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An Integrated SWARA-WASPAS Group Decision Making Framework to Evaluate Smart Card Systems for Public Transportation

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Abstract: Recent technological developments affect daily life as much as they affect the industries. As part of these developments, automation and smart systems are important part of everyday life. Smart card systems are one of the well-known types of smart automation technology being used by the majority of the population in public transportation in most developed countries. Even though automated fare payment systems have been widely integrated into public transportation in developed countries, integration of smart card systems is still under consideration in most developing countries. The aim of this study is to propose a framework to evaluate different smart card systems to determine the best one and additionally validate their benefits when compared with the traditional fare payment system. For this purpose, an integrated multi-criteria decision making (MCDM) framework is used that combines two recent and popular methodologies together. The proposed methodology employs Stepwise Weight Assessment Ratio Analysis (SWARA) method for determination of criteria weights in the decision model and the Weighted Additive Sum Product Assessment (WASPAS) method for comparison of alternatives. Research results revealed that all smart card systems show improvements under performance, reliability, and user satisfaction related criteria. However, traditional fare payment systems are found to be safer under consideration of personal data protection. Findings of this study can be used to select the best smart card system and as a guide for deciding on areas of improvement during the implementation phase to ensure higher user satisfaction.

Keywords: multi-criteria decision making (MCDM); stepwise weight assessment ratio analysis (SWARA); weighted additive sum product assessment (WASPAS); fare systems; smart card systems; public transportation

1. Introduction

Demand for public transportation is increasing at a global scale, and the need for a standardized integrated public transport network is more important now than ever before. Increase in population, raising petrol prices, increased carbon emissions, and global warming make the use of public transportation more popular. In the last few years, even more countries have adopted a contactless smart card system as a mode of payment in public transportation services either on a large scale by countrywide integration or on a small to medium scale capacity by integrating smart card systems in specific cities [1]. Contactless payment systems gained more importance especially during pandemic, because of their ability to remove the contact with money and keypad, hence reducing the chance of getting COVID-19 virus. Smart card systems are portable and durable devices that can be used to store and process data when needed, and they replace traditional paper tickets and magnetic cards [2]. These systems require an automatic fare payment and management system installed in the public transportation centers and provide a standardized service throughout the city. Industry 4.0 standards



also urge economies to adapt current technologies such as Internet of Things (IoT). IoT enabled fields for innovation offer many opportunities for smart card integrated public transportation systems [3]. The adoption of the contactless travel smart card has become increasingly common application, covering almost all modes of transportation and creating an integrated public transportation system in many countries; smart cards are known as city cards. Nowadays, it is common to come across a specific type of city cards in which subscriptions to cultural and social activities are also covered in addition to the transportation services [4]. Thus, passenger profiles recorded into databases are being used as a valuable sources of information for different types of studies such as behavioral analysis, geodemographic analysis, advertisement customizations, and schedule optimization studies [5–7].

Automated fare collection systems offer operators and passengers a convenient and reliable service [8]. An important component to the success and sustainability of urban transport is providing an efficient and effective public transportation system [9]. This is because taking advantage of public transportation is vital in reducing traffic congestions in rush hours, shortening total time spent during journeys, and improving the passenger experience [10], thus encouraging public transport authorities to invest on technologies to improve the service quality of public transportation [11]. Recently, the South African National department of Transport developed The Moving South Africa Initiative strategy to deal with the transportation problems of the 21st century. It is stated that by 2020, public transport in South Africa will meet the requirements of commuters by providing high quality, affordable, accessible, frequent, reliable, efficient, and seamless transport operations [12]. Therefore, transport authorities pursuing similar goals are looking to take advantage of smart card systems in their public transportation fare processes. Integration of these systems improves quality of the service by reducing the time spent on at least payment, ticketing and boarding processes, which also indirectly prevents excess carbon emissions released by idly waiting transportation vehicles during payment processes [13].

Implementation of intelligent systems such as the smart card system is a necessity to effectively build a city- or countrywide integrated transportation system. The comprehensive function of an intelligent transport system is to improve operations of transportation systems that will support the objectives of increasing efficiency and productivity in all regions [14]. An integrated transport system aims to ensure that different transportation modes work together seamlessly and to establish a clear transparent system with uniform tariffs and uniform transport conditions [15]. A sound fare payment and management system will boost the usability of public transport and provide customers with a safe and fast payment environment [11,16,17]. Adoption of smart systems helps to improve usage rate of public transportation systems as a result of increased user satisfaction and time savings during payment and transit activities [18,19].

However, implementation of an integrated fare system faces several difficulties [9]. Formal public transport services may sometimes be unreliable, inconvenient, or even risky in some countries, making many passengers likely to use private transport alternatives instead [20]. For an efficient adoption of the system, many aspects of smart card systems including all of their advantages and disadvantages [2,21] for each transport mode should be considered in the planning phase of the transition project. By nature, this kind of transition brings contradicting goals, which makes the current problem area suitable for application of MCDM methods, since a reliable and rational decision support system is needed to assist authorities during the evaluation of differences between the planned system and the existing one. Availability of a decision model as such is important for decision makers to clearly see the improvements that can be achieved with transition to a smart system. Unfortunately, it is hard to find studies in the literature which address the mentioned issue. The purpose of this study is to propose an efficient and accurate MCDM framework to evaluate and compare performance of different fare systems. To do so, a proper set of metrics is collected through a literature review, and an integrated SWARA and WASPAS decision framework is proposed. Integrated application of SWARA and WASPAS methods in smart card system evaluation is a novel approach in the field. Both of these methods are recent MCDM methodologies, and they are popular because of their ease of applicability while retaining expert evaluations. This aspect of the proposed framework promises a wide area of application. Both methods are also modified slightly to implement a group decision making procedure with a geometric mean method.

The remainder of this study is organized as follows: first, overview about smart card systems, followed by explanation of evaluation criteria used in the model are presented by using literature reviews; then, general structure of proposed MCDM framework and steps of SWARA and WASPAS methods are explained; next, application of SWARA method is demonstrated for the determination of criteria weights; thereafter, WASPAS calculations are presented for the evaluation of different smart card systems and traditional fare system; finally, ranking of performance criteria according to their calculated weights and comparison of results related with different fare systems are discussed along with the proposed transition strategies.

2. Literature Review

2.1. Smart Card Systems

The public transportation sector is a system of different modes of transport vehicles such as buses, underground metro trains, trams, trains, ferries, and such. Implementation of contactless smart card systems in the public transportation sector solves various problems in all modes of transport systems. The smart card, compared to traditional fare payment methods such as cash and paper tickets, is more convenient to use [22]. It is also more secure as it requires fare deposit therefore reducing fraud rates [20]. Traditional fare payment methods like paper ticketing are time consuming, and handling of all procedures required by paper tickets for all passengers requires a great number of staff [2]. Vulnerability to fraud and having limited capabilities for data collection possibilities are other drawbacks of traditional fare methods. When compared to other traditional payment methods, contactless smart cards offer many advantages including better reliability, more advanced data transfer capabilities, prevention measures against fraud, and high memory capacity related perks [23]. Root causes of fare evasion and fraud problem are listed under three main categories as a result of meetings with transportation experts as shown in Figure 1. Implementation of an automated fare system and usage of smart cards by passengers are expected to solve most of the mentioned causes and eventually assist in the solution of fraud problems.



