of the data, and the goals of the study. Other models like Nested Logit, Probit, or more advanced choice models like Latent Class Choice Models or Mixed Logit with more complex structures may be appropriate for different research questions or data characteristics. In the case of the current research, MNL and ML were likely chosen because they provided a suitable balance between model complexity and the ability to capture the essential aspects of public transportation mode choice in Amman. The MNL model was selected for its simplicity and ability to estimate coefficients in utility functions, shedding light on the factors influencing mode choices for public transportation users. MNL's ease of interpretation and its role as a benchmark model in transportation studies make it a valuable starting point for understanding the average behavior of the population. However, acknowledging the limitations of MNL, particularly its assumption of identical preferences among all individuals, the researchers also employed the ML model. ML was chosen because it accommodates preference heterogeneity, recognizing that individuals may have diverse mode preferences. By allowing for random variation in coefficients, ML captures the richness of individual choices and accounts for correlations and heterogeneity among users. The additional parameters introduced by ML, such as standard deviations of random parameters, provide a deeper understanding of the variation in preferences within the population [58]. Thus, the use of MNL and ML in this study not only helps identify the factors influencing mode choice but also accounts for the diversity of user preferences, ultimately guiding the development of effective transportation policies to alleviate Amman's traffic congestion.

4.2.1. ML for the Current Transportation Conditions

As shown in Table 6, the Study analysis includes parameters related to Private Vehicle, Ride-Sourcing, and Bus Rapid Transit (BRT). When considering the 'βIncome' parameter, it is evident from the table that Private Vehicle and Ride-Sourcing exhibit higher values compared to BRT, indicating a potential relationship between income and mode choice.

Table 6. ML for the current transportation conditions.

Parameter	Variables		
	Private Vehicle	**Ride-Sourcing**	**BRT**
ASC_{pv}	1	-	-
$ASC_{Ride\text{-}Sourcing}$	-	1	-
β_{Age}	2	1	1
β_{Income}	3	2	1
$\beta_{Current\_Status}$	2	1	1
$\beta_{Current\_Status\_S}$	2	1	1
β_{Number_Veh}	-	1	1
β_{Main_Mode}	-	-	3
$\beta_{Main\_Mode\_S}$	-	-	3
$\beta_{Parking}$	1	-	3
β_{Cost}	Cost_PV	Cost_Ride-Sourcing	Cost_BRT

4.2.2. ML for the Proposed Scenarios of Integrating Modes

This research explores integrating various modes of transportation in the proposed scenarios. As shown in Table 7, we consider various variables, including Public Modes, Private Mode, and different parameters.

Table 7. ML for the proposed scenarios of integrating modes.

Parameter	Variables			
	Public Modes			**Private Mode**
	PV_BRT	**Ride-Sourcing_BRT**	**BoD_BRT**	**PV**
ASC_{PV_BRT}	1	-	-	-
$ASC_{Ride\text{-}Sourcing\_BRT}$	-	1	-	-
ASC_{BoD_BRT}	-	-	1	-
β_{Gender}	-	-	-	1
β_{Age}	3	1	1	2
β_{Age_S}	3	1	1	2
β_{Income}	3	1	2	3
$\beta_{Education\_Lev}$	2	4	1	1
$\beta_{Current\_Status}$	2	3	1	3
β_{Number_Veh}	2	1	1	2
β_{Main_Mode}	-	4	3	2
$\beta_{Average\_Daily\_Trips}$	1	1	1	2

Table 7. *Cont.*

Parameter	Variables			
	Public Modes			Private Mode
	PV_BRT	Ride-Sourcing_BRT	BoD_BRT	PV
β_{WT}	WT_PvBRT	WT_Ride-SourcingBRT	WT_BoDBRT	WT_PV
β_{WT_S}	WT_PvBRT	WT_Ride-SourcingBRT	WT_BoDBRT	WT_PV
β_{Cost}	Cost_PvBRT	Cost_Ride-SourcingBRT	Cost_BoDBRT	Cost_PV
β_{Cost_S}	Cost_PvBRT	Cost_Ride-SourcingBRT	Cost_BoDBRT	Cost_PV

5. Results and Discussion

This section presents the results obtained from the survey and the model.

5.1. Survey Results

The survey results indicated that 30% of respondents could use the BRT in the current situation, but when providing integrated services to feed the BRT stations, the percentage rose to 70%. In addition, the sociodemographic characteristics obtained from the survey respondents showed that the sample is close to the Jordan population, as presented in Table 8.

Table 8. Description of the observed variables and Jordanian population.

Variable	Level	Sample (%)	Jordanian Statistics (%)
Gender	Female	49%	53%
	Male	51%	47%
Age	Young (18–29)	38.7%	33.5%
	Adults (25–44)	46.8%	36.7%
	Middle-age (45–64)	14.1%	23.3%
	Old (65 and above)	0.4%	6.6%
Family members	Two or less	8.8%	16%
	Three or four	35.9%	28.9%
	Five or six	36.9%	34.1%
	Six and more	18.5%	21.1%
Income	Low (<499 JD)	22%	17.1%
	Medium (500–1499 JD)	50.9%	66.4%
	High (>1500 JD)	19.6%	16.5%
Education	Secondary school	1.7%	N.A
	Tawjihi (General Secondary Education Certificate Examination in Jordan)	10.7%	
	Diploma	12.4%	
	Bachelor	57.8%	
	Higher education	17.4%	

The average daily trip data revealed that approximately 34% of respondents reported trip durations falling within the 20 to 40 min range. Interestingly, respondents expressed a willingness to embrace public transportation services, provided they offer comfort and reliability, as this could significantly alleviate traffic congestion. Conversely, the same respondents cited several key factors that discourage them from using public transportation. These included the unreliability of services, the absence of well-defined schedules, and the availability of alternative, more comfortable transportation options. Furthermore, respondents highlighted potential solutions to mitigate traffic congestion. They proposed the provision of buses for commuting to work or university, ridesharing arrangements with others, the adoption of flexible working hours, and the integration of public transport with ride-sourcing services as promising strategies to address the issue.

