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Prioritizing Smart City Technologies Using ELECTRE Multi-Criteria Decision Analysis

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Abstract. The objective of this study is to investigate the utilization of the ELECTRE decision support system for the purpose of enhancing the process of technology selection within the framework of smart cities. The study was conducted with the primary aim of determining the most suitable technological solutions for smart cities, guided by pre-established criteria. In order to tackle the intricacies associated with assessing and ranking the wide array of technical options, the study approach of choice was the utilization of the ELECTRE methodology. The findings of the study indicated that, when considering several technology possibilities, Alternative D consistently shown greater performance compared to other alternatives. This suggests that Alternative D is highly suitable for implementation within the context of a smart city. The aforementioned result highlights the potential advantages of implementing this technology in promoting the progress of intelligent urban areas and augmenting their operational capabilities. However, it is crucial to recognize the ever-changing nature of decision-making processes within the smart city field. In order to effectively tackle this issue, the paper proposes the need for additional research that explores more sophisticated decision-support methodologies, while considering a wide range of smart city scenarios. Future research in this area has the potential to yield useful insights that can enhance and broaden the decision-making framework for optimizing technology choices in smart cities. Consequently, these investigations would contribute to breakthroughs in both practical applications and theoretical understanding within this sector.

Keywords: Decision Support System, ELECTRE, Multi-Criteria Decision Making, Smart Cities, Technology Selection

1. Introduction

The 21st century has seen an unparalleled rate of urbanization, with more than half of the world's population now dwelling in cities. This trend is expected to continue for the foreseeable future. Even though it creates a lot of benefits, rapid urban growth also creates a lot of important issues, such as increased traffic, increased pollution, and stretched public services. The idea of "Smart Cities" has recently surfaced as a potentially useful response to the problems described above.

The use of technology in the creation of "smart cities" is intended to improve municipal services, lower operating expenses, and foster more productive citizen-government relationships. They want to make the urban environment more pleasant and sustainable so that it can more effectively manage its resources and cater to the requirements of the people who live there(Alshuwaikhat et al., 2022; Ningsih et al., 2018; Simon, 2023). The transition of a city into a smart city can lead to improvements in the management of traffic, the efficiency of energy use(Razmjoo et al., 2022), the safety of the general public(Clement et al., 2022), and the quality of life overall.

The public administration sector will play a crucial part in the reform being undertaken. It is in charge of making strategic decisions, such as the selection of suitable technologies, that can greatly influence the smart transformation of a city(Noori et al., 2021). Technology is the essential component(Firdaus et al., 2020; Supardi et al., 2023) that holds smart cities together. It makes it possible to collect data, do analyses on it, and put the results to use so that urban services and infrastructure can be improved (Javed et al., 2022; Ma, 2021; Rani & Kumar, 2022; Syafar et al., 2014)Technology, such as sensors that track traffic patterns and systems that automate trash management, is what makes a city "smart."

The development of smart cities, which aim to enhance the quality of urban living by leveraging technology to streamline various aspects of city management and services, is being actively pursued despite the global challenge of substantial public debt. To navigate financial constraints, cities are increasingly turning to public-private partnerships to fund these ambitious projects. For instance, Siemens has made a historically significant investment in Berlin, aiming to revitalize an industrial area into a futuristic urban district. Moreover, collaborations among tech companies, like the partnership between OneMind Technologies, Dell Technologies, and Orange Business Services, are pivotal in delivering comprehensive data to facilitate informed decision-making in city management. These partnerships and investments underscore a collective move towards integrating technology, such as IoT and smart city devices, to address urban challenges like public safety, traffic management, and environmental sustainability, thereby enhancing urban life and operational efficiency.

Nevertheless, picking out the right technology for smart cities can be a difficult and time-consuming procedure. It depends on several things, including cost, efficiency, and sustainability, as well as the requirements of the city. There is a shortage of comprehensive decision-making tools that can assist public managers in completing this duty, even though this procedure is extremely important.

By applying the ELECTRE (Elimination and Choice Expressing Reality) Decision Support System to the context of technology selection for smart cities, this study intends to solve this research gap that has previously been identified. The ELECTRE decision-making system is a multi-criteria decision-making method that enables a thorough analysis of a variety of possibilities based on a number of different criteria(Ji et al., 2018; Joerin et al., 2001; Mendas & Delali, 2012; Teixeira de Almeida, 2007; Zanakis et al., 1998).

