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Consumer Satisfaction Benchmarking Analysis Using Group Decision Support System (GDSS) PROMETHEE Methodology in a GIS Environment

Anastasia S. Saridou and Athanasios P. Vavatsikos *

Production and Management Engineering Department, Democritus University of Thrace, 67 100 Xanthi, Greece; asaridou@pme.duth.gr
* Correspondence: avavatsi@pme.duth.gr; Tel.: +30-2541079853

Abstract: In today's competitive environment, multi-branch companies allocate their stores with the aim of expanding their territorial coverage to attract new customers and increase their market share. Consumer satisfaction surveys either produce global performance results or they are not able to differentiate consumer perceptions using location analytics. This research develops a novel framework to assist multi-branch companies in mapping the consumer satisfaction performance of their stores, expanding conventional customer relationship management to the spatial context. The framework developed proposes a decision model that combines the Group Decision Support extension of the PROMETHEE and CRITIC methods in a GIS environment to generate satisfaction performance mappings. The developed decision-making framework converts consumer responses into satisfaction performance maps, allowing the company's stores and their competitors to be evaluated. Moreover, it provides insight into the potential opportunities and threats for each store. The performance of the proposed framework is highlighted through a case study involving a multi-branch coffeehouse company in a Greek city. Finally, a tool developed to assist the computational part of the framework is presented.

Keywords: group decision support system (GDSS); PROMETHEE; CRITIC; geographic information system (GIS); spatial analysis; spatial benchmarking; consumer satisfaction mapping

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1. Introduction

The competitive landscape of the retail sector has become a complex and intensifying phenomenon that has attracted the attention and interest of the academic community [1]. Over the years, several Key-Performance-Indicator-based systems have been developed to monitor retail stores' performance to reflect companies' performances [2,3]. According to Gauri et al. [4], the stochastic frontier approach and the data envelopment analysis methods occupy a central position in benchmarking research investigations. Regardless, the methodology used to assist benchmarking analysis studies, Consumer Satisfaction (CS) has long been considered an important management issue and has been extensively studied in marketing research [5].

CS studies reveal a palpable concern among store owners and managers about the key factors that determine CS levels. Managers' overarching goal is to improve the overall performance of their stores, and they recognize CS as a critical means of achieving such improvements. This complex interplay between competition, CS, and managerial aspirations highlights the dynamic and interconnected nature of the retail sector [6]. Over time, various approaches have been developed to quantify CS, such as the SEVQUAL model [7]. Additionally, the Customer Satisfaction Index (CSI) is a structure that suggests that CS is influenced by factors such as the perceived quality and value of a product or service, customer expectations, and the reputation of the company. It is, therefore, of vital importance for companies to maintain a high level of CS to maintain or increase their current level of profitability [8].

Nowadays, the literature confirms that CS is determined by both the perceived quality and the difference between expectations and reality [9]. These factors are considered to be the causes of overall CS. In addition to that, CSI predicts the outcomes of CS, such as consumer complaints or loyalty. In their survey, Grigoroudis and Siskos [10] present a number of developed CSIs and CS barometers. Regression, optimization, data mining and simulation models are also used to analyze and process CS data. Further, CS can also be seen as a Multi-Criteria Decision Analysis (MCDA) problem, where the different satisfaction dimensions represent the analysis criteria for evaluating the services provided [11]. MCDA methods include approaches that support the decision-making process considering consumer judgements.

The capabilities of MCDA models to address selection, ranking and classification problem types resulted in the publication of a considerable number of articles in the related literature. These articles mainly present MCDA analysis frameworks for the evaluation of various companies and/or service providers [12]. For instance, AHP has been used to evaluate CS performance in the banking sector [13] and to assess CS in relation to intercity bus transportation providers [14]. Song et al. [15] proposed a multi-attribute utility-based decision support model to help consumers make better purchase choices using the MAUT method. Tsai et al. [16], in their research, present an assessment model for the consumer selection of online food delivery services using AHP, CORPAS and VIKOR decision models in parallel. Ahani et al. [17] used TOPSIS to assess the importance of features in TripAdvisor's hotels in the Canary Islands. However, CS is usually treated as a criterion to assist benchmarking analysis rather than as a separate type of analysis. On the other hand, the Multi-Criteria Satisfaction Analysis (MUSA) [18] is explicitly designed to support CS analysis generating action and improvement diagrams as well as demandingness and satisfaction indices. MUSA has been used, among others, to investigate the level of CS in the context of short food supply chains [19], to measure CS in the healthcare sector [20] and to investigate the satisfaction gained by the implementation of an e-appointment system in a Greek hospital [21].

To enrich sales potential and to provide efficient services to their customers, spatial analysis approaches have also been utilized in the retail sector using Geographic Information Systems (GISs) [22]. As the attractiveness of a retailer's store is directly influenced by its proximity [23], GISs have been enhanced with competitive location models that relate a store's market share to both its distance and its attractiveness [24]. Additionally, Merino and Ramirez-Nafarrate [25] suggest that the knowledge provided by the retailer's trade area analysis is significant not only for site selection but also for marketing and merchandising purposes. However, marketing and expansion decisions should consider customer perceptions in a dynamically changing retail environment in order to avoid the phenomenon of sales cannibalization [26]. In the same direction, Zou et al. [27] relate spatial and non-spatial datasets to define the factors influencing CS to support targeted management.

GIS functionalities, when combined with decision analysis and operations research methods, give rise to the so-called Spatial Decision Support Systems (SDSSs). SDSS significantly benefits retail companies in terms of consumer experience and satisfaction gains [28]. Their main advantage relates to their capacity to integrate consumer preferences and service availability in a spatial context. Undoubtedly, a major contributor to the widespread adoption of GIS in the retail sector has been the ability of GIS software packages to support geo-visualization techniques and to transform decision support outputs from a static to a highly dynamic visual environment [29]. Harnessing the power of GIS, geomarketing [30] introduces a new dimension by incorporating spatial characteristics, giving rise to an emerging discipline at the confluence of geography and marketing.