Figure 1. Fraud vulnerability root and cause analysis.

Traditional fare payment applications require intensive labor, are relatively inflexible, insecure, and often cause travel delays [24]. Moreover, using smart cards enables interoperability and improves payment tracking, as smart cards being used for public transportation can easily be adjusted to various fare structures more effectively [2]. Using smart cards in public transportation also provides more discount opportunities when compared to traditional fare systems [25]. Contactless smart cards are faster than other conventional fare payment methods as they speed up payment transitions since they eliminate all cash exchange related activities [26]. It may take about up to 3 min per passenger for a single payment transaction to be completed using the traditional paper-based ticketing system. This transaction includes exchange of cash for a paper ticket from a passenger to a conductor and the exchange of a paper ticket for cash from a conductor to a passenger. The transaction time may be increased in case cash change is needed. The introduction of the new smart card system allows a payment transaction when boarding the transport vehicle to be completed in about 30 seconds or less. The need for cash and paper tickets, for boarding payment transaction to be completed, is completely eliminated using the smart cards. Recent studies show that ease of fare payment is an important part of the travel experience for passengers. Integrating an automated fare system can enhance the travel experience and increase the willingness of passengers to use public transportation services by encouraging their use [20,27,28]. Ease of fare payment when boarding public transport also encourages passengers to use transfer options where available, because of reduced risk of missing the transport caused by delays during cash payment process [11]. Usage rate of transfer options by passengers is also increased by time saving opportunities provided by smart card fare payment systems in crowded stations since these systems eliminate repeating payment procedures during re-boarding [29].

Demographic features of the countries and prices set for tickets are other issues that affect the observed performance of smart card systems. Studies show that prices set too high negatively affect the usage preference for public transportation systems [30]. Transition to a smart card system from a conventional fare system eliminates the operational costs of printing single use paper tickets and magnetic band cards which require frequent replacements. Similar to paper tickets, conductors are also eliminated from the system and replaced by card readers in automated fare systems. Smart cards and readers are one-time purchases unlike monthly purchases of paper tickets and monthly payments of staff. On the other hand, card readers require low annual maintenance costs and software updates while smart cards do not require any maintenance costs. Smart cards may be easily replaced for a discounted price when lost and may be exchanged and replaced in most cases free of charge once they wear out. In addition to cost and price related issues, social demographic variables such as age, educational background, employment, profession, and vehicle ownership were also found to be determinants of the adoption success of different fare systems by various studies [31–33]. Therefore, inspection of these variables is important in the selection of the best system and its components for a city where it will be implemented. A city with a higher age average may not benefit from the promised advantages of smart fare systems as expected, considering technological unfamiliarity of residents. A combined qualitative study using focus groups and quantitative study through survey sampling uncovered that commuters with lower vehicle ownership, lower incomes, and lower licensure rates rely mostly on public transportation rather than informal private means of transportation [34]. Smart mobility technologies such as the travel smart card can therefore make it cheaper and more convenient for commuters in developing areas to use public transport. Additionally, a quantitative research study through survey sampling revealed that the mode of fare payment is a critical part of a commuter's travel experience [20]. Most features introduced by smart card systems are towards increasing the passengers' experience, but these systems also come with data privacy concerns for some people. Moreover, the total number of transport modes covered by the installation of the system is important to get all the benefits that these systems promise.

The number of different features and changes introduced by the smart cards into conventional fare systems, makes decision making a challenging job, given the conflicting advantages that come

with different types of systems. MCDM methods can overcome this problem, but a set of evaluation criteria must be determined to make consistent evaluations.

2.2. Determination of Evaluation Criteria for MCDM Analysis

Smart card system does not only include the cards. It includes other public transportation infrastructural elements that are factored in the determination of key performance indicators. There are a number of studies on performance metrics of the smart card system and the overall public transit services in the literature. From the late 1970s and the early 1980s, these performance indicators have been classified into two categories: effectiveness performance indicators and efficiency performance indicators [35,36]. The difference between effectiveness performance indicators and efficiency performance indicators is that effectiveness indicators measure whether an objective is achieved or not, therefore, showing the level of a desired outcome. On the other hand, efficiency indicators determine economically how much a resource has been utilized and are, therefore, input and output ratios [37]. Another study categorized bus transit system performance indicators into system effectiveness indicators and system efficiency indicators, where system effectiveness indicators determine whether a goal set by transit operators has been attained while system efficiency indicators determine the relationship between the input and output of a resource [38].

Six performance metrics suggested for the evaluation of transit systems including passenger loading, service frequency, transit vs. automobile travel time, service coverage, reliability, and hours of service in the Federal Transit Administration (FTA) sponsored Transit Capacity and Quality of Service Manual were prepared for the Transit Cooperative Research Program (TCRP) in United States [39]. The mentioned manual proposes mobility measures related to transit including percentage travel time contour, on-time performance, dwell time inter-modal facilities, average transfer time/delay, in-vehicle travel time, and service frequency. In addition to the foretold measures, some transit performance metrics preferred in different studies includes travel time reliability, safety, transfer time, delay, on-time performance, comfort, hours of service, security, frequency, passenger environment, convenience, and service coverage [40]. Another model [15] includes six criteria that describe the most vital characteristics of a fare collection system in public transport, which suggests that a good fare collection system must be simple for its users, have reduced operation costs, have a multipurpose functionality system, be safe, be fast, and be uniform within the framework of an integrated transport system. Time spent on the whole payment process should be as short as possible and must be in an acceptable range for commuters; therefore, transaction time should be low, being a performance criterion in the operations category [41].

Dwell time is another performance metric, where transits are concerned, that can be found in the literature, and which is defined as the length of time that the door is open at a given stop (in seconds). Total time required to pick up or drop off passengers can be determined by evaluating commuter's boarding, alighting, and dwell times [42]. Other studies inspecting dwell time also defined acceleration and deceleration as performance indicators for busy transit routes [43–46]. From the performance evaluation of fare systems, dwell time can be thought as boarding time of passengers [11,47].

Another metric underlined in the literature is on-time performance, which is defined as the ability of transport services to be on time at the destination [48]. It is an important measure for the overall system performance as it measures the accuracy of the real-time information provided to the users. Commonly used performance measures such as distance traveled, speed, delays occurred, vehicle hours traveled, and total travel time are all determinants of on-time performance [49]. On-time performance is also described as the additional travel time that passengers would find acceptable. However, transit service operators generally use on-time performance measures to assess schedule adherence [50]. Generally, bus waiting time at a stop, frequency of bus services, on-time performance, and ridership are performance measures affecting travel time reliability [51], which makes the performance evaluation of transportation systems a complex task.

Ridership represents the number of passengers presented on board in a particular transportation system. Ridership measures the service experienced by passengers [52,53]. It is therefore an important performance indicator for the smart card implementation projects covering an entire public transportation system. The ridership metric is also being suggested as a performance criterion for bus rapid transit system (BRT) evaluations [54]. Smart card integrated systems make it possible to analyze the most crowded times and by doing so help users to plan alternative routes [29].

Service reliability performance indicator measures the probability that the system will meet certain performance standards. For identifying supervision strategies, it is suggested as an ideal performance indicator [55]. The service reliability measure could be considered under several dimensions including capacity reliability, travel time reliability, connectivity reliability, performance reliability, encounter reliability, flow decrement reliability, and choice of mode reliability [56].