Another point was found from the results that the preference to use ride-sourcing services rather than taxi services due to the ability to follow the driver, knowing the travel time needed, the possibility to pre-order trips, and knowing the cost in advance.

The respondents showed that the BRT serves only 30% of the users since it is still under its soft operation, so the coverage area is considered low, making it challenging to reach BRT stations. Therefore, PV was the primary mode to reach BRT station, followed by walking, public transportation, and ride-sourcing services. The users also preferred to use BRT in the summer and spring seasons.

The proposed scenario of integrating more than one mode of transportation services showed that the respondents highly accepted this idea in reducing the cost of trips, enhancing public transportation and conversation, and creating jobs for young people.

5.2. Model Results

The results of the mode of transport, for example, Private Vehicles, BRT, or ride-sourcing based on the obtained work-based trips, revealed that about 64.4% of the participants used private vehicles. This reflects the current situation in Jordan, as using private vehicles is affordable, and the flexibility allows users to make secondary trips easily. On the other hand, about 21.3% of the participants used Ride-sourcing services. This could be referred to as the fact that this service has flexible schedule trips, comfort, and reliability. On the other hand, the BRT service was selected by 14.3%, which indicated that few people were attracted to the BRT service under the existing situation of the soft operation of BRT.

According to the current situation in Jordan, public transportation services suffer from several barriers related to accessibility, flexibility, affordability, reliability, and convenience. So, to increase the ridership of public transportation, new services are suggested to connect and integrate with BRT. It was found that when integrating the BRT with other modes of transportation, the percentage of mode choice increased to 70.8%, classified as 32.1% when integrated with private vehicles and providing parking services; about 20.3% when integrated with ride-sourcing services; almost 18.4% when integrated with on-demand mobility services; and about 29.2% of users still preferred to use their private vehicles, and these users preferred to use their vehicles since they have secondary trips. Under the existing transportation services, most of the participants who chose private vehicles held a driving license, with a percentage of 93.2%. Moreover, private vehicles were chosen by highly educated participants, with a percentage of 78.3%. On the other hand, participants who chose ride-sourcing services were employers, with a percentage of 65.6%.

After integrating BRT with other modes of transportation, participants who chose the BRT service were employers with a percentage of 70.2%. Also, participants who chose BRT held a driving license with a percentage of 83.3%. Finally, participants who chose private vehicles were graduate and postgraduate degree users, with a percentage of 74.6%.

5.2.1. Model Estimation

All models were estimated using the PandasBiogeme software package in Python, which used the maximum likelihood estimation technique to find the optimal way to fit a distribution to the data [55]. This study used the MNL model as a starting model, considering it simpler. The ML model was used after the MNL to test the taste variation of variables.

The *T*-test is a type of inferential statistics based on the t-distribution of the bell-shaped curve, which is used to test if there is a significant difference between the means of groups. The *t*-test is used in this study since the variance is unknown and the sample size is large.

The general preference based on the Associated Constants (ASCs) under the current situation was for private vehicle alternatives followed by ride-sourcing and ride-sourcing with BRT, respectively. This might be related to the soft operation of the BRT and the flexibility of using PVs in which the user can make secondary trips easily. Figure 3 shows how observable factors affect the scenario. The Associated Constants (ASCs) preferred private vehicles, ride-sourcing, and ride-sourcing with BRT. This might be related to the soft operation of the BRT and the flexibility of using PVs in which the user can make secondary trips easily.