Multi-criteria CS analysis is a group decision-making problem, as the preferences of multiple consumers must be combined to generate a single ranking order of the examined alternatives. Thus, the developed approaches aim at combining decision matrices of each individual consumer, using methodological extensions to allow for the development of Group Decision Support Systems (GDSSs). Introduced in the early 1990s, the Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) allows for both partial and full ranking of the alternatives examined [31]. Moreover, the GDSS PROMETHEE extension combines individual preferences forming a decision matrix containing the preference flows estimated by each individual Decision Maker (DM) [32].

A review of the literature enumerates articles that implement the PROMETHEE methodology to support benchmarking analysis [33–41]. However, in none of the above articles was CS the sole objective of the analysis, as, in most cases, it was treated as one criterion among others to derive rankings for the companies under evaluation. In addition, none of the above articles takes the GDSS process into account. Despite the widespread popularity of the PROMETHEE family of methods, it is notable that only a limited number of studies have been conducted specifically using the GDSS PROMETHEE. Macharis et al. [42] provide a literature review of eighteen GDSS PROMETHEE applications from the period spanning from 2000 to 2011. According to them, the method has been used in various fields, including watershed management, civil construction projects, and strategic environmental assessment for transportation planning scenarios. An up-to-date review of the literature identified a total of seventeen articles in journals that were published over a period from 2011 to 2023 [43–59]. Although the GDSS PROMETHEE is implemented in a wide range of research areas, none of the articles examined uses the GDSS extension of the PROMETHEE II method to assist CS analysis. Consequently, the implementation of the GDSS PROMETHEE to assist CS studies, in both spatial and non-spatial environments, has not been identified in the literature.

This research is the first to integrate GIS-based tools and the concept of GDSS PROMETHEE extension in CS analysis studies. Thus, it is an innovative approach that seamlessly integrates spatial and marketing concepts, with the overall aim of increasing profitability through the analysis of location data. To the best of our knowledge, no previous research has addressed the study of CS while merging GIS and GDSS PROMETHEE methodology to spatially delineate market areas and provide insights into store performance. The developed framework is illustrated in a case study by examining CS analysis within a multi-branch coffeehouse company in a competitive location environment. It is further supported by a computational tool capable of generating service areas using Voronoi (Thiessen) polygons, aiming to enable CS GDSS PROMETHEE analysis to the boundaries of each store. The proposed approach allows for comparative analysis of store performance based on consumer preferences in the service area of each store. The framework provides feedback regarding the perceived satisfaction between the stores of each company and for each company examined.

2. Materials and Methods

2.1. GDSS PROMETHEE

The Preference Methods for Enrichment Evaluations (PROMETHEE) are MCDA tools with a vastly increasing number of papers published throughout the years [60]. They assist DMs in evaluating and ranking multiple alternatives based on a set of criteria. The PROMETHEE I method provides a partial ranking of the alternatives by combining positive and negative flows, while PROMETHEE II provides a complete ranking using the net preference flow [61]. Macharis et al. [32] introduced the GDSS PROMETHEE procedure, which can assist multiple DMs in arriving at an overall outcome among multiple alternatives. PROMETHEE methods belong to the family of outranking methods, and, therefore, preferences are established based on the differences between the attribute of the values of candidate alternatives. The process starts by forming an evaluation table and then filling in the information requested according to the version of the PROMETHEE method. This additional information refers to information between criteria $(J = 1, \ldots, j, \ldots, k)$ and information within each criterion. All criteria have weights (w_j) with a relative importance that are normalized in a [0, 1] interval such that their sum equals one. For each criterion, a generalized criterion type has to be defined among the six existing types [31].

Six different preference functions $P_j(d)$ are available for defining the criteria. Depending on the type of criterion, the associated parameters must be defined. The indifference threshold (q), the strict preference threshold (p), and the intermediate value (s). Criterion type a/I represents the usual preference criterion, which assumes that higher values are preferred to lower values. b/II represents the U-shape preference criterion, and it takes into account the parameter q. It expresses a range of values where the alternatives are considered independent and beyond that range, that is, the q value, and the preference starts to emerge. c/III represents the V-shape criterion, with a linear preference up to a determined p preference threshold. d/IV represents the levelized criterion, assuming that values below q are not preferred in contrast with the values above p. e/V represents a V-shape criterion with indifference and linear preference. Both q and p parameters have to be considered among which preference increases. f/VI represents a Gaussian criterion due to its particular shape [31].

The GDSS PROMETHEE procedure consists of eleven steps grouped in three phases (Figure 1). The first phase includes the following steps: a/the generation of the alternatives that need to be ranked and the associated criteria, b/the evaluation of each alternative per criterion of each DM, and c/a global evaluation by the group. The first phase is a group process, referring to the brainstorming procedure among DMs to come to an agreement considering the set of alternatives $(A = a_1, \ldots, a_i, \ldots, a_n)$ and criteria $\left(J = g_1, \ldots, g_j, \ldots, g_k\right)$ used in the decision-making process. At the end of this phase, a stable $(n \times k)$ matrix is formed.