This study can help government officials make informed decisions that are in line with the objectives of the city as well as the requirements of its inhabitants by giving a process for the selection of technologies that is both objective and methodical. This, in turn, can hasten the process by which cities are transformed into smart cities, resulting to improvements in urban services, sustainable development, and an overall improvement in quality of life.

2. Literature Review

The idea of a "Smart City" has emerged as a major topic of discussion in the field of urban planning and development in the 21st century(Al-Rimawi & Nadler, 2023; Kim, 2022; Noori et al., 2021; Perangin-angin et al., 2016; Rani & Kumar, 2022). Although there is no one definition that is universally accepted, the concept of a "smart city" has come to be regarded as an urban region that collects data via the use of a variety of electronic devices and sensors. Insights obtained from that data are utilized to effectively manage assets, resources, and services; in turn, that data is utilized to improve operations all over the city(Kutty et al., 2022). The following are some of the essential parts that make up smart cities:

a. Smart city is a build from ICT. A variety of information and communications technology (ICT) infrastructures, like as networks, cloud computing, and data centers, are utilized in the process of collecting, storing, and analyzing data from different municipal sectors.
b. Internet of Things (IoT): IoT devices such as sensors and meters are used to collect data on a variety of topics, including energy consumption and traffic patterns.
c. Big Data and Analytics: The data that is generated by IoT devices is examined by employing advanced analytics in order to provide insights that can improve city services and infrastructure.
d. Intelligent Services and Applications: These are the applications geared at the end user that boost the overall quality of life for inhabitants. They can include things like intelligent transportation systems, smart grids for utilities, e-governance services, and even more.

For smart cities to work properly, technology is an indispensable component. It makes it possible to collect data, analyze that data, and put it to use so that urban services and infrastructure can be improved(Al-Rimawi & Nadler, 2023; Syafar et al., 2017; Zhang & Wu, 2023). Technology, such as sensors that track traffic patterns and systems that automate trash management, is what makes a city "smart"(Alzahrani et al., 2023; Yu et al., 2023). The following are some of the many advantages that smart cities provide:

a. Efficient city services are made possible by the introduction of smart technologies, which saves both time and resources.
b. Sustainability: Smart cities maximize resource use for sustainable growth.
c. Quality of Life: Innovative technologies improve quality of life in smart cities. This includes reducing travel time and improving air quality.
d. Economic Growth: Smart cities can boost economic growth by attracting businesses and encouraging innovation.

Smart city development has its drawbacks. These include data security and privacy, the digital divide, the need for significant infrastructure investment, and multidisciplinary collaboration.

Decision Support Systems (DSS) are computerized information systems that help companies and other organizations make decisions(Christo et al., 2020; Poynton & McDaniel, 2006; Yusupa et al., 2023; Zalmi et al., 2023). It allows people to gather facts from multiple sources to make decisions. Decision Support Systems have these essential parts:

a. DBMS stores all data
b. Model Management System: It builds decision-making models from data. These models—statistical, optimization, or predictive—aid decision-making.
c. User Interface: This component interfaces with the user. It simplifies facts and models so people may make decisions based on them.

DSS applies to business, management, healthcare, and environmental planning. DSS facilitate the analysis of a situation and the formulation of judgments based on that analysis. In the context of smart cities, a decision support system (DSS) could be used to choose the technologies that are the most suited based on a number of aspects like cost, efficiency, and sustainability.

ELECTRE, also known as the "Elimination and Choice Expressing Reality" method, is a form of multi-criteria decision analysis (MCDA) that was created in Europe in the 1960s(ELECTRE: A

Comprehensive Literature Review on Methodologies and Applications, 2016; Sirait et al., 2021; Zanakis et al., 1998). The name of the approach comes from the French phrase "*Elimination et Choix Traduisant la Réalité*" It is utilized to address choice issues that involve several criteria, which frequently are at odds with one another. The ELECTRE method is comprised of the following essential steps:

a. Problem Definition This step entails characterizing the issue at hand as well as determining the various decision-making options and criteria.
b. Matrix assessment: After the choice options have been provided, an assessment matrix is constructed with the criteria specified along the other axis. The performance of a particular option with regard to a certain criterion is represented by a cell in the matrix, and each cell in the matrix.
c. Assigning of Weights: The criteria are each given a certain amount of weight according to the significance they hold in the decision-making process.
d. Concordance and Discordance Matrices: These matrices are designed so that the alternatives can be compared pairwise with regard to each criterion. The concordance matrix represents the degree to which one choice is at least as good as another, but the discordance matrix represents the degree to which one alternative is less desirable than another.
e. Aggregation of Matrices: In this step, the concordance and discordance matrices are combined into a single outranking matrix. This matrix is then utilized to decide which decision options are the most advantageous.