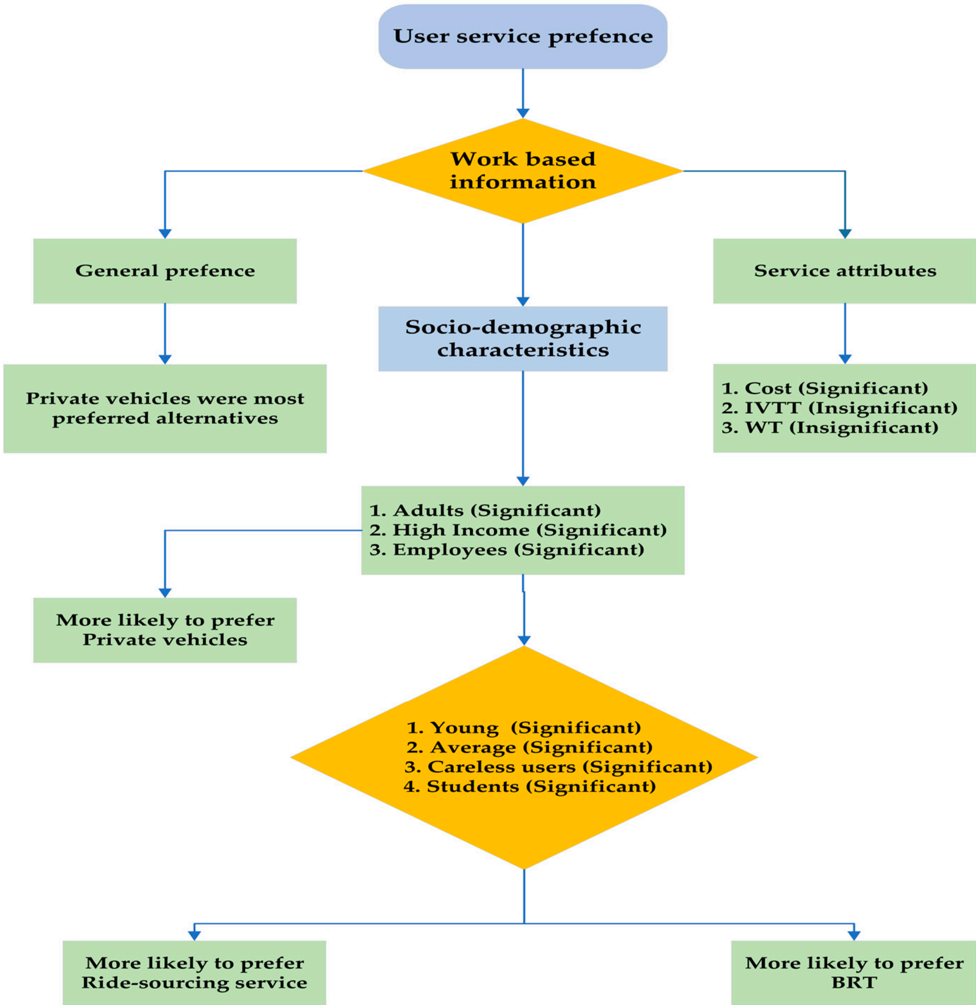

Figure 3. The effect of the observable variables on the current situation.

The parameter estimates of the MNL and ML models for the current situation are presented in Table 9. Based on the sociodemographic characteristics, affluent adults were more likely to prefer private vehicles in employment. On the other hand, ride-sourcing services were more likely to be preferred by young students with average incomes. Moreover, the BRT service was more likely to be preferred by young students with low incomes. Public transportation users were generally more willing to use the BRT service. Another point related to car ownership is that the users who do not own a private vehicle were more willing to use ride-sourcing and BRT services. Also, the unavailability of parking was one of the reasons for choosing the BRT.

Table 9. Estimated parameter for MNL and ML models (Current public transport).

Model Parameter Choice	MNL			ML		
	Estimate	**Robust *t*-Test**	***p*-Value**	**Estimate**	**Robust *t*-Test**	***p*-Value**
ASC_{PV}	2.279	7.937	1.999×10^{-15} (***)	2.492	7.989	3.995×10^{-13} (***)
$ASC_{Ride\text{-}sourcing}$	1.882	7.677	1.643×10^{-14} (***)	2.019	7.357	2.199×10^{-12} (***)
β_{Age}	0.314	2.908	3.643×10^{-3} (*)	0.375	2.683	6.088×10^{-3} (*)
β_{Income}	0.240	2.037	4.168×10^{-2} (*)	0.336	2.211	2.427×10^{-2} (*)
$\beta_{Current\_Status}$	0.344	2.669	7.603×10^{-3} (*)	0.489	2.204	1.585×10^{-2} (*)
$\beta_{Current\_Status}{}^{SD}$	-	-	-	1.607	2.611	4.92×10^{-3} (*)
β_{Number_Veh}	1.072	3.878	1.055×10^{-4} (*)	1.452	3.635	1.541×10^{-4} (*)
β_{Main_Mode}	1.862	5.497	3.845×10^{-8} (**)	1.944	5.108	4.076×10^{-7} (**)
$\beta_{Main\_Mode}{}^{SD}$	-	-	-	0.683	1.302	1.364×10^{-1}
$\beta_{Parking}$	0.436	2.637	8.354×10^{-3} (*)	0.550	2.654	6.792×10^{-3} (*)
β_{IVTT}	−0.179	−0.299	7.639×10^{-1}	-	-	-
β_{Cost}	−2.035	−2.371	1.78×10^{-2} (*)	−2.422	−4.978	2.235×10^{-2} (*)
$\beta_{Cost}{}^{SD}$	-	-	-	0.963	1.225	1.1×10^{-1}

SD represents the standard deviation; * indicates statistical significance at a significance level of 0.05. ** indicates moderate statistical significance. *** indicates highly statistical significance.

The cost parameter for all modes has a negative sign in both models, representing an inverse relationship with a preference; the more the cost, the less the users choose. Again, this is consistent with what was found in previous studies.

The problems related to the connectivity and low coverage areas of public transportation were the main reason for the proposed model, which is to have integrated and connected modes of public transportation. The general preference based on the ASCs was for PV with BRT followed by ride-sourcing with BRT, then followed by BoD with BRT compared to a fixed constant of private vehicles.

The parameter estimates of MNL and ML models for the integration services are presented in Table 10. Based on the sociodemographic characteristics, PV with BRT was more likely to be preferred by the employer middle-aged with high income who had a diploma certificate. Ride-sourcing with BRT was more likely preferred by young and low-income users with postgraduate degrees. BoD with BRT was more likely to be preferred by young students who live in a family with an average income. Males and housewife users who live in a family with a high income were more likely to prefer their own private vehicles. The availability of private vehicles has a significant effect on the choice; the users who live in a family without a private vehicle selected the choices of Uber and BoD with BRT, while the users who live in a family with one vehicle selected, such as private vehicles and private vehicles with BRT when parking is provided (Figure 4).