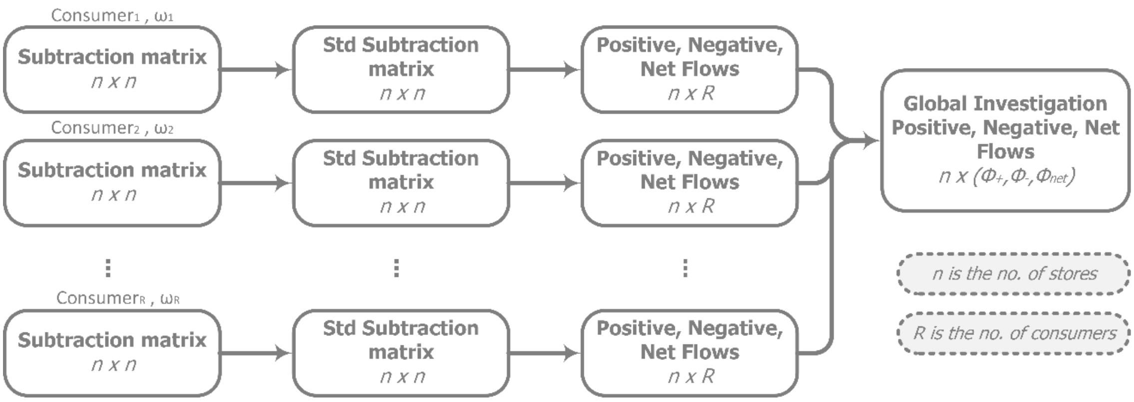


Figure 1. CS-GDSS PROMETHEE summarized procedure.

The second phase is a more individual process as each DM evaluates a $(n \times k)$ table. In advance, all DMs $(R = 1, \ldots, r, \ldots, m)$ have a decision power given by a non-negative weight (ω_r) expressed in a zero to one interval, while their sum must be equal to one. If any of the analysis criteria hold no interest for the r^{th} DM, a weight (w_{rj}) of zero is assigned to the criterion. The PROMETHEE II algorithm is then developed for each DM. Initially, the DMs establish their preferences to the analysis criteria in J to evaluate candidate alternatives' performances in pairs. Thus, for the r^{th} DM, the preference index π_{rj} of alternative a when compared with every other of its peers (a_i) is estimated using Equation (1). Respectively, the positive $(\Phi_r^+(a))$, negative $(\Phi_r^-(a))$ as well as the net flows $(\Phi_r^{net}(a))$ for each DM are estimated using Equations (2)–(4). In that way, the individual perspectives of the DMs are preserved.

$$\pi_{rj}(\alpha, a_i) = P_{rj}\left(d_j(\alpha, a_i)\right) = P_{rj}\left(g_j(\alpha) - g_j(a_i)\right), \tag{1}$$

$$\Phi_r^+(a) = \frac{1}{n-1}\sum_{i=1}^{n}\sum_{j=1}^{k} w_{rj} \times \pi_{rj}(\alpha, a_i) \tag{2}$$

$$\Phi_r^-(a) = \frac{1}{n-1}\sum_{i=1}^{n}\sum_{j=1}^{k} w_{rj} \times \pi_{rj}(a_i, \alpha) \quad (3)$$

$$\Phi_r^{net}(a) = \Phi_r^+(a) - \Phi_r^-(a) \quad (4)$$

The third phase consists of gathering the net flows ($\Phi_r^{net}(a)$) of each DM and constructing a $(n \times m)$ matrix. Each column of the matrix represents the perspective of a specific DM. In addition, the decision power of the DMs is implemented in the analysis, taking into consideration the DM weight vector (ω_r). Pairwise comparisons of the derived $\Phi_r^{net}(a)$ are generated to preferences implementing type III generalized criterion, so that preferences that are allocated to the $\Phi_r^{net}(a)$ values are also proportional to these deviations. A criterion of type III is characterized by a V-shaped criterion that necessitates a p value as its input. In GDSS PROMETHEE, the default value for p is set equal to two, which corresponds to the maximum deviation that occurs in cases where the compared pair of alternatives (a, b) receives the highest ($\Phi_r^{net}(a) = 1$) and the lowest ($\Phi_r^{net}(b) = -1$) preference flow values, respectively. Thus, DMs are handled as 'criteria' to continue the analysis by repeating PROMETHEE II algorithm [31]. Equivalently, phase two of the overall GDSS net flow is estimated using Equation (5).

$$\Phi_{GDSS}^{net}(a) = \frac{1}{n-1}\sum_{r=1}^{m}\sum_{i=1}^{n} \omega_r \times \left(P_r^{III}\left(\Phi_r^{net}(a) - \Phi_r^{net}(a_i)\right) - P_r^{III}\left(\Phi_r^{net}(a_i) - \Phi_r^{net}(a)\right)\right) \quad (5)$$

2.2. CRITIC

The Criteria Importance Through Intercriteria Correlation (CRITIC) is used for determining criterion weights. The main advantage is that the method derives the weights directly from the consumer preference decision matrix without adding extra questions to the questionnaire. The method proposed by Diakoulaki et al. [62] belongs to the class of correlation methods. It uses a $(n \times k)$ decision matrix consisting of k criteria in J and n alternatives in A to determine the criteria weights. This matrix is formed by the DM preferences based on each criterion and each alternative according to Equation (6), where $g_j(a_i)$ is the value of alternative a_i in the j^{th} criterion.

$$X = \begin{bmatrix} g_1(a_1) & \cdots & g_k(a_1) \\ \vdots & \ddots & \vdots \\ g_1(a_n) & \cdots & g_k(a_n) \end{bmatrix}_{\mathrm{n} \times k}, i = 1, \ldots, n \text{ and } j = 1, \ldots, k \quad (6)$$

The method consists of five phases, starting with the score range linear normalization of the decision matrix values. Equations (7) and (8) illustrate the implemented normalization functions for both ascend and descend attribute values, where x_{ij} is the normalized value of the decision matrix for the i^{th} alternative in j^{th} criterion and $\max(g_j(a))$ is the maximum and $\min(g_j(a))$ is the minimum observed performance at the same criterion.