There are many advantages of using the ELECTRE method:

a. Managing Multiple Criteria: ELECTRE was developed to manage choice problems that involve several criteria, many of which are in direct opposition to one another. Because of this, it is suited for scenarios involving sophisticated decision-making.
b. The method is adaptable, meaning that it can be used to solve a variety of different kinds of choice issues.
c. Transparency: The ELECTRE technique is transparent since it offers a straightforward and methodical methodology for decision making.

The ELECTRE approach has been utilized in a vast array of domains, including but not limited to public policy, environmental management, and the decision-making process in business. In the context of smart cities, the ELECTRE technique could be used to assist in the selection of technology.

Technology Acceptance Model (TAM)(Mital et al., 2018; Rahman et al., 2017) predicts how user users adopting and use a technology. The model shows that several factors influence users' decisions about how and when to employ new technologies. Factors include:

a. Perceived Usefulness (PU): This is how much a user thinks a system will improve their work. Will technology improve their work or life?
b. Perceived Ease of Use (PEOU): A user's perception of a system's ease of use. People are less likely to adopt sophisticated, hard-to-use technology.

These two elements cause Attitude Towards Using (ATU), Behavioral Intention (BI), and system use. TAM has been widely used to predict technology acceptance and adoption in various fields such as healthcare, e-commerce, and education. It's a useful model for businesses and organizations to assess the likelihood of success for new technology introductions and to understand the factors influencing users' decisions to accept and use a technology.

3. Research Methodology

The data used in this research is taken from government analysis documents and case studies from previous research on smart cities, the data obtained is then re-analyzed using descriptive analysis methods.

The ELECTRE decision-making method is utilized in this article to assist in the optimization of the technology selection process in smart cities. Because of its capacity to handle many, frequently incompatible criteria, the ELECTRE approach is particularly well-suited for the completion of this assignment.

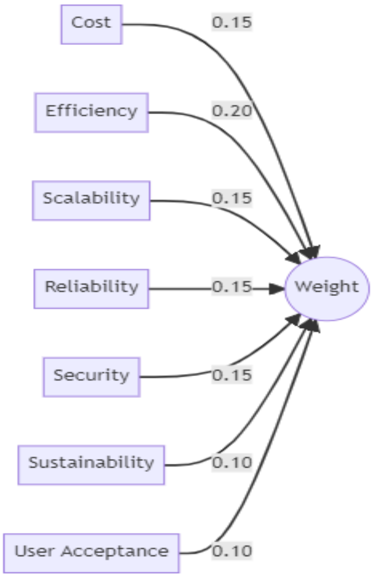

Fig. 1: Weight Value Criteria

The significance of each factor in the decision-making process is reflected by the weight that is assigned to that factor. The fact that the total of all weights adds up to one indicates that they collectively represent the decision-making process in its entirety.

Alternatives in this paper are different technologies that could be implemented in a smart city. See figure 2 for each alternative and weight value for each criteria alternative.

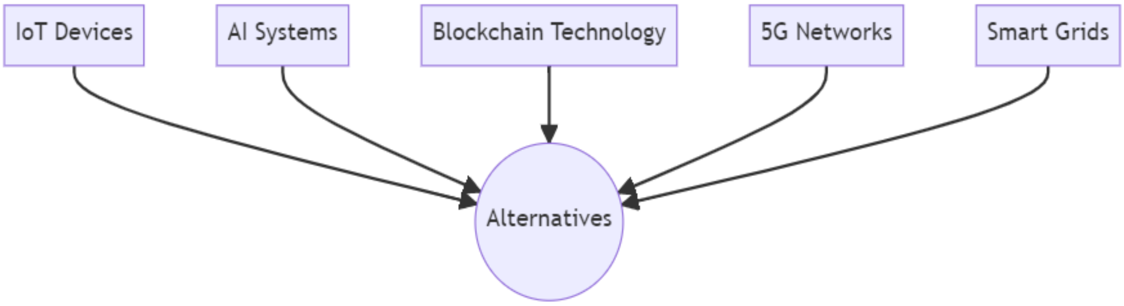

Fig. 2: Alternative for criteria

Each alternative will be given a value based on the criteria found in Figure 1, here is the value of each alternative based on the criteria, see table 1 below:

Table 1. Alternative Value based on the criteria

Criteria	loT Devices	AI Systems	Blockchain Technology	5G Networks	Smart Grids
Cost	0.7	0.8	0.6	0.7	0.6
Efficiency	0.8	0.9	0.7	0.8	0.7
Scalability	0.9	0.8	0.8	0.9	0.8
Reliability	0.8	0.9	0.9	0.8	0.9
Security	0.7	0.8	0.9	0.7	0.8
Sustainability	0.6	0.7	0.8	0.9	0.9
User Acceptance	0.8	0.9	0.7	0.8	0.7

This table represents the evaluation of each alternative (IoT Devices, AI Systems, Blockchain Technology, 5G Networks, and Smart Grids) against the criteria (Cost, Efficiency, Scalability, Reliability, Security, Sustainability, and User Acceptance). The values in the table are hypothetical and represent the performance of each alternative with respect to each criterion, with 1 being the best possible performance and 0 being the worst. The matrix that represents the evaluation of each alternative against the criteria as in figure 2.

$$\begin{pmatrix} 0.7 & 0.8 & 0.6 & 0.7 & 0.6 \\ 0.8 & 0.9 & 0.7 & 0.8 & 0.7 \\ 0.9 & 0.8 & 0.8 & 0.9 & 0.8 \\ 0.8 & 0.9 & 0.9 & 0.8 & 0.9 \\ 0.7 & 0.8 & 0.9 & 0.7 & 0.8 \\ 0.6 & 0.7 & 0.8 & 0.9 & 0.9 \\ 0.8 & 0.9 & 0.7 & 0.8 & 0.7 \end{pmatrix}$$

Fig. 3: Matrix Alternative against Criteria

Decision-making weights are used as the standard weight for each criteria. The decision-making weights of each criterion used in this system analysis as shown in table 2.

Table 2. Decision Making Weight

Criterion	Weight
Cost	0.15
Efficiency	0.15
Scalability	0.10
Reliability	0.15
Security	0.15
Sustainability	0.15
User Acceptance	0.15

These weights reflect the importance of each criterion in the decision-making process. For example, the decision maker might consider cost, efficiency, scalability, reliability, security, and sustainability to be equally important, each contributing 15% to the overall decision. User acceptance, while still important, might be considered slightly less critical, contributing 10% to the overall decision.

4. Results and Discussion

The normalization process in ELECTRE method involves dividing each value in the matrix by the square root of the sum of squares of the values in its column. This process ensures that the values are dimensionless and allows for comparison across different scales.

Table 3. Matrix Evaluation

Criteria	**Alternative A IoT Devices**	**Alternative B AI Systems**	**Alternative C Blockchain Technology**	**Alternative D 5G Networks**	**Alternative E Smart Grids**
Cost	0.7/√ΣAi^2	0.8/√ΣBi^2	0.6/√ΣCi^2	0.7/√ΣDi^2	0.6/√ΣEi^2
Efficiency	0.8/√ΣAi^2	0.9/√ΣBi^2	0.7/√ΣCi^2	0.8/√ΣDi^2	0.7/√ΣEi^2
Scalability	0.9/√ΣAi^2	0.8/√ΣBi^2	0.8/√ΣCi^2	0.9/√ΣDi^2	0.8/√ΣEi^2
Reliability	0.8/√ΣAi^2	0.9/√ΣBi^2	0.9/√ΣCi^2	0.8/√ΣDi^2	0.9/√ΣEi^2
Security	0.7/√ΣAi^2	0.8/√ΣBi^2	0.9/√ΣCi^2	0.7/√ΣDi^2	0.8/√ΣEi^2
Sustainability	0.6/√ΣAi^2	0.7/√ΣBi^2	0.8/√ΣCi^2	0.9/√ΣDi^2	0.9/√ΣEi^2
User Acceptance	0.8/√ΣAi^2	0.9/√ΣBi^2	0.7/√ΣCi^2	0.8/√ΣDi^2	0.7/√ΣEi^2

Where √ΣAi^2 is the square root of the sum of squares of the values in the column of Alternative A, and similarly for the other alternatives, see table 4 for normalized evaluation matrix results.