The average daily trips also significantly impacted the choices; when the trips were considered low, the preference for public modes was high, but when the trips were high, the preference for private vehicles was high since the users could make secondary trips easily.

Cost and WT parameters were highly significant, with an inverse relationship with the preference. The selection of a mode decreases as the cost increases. The same applies to the WT. Conversely, when the WT is high, the mode is least selected.

Table 10. Estimated parameters of MNL and ML models (After integration).

Parameter	MNL		ML	
	Estimate	**Robust *t*-Test**	**Estimate**	**Robust *t*-Test**
Choice Model				
ASC_{PV_BRT}	0.816	4.882	0.919	5.001
$ASC_{Ride\text{-}sourcing\_BRT}$	0.926	4.519	1.073	4.418
β_{Age}	0.308	3.632	0.268	2.356
β_{Age} SD	-	-	0.962	1.615
β_{Income}	0.254	2.474	0.277	2.496
$\beta_{Current\_Status}$	0.219	2.054	0.242	1.988
$\beta_{Education\_Lev}$	0.320	2.493	0.349	2.519
β_{Number_Veh}	0.229	2.017	0.255	1.997
β_{Main_Mode}	0.417	3.318	0.418	3.075
β_{WT}	−0.542	−2.661	−0.512	−2.299
β_{WT} SD	-	-	0.655	1.185
β_{Cost}	−1.868	−4.277	−2.288	−3.965
β_{Cost} SD	-	-	0.956	1.346

SD represents the standard deviation.

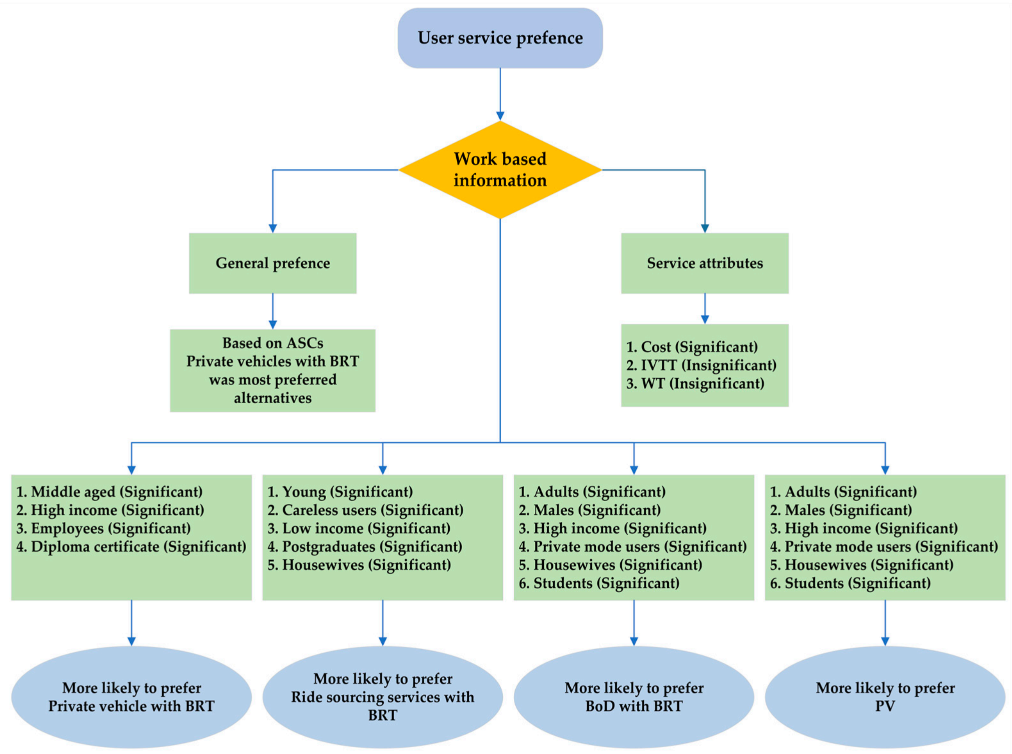

Figure 4. The effect of the observable variables under the proposed scenario.

5.2.2. Model Performance

Table 11 shows the outcomes of MNL and ML under existing transportation modes and integrated transportation modes. In the existing transportation modes scenario, the MNL model demonstrates a higher model fit and rho-squared value of 0.367 compared to the ML model, which has a rho-squared value of 0.355. First, it is important to note that pseudo R-squared values in logit analysis tend to be considerably lower than the

R-squared values in ordinary regression analysis. This is because the nature of logistic regression is different from linear regression, and the concept of R-squared does not directly apply. Instead, logit models use pseudo R-squared values as a measure of goodness-of-fit. According to (Kusumastuti & Nicholson, 2017), a pseudo R-squared value between 0.2 and 0.4 can be considered equivalent to an R-squared value between 0.5 and 0.8 in ordinary regression analysis.

Table 11. Models outcomes.

Performance Measures	Existing Transportation Modes		Integrated Transportation Modes	
	MNL	ML	MNL	ML
Rho-square-bar	0.367	0.355	0.231	0.314
Initial log-likelihood	−718.492	−705.149	−1513.214	−1425.779
Final log-likelihood	−444.857	−443.124	−1153.31	−963.672
No. of estimated parameters	10	12	11	15
BIC	954.546	964.045	2378.823	2025.782

Additionally, McFadden stated that a pseudo R-squared value between 0.2 and 0.4 denotes an excellent fit. In the current research, a rho-squared value of 0.367 falls within the range of 0.2 to 0.4, denoting an excellent fit. Therefore, a rho-squared value of 0.367 can be considered satisfactory and indicative of a good fit for the mixed-logit transportation model [59].