$$x_{ij}^{ascend} = \frac{g_j(a_i) - \min(g_j(a))}{\max(g_j(a)) - \min(g_j(a))} \quad (7)$$

$$x_{ij}^{descend} = 1 - x_{ij}^{ascend} = \frac{\max(g_j(a)) - g_j(a_i)}{\max(g_j(a)) - \min(g_j(a))} \quad (8)$$

Then, the correlation coefficient (ρ_{jk}) of the alternatives is estimated using Equation (9), where ρ_{jk} is the correlation coefficient among the j^{th} and k^{th} criteria attributes, and $\overline{x}_j$ and $\overline{x}_k$ are their mean values, respectively (Equation (10)). Then, index C is derived using Equation (11), where σ_j denotes the standard deviation of the j^{th} criterion attributes (Equation (12)).

Last, the criterion elicitation weights are calculated by dividing the C_j index by their sum (Equation (13)).

$$\rho_{jk} = \sum_{i=1}^{m} \left(x_{ij} - \overline{x}_j\right)\left(x_{ik} - \overline{x}_k\right) / \sqrt{\sum_{i=1}^{m} \left(x_{ij} - \overline{x}_j\right)^2 \sum_{i=1}^{m} \left(x_{ik} - \overline{x}_k\right)^2} \tag{9}$$

$$\overline{x}_j = \frac{1}{n} \sum_{i=1}^{n} x_{ij} \tag{10}$$

$$C_j = \sigma_j \sum_{k=1}^{n} \left(1 - \rho_{jk}\right) \tag{11}$$

$$\sigma_j = \sqrt{\frac{1}{n-1} \sum_{j=1}^{n} \left(x_{ij} - \overline{x}_j\right)^2} \tag{12}$$

$$w_j = \frac{C_j}{\sum_{j=1}^{n} C_j} \tag{13}$$

3. Proposed Framework

3.1. Description

In the context of maintaining their competitive advantage and the ongoing commitment to enhancing their services, companies endeavor to gather data that can be leveraged to their advantage. These data constitute one of the fundamental components for constructing a decision problem that frames an evaluation scenario for the company. A decision problem uses the collected data that pertain to the specific issue that the company seeks to answer, and using the right techniques yields a result.

To evaluate a company's performance in relation both to the competition and its branches while evaluating the performance of each store, a new framework is developed, which utilizes the multi-criteria GDSS PROMETHEE procedure (Figure 2). The procedure begins with the formulation of the questionnaire that is based on criteria reflecting the problem that needs to be solved. The criteria used in the research must be properly formulated and chosen wisely in order to offer valuable insights. The answers obtained from the questionnaires are given numerical values by means of a linguistic preference scale. Consumer scale was rated from completely unsatisfied to very satisfied.

Nowadays, electronic ordering platforms store consumers' ordering addresses, enabling the development of spatial databases that provide their longitude and latitude geographical coordinates. This allows businesses to take advantage of the benefits of spatial analysis, even if they do not already have a developed professional spatial infrastructure. A spatial database contains data on city blocks, branches' locations, and consumer stigma. Taking advantage of GIS capabilities, Voronoi polygons are formed that reflect the influence area of each branch. Voronoi polygons are convex polygons constructed around each one of the branches located at their center. Each polygon covers an area representing the locations sited closest to the branches examined. In this way, each area of influence simulates the service area of a store based on the aspect that consumers usually use the closer point of interest to fulfill their needs. Consumers are assigned to the service they belong to by joining their locations with those of the Voronoi polygons that contain them. Thus, the primary key of the service areas is assigned to the consumer dataset, enabling a one-to-many relationship generation.

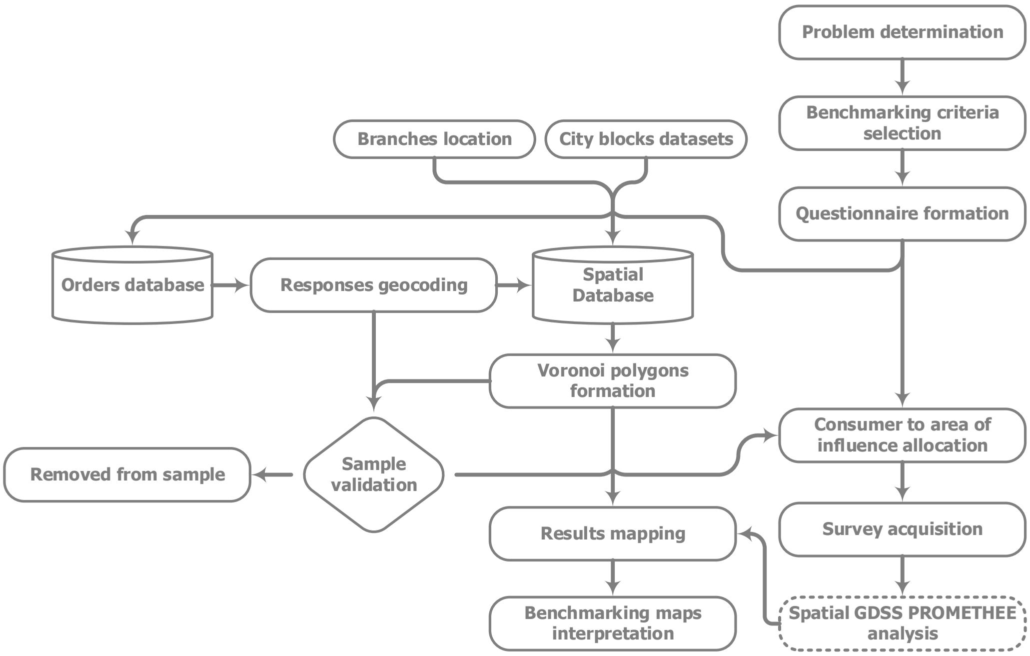


Figure 2. CS-GDSS PROMETHEE workflow for spatial multi-branch benchmarking analysis.