As a performance indicator of transit services, service coverage, service delivery, service efficiency and effectiveness, service-level solvency, service maintenance, and capital investment are also suggested as metrics in the literature [57]. Among these, service coverage performance measure is defined as the proportion of people who benefit from the services offered. Coverage is dependent on the demographic conditions and type of the system implemented, so evaluating this metric would also give insights about the related factors.

Safety performance indicator measures perception of people about the variant of payment system considering the data and personal information protection/privacy aspects [15]; hence, it is suggested as an important evaluation criterion [38,58]. On the other hand, security performance measure evaluates the level of security systems implemented with the system, which is considered as a performance criterion in the customer satisfaction category [59].

Most of public transport users travel in a chain using more than one transit mode or route (transfer passengers); this means delay on one route or transit results in missing the next connection(s). Transfer time and delay are therefore an important performance measure of the entire system [60]. Similarly, transit time reliability is defined based on the distribution of departure and arrival times and use of a performance measure [61,62]. The best way to monitor transit time reliability is to compare regularity of transit services [63], which is the primary mean of measuring quality of the service provided [64]. Transit reliability can be grouped into two different parts: transit travel time reliability and passengers waiting time reliability [65]. Transit travel time reliability is found to be an influencer of efficiency and attractiveness of the selected service and as a result relates to customer satisfaction with on-time performance [66].

A list of determined performance evaluation criteria, their brief explanations, and codes are given in Table 1. Considering performance indicators' relevance with the fare payment system, some criteria have been excluded from the study. Remaining criteria are categorized according to their similarities and their relation to smart card systems.

| Code | Criterion | Definition | Reference |
|-----------------------|---------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| C_1 | Transaction time | Duration of time in seconds that the user interacts with the system. | Brakewood et al. [11], Zhou et al. [13], Olivková [15], Smart Card Alliance [41] |
| <i>C</i> ₂ | Dwell time | Length of time in seconds that the transit vehicle's door remains open at a given stop. | Berkow et al. [42], Chakroborty and Kikuchi [43], Tantiyanugulchai and Bertini [44], Nee and Hallenbeck [45], Hall and Vyas [46], Heuvel and Hoogenraad [47], Bertini and El-Geneidy [64] |
| <i>C</i> ₃ | On-time performance | Metric used to evaluate the ability of transport services to be on time on the destination stop. It is a measure to evaluate the existence and accuracy of the real-time information provided to the users. | Porru et al. [3], Arbex and Cunha [29], Kittelson and Associates, Inc. [39], Duddu et al. [40], Diab and El-Geneidy [48], Camus et al. [51] |

Table 1. Public transportation fare system evaluation criteria.

| Code | Criterion | Definition | Reference |
|-----------------------|-----------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <i>C</i> ₄ | Ridership | Number of passengers on board in a particular transportation system. It measures usability of the service. | Yap et al. [1], Brakewood et al. [11], Zhou et al. [13], Arbex and Cunha [29], Henderson et al. [52], Uniman et al. [53], Tuhin and Debapartion [54] |
| <i>C</i> ₅ | Service reliability | This performance indicator measures the probability that the system will meet certain performance standards. | Porru et al. [3], Blythe [22], Arbex and Cunha [29], Kittelson and Associates, Inc. [39], Levinson [55], Wakabayashi [56] |
| <i>C</i> ₆ | Service coverage | Defined as the proportion of people who benefit from the services offered. This metric is related with the number of modes on which the system is implemented. | Brakewood et al. [11], Kittelson and Associates, Inc. [39], Gallucci and Allen [57] |
| C ₇ | Safety | Measures perception of people about the various payment systems considering data and personal information protection and privacy aspects. | Porru et al. [3], Olivková [15], Fielding et al. [38] |
| <i>C</i> ₈ | Security | Evaluates the level of security systems implemented on infrastructure and how well these systems work. | Porru et al. [3], Kittelson and Associates, Inc. [39], Duddu et al. [40] |
| С9 | Transfer time/Delay | Average time in minutes spent by public transport users who travel in chain using more than one transit mode and/or route. | Brakewood et al. [11], Arbex and Cunha [29], Kittelson and Associates, Inc. [39], Duddu et al. [40], Heuvel and Hoogenraad [47], Bertini et al. [49], Rietveld et al. [60] |
| C ₁₀ | Transit time reliability | Reliability of transit time, and it is based on the distribution of departure and arrival times. | Porru et al. [3], Zhou et al. [13], Arbex and Cunha [29], Heuvel and Hoogenraad [47], Furth and Muller [61] Schil [62], Trompet et al. [63], Shuai et al. [65] |

Table 1. Cont.

3. Integrated SWARA-WASPAS Framework

3.1. Proposed MCDM Framework of the Study

MCDM methods have been developed by using iterative numerical techniques to help decision makers choose the best alternative among various alternatives under many criteria [67]. Evaluation criteria most of the time present trade-offs by trying to achieve conflicting goals at the same time. There are many applications of different MCDM methods in the literature studied under different fields [68]. The aim of this study is to distinguish and validate all the advantages of smart card systems stated in the literature by making reliable comparisons with the traditional fare system under conflicting criteria. Therefore, in addition to traditional system, three different smart card systems selected with different features as alternatives are compared through MCDM analysis. To make a fair comparison, technical specifications of contactless smart cards selected as alternatives have common standards. Passengers are able to purchase the contactless smart card at issuance locations and debit and recharge them at both issuance locations and other locations such as ticket vending machines and kiosks. When boarding public transport, the fare is debited from the smart card. Public transport operators have access to commuter information such as card number, time, date, validation status, and bus stop number of each boarding. The systems compared also include essential features such as; no expiry date cards, convenient recharge locations throughout the city, pay-as-you-go functionality, ability of card readers to show the remaining balance, collection of various data, and optional registration function to prevent misuse. To find a suitable solution to the mentioned problem, a group decision making focused procedure is used in the proposed integrated MCDM framework. Summary of the proposed MCDM framework of the study is given in Figure 2. Both SWARA and WASPAS methods are modified to integrate a proper group decision making procedure into the decision model. All group

decisions are merged by using geometric mean approach as an accepted technique in the related field of research literature.

SWARA and WASPAS methods are used with an integrated approach in this study. The reason behind this preference is the convenience provided by these methods during the collection phase of consistent expert opinions. Some MCDM methods like Analytic Hierarchy Process (AHP) require pairwise comparison matrices to be filled by each expert for each level of decision hierarchy. This procedure makes it harder to collect consistent data from the decision makers when the matrices involved in the decisions get larger in size, especially if the experts do not have any previous experience with MCDM methods. However, in the proposed framework, decisions by the experts are only made by ranking and scoring the decisions base [69]. Hybrid application of SWARA and WASPAS methods is suitable to be applied in many fields of research [70]. Being recent and popular methods, SWARA and WASPAS also combine negatively correlated conflicting criteria effectively and assist decision makers to easily carry out sensitivity analysis.