This difference could be attributed to the ML model utilizing a larger number of estimated parameters and including those that are insignificant in the model. On the other hand, in the integrated transportation modes scenario, the ML model achieves a higher model fit and rho-squared value of 0.314, whereas the MNL model shows a rho-squared value of 0.231. It is worth noting that the initial log-likelihood values of the models were low, but the final log-likelihood values were high, indicating that the estimated models provided a better fit to the data sets. The Bayesian Information Criterion (BIC) is used to estimate the likelihood of the model's predictions. Generally, the model with the lowest BIC value is considered the best. The MNL model demonstrates a high model fit in the existing transportation modes scenario with a BIC value of 954.54. On the other hand, the machine learning model demonstrates a strong level of compatibility in the context of integrated transportation modes, as evidenced by a BIC value of 2025.782. These results are consistent with findings from previous studies and provide further support for the effectiveness of the MNL and ML models in analyzing transportation scenarios [38,39,60,61].

The study addressed various inadequacies of prior transportation mode choice studies. This study used real-world user preferences and demographic data, unlike previous research. This study used Maximum Likelihood models to account for taste differences, unlike earlier studies that assumed homogeneous preferences. It also stressed the convergence of transportation modes to improve mobility and reduce private automobile use. Despite previous research constraints, this study revealed more realistic insights into mode-choosing behavior.

5.2.3. Recommendations

The following are the recommendations that are based on the research results and aim to address the key factors influencing mode choice and public transportation usage as identified in the survey. To ensure the effectiveness of these recommendations, it is important to continuously monitor and adjust strategies based on evolving transportation needs and preferences.

The results show that when integrated services are provided to feed the BRT stations, the percentage of respondents willing to use the BRT service increases from 30% to 70%.

Therefore, it is recommended to focus on integrating various modes of transportation, such as private vehicles, ride-sourcing services, and on-demand mobility services with the BRT system. This integration can help improve the overall convenience and accessibility of public transportation.

Respondents expressed a willingness to embrace public transportation services if they offer comfort and reliability. To address this, it is recommended to work on enhancing the reliability of public transportation services, including BRT. This may involve implementing well-defined schedules, real-time tracking, and better maintenance of vehicles to reduce service disruptions.

The survey results suggest that respondents see flexible working hours as a promising strategy to mitigate traffic congestion. Encouraging employers to adopt flexible working hours could help reduce peak-hour congestion and make public transportation more attractive.

The analysis shows that cost parameters have a significant impact on mode choice. To enhance public transportation ridership, it is recommended to explore measures aimed at lowering the expenses associated with public transportation use, which may include the implementation of subsidies, discounts for students, or the introduction of monthly passes.

Since the BRT service currently has low coverage, it is important to expand the coverage area to make it more accessible to a larger population. This expansion can encourage more people to use the BRT system, especially if integrated with other transportation modes.

The preference for ride-sourcing services over traditional taxis is influenced by factors like knowing travel time, pre-ordering trips, and knowing the cost in advance. To compete with ride-sourcing services, public transportation should provide similar levels of information and communication to users.

For integrated transportation modes, it is recommended to provide parking services for private vehicle users who choose to combine their trips with BRT. This can make the transition from private vehicles to public transportation more seamless.

Understanding the sociodemographic characteristics of mode preferences is crucial. Targeted marketing campaigns can be designed to attract specific groups of users to public transportation services, for example, focusing on young students with low incomes for BRT promotion and affluent adults for private vehicle alternatives.

Continuing to use statistical models like MNL and ML to monitor and evaluate the impact of policy changes and improvements in the transportation system is encouraged, such as regularly updating strategies based on the results of these models to optimize public transportation services.

By involving the public in decision-making processes related to transportation improvements, gathering feedback and insights from users can help identify specific pain points and areas for improvement.

This study incorporates interdisciplinary insights, such as the environment, safety and security, infrastructure development, technology, community engagement, private-public integration, and long-term sustainability, which can aid in the development of an effective public transportation system that attracts a diverse range of users and evolves in response to changing preferences and needs; thus, transportation planners, urban designers, and behavioral psychologists work together. This can facilitate the development of transportation systems that consider the policy implications of psychological and social elements influencing mode selection.

6. Conclusions

The study employs SP surveys and advanced choice models, including Multinomial Logit (MNL) and Mixed Logit (ML), to model user preferences for integrated transit services. This contributes to the academic literature by offering a comprehensive understanding of the factors influencing commuters' mode choices, including cost, waiting time, and sociodemographic variables. By analyzing user preferences, the research also predicts traffic demand for future public transportation improvements in various integrated transit system scenarios. This predictive modeling adds valuable insights to the field, assisting urban planners and policymakers in making data-driven decisions about transportation infrastructure development. The study explores the integration of various transportation modes, including private vehicles, ride-sourcing services, and Book-on-Demand (BoD) services with the BRT system. This holistic approach to transportation planning provides a novel perspective on addressing congestion and improving public transportation systems. The findings of this research also offer practical solutions to address the significant traffic congestion issues faced by Amman, Jordan. The recommendation of integrating BRT with on-demand services can alleviate congestion, making transportation more efficient and accessible for residents. The study emphasizes the importance of reducing waiting times and trip costs for commuters. Public and private transportation service providers can use this insight to collaborate and offer affordable, efficient, and user-friendly transit options, ultimately enhancing the overall commuting experience for the residents of Amman. The research recognizes the upcoming expansion of BRT routes and the potential impact on transportation patterns. This practical insight allows for proactive planning and coordination among relevant stakeholders to ensure a smooth transition and integration of the new routes into the existing transportation network. The study acknowledges the limitations imposed by the COVID-19 pandemic and suggests potential avenues for future research, including personal interviews and focus-group discussions. This practical adaptability highlights the importance of continuing research in the face of unforeseen challenges to improve transportation systems. This research not only advances the academic understanding of user preferences and transit integration, but also offers practical recommendations for policymakers, transportation authorities, and service providers in Amman, Jordan, and similar urban settings. By addressing traffic congestion, enhancing commuting experiences, and planning for future growth, the study contributes to the ongoing efforts to create sustainable and efficient transportation systems in rapidly growing cities.