The CS-GDSS PROMETHEE model delivers results to assist the analysis in understanding the stores' performance. Initially, the CRITIC method elicits criterion weights that are mandatories for the PROMETHEE method. Weights reflect the importance for each criterion and for every consumer in each service area, providing the inter-criterion information. Although the PROMETHEE method can be combined with various criterion weight elicitation options, CRITIC was chosen due to its ability to generate weights directly from the decision matrix dataset. Thus, it forms a unified criterion weight elicitation environment that minimizes the third parties' intervention effect [63], which is essential in benchmarking analysis. The PROMETHEE method is then implemented for each consumer to generate individual net preference flows for each one of the responders in R. As a result, the model provides the positive, negative, and net flows of the GDSS PROMETHEE method for spatial interpretation. By extending the method to its spatial context, maps can be formulated reflecting the stores' performance. As long as Likert scales are used to derive consumer preferences, which are coded in an ascending order, the criteria implemented are always of the ascending (benefit) preferential type.

The proposed framework adopts a five-level Likert-type scale, where the criteria are rated from zero (completely unsatisfied) to four (very satisfied). By default, the criterion type III preference function is utilized to transform performance deviations to preference indices with a strict preference p value that equals four, which is the maximum possible deviation that can be generated from the adopted Likert scale. In accordance with the GDSS PROMETHEE extension, consumers are transformed into the model's DMs. Weights (ω_r) are assigned equally to each consumer $r \in R$, that is, one divided by the number of consumers. The procedure then follows the principles of the GDSS PROMETHEE model, providing a final matrix with attributes regarding each store's positive, negative, and net flows based on consumers' preferences [31]. Based on the net flows generated, a store under investigation can either outrank others or be outranked by its rivals.

3.2. Model Development

To assist the computational part of the proposed spatial CS-GDSS PROMETHEE framework, a model is developed in Quantum GIS (QGIS), a free opensource GIS software, compatible with 3.20 version or later. The model consists of the "GDSS PROMETHEE" script developed in python 3.0 and operates along with the other "Voronoi polygons", "Dissolve", "Clip", "Join attributes by location" and "Join attributes by field value" preexisting scripts. The python libraries used to implement "GDSS PROMETHEE" script are SciPy, NumPy, Pandas and Math. Within the "GDSS PROMETHEE" script, both the GDSS PROMETHEE and CRITIC methods have been coupled to assist both criterion weight elicitation and preference flow estimation. "Graphical modeler" is used to form the workflow by combining the aforementioned geospatial processing tools (Figure 3).

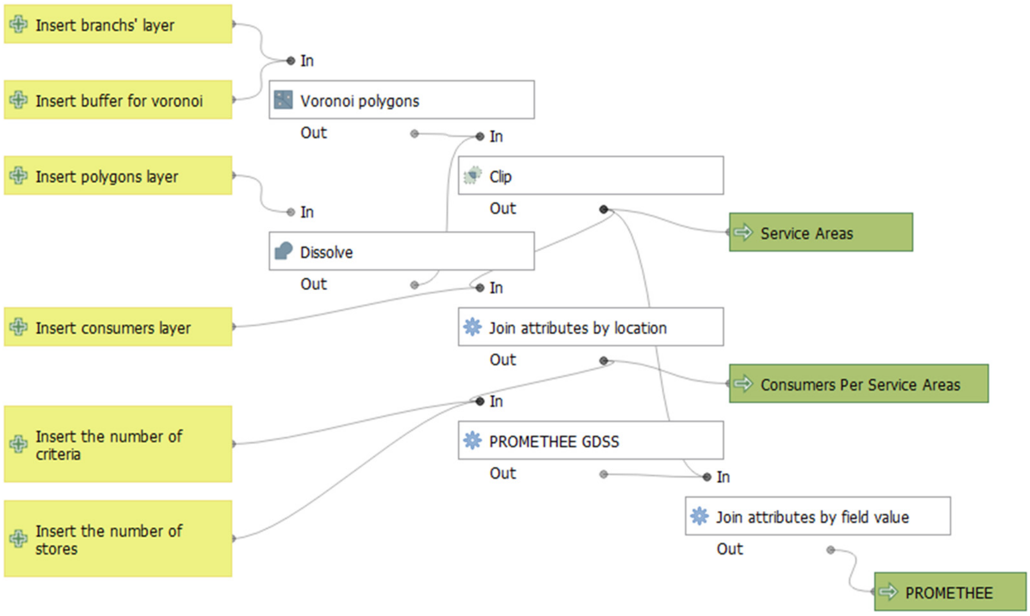


Figure 3. Spatial CS-GDSS PROMETHEE Model Workflow in Graphical modeler.

The first part of the workflow is about the service area formation (Figure 4b). For that, the "Voronoi polygons", "Clip", and "Dissolve" tools are used. The "Voronoi polygons" tool enables partition of an area using convex polygons that indicate the closest locations to the dataset used to generate them (Figure 4a). Voronoi polygons simulate the formation of service areas for the examined branches in the analysis. Consequently, Voronoi polygons are created using a buffer distance threshold and a point dataset that contains the examined coffeehouse's locations. The value of the buffer size ensures that the Voronoi polygons generated cover the entire area under investigation. To bring the analysis to the city block level of information, the "Dissolve" spatial operator is performed. The "Clip" tool restrains the boundaries of the "Voronoi polygons" output layer. Thus, the output of this stage of the analysis enumerates equal number of records with the examined branches' dataset and provides the "Service areas" output layer. The process aims to combine Voronoi polygons and city blocks datasets, returning a polygon dataset of the city blocks, consolidating city blocks in each one of the service areas examined.