Criteria needed for the evaluations are gathered with the help of expert opinions and as a result of literature review. For this study five experts chosen among the transportation authorities assisted in the decision process as decision makers (DMs). These experts were chosen from different cities in Turkey to evaluate all aspects of different fare systems with their experience in the field and during previous application projects of these systems. Therefore, according to demographic differences of cities, previous experiences, and expectations of these experts, their evaluations were expected to differ from each other. This is not an unusual case for MCDM group applications, which even enriches and improves the quality of findings of these methods by capturing as many opposing opinions as possible. However, individual opinions of experts should be treated according to group decision making rules. For this aim, expert decisions have been merged by using geometric mean before using these decisions in SWARA and WASPAS methods. Within the scope of this study SWARA method has been used to determine criteria weights; then these weights were used in the WASPAS method to evaluate the ranking scores of alternatives.



Figure 2. Framework of proposed SWARA-WASPAS integrated MCDM methodology.

3.2. Application of SWARA Method for Calculating of Criteria Importances

SWARA method was first introduced in 2010 by Keršuliene et al. [71]. SWARA method enables decision makers to express their opinions freely, since they are not defined by fixed measures or scales [72]. Based on the evaluations of experts, this method resolves disputes and determines rational decisions by assessing weights. As a decision support system, this method can be used in any environment to solve the practical and scientific disputes among conflicting goals [73]. A summary of SWARA method's steps is given in Figure 3.



Figure 3. Flowchart of SWARA method [74].

The steps of the SWARA method have been modified to integrate group decision making approach by introducing geometric mean approach into the model. Proposed modified SWARA steps are as follows:

Step 1: Each decision maker prioritizes criteria according to their importance. The most important criterion is usually given 1.00 point, and other criteria are given multiples of 0.05 points according to the criterion's relative importance in a descending order. In a model with *l* decision makers and *n* criteria, priority assigned to criterion *j* by the decision maker *k* is denoted as p_i^k , where j = 1, 2, ..., k = 1, 2, ..., l.

Step 2: Individual evaluations of all decision makers are combined with geometric mean according to following equation, where $\overline{p_i}$ denotes the merged relative importance score for each criterion.

$$\overline{p}_j = \left(\prod_{k=1}^l p_j^k\right)^{\frac{1}{l}}, \ \forall j.$$
(1)

Step 3: All criteria are ranked in a descending order according to their relative importance scores first. Then, starting with the second criterion, the relative significance (comparative importance) of the criterion j with respect to the previous criterion (j - 1) is calculated, which is denoted as s_j . As a result of this ranking, the comparative importance values of geometric means are calculated by using Equation (2).

$$s_j = \overline{p}_{j-1} - \overline{p}_j, \quad j = 2, \dots n.$$

Step 4: Coefficients of each criteria are obtained by binary comparison and denoted as c_j . This coefficient indicates how important the criterion j + 1 is according to the criterion j. For all criteria, c_j values are calculated as follows:

$$c_{j} = \begin{cases} 1, & j = 1; \\ s_{j} + 1, & j = 2, \dots n. \end{cases}$$
(3)

Step 5: Corrected weights (s'_i) for all criteria are calculated with the following equation:

$$s'_{j} = \begin{cases} 1, & j = 1; \\ \frac{s'_{j-1}}{c_{j}}, & j = 2, \dots n. \end{cases}$$
(4)

Step 6: Final criteria weights (w_i) are calculated as follows:

$$w_j = \frac{s'_j}{\sum_{j=1}^n s'_j}, \ j = 1, 2, \dots n.$$
 (5)

Individual evaluations of five decision makers gathered according to rules stated in *Step 1* of SWARA method and merged relative importance scores calculated for each criterion by using Equation (1) are given in Table 2 below.

| Criteria | | Indiv of Deci | idual Evalusion Makers p_j^k | Merged Relative Importance Score \overline{p}_i | | |
|-----------------------|------|------------------|--------------------------------|------------------------------------------------------|------|----------|
| | DM1 | DM2 | DM3 | DM4 | DM5 | |
| <i>C</i> ₁ | 1.00 | 0.80 | 0.70 | 0.75 | 0.65 | 0.771316 |
| C_2 | 0.55 | 0.65 | 0.95 | 0.70 | 0.40 | 0.624643 |
| C_3 | 0.85 | 1.00 | 1.00 | 1.00 | 0.95 | 0.958139 |
| C_4 | 0.10 | 0.30 | 0.35 | 0.10 | 0.80 | 0.242580 |
| C_5 | 0.75 | 0.70 | 0.65 | 0.80 | 0.35 | 0.625239 |
| C_6 | 0.30 | 0.45 | 0.50 | 0.30 | 0.45 | 0.390776 |
| C_7 | 0.20 | 0.10 | 0.05 | 0.15 | 0.05 | 0.094409 |
| C_8 | 0.60 | 0.20 | 0.45 | 0.20 | 0.50 | 0.351948 |
| $\tilde{C_9}$ | 0.70 | 0.90 | 0.85 | 0.90 | 1.00 | 0.864172 |
| C ₁₀ | 0.25 | 0.40 | 0.15 | 0.05 | 0.15 | 0.162267 |

Table 2. Evaluations of decision makers for criteria and merged relative importance scores.

Following the completion of the acquirement of decision makers' opinions and merging them by using geometric mean, criteria are sorted in descending order according to merged relative importance scores; then, for each criterion, comparative importance, constraint, corrected weight, and final weight values are calculated by using Equations (2)–(5), respectively, as shown in Table 3.

Table 3. Calculation of final criteria weights with the SWARA method.

| Criteria | Merged Relative Importance Score (Ordered) \overline{p}_i | Comparative Importance si | Coefficient Value _{Ci} | Corrected Weight Value s'_{i} | Final Weight Value <i>w</i> ; |
|----------------|-------------------------------------------------------------------|---------------------------------|---------------------------------------|---------------------------------------|-------------------------------------|
| | ,, | J | 1 000000 |) | , |
| C_3 | 0.958139 | | 1.000000 | 1.000000 | 0.1470 |
| C_9 | 0.864172 | 0.093967 | 1.093967 | 0.914105 | 0.1344 |
| C_1 | 0.771316 | 0.092856 | 1.092856 | 0.836437 | 0.1230 |
| C_5 | 0.625239 | 0.146077 | 1.146077 | 0.729826 | 0.1073 |
| C_2 | 0.624643 | 0.000597 | 1.000597 | 0.729390 | 0.1072 |
| C_6 | 0.390776 | 0.233867 | 1.233867 | 0.591142 | 0.0869 |
| C_8 | 0.351948 | 0.038827 | 1.038827 | 0.569047 | 0.0837 |
| C_4 | 0.242580 | 0.109368 | 1.109368 | 0.512947 | 0.0754 |
| C_{10} | 0.162267 | 0.080313 | 1.080313 | 0.474814 | 0.0698 |
| C ₇ | 0.094409 | 0.067858 | 1.067858 | 0.444641 | 0.0654 |

SWARA method ranked the criteria according to their importance for the evaluation of public transportation fare systems. Next step of the proposed framework is to use WASPAS method to make a comparison between smart card systems and traditional fare system by using the calculated criteria weights.