Supplementary Materials: The following are available online at https://www.mdpi.com/article/10.3390/urbansci7040111/s1, Questionnaire S1: Survey of the research study, and Blank consent form S2: Consent to participation in a research study.

Author Contributions: Conceptualization, F.A.; Methodology, F.A.; Validation, F.A.; Formal Analysis, F.A.; Investigation, F.A.; Data Curation, F.A.; Writing—Original Draft Preparation, F.A.; Writing—Review and Editing, F.A., N.L., D.A. and T.A.; Supervision, N.L.; Project Administration, N.L.; Funding Acquisition, N.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data presented in this study are available in this article.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Department of Statistics. 2020. Available online: http://dosweb.dos.gov.jo/databank/yearbook/YearBook_2020.pdf (accessed on 10 October 2023).
2. Department, T. *Overview*. Public Security Directorate. 2021. Available online: https://psd.gov.jo/en-us/psd-department-s/traffic-department/publications/?page=1&SC=&MC= (accessed on 10 October 2023).
3. Jamal, A.; Rahman, M.T.; Al-Ahmadi, H.M.; Ullah, I.; Zahid, M. Intelligent Intersection Control for Delay Optimization: UsingMeta-Heuristic Search Algorithms. *Sustainability* **2020**, *12*, 1896. [CrossRef]
4. Li, C.; Cao, D.; Du, Q. Exact solutions to the nonlinear equation in traffic congestion. *Adv. Differ. Equ.* **2020**, *2020*, 68. [CrossRef]
5. Wang, C.; Shi, H.; Zuo, X. A multi-objective genetic algorithm based approach for dynamical bus vehicles scheduling under traffic congestion. *Swarm Evol. Comput.* **2020**, *54*, 100667. [CrossRef]
6. Magaji, J. An Assessment of the Effects of Traffic Congestion on Man Hour and Productivity in Gwagwalada Town. *Int. J. Innov. Environ. Stud. Res.* **2020**, *4*, 10–20.
7. Zahid, M.; Chen, Y.; Jamal, A.; Memon, M.Q. Short Term Traffic State Prediction via Hyperparameter Optimization Based Classifiers. *Sensors* **2020**, *20*, 685. [CrossRef]