Coffeehouse service area establishment allows for consumer locations allocation using the "Join attributes by location" processing tool by combining the "Service Areas" output layer and the "Consumers" input point dataset. The resulting output layer consists of the consumer features dataset that now facilitates an additional field consisting of the service's area id code. The third part concerns the results derived from the developed "CS-GDSS PROMETHEE" processing tool. To generate the overall analysis output layers, the developed model must be provided with the information on the number of CS criteria and the number of competitive stores integrated into the research. The PROMETHEE output layer encompasses comprehensive information pertaining to the positive and negative flows inherent in each coffeehouse, along with the net flows calculated for each establishment. The derived GUI generated by the QGIS graphical modeler is illustrated in Figure 5. It displays the model inputs and key metrics in a clear layout, requiring three input layers and three adjustable parameters to run the process. The 'Consumers' layer needs to contain responses coded from zero to four, the 'Polygons' layer needs to contain the city block data in polygon form, and the 'Branches' layer must contain the location of the company's stores.

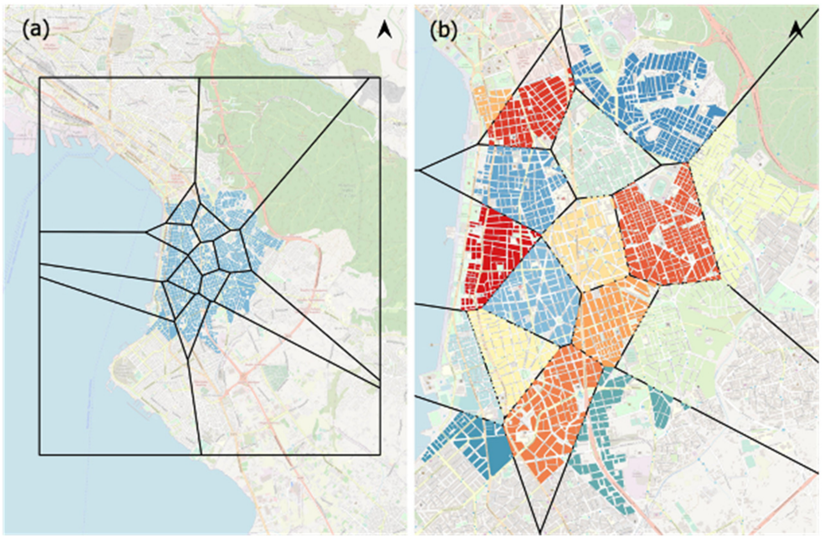


Figure 4. (**a**) Voronoi polygons' formation, (**b**) Voronoi service areas.

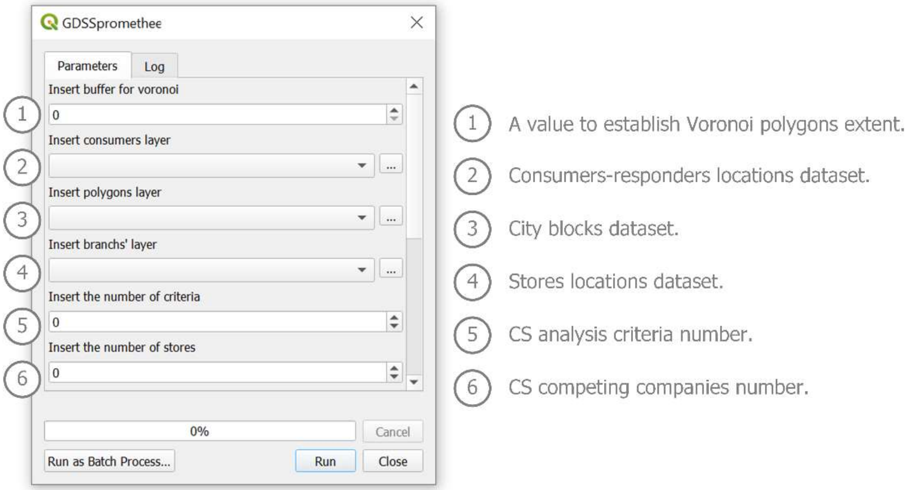


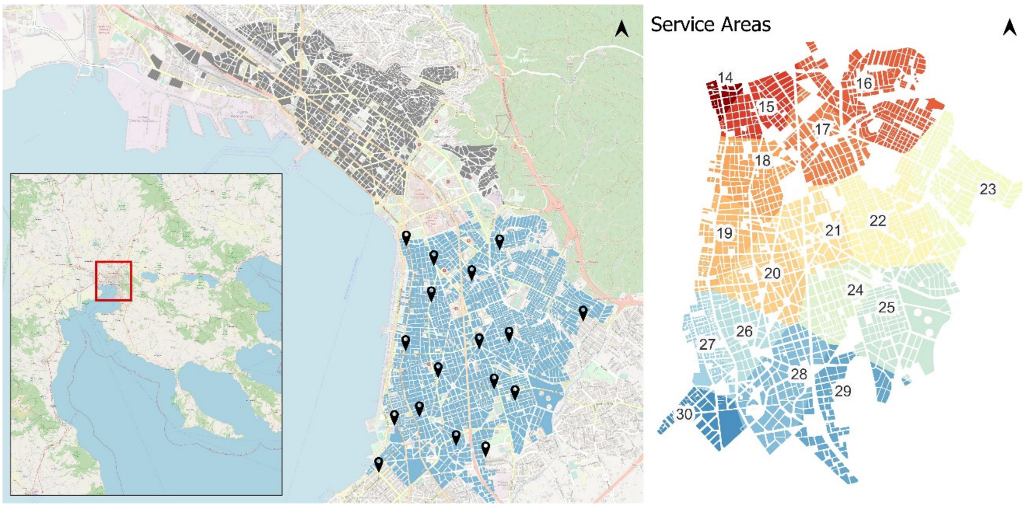
Figure 5. Model's GUI.