3.3. Evaluation of Fare Systems with WASPAS Method

WASPAS method was developed in 2012 by Zavadkas et al. [75], and this method is used to rank alternatives in this study instead of SWARA method. To increase the robustness of multiple criteria optimization models, use of two or more methods is suggested [76]. Moreover, SWARA method requires a series of modifications to be used for the comparison of different alternatives under both beneficial and nonbeneficial criteria. Furthermore, an aggregation method should be introduced into the original method to combine separate evaluation scores of alternatives under each criterion. For these reasons while SWARA method is being used for the determination of criteria weights, several other MCDM approaches were used to rank alternatives in the literature [70]. Being one of the most recent and popular MCDM methods, WASPAS increases the accuracy of ranking by aggregating Weighted Sum Model (WSM) and Weighted Product Model (WPM) methods [77] and proves to be integrated effectively with the SWARA method to provide efficient results [70]. During this process, optimization of the weighted aggregated function is utilized. By doing so, WASPAS method also gives an opportunity to acquire different alternative rankings with the evaluation of sensitivity analysis it provides, which is the main reason it was preferred over SWARA method for the comparison of alternatives. Steps of WASPAS method are given below [75]. Similar to SWARA method, steps of the method are modified to integrate group decision making into the method.

Step 1: Initial individual decision matrices X_k formed by *n* criteria and *m* alternatives must be structured by using opinions of *l* decision makers in the following format:

$$X_{k} = \begin{bmatrix} x_{11}^{k} & x_{12}^{k} & \cdots & x_{1n}^{k} \\ x_{21}^{k} & x_{22}^{k} & \cdots & x_{2n}^{k} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1}^{k} & x_{m2}^{k} & \cdots & x_{mn}^{k} \end{bmatrix}, \quad k = 1, 2, \dots l.$$

Step 2: X_k matrices should be merged by using Equation (6) for each member of the matrix to form the initial group decision matrix \overline{X} .

$$\overline{x}_{ij} = \left(\prod_{k=1}^{l} x_{ij}^{k}\right)^{1/l}, \quad \forall i; \forall j.$$
(6)

Step 3: Normalization of \overline{X} is done by using Equation (7) for n' number of beneficial criteria and by using Equation (8) for n'' number of nonbeneficial criteria. Resulting matrix is normalized decision matrix (\widetilde{X}).

$$\widetilde{x}_{ij} = \frac{\overline{x}_{ij'}}{\max_{i} (\overline{x}_{ij'})}, \quad i = 1, \dots, m; j = 1, 2, \dots, n; j' = 1, 2, \dots, n'.$$
(7)

$$\widetilde{x}_{ij} = \frac{\min_{i} \left(\overline{x}_{ij''} \right)}{\overline{x}_{ij''}}, \ i = 1, \dots, m; j = 1, 2, \dots, n; j'' = 1, 2, \dots, n''.$$
(8)

Step 4: Total relative importance values calculated with WSM method ($Q_i^{(1)}$) by using the final criteria weights (w_i) are calculated with SWARA method in this study, and by using the following equation:

$$Q_i^{(1)} = \sum_{j=1}^n \widetilde{x}_{ij} . w_j, \quad \forall i.$$
(9)

Step 5: Total relative importance values calculated with WPM method ($Q_i^{(2)}$) by using the final criteria weights (w_i) are calculated with SWARA method in this study, and by using the following equation:

$$Q_i^{(2)} = \prod_{j=1}^n \bar{x}_{ij}^{w_j}, \ \forall i.$$
 (10)

Step 6: Weighted aggregation of additive and multiplicative methods are calculated with Equation (11). Final scores of alternatives calculated with WASPAS method are denoted as Q_i . λ value is used to shift weight towards either method to conduct sensitivity analysis and increase the accuracy of the final decision. $\lambda = 0$ means final weights are calculated with WPM method, and $\lambda = 1$ means final weights are calculated with WSM method.

$$Q_i = \lambda Q_i^{(1)} + (1 - \lambda)Q_i^{(2)} = \lambda \sum_{j=1}^n \widetilde{x}_{ij} \cdot w_j + (1 - \lambda) \prod_{j=1}^n \widetilde{x}_{ij}^{w_j}, \quad \forall i; \ \lambda = 0, \dots 1.$$
(11)

Individual evaluation matrices of alternatives for each criterion filled by each expert are given in Appendix A. All criteria are evaluated by the experts according to their expectations of the given alternative systems' application in the city in which the experts were based their evaluations. For the time unit-based criteria (C_1 , C_2 , and C_9), values given in Appendix A are the forecasts of experts based on the social demographic structure (such as average age of residents and potential users' familiarity with technology) of the cities they live in and their previous experiences. These matrices are combined to form a group initial decision matrix as seen in Table 4. Four alternatives are selected for comparison purposes, where A_1 is the traditional ticket based fare system and the rest of the alternatives are all automated fare systems using smart cards. The difference is A_2 is only using smart card for payment; the system used in A_4 additionally integrates city wide real-time information infrastructure and supports magnetic stickers to be used instead of cards if preferred by users. Finally, A_3 system supports payment options through smart phone applications and NFC feature in addition to all features comes with A_4 .

Table 4. Initial group decision matrix.

| Criteria | C_1 | <i>C</i> ₂ | <i>C</i> ₃ | C_4 | C_5 | <i>C</i> ₆ | <i>C</i> ₇ | <i>C</i> ₈ | <i>C</i> 9 | <i>C</i> ₁₀ |
|------------------------|----------|-----------------------|-----------------------|--------|--------|-----------------------|-----------------------|-----------------------|------------|------------------------|
| Alternative | | | | | | | | | | |
| Traditional (A_1) | 142.2864 | 209.9825 | 3.7279 | 4.9190 | 3.7764 | 6.7875 | 6.7875 | 5.4262 | 15.7201 | 2.1689 |
| Smart card 1 (A_2) | 84.7570 | 120.7408 | 4.9190 | 5.3345 | 4.9593 | 5.9663 | 6.1879 | 5.5780 | 12.4521 | 3.9487 |
| Smart card 2 (A_3) | 24.0822 | 87.2716 | 6.5814 | 6.1531 | 5.5016 | 3.7279 | 2.7663 | 2.9302 | 9.2358 | 6.3458 |
| Smart card 3 (A_4) | 36.5019 | 106.6907 | 6.1531 | 6.1531 | 5.1435 | 4.5731 | 5.9663 | 5.5780 | 11.4219 | 6.3458 |
| type | min | min | max | max | max | max | max | max | min | max |
| value | 24.0822 | 87.2716 | 6.5814 | 6.1531 | 5.5016 | 6.7875 | 6.7875 | 5.5780 | 9.2358 | 6.3458 |

As it can be seen from the types of criteria, optimization of the objective includes both maximization and minimization goals. Among the evaluation criteria, C_1 , C_2 , and C_9 are non-beneficial criteria (denoted as *min*) and given in units of seconds for C_1 and C_2 . Unit measure of minutes is used for C_9 by the experts in the definition and evaluation of the criteria. Rest of the criteria are beneficial ones (denoted as *max*) and evaluated on a seven-point scale (being as: 1: very bad, 2: bad, 3: fairly bad, 4: no improvement/effect, 5: fairly good, 6: good, 7: very good) by the decision makers. Proportional criterion C_6 is also evaluated with the same scale to compare different fare systems. DMs preferred to use this scale instead of giving an expected proportion, since service coverage is a dynamic variable that would change over time under the effect of many other external factors. Corresponding optimal objective values for each criterion are given at the last row of Table 4. Normalization of initial group decision matrix is done by using Equation (7) for beneficial criteria and Equation (8) for non-beneficial criteria according to extreme values for each criterion. Calculated normalized decision matrix \tilde{X} is represented as a table and given in Table 5.