8. Safdar, M.; Jamal, A.; Al-Ahmadi, H.M.; Rahman, M.T.; Almoshaogeh, M. Analysis of the Influential Factors towards Adoption of Car-Sharing: A Case Study of a Megacity in a Developing Country. *Sustainability* **2022**, *14*, 2778. [CrossRef]
9. Becker, H.; Balac, M.; Ciari, F.; Axhausen, K.W. Assessing the welfare impacts of Shared Mobility and Mobility as a Service (MaaS). *Transp. Res. Part A Policy Pr.* **2019**, *131*, 228–243. [CrossRef]
10. Nieberg, H. Public Transportation in the Middle East: A Study on the Sustainability and Efficacy of Taxis in Amman and the Future of Public Transportation. *Indep. Study Proj. ISP Collect.* **2018**, *2665*, unpublished paper.
11. GAM. *The Bus Rapid Transit (BRT) Project*. Al-Bhas ul Sari. 2023. Available online: http://www.ammanbrt.jo/?l=en (accessed on 10 October 2023).
12. Mane, A.; Sarkar, A.; Arkatkar, S. Study of Modal Shift to Bus Rapid Transit (BRT) in Developing Country: A Case Study in India. In Proceedings of the Transportation Research Board 94th Annual Meeting, Washington, DC, USA, 11–15 January 2015.
13. Jittrapirom, P.; Neerven, W.; Martens, K.; Trampe, D.; Meurs, H. The Dutch Elderly's Preferences Toward a Smart Demand-responsive Transport Service. *Res. Transp. Bus. Manag.* **2019**, *30*, 100383. [CrossRef]
14. Zhang, Y.; Farber, S.; Young, M. Eliminating barriers to nighttime activity participation: The case of on-demand transit in Belleville, Canada. *Transportation* **2021**, *49*, 1385–1408. [CrossRef]
15. Kaewkluengklom, R.; Satiennam, W.; Jaensirisak, S.; Satiennam, T. Influence of psychological factors on mode choice behaviour: Case study of BRT in Khon Kaen City, Thailand. *Transp. Res. Procedia* **2017**, *25*, 5072–5082. [CrossRef]
16. Youssef, Z.; Alshuwaikhat, H.; Reza, I. Modeling the Modal Shift towards a More Sustainable Transport by Stated Preference in Riyadh, Saudi Arabia. *Sustainability* **2021**, *13*, 337. [CrossRef]
17. Abid, M.M.; Ayaz, A.; Nawaz, N.; Iqbal, M.; Yang, H.; Tehseen, A.S.; Jafar, S.T.A. Attraction of Bus Rapid Transit (BRT) for Car and Bike Owners. *Rom. J. Transp. Infrastruct.* **2020**, *9*, 1–21. [CrossRef]
18. Tuan, V.A. Mode choice behavior and modal shift to public transport in developing countries-the case of Hanoi city. *J. East. Asia Soc. Transp. Stud.* **2015**, *11*, 473–487.
19. Seraj, M.; Hadiuzzaman, M.; Hasan, S.; Musabbir, S.R. Traveler preference analysis for the proposed bus Rapid Transit (BRT) service in Dhaka. *J. Civ. Eng. IEB* **2015**, *43*, 133–144.
20. Wang, W.; Yun, M.; Yang, D. *Research on Method of Urban Traffic Mode Split Forecast in the Case of Introduction of Bus Rapid Transit*; CICTP, 2015; pp. 1358–1366. Available online: https://ascelibrary.org/doi/10.1061/9780784479292.124 (accessed on 10 October 2023).
21. Hazoor, W.; Hazoor, A.; Hazoor, A. Estimation of Modal Shift for Bus Rapid Transit System (BRTS) in Quetta. In Proceedings of the 8th International International Civil Engineering Congress (ICEC-2016), Karachi, Pakistan, 23–24 December 2016.
22. Liu, Y.; Bansal, P.; Daziano, R.; Samaranayake, S. A framework to integrate mode choice in the design of mobility-on-demand systems. *Transp. Res. Part C Emerg. Technol.* **2018**, *105*, 648–665. [CrossRef]
23. Cascajo, R.; Garcia-Martinez, A.; Monzon, A. Stated preference survey for estimating passenger transfer penalties: Design and application to Madrid. *Eur. Transp. Res. Rev.* **2017**, *9*, 42. [CrossRef]
24. Academies, N. Shared Mobility Public Transit. *Sci. Eng. Med.* **2020**. Available online: https://www.trb.org/TCRP/Blurbs/174653.aspx (accessed on 9 December 2020).
25. Bentley, J.; Collins, B.S.; Ranjitkar, P.; McArthur, J. Emerging Technologies for Rapid Transit: Part Two An Evaluation of Specific Technologies. 2016. Available online: https://at.govt.nz/media/1971161/jmac_report2016-02_emergingtechrapidtransit-part2_jul16.pdf (accessed on 13 July 2016).
26. Mahéo, A.; Kilby, P.; Van Hentenryck, P. Benders Decomposition for the Design of a Hub and Shuttle Public Transit System. *Transp. Sci.* **2019**, *53*, 77–88. [CrossRef]
27. Mayaud, J.; Ward, F.; Andrews, J. Microtransit Has the Potential to Flip Transit on Its Head. *Transp. Res. Rec. J. Transp. Res. Board* **2021**, *2675*, 77–88. [CrossRef]
28. Sörensen, L.; Bossert, A.; Jokinen, J.-P.; Schlüter, J. How much flexibility does rural public transport need?—Implications from a fully flexible DRT system. *Transp. Policy* **2020**, *100*, 5–20. [CrossRef]
29. Tangphaisankun, A.; Nakamura, F.; Okamura, T. Study on role of paratransit as a feeder mode in urban transportation in developing countries. In Proceedings of the 8th International Conference of Eastern Asia Society for Transportation Studies, Surabaya, Indonesia, 16–19 November 2009.
30. Smith, A. *Shared, Collaborative and on Demand: The New Digital Economy*; Pew Research Center: Washington, DC, USA, 2016.
31. Zhang, Y.; Farber, S.; Young, M. The Benefits of on-Demand Transit in Belleville: Findings from a User Survey. 2020. Available online: https://tspace.library.utoronto.ca/bitstream/1807/100570/4/THE%20BENEFITS%20OF%20ON-DEMAND%20TRANSIT%20IN%20BELLEVILLE%20-%20FINAL%20-%20MAY%2018%202020.pdf (accessed on 10 October 2023).
32. Alizadeh, H.; Farooq, B.; Morency, C.; Saunier, N. Frequent versus occasional drivers: A hybrid route choice model. *Transp. Res. Part F Traffic Psychol. Behav.* **2019**, *64*, 171–183. [CrossRef]
33. Hurtubia, R.; Nguyen, M.H.; Glerum, A.; Bierlaire, M. Integrating psychometric indicators in latent class choice models. *Transp. Res. Part A Policy Pract.* **2014**, *64*, 135–146. [CrossRef]
34. Zhou, H.; Norman, R.; Xia, J.; Hughes, B.; Kelobonye, K.; Nikolova, G.; Falkmer, T. Analysing travel mode and airline choice using latent class modelling: A case study in Western Australia. *Transp. Res. Part A Policy Pr.* **2020**, *137*, 187–205. [CrossRef]
35. Lassarre, S.; Papadimitriou, E.; Yannis, G.; Golias, J. Measuring accident risk exposure for pedestrians in different micro-environments. *Accid. Anal. Prev.* **2007**, *39*, 1226–1238. [CrossRef] [PubMed]