4. Case Study

4.1. Problem Formation

The proposed framework is applied in a case study, in the city of Thessaloniki, the capital of the prefecture of central Macedonia in Greece. The regional unit of Thessaloniki is the second biggest urban area in Greece with a population of 1,092,919. The largest municipality is Thessaloniki, with a population of 319,045 [64]. The city serves as a vibrant testament to its historical legacy. Throughout the ages, every period has imprinted its legacy through landmarks and points of interest scattered throughout the city. Moreover, owing to its strategic geographical position, it has been a focal point for numerous pivotal historical occurrences. As a result, the city draws in a multitude of tourists hailing from various parts of the globe. The total number of the municipality's building blocks is 2903 occupying a total area of 18.64 km^2 [65]. The primary objective of this research is to assess the performance of the stores in alignment with consumer preferences, utilizing the provided framework.

A comprehensive survey conducted by Kaparesearch in 2023 [66], commissioned by the Hellenic Coffee Association regarding Greek consumers' habits, reveals that coffee drinks are a highly lucrative industry within the catering sector. This extensive study, encompassing a sample size of 1003 individuals, revealed that 50% of the respondents consume more than one coffee drink on a daily basis. Coffeehouses in Greece offer delivery options for their products, a necessity that gained prominence, particularly during the COVID-19 era. The ownership under investigation encompasses a network of more than thirty coffeehouses distributed across Thessaloniki. Of this total, establishments located in the southern region are examined, as depicted in Figure 6a. The proposed framework is performed to obtain company branches' CS performance when compared with another two of its rivals.



(**a**) (**b**)

Figure 6. (**a**) Coffeehouses under investigation; (**b**) service areas formed for each coffeehouse.

The company under investigation established seventeen branches in the region, and it is noted that each coffeehouse within this subset is located at an approximate distance of 600 m from its nearest neighbor. According to Han et al. [67], the location of a store is a critical success factor that influences both the quantity and composition of sales. Location based on proximity estimations defines an area of influence widely known as a service area. Voronoi (or Thiessen) polygons (Figure 6b) were used to estimate the service areas of the examined coffeehouse branches because of their ability to partition the examined area based on the nearest neighbor rule. Thus, the coffeehouse branches' influence zone is defined by forming convex polygons that can be spatially visualized.

The total area under investigation consists of 1878 city blocks, occupying a living area of 11.09 km^2. The population in this total area is approximately 189,710. The survey successfully collected a total of 749 questionnaires in total, with the specific number of questionnaires per service area elaborated in detail and outlined in Table 1. Consumers' preferences were expressed according to five criteria reflecting their level of satisfaction. The questions were scored on a five-point Likert-type scale, ranging from completely dissatisfied to highly satisfied.

Table 1. Coffeehouses' ids and questionnaires gathered.

Store ID	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**
Responders #	20	44	57	37	43	60	54	44	60	50	43	52	48	34	54	21	28

The literature identifies several factors that influence CS, including product-related aspects, such as quality, diversity, and price; customer-related factors, such as perceived value, loyalty, and satisfaction; managerial factors, such as pricing, delivery speed, and service quality; and store-specific elements, such as store atmosphere and online food delivery services [68–74]. The manager of the company attempted to assess the company's performance based on the criteria outlined below. To begin with, consumers were asked to state their satisfaction regarding the prices offered by the store. Price has a direct impact on how consumers perceive the quality of the goods and services offered. As a satisfaction dimension, it has a direct impact on the store's profitability [68]. Price (Criterion 1) performance research assists companies in optimizing pricing strategies to maximize revenue and profit margins while remaining competitive [69]. Studying the impact of pricing on CS helps retailers strike a balance between offering competitive prices and meeting consumer expectations.

In addition, respondents were asked about the quality (Criterion 2) of the products provided, which is the cornerstone of a store's success [70]. Prioritizing the highest-quality standards meets consumer expectations and is a strategic differentiator in today's competitive business environment. Product quality can influence factors, such as reputation, inclination to switch, likelihood of repeat purchases, customer loyalty, and, ultimately, leads to high levels of CS [71]. Companies that regularly provide high-quality items set themselves up for long-term profitability and strong consumer connections.

For online shopping, delivery speed (Criterion 3) is a key factor in CS. The importance of this service cannot be neglected, given its direct relationship to the company's general image. Thus, it is examined as a discrete criterion in this research. Jie et al. [72], in their study, refer to the importance of delivery service and its relationship with CS. Maintaining a commendable level of delivery service quality is not only a necessity but also positions itself as a strategic advantage for the company in today's competitive environment.

The availability and diversity of products (Criterion 4) play a crucial role in shaping the overall shopping experience. Product diversity has a positive impact on CS by providing choices, enhancing the overall shopping experience, and meeting the specific needs of a diverse consumer base. The greater the product variety, the greater the CS is [73]. Moreover, having a diverse assortment means more than offering choices. It becomes a strategic asset that is carefully curated to meet the nuanced and specific needs of a diverse customer base.