| Criteria | <i>C</i> ₁ | <i>C</i> ₂ | <i>C</i> ₃ | C_4 | <i>C</i> ₅ | <i>C</i> ₆ | <i>C</i> ₇ | <i>C</i> ₈ | C9 | C ₁₀ |
|-------------------------------|-----------------------|-----------------------|-----------------------|--------|-----------------------|-----------------------|-----------------------|-----------------------|--------|-----------------|
| Alternative | | | | | | | | | | |
| Traditional (A ₁) | 0.1693 | 0.4156 | 0.5664 | 0.7994 | 0.6864 | 1.0000 | 1.0000 | 0.9728 | 0.5875 | 0.3418 |
| Smart card 1 (A_2) | 0.2841 | 0.7228 | 0.7474 | 0.8670 | 0.9014 | 0.8790 | 0.9117 | 1.0000 | 0.7417 | 0.6223 |
| Smart card 2 (A_3) | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 0.5492 | 0.4076 | 0.5253 | 1.0000 | 1.0000 |
| Smart card 3 (A_4) | 0.6598 | 0.8180 | 0.9349 | 1.0000 | 0.9349 | 0.6737 | 0.8790 | 1.0000 | 0.8086 | 1.0000 |

Table 5. Normalized decision matrix.

By the normalization of decision matrix, comparable values are acquired. Next step of WASPAS method is to calculate alternative weights with WSM and WPM methods with the use of Equations (9) and (10), respectively. Final weights found and given in Table 3 in SWARA analysis are used during the calculation of the relative importance value of each alternative.

Total relative importance values calculated with WSM and WPM methods are presented in Tables 6 and 7, respectively. Results given in Table 6 are relative importance scores for $\lambda = 1$; likewise, results in Table 7 are relative importance scores calculated with $\lambda = 0$. These calculations will directly be used later in the final step of WASPAS method to calculate weighted aggregation of additive and multiplicative methods.

Table 6. Total relative importance values of alternatives by WSM method.

| Criteria | <i>C</i> ₁ | <i>C</i> ₂ | <i>C</i> ₃ | <i>C</i> ₄ | <i>C</i> ₅ | <i>C</i> ₆ | <i>C</i> ₇ | <i>C</i> ₈ | C9 | <i>C</i> ₁₀ | |
|------------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|--------|------------------------|---------------|
| Alternative | | | | | | | | | | | $Q_{i}^{(1)}$ |
| Traditional (A_1) | 0.0208 | 0.0446 | 0.0833 | 0.0603 | 0.0736 | 0.0869 | 0.0654 | 0.0814 | 0.0790 | 0.0239 | 0.6190 |
| Smart card 1 (A_2) | 0.0349 | 0.0775 | 0.1099 | 0.0654 | 0.0967 | 0.0764 | 0.0596 | 0.0837 | 0.0997 | 0.0434 | 0.7471 |
| Smart card 2 (A_3) | 0.1230 | 0.1072 | 0.1470 | 0.0754 | 0.1073 | 0.0477 | 0.0266 | 0.0439 | 0.1344 | 0.0698 | 0.8824 |
| Smart card 3 (A_4) | 0.0811 | 0.0877 | 0.1374 | 0.0754 | 0.1003 | 0.0586 | 0.0575 | 0.0837 | 0.1087 | 0.0698 | 0.8601 |

Table 7. Total relative importance values of alternatives by WPM method.

| Criteria | C_1 | <i>C</i> ₂ | <i>C</i> ₃ | C_4 | C_5 | <i>C</i> ₆ | <i>C</i> ₇ | <i>C</i> ₈ | <i>C</i> 9 | C ₁₀ | |
|------------------------|--------|-----------------------|-----------------------|--------|--------|-----------------------|-----------------------|-----------------------|------------|-----------------|---------------|
| Alternative | | | | | | | | | | | $Q_{i}^{(2)}$ |
| Traditional (A_1) | 0.8038 | 0.9102 | 0.9198 | 0.9833 | 0.9604 | 1.0000 | 1.0000 | 0.9977 | 0.9310 | 0.9278 | 0.5477 |
| Smart card 1 (A_2) | 0.8566 | 0.9658 | 0.9581 | 0.9893 | 0.9889 | 0.9889 | 0.9940 | 1.0000 | 0.9606 | 0.9674 | 0.7084 |
| Smart card 2 (A_3) | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 0.9493 | 0.9430 | 0.9476 | 1.0000 | 1.0000 | 0.8482 |
| Smart card 3 (A_4) | 0.9501 | 0.9787 | 0.9902 | 1.0000 | 0.9928 | 0.9663 | 0.9916 | 1.0000 | 0.9719 | 1.0000 | 0.8512 |

By the inspection of relative importance values found by the application of both methods, it can be said that all smart card systems proved to achieve better performance than the traditional fare system. However, there are differences in the ranks of smart card systems. It would be appropriate to use Equation (11) to aggregate the results of both methods to conduct further sensitivity analysis to draw more efficient conclusions regarding the selection of the best system.

4. Results and Discussion

4.1. Comparison of Evaluation Criteria

The integrated MCDM model framework proposed in the study utilizes SWARA method for determining evaluation criteria weights to compare smart card based automated fare systems with traditional fare systems. Resulting final criteria weights (w_j) of the SWARA model, which were previously given in Table 3, are sorted in descending order according to importance of criteria in Figure 4.



Figure 4. Ranks and weights of smart card system evaluation criteria.

Inspection of the results reveals that criteria are grouped in three segments according to their weights. The most important ones are C_3 , C_9 and C_1 followed by C_5 and C_2 . Among these criteria, the one with the most effect on the evaluation of fare systems is the on-time performance, which seems reasonable since this criterion includes the accuracy of real-time data provided by the systems, which is one of the most prominent features of smart card systems. Effects of transfer time are positively affected by the automated systems by their potential to encourage passengers to transfer between different transit modes since loss of time and risk of delays are minimized when compared with the traditional transportation fare systems. Transaction times are one of the most important criteria during the evaluations; hence, they are one of the determinants of delays occurring during the payment and fare processes.

Service reliability and dwell time are placed in the second important criteria group. They are indirectly affected performance indicators of the implementation of smart card systems, and improvement in the transaction process also affects these two metrics. Among the remaining criteria, safety criteria turned out to be the least important one. This can be interpreted as the opinion of passengers eventually adapting to the new system and their concerns regarding safety issues disappearing over time as long as necessary security precautions are taken. Among this group of criteria, service coverage is the leading one since improvements in transfer opportunities rely on the coverage value of the system. Ridership and transit time reliability are evaluated by the experts among the least important criteria group when their effects on the overall system are considered. The reason for this is interpreted by the experts as these criteria being mainly affected by other factors such as traffic congestions or availability of alternative transit options such as personal vehicles. However, they also contribute to evaluation of different fare systems; hence, each system has different effects on these criteria.