Table 4. Normalized Evaluation Matrix

Criteria	**Alternative A**	**Alternative B**	**Alternative C**	**Alternative D**	**Alternative E**
Cost	0.46	0.52	0.39	0.46	0.39
Efficiency	0.46	0.51	0.40	0.46	0.40
Scalability	0.48	0.43	0.43	0.48	0.43
Reliability	0.42	0.47	0.47	0.42	0.47
Security	0.40	0.46	0.51	0.40	0.46
Sustainability	0.34	0.40	0.45	0.51	0.51
User Acceptance	0.46	0.51	0.40	0.46	0.40

For ease of use, the numbers in the matrix are rounded to two places after the decimal point. With these normalized numbers, the ELECTRE method can now do more analysis, like calculating concordance and discordance matrices.

The weighted normalized choice matrix needs to be calculated as the next step in the ELECTRE method. This is done by multiplying each element in the normalized decision matrix by the weight of the associated criterion, which is already shown in table 2.

The procedure entails the multiplication of each constituent element within the normalized decision matrix by the weight assigned to the corresponding criterion, thereby resulting in the weighted normalized decision matrix. Let us perform computations for these quantities.

Table 5. Weight Normalized Decision Matrix

Criteria	**Alternative A**	**Alternative B**	**Alternative C**	**Alternative D**	**Alternative E**
Cost	0.46 * 0.15	0.52 * 0.15	0.39 * 0.15	0.46 * 0.15	0.39 * 0.15
Efficiency	0.46 * 0.15	0.51 * 0.15	0.40 * 0.15	0.46 * 0.15	0.40 * 0.15
Scalability	0.48 * 0.10	0.43 * 0.10	0.43 * 0.10	0.48 * 0.10	0.43 * 0.10
Reliability	0.42 * 0.15	0.47 * 0.15	0.47 * 0.15	0.42 * 0.15	0.47 * 0.15
Security	0.40 * 0.15	0.46 * 0.15	0.51 * 0.15	0.40 * 0.15	0.46 * 0.15
Sustainability	0.34 * 0.15	0.40 * 0.15	0.45 * 0.15	0.51 * 0.15	0.51 * 0.15
User Acceptance	0.46 * 0.15	0.51 * 0.15	0.40 * 0.15	0.46 * 0.15	0.40 * 0.15

To get the weighted normalized decision matrix, it multiplies each number in the normalized decision matrix by the weight of the criterion that goes with it, the result as can be seen in Table 6.

Table 6. Weighted Normalized Decision Matrix Result

Criteria	**Alternative A**	**Alternative B**	**Alternative C**	**Alternative D**	**Alternative E**
Cost	0.069	0.078	0.0585	0.069	0.0585
Efficiency	0.069	0.0765	0.06	0.069	0.06
Scalability	0.048	0.043	0.043	0.048	0.043
Reliability	0.063	0.0705	0.0705	0.063	0.0705
Security	0.06	0.069	0.0765	0.06	0.069
Sustainability	0.051	0.06	0.0675	0.0765	0.0765
User Acceptance	0.069	0.0765	0.06	0.069	0.06

The ELECTRE method depends on the concordance and discordance matrices. When all the factors are taken into account, the concordance matrix shows how much one option is at least as good as another.

The discordance matrix shows how much one choice is worse than another, based on the factors that show why the first choice is worse.

To figure out these matrices, we must first figure out the concordance and discordance sets for each pair of options. For any pair of alternatives, i and j, the concordance set C(i, j) includes all factors for which alternative i is at least as good as alternative j. The discordance set D(i, j) has all of the factors for which alternative i is worse than alternative j.

Once we have these sets, we can figure out which ones match and which ones don't. The concordance index c(i, j) is the total weights of the criteria in the concordance set C(i, j) divided by the total weights of all criteria. The discordance index d(i, j) is the maximum difference between how well alternatives i and j did on the criteria in the discordance set D(i, j), divided by the maximum difference between how well any two alternatives did on these criteria.