Ordering platforms (Criterion 5) have a significant impact on CS, with efficiency, ease of use, and overall experience being key factors for consumers. The paradigm of online food delivery platforms and applications has evolved from a mere trend to an indispensable necessity, especially in light of the mobility restrictions imposed by the COVID-19 pandemic. In particular, in the context of Greece, online food delivery services rank prominently among the top three categories of online shopping [74]. In the Greek market, a number of ordering platforms facilitate the sale of products in different retail sectors, each with its own user interface.

The primary objective of this research is to delve into the analysis of CS in relation to the service area of each coffeehouse, with its competitors represented by two large prominent chains operating in the coffee sector. In order to assess consumer satisfaction, a questionnaire was designed that included the predetermined criteria as a basis for CS measurement. The respondents who participated in this study had to meet certain conditions. They had to be regular customers of the coffeehouse in their service area, and they had to have visited the two designated competing outlets that were also included in this study. A first overview of the results shows that most customers are moderately satisfied with the criteria 'price' and 'speed of delivery', with 27.24% and 25.63% of respondents rating these criteria in the middle of the Likert scale. On the other hand, for all the other criteria, 'quality', 'diversity of products', and 'ordering platforms', a significant proportion of customers expressed a high level of satisfaction, choosing a rating of four on the Likert scale for these aspects of the company surveyed (Company A). Specifically, the customer satisfaction rates were 24.83%, 33.64%, and 33.64% respectively. While these results provide a broad understanding of the company's performance across all the criteria surveyed, they primarily represent a general view. Without deeper, location-specific insights, it is difficult to assess how well each store is meeting customer expectations. Therefore, the analysis is further broken down by service area to better understand the impact of each criterion on specific stores. By focusing on individual stores, analysis can show how factors such as price, speed of delivery, and quality vary locally, which can reveal unique trends, strengths, or areas for improvement within specific regions. This localized approach is essential to gain actionable insights and ensure that each store is effectively aligned with customer expectations.

4.2. Results

The study of coffeehouse performance based on CS yielded comprehensive and nuanced results. Based on the results provided by the CRITIC and GDSS PROMETHEE methods, maps were created that provided insights for store benchmarking analysis. Initially, the research focused on the service areas of Company A, which is the retailer under investigation. Figure 7 provides a visual representation of the results derived from the positive (Series A) and negative (Series B) flows generated by the GDSS-PROMETHEE application. Higher values of positive flows indicate the outranking capacity when compared with its rivals in the specific service area.

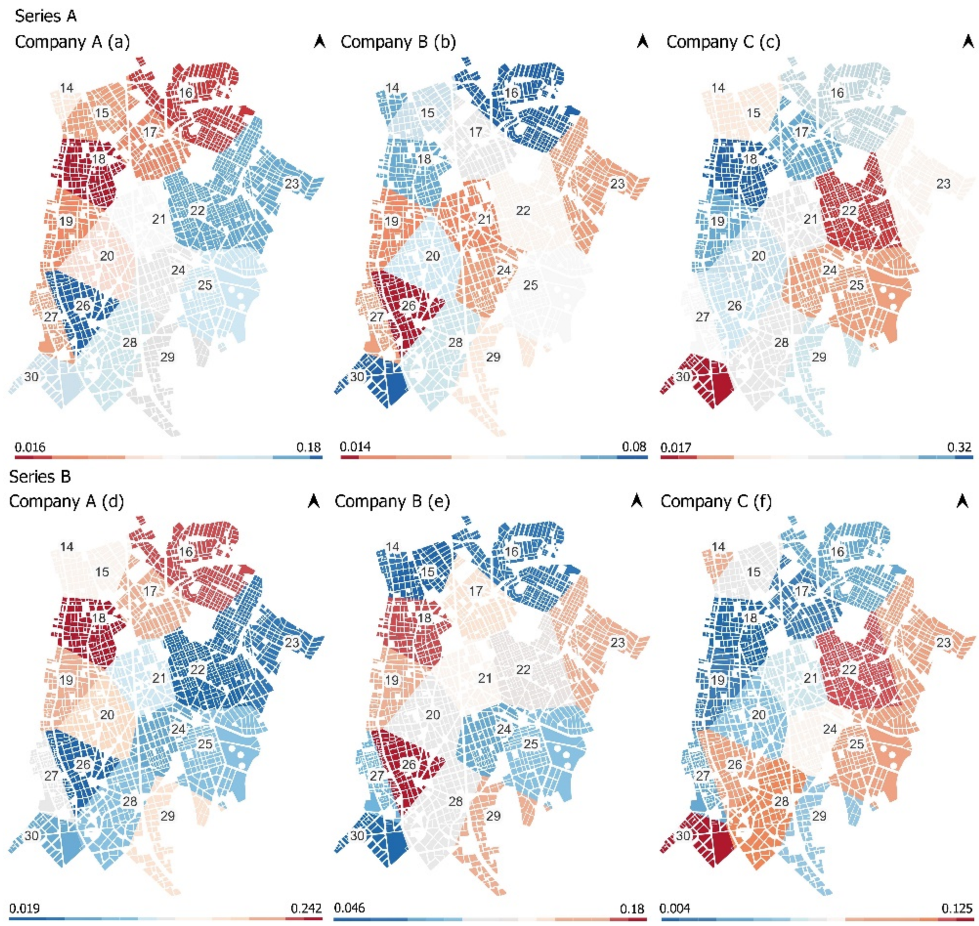


Figure 7. Positive (Series A) and negative (Series B) flow values per company.

On the contrary, high values of negative preference flows indicate that the store is outranked by its competitors in its area of influence. The details of this diagram unfold as Figure 7a,d show the positive and negative store flows corresponding to Company A across the service areas formed for each of its individual stores. In addition, Figure 7b,e and Figure 7c,f present the positive and negative flows associated with Company B and

Company C, respectively