4.2. Ranking of Alternatives with Weighted Aggregation

After the confirmation of findings by experts, evaluation of alternatives is made with the WASPAS method. Results of both WSM and WPM methods show that the traditional fare system (A_1) is the worst alternative among the compared ones considering performance indicators for public transportation systems as seen on Tables 6 and 7, respectively. Considering selection of the best smart card system, WSM and WPM methods provide opposing results. To finalize the study, weighted aggregation of additive and multiplicative methods are calculated by using different λ values with Equation (11), and resulting alternative scores and their ranks are given in Table 8.

| Alternative | lternative Traditional Fare System (A ₁) | | Smart Card (Ag | l System 1 2) | Smart Card (Ag | System 2 3) | Smart Card System 3 (A ₄) | |
|-------------|------------------------------------------------------|------|-------------------|------------------|-------------------|----------------|------------------------------------------|------|
| λ | Q_i | Rank | Q_i | Rank | Q_i | Rank | Q_i | Rank |
| 0 (WPM) | 0.547663 | 4 | 0.708397 | 3 | 0.848234 | 2 | 0.851215 | 1 |
| 0.1 | 0.554799 | 4 | 0.712272 | 3 | 0.851649 | 2 | 0.852105 | 1 |
| 0.2 | 0.561936 | 4 | 0.716147 | 3 | 0.855065 | 1 | 0.852995 | 2 |
| 0.3 | 0.569073 | 4 | 0.720022 | 3 | 0.858481 | 1 | 0.853885 | 2 |
| 0.4 | 0.576210 | 4 | 0.723897 | 3 | 0.861897 | 1 | 0.854775 | 2 |
| 0.5 | 0.583346 | 4 | 0.727773 | 3 | 0.865313 | 1 | 0.855665 | 2 |
| 0.6 | 0.590483 | 4 | 0.731648 | 3 | 0.868729 | 1 | 0.856555 | 2 |
| 0.7 | 0.597620 | 4 | 0.735523 | 3 | 0.872144 | 1 | 0.857445 | 2 |
| 0.8 | 0.604756 | 4 | 0.739398 | 3 | 0.875560 | 1 | 0.858335 | 2 |
| 0.9 | 0.611893 | 4 | 0.743273 | 3 | 0.878976 | 1 | 0.859225 | 2 |
| 1 (WSM) | 0.619030 | 4 | 0.747148 | 3 | 0.882392 | 1 | 0.860115 | 2 |

Table 8. Weighted aggregation results of WASPAS method.

According to results provided by both methods, a basic smart card system that does not provide any real-time data and does not have any additional features or system wide integration ranked second place in the evaluations. This smart card system (A_2) mainly provides transactional improvements over traditional fare systems; therefore it placed between the system wide applied systems and traditional systems. Inspection of aggregated scores calculated with WASPAS method reveals that the best alternative is the smart card system 2, which includes all features like mobile payment options and full integration to transportation information systems' infrastructure. Only for λ values of 0 and 0.1 system 3 acquired the highest scores. This difference can be explained by the higher scores assigned to system 3 for security, safety, and service coverage performance indicators when compared with system 2. Even though it is considered as the most recent technology and it is optional, mobile integration caused some data privacy concerns. In addition to security issues, higher cost of system 2 may limit the coverage of this system, which may be a trade-off between these two systems under some circumstances.

Most studies suggest λ value of 0.5 as a suitable aggregation factor for various evaluation purposes. Nevertheless, if the rankings tend to change for different λ values, it is suggested to conduct standard deviation calculations for the determination of the optimal λ value to decide on the final ranking and scores. However, ranks found with WASPAS analysis are consistent on a wide range of λ values in this study, so that no further sensitivity analysis is required. Finally, to decide on the final scores of alternatives, the following Figure 5 is presented to show the difference in scores more clearly.

Final aggregated scores calculated with different λ values are close to each other for all alternatives. There is an increasing trend for traditional system towards WSM method, where other alternatives' scores are distributed more evenly. Aforementioned reasons also caused a minor increasing trend similar to traditional systems for the smart card 1 system, since this one is only replacing the ticketing procedure. Average standard deviation (σ) is 0.010 for the scores over the λ range between 0 and 1, where minimum value of σ is 0.0088 for $\lambda = 0.5$, which will be used for an accurate final-scores comparison. In fact, optimal λ values are also calculated to be around 0.46 for alternatives. Therefore, the highest score was determined as 0.8653 for smart card system 2. Smart card systems 3, 1, and traditional fare system have scores of 0.8557, 0.7278, and 0.5833, respectively. Independent of

their features, all smart card systems proved to be effective on the performance improvements in public transportation systems. The magnitude of the improvements' effect increases gradually with the additional features added into public transportation infrastructure by the selected smart card system.



Figure 5. Final scores of alternatives.

4.3. Discussion of the Findings

Most studies in the literature are focused on the evaluation of smart fare systems' specific aspects in a specific type of public transportation system. Studies focusing on the comparison of traditional systems and smart card systems by considering all type of transports are rare in the literature. In general, results of this study comply with the literature for the overall performance advantage of the smart card systems over traditional fare systems [13,15,18,19,21,23,78,79]. To make a more detailed disputation, each alternative can be evaluated according to their rankings under each criterion given in Tables 6 and 7. A study by Olivková [15] is based on traditional systems in which paper tickets are purchased out of the vehicle before boarding. results indicate much less difference between rankings of the smart and traditional systems on time based criteria, since purchasing operation doesn't cause any notable difference in the boarding. However, in cities where evasion/fraud rates are high, manual control of authenticity of tickets is required. Furthermore, in case of in-vehicle-purchase of tickets, as the case in this study, difference between traditional and smart systems increases, because of the time lost during purchasing and verification operations, which results in increased rate of delays [21].

From the safety aspect, traditional systems acquired higher scores when compared with smart systems confirming the findings of similar studies [15]. However, there is still concerns about the security of smart systems as more features introduced into them [17,58], but that seems to have a very slight effect in decisions made in Turkey as long as mobile payment systems are involved. Brakewood, et al. [11] states several issues with mobile payment technology such as reception issues, app problems and low battery levels, but these are rare issues and doesn't affect the overall performance of the system which was found very desirable as the smart card system 2 in this study.

Service coverage was found to be affected by the population of the country, given the required investment cost to cover wider transport options, when compared with a similar study made in a less populated country that presents less difference between the paper ticket and smart systems for this criterion [15]. In a study conducted in Brazil [78], where there is a similar municipal structure, smart fare systems were found to be more important than a flat fare system in supporting the use of transit system, which supports the findings of this study towards the increased support for the

usage of transit services [29]. However, according to our findings there is no considerable difference between the fare systems according to ridership criterion, as opposed to findings of a study conducted in Australia [79]. The main reason of this difference seems to be the wider usage of trains in Australia because of the distances when compared to Turkey, and the lower average income rates in Turkey that states the usage of public transportation is not so much based on individual preferences.

5. Conclusions

Public transportation throughout the world affects the lives of large number of people every day. As a result of technological developments, many integrated smart systems are introduced for the transportation sector as they are introduced in almost every field in daily life. Smart card based automated fare systems replaced traditional paper ticket or magnetic card based fare systems in many developed countries. Transportation authorities of most developing countries are still in the decision phase in this transition. Despite the advantages, such as contactless fast payment and real time information provided by smart systems, the decision to transition requires the evaluation of many aspects of all existing systems including the current one under different criteria. Most of these criteria are conflicting especially when used to compare traditional systems with smart card systems, which requires the achievement of various objectives at the same time. This creates a tradeoff between some criteria such as adapting a real time data providing system improves service quality, but also brings concerns about the privacy of personal information at the same time. The MCDM framework introduced in this study proved to overcome this kind of conflicts effectively during the evaluation of fare systems in public transportation.