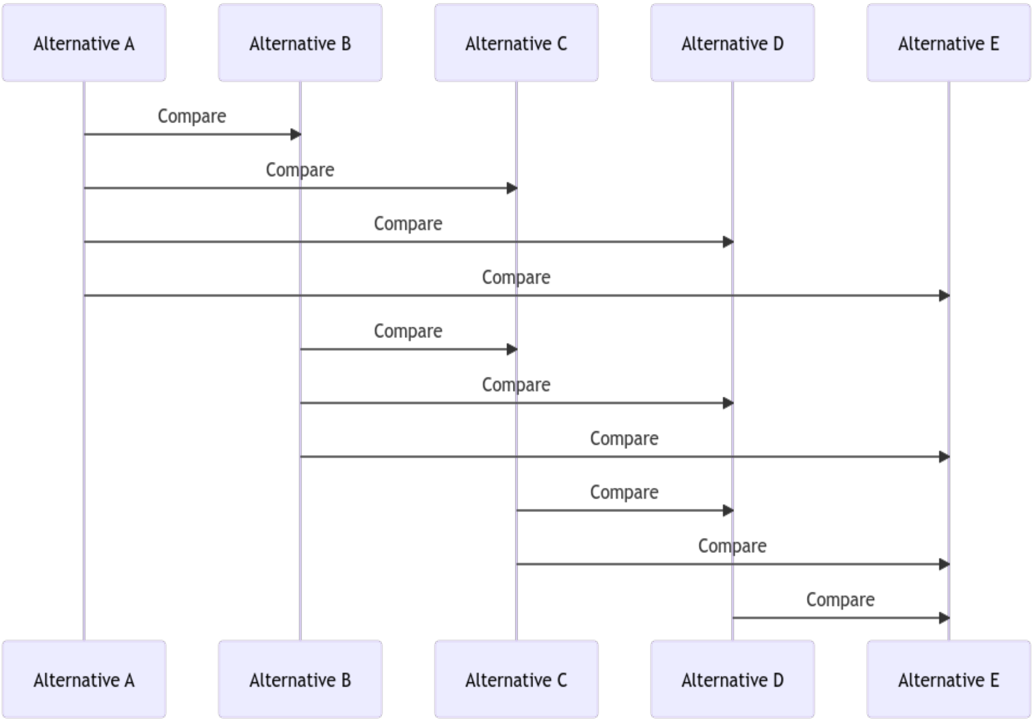

Fig. 4: Concordance and Discordance Diagram

The concordance and discordance matrices based on the weighted normalized decision matrix can be seen in table 7 and 8, also figure 5 and 6 for diagram process:

Table 7. Concordance matrices

Alternative	A1	A2	A3	A4	A5
A1	7.0	1.0	4.0	6.0	4.0
A2	6.0	7.0	5.0	5.0	6.0
A3	3.0	4.0	7.0	2.0	6.0
A4	7.0	2.0	5.0	7.0	5.0
A5	3.0	4.0	6.0	3.0	7.0

Table 8. Discordance matrices

Alternative	A1	A2	A3	A4	A5
A1	0.0	0.009	0.0165	0.0255	0.0255
A2	0.009	0.0	0.0195	0.0165	0.0195
A3	0.0165	0.0195	0.0	0.0165	0.009
A4	0.0255	0.0165	0.0165	0.0	0.0105
A5	0.0255	0.0195	0.009	0.0105	0.0