36. Anspacher, D.; Khattak, A.J.; Yim, Y. *Demand-Responsive Transit Shuttles: Who Will Use Them?* Institute of Transportation Studies, UC Berkeley: Berkeley, CA, USA, 2004.
37. Yan, X.; Zhao, X.; Han, Y.; Van Hentenryck, P.; Dillahunt, T. Mobility-on-demand versus fixed-route transit systems: An evaluation of traveler preferences in low-income communities. *Transp. Res. Part A Policy Pr.* **2021**, *148*, 481–495. [CrossRef]
38. Frei, C.; Hyland, M.; Mahmassani, H.S. Flexing service schedules: Assessing the potential for demand-adaptive hybrid transit via a stated preference approach. *Transp. Res. Part C Emerg. Technol.* **2017**, *76*, 71–89. [CrossRef]
39. Yan, X.; Levine, J.; Zhao, X. Integrating ridesourcing services with public transit: An evaluation of traveler responses combining revealed and stated preference data. *Transp. Res. Part C Emerg. Technol.* **2019**, *105*, 683–696. [CrossRef]
40. Ryley, T.J.; Stanley, P.A.; Enoch, M.P.; Zanni, A.M.; Quddus, M.A. Investigating the contribution of Demand Responsive Transport to a sustainable local public transport system. *Res. Transp. Econ.* **2014**, *48*, 364–372. [CrossRef]
41. Louviere, J.; Hensher, D.; Swait, J. *Stated Choice Methods: Analysis and Application*; Cambridge University Press: Cambridge, UK, 2000; Volume 17. [CrossRef]
42. Shaheen, S.; Chan, N. Mobility and the Sharing Economy: Potential to Facilitate the First- and Last-Mile Public Transit Connections. *Built Environ.* **2016**, *42*, 573–588. [CrossRef]
43. Hall, J.D.; Palsson, C.; Price, J. Is Uber a substitute or complement for public transit? *J. Urban Econ.* **2018**, *108*, 36–50. [CrossRef]
44. Alemi, F.; Circella, G.; Handy, S.; Mokhtarian, P. What influences travelers to use Uber? Exploring the factors affecting the adoption of on-demand ride services in California. *Travel Behav. Soc.* **2018**, *13*, 88–104. [CrossRef]
45. Clewlow, R.R.; Mishra, G.S. *Disruptive Transportation: The Adoption, Utilization, and Impacts of Ride-Hailing in the United States*; University of California: Berkeley, CA, USA, 2017.
46. Ababio-Donkor, A.; Saleh, W.; Fonzone, A. The role of personal norms in the choice of mode for commuting. *Res. Transp. Econ.* **2020**, *83*, 100966. [CrossRef]
47. McFadden, D. The Choice Theory Approach to Market Research. *Mark. Sci.* **1986**, *5*, 275–297. [CrossRef]
48. Kedia, A. Estimating the Effect of Online Shopping and Collection-Delivery Points on Shopping Travel in New Zealand. Ph.D. Thesis, University of Canterbury, Christchurch, New Zealand, 2020.
49. Shtayat, A.; Al-Masaied, H.; Moridpour, S. Performance of Urban Transit in Jordan. *EasyChair* **2018**, preprint.
50. Al Hurr, N.; Tashman, L. Measuring the sustainability of transport system in Amman. *Int. Conf. Transp. Dev.* **2019**, 171–183. [CrossRef]
51. Traffic in Amman, Jordan. NUMBEO. 2023. Available online: https://www.numbeo.com/traffic/in/Amman (accessed on 10 October 2023).
52. Declan McManus, T.H.; Bedolla, O.; Foda, K. *Accelerating Mobility: Optimizing Transit in Response to Rapid Disruptions in Technology and Consumer Behavior*. KPMG. 2019. Available online: https://assets.kpmg.com/content/dam/kpmg/tw/pdf/2019/05/accelerating-mobility-final-web-115-final.pdf (accessed on 10 October 2023).
53. Rea, L.M.; Parker, R.A. *Designing and Conducting Survey Research: A Comprehensive Guide*; John Wiley & Sons: Hoboken, NJ, USA, 2014.
54. Bierlaire, M. BIOGEME: A free package for the estimation of discrete choice models. *Swiss Transp. Res. Conf.* **2003**. Available online: http://transp-or.epfl.ch/documents/proceedings/Bier03.pdf (accessed on 10 October 2023).
55. Al-Salih, W.Q.; Esztergár-Kiss, D. Linking Mode Choice with Travel Behavior by Using Logit Model Based on Utility Function. *Sustainability* **2021**, *13*, 4332. [CrossRef]
56. McFadden, D.; Train, K. Mixed MNL models for discrete response. *J. Appl. Econom.* **2000**, *15*, 447–470. [CrossRef]
57. Chandra, M.; Chalumuri, R.S. Mode choice analysis: The data, the models and future ahead. *Int. J. Traffic Transp. Eng.* **2014**, *4*, 269–285. [CrossRef]
58. Kusumastuti, D.; Nicholson, A. Mixed-use development in Christchurch, New Zealand: Do you want to live there? *Urban Stud.* **2018**, *55*, 2682–2702. [CrossRef]
59. Greene, W.H.; Hensher, D.A. A latent class model for discrete choice analysis: Contrasts with mixed logit. *Transp. Res. Part B: Methodol.* **2003**, *37*, 681–698. [CrossRef]
60. Shen, J. Latent class model or mixed logit model? A comparison by transport mode choice data. In *The Applied Economics of Transport*; Routledge: London, UK, 2014; pp. 127–136.
61. AmmanBRT. Rapid Bus Project. Available online: http://www.ammanbrt.jo/ (accessed on 10 October 2023).