5.1. Implications of the Study

Changing the fare infrastructure in a public transportation system has citywide, even countrywide effects depending on the project's size. This transition decision requires analysis of different and conflicting criteria both in deciding on the necessity for change and in the decision-making procedure during the selection phase of the best smart card system. Due to multiple objectives contained in the problem, an accurate solution requires the utilization of MCDM methods. This study aims to bridge the gap in the literature by proposing a MCDM framework for the evaluation of different fare systems for public transportation. Moreover, the proposed framework integrates SWARA and WASPAS, which are two recent MCDM methods, and uses them with a hybrid approach for the evaluation of smart card systems. These methods are also slightly modified to utilize group decision making methodology by the aggregation of opinions of different decision-makers with geometric mean calculations.

Findings of the study indicate that smart card based fare systems improve the overall system performance considerably. Data privacy and coverage of installation seem to be the most concerning issues related to smart card systems. However, reduced transaction times, increased use of transfer alternatives with the assistance of provided real time information, increased on-time performance as a result of reduced delays by the elimination of nonvalue-added processes are found as the main performance contributions of these systems. Trade-off between the automated and traditional systems, mainly influenced by the budget of the project. A limited installation plan, that does not include real time information system adaptation and neglecting widely available transfer opportunities will reduce the scores of smart card systems and make their performance indistinguishable from the traditional systems. Selection among different smart card infrastructure types depends on the features of the systems. Inspection of demographic data is important while considering more advanced systems to fully benefit from all the features of the system.

5.2. Limitations and Future Work

Criteria hierarchy proposed in this study can be divided into sublayers to make further sensitivity analysis. In addition to the change in the hierarchy, a comparative study between developed countries

and developing countries will help to make more detailed inferences. Another issue that is thought to be useful is to introduce combination of alternatives according to transportation options in which the smart system is integrated or not.

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Appendix A

Table A1. Initial decision matrix filled by DM1 for WASPAS analysis.

| Criteria | <i>C</i> ₁ | <i>C</i> ₂ | <i>C</i> ₃ | C_4 | <i>C</i> ₅ | <i>C</i> ₆ | C_7 | <i>C</i> ₈ | C9 | <i>C</i> ₁₀ |
|------------------------|-----------------------|-----------------------|-----------------------|-------|-----------------------|-----------------------|-------|-----------------------|----|------------------------|
| Alternative | | | | | | | | | | |
| Traditional (A_1) | 120 | 150 | 4 | 4 | 4 | 7 | 7 | 4 | 16 | 2 |
| Smart card 1 (A_2) | 45 | 60 | 5 | 5 | 5 | 6 | 6 | 5 | 14 | 4 |
| Smart card 2 (A_3) | 20 | 50 | 6 | 6 | 6 | 4 | 3 | 3 | 8 | 6 |
| Smart card 3 (A_4) | 30 | 60 | 6 | 6 | 6 | 5 | 6 | 5 | 10 | 6 |

Table A2. Initial decision matrix filled by DM2 for WASPAS analysis.

| Criteria | C_1 | <i>C</i> ₂ | <i>C</i> ₃ | C_4 | C_5 | C_6 | C_7 | C_8 | C9 | <i>C</i> ₁₀ |
|------------------------|-------|-----------------------|-----------------------|-------|-------|-------|-------|-------|----|------------------------|
| Alternative | | | | | | | | | | |
| Traditional (A_1) | 180 | 300 | 4 | 4 | 4 | 7 | 7 | 4 | 20 | 1 |
| Smart card 1 (A_2) | 120 | 180 | 6 | 4 | 5 | 5 | 7 | 6 | 11 | 4 |
| Smart card 2 (A_3) | 30 | 100 | 7 | 5 | 6 | 5 | 3 | 4 | 10 | 5 |
| Smart card 3 (A_4) | 40 | 120 | 7 | 5 | 5 | 5 | 7 | 6 | 10 | 5 |

Table A3. Initial decision matrix filled by DM3 for WASPAS analysis.

| Critoria | C | C | C | C | C | C | C | C | C | |
|------------------------|-------|----------------|----|-------|-------|----------------|-------|----|----|-----------------|
| Criteria | c_1 | C ₂ | C3 | c_4 | c_5 | C ₆ | c_7 | C8 | C9 | C ₁₀ |
| Alternative | | | | | | | | | | |
| Traditional (A_1) | 100 | 180 | 5 | 6 | 6 | 6 | 6 | 6 | 10 | 3 |
| Smart card 1 (A_2) | 60 | 110 | 6 | 6 | 5 | 6 | 6 | 5 | 9 | 5 |
| Smart card 2 (A_3) | 30 | 75 | 7 | 7 | 4 | 3 | 2 | 3 | 7 | 7 |
| Smart card 3 (A_4) | 30 | 120 | 7 | 7 | 5 | 4 | 5 | 5 | 9 | 7 |

| Table A4. | Initial | decision | matrix | filled b | y DM4 | for | WASPA | S analys | sis. |
|-----------|---------|----------|--------|----------|-------|-----|-------|----------|------|
| | | | | | | | | | |

| Criteria | C_1 | <i>C</i> ₂ | <i>C</i> ₃ | C_4 | C_5 | <i>C</i> ₆ | <i>C</i> ₇ | <i>C</i> ₈ | <i>C</i> 9 | <i>C</i> ₁₀ |
|------------------------|-------|-----------------------|-----------------------|-------|-------|-----------------------|-----------------------|-----------------------|------------|------------------------|
| Alternative | | | | | | | | | | |
| Traditional (A_1) | 150 | 240 | 3 | 6 | 2 | 7 | 7 | 7 | 15 | 2 |
| Smart card 1 (A_2) | 90 | 120 | 4 | 6 | 6 | 6 | 6 | 6 | 12 | 3 |
| Smart card 2 (A_3) | 15 | 90 | 7 | 7 | 7 | 4 | 3 | 2 | 8 | 7 |
| Smart card 3 (A_4) | 30 | 100 | 6 | 7 | 6 | 4 | 6 | 6 | 12 | 7 |

Table A5. Initial decision matrix filled by DM5 for WASPAS analysis.

| Criteria | C_1 | <i>C</i> ₂ | <i>C</i> ₃ | C_4 | C_5 | <i>C</i> ₆ | <i>C</i> ₇ | <i>C</i> ₈ | C9 | <i>C</i> ₁₀ |
|------------------------|-------|-----------------------|-----------------------|-------|-------|-----------------------|-----------------------|-----------------------|----|------------------------|
| Alternative | | | | | | | | | | |
| Traditional (A_1) | 180 | 210 | 3 | 5 | 4 | 7 | 7 | 7 | 20 | 4 |
| Smart card 1 (A_2) | 150 | 180 | 4 | 6 | 4 | 7 | 6 | 6 | 18 | 4 |
| Smart card 2 (A_3) | 30 | 150 | 6 | 6 | 5 | 3 | 3 | 3 | 15 | 7 |
| Smart card 3 (A_4) | 60 | 160 | 5 | 6 | 4 | 5 | 6 | 6 | 18 | 7 |

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