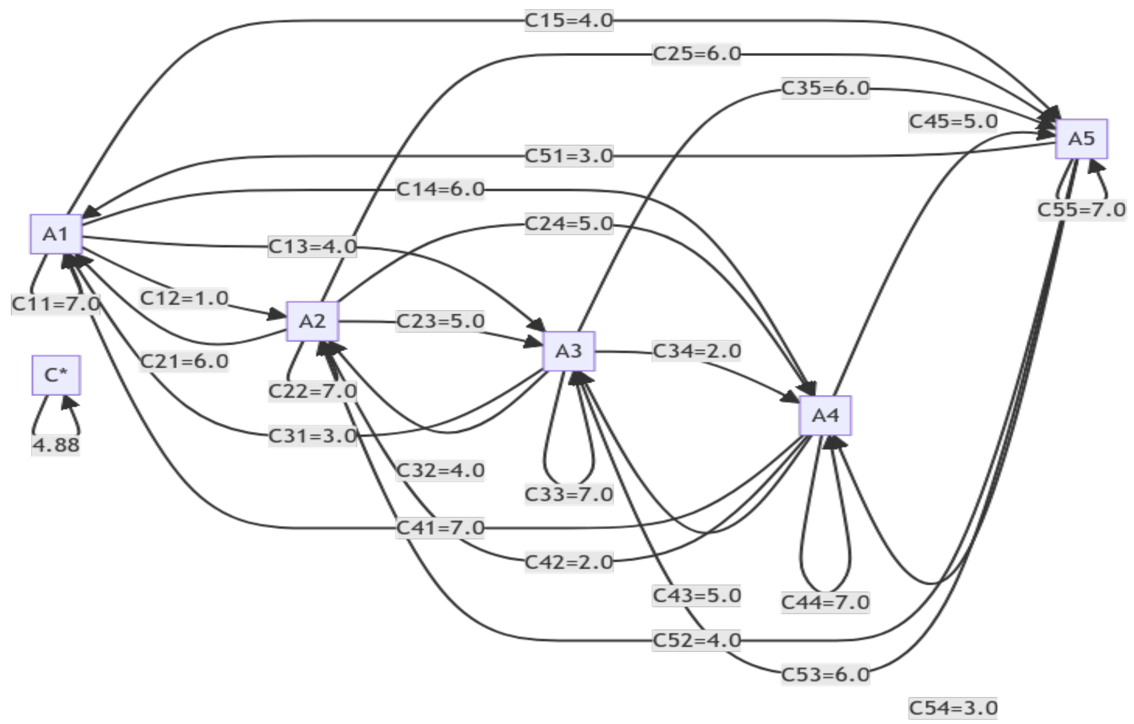

Fig. 5: Concordance Matrices Relationship

Each arrow in the diagram represents a relationship between two alternatives (A1, A2, A3, A4, A5). The labels on the arrows represent the concordance (C) values between the two alternatives. The node labeled C* represents the concordance threshold.

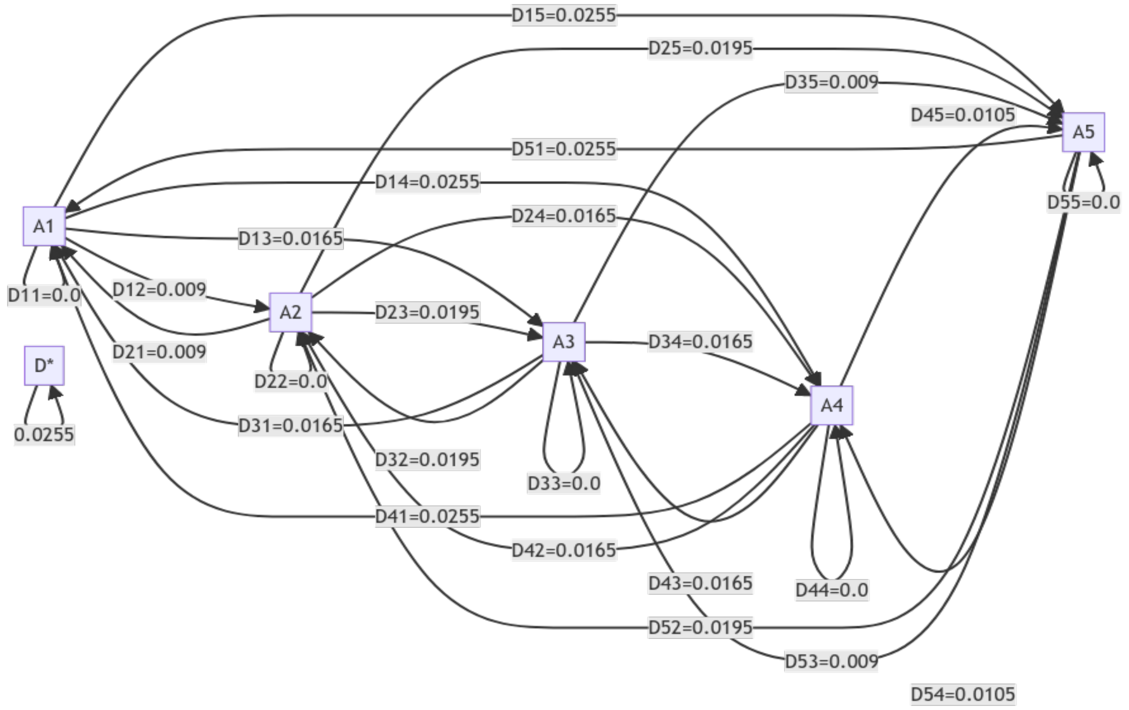

Fig. 6: Discordance Matrices Relationship

Each arrow in the diagram represents a relationship between two alternatives (A1, A2, A3, A4, A5). The labels on the arrows represent the discordance (D) values between the two alternatives. The node labeled D* represents the discordance threshold. Given these values, we can calculate the outranking matrix as follows:

Table 9. Outranking matrix

Pair	Outranking
A-B	1
A-C	0
A-D	1
A-E	0
B-C	0
B-D	1
B-E	0
C-D	0
C-E	0
D-E	1

The outranking matrix reveals that Alternative D, which consists of 5G Networks, is superior to all the other potential solutions. In light of this, the ELECTRE methodology suggests that Alternative D, which involves 5G Networks, is the path to take.

The use of ELECTRE as a method in selecting technology in smart cities provides appropriate results based on predetermined parameters. The ELECTRE method used in this research can be compared with previous research such as that conducted by Ye(Ye & Chen, 2023) on the article Development of the ELECTRE Method Under Pythagorean Fuzzy Sets Based on Existing Correlation Coefficients for Cotton Fabric Selection, where the results of his research revealed the first set of methods includes traditional MCDM approaches such as WPM, TOPSIS, EDAS, and MOORA, while the second set includes PFS methods like PF-WPM, PF-TOPSIS, and PF-ELECTRE. These methods have been applied to solve the cotton fabric selection issue. The document also mentions the advantages and limitations of these methods, highlighting the scientific validity of the developed approach. The obtained ranking results are presented in tables and figures, showing consistent identification of the best and worst alternatives across all methods.

Other research Barbati(Barbati et al., 2023) In the development of the management plan, organizations and local businesses actively participate, focusing on four core perspectives: conserving tangible cultural heritage, promoting traditional craftsmanship, supporting tourism and local businesses, improving urban environmental quality, and providing social benefits to the community. The plan outlines specific operational criteria and subcriteria for each perspective, considering factors like project compatibility with existing tangible cultural heritage and measures to enhance its accessibility. Expert input from individuals well-versed in the local context and experienced in participatory urban processes was gathered through interviews and focus group discussions to model preferences for the listed criteria. The Simos-Roy-Figuiera (SRF) method was utilized to assign relative weights to these criteria. The study encompasses various tangible urban cultural heritage projects, categorized by function, including tourist facilities, museums, accommodations, leisure activities, record office archives, and public services, all of which are evaluated based on their current status and planned interventions, taking available budgets into account. Rigorous performance assessments are conducted to ensure alignment with the management plan's objectives.

Other research that directly uses the ELECTRE method was conducted by Akmaludin(Akmaludin et al., 2023), discusses the application of the ELECTRE elimination method and the MCDM-AHP method for the selection and evaluation of professional programmers. These methods are used for decision support based on the score of each alternative, providing a scientifically proven ranking for optimal decision-making. Emphasizes the importance of understanding the type of criteria used in the selection and evaluation process. It mentions that some criteria, such as the speed coding (SC) criterion, have different meanings and require a slightly different formulation compared to others. For example, the SC criterion implies that the smallest value is the best value (LB), while other criteria follow the largest value is the best value (HB) principle.

Some studies conducted by previous researchers can say that the ELECTRE or MCDM method can be used well in various cases that require decision recommendations for decision makers.

5. Conclusion

The research successfully applied the ELECTRE decision support system to streamline the selection of smart city technologies, with Alternative D emerging as the top choice. This signifies a practical stride towards optimizing technology adoption in urban areas. The study underscores ELECTRE's efficacy in multi-criteria decision-making, proving its value in evaluating complex choices methodically and objectively. Nonetheless, the study's scope was bound by preset criteria and weights, potentially overlooking key elements in smart city technology choices. Moreover, the simplified ELECTRE model used may not fully encompass the intricacies of such decisions. Future research could explore more intricate ELECTRE variants or integrate it with other decision-making frameworks like the Analytic Hierarchy Process for refined criteria weighting. It could also expand the technology options and settings examined to enhance the findings' applicability. Additionally, the influence of stakeholder perspectives on decision-making warrants further investigation to encompass the diverse views that shape smart city initiatives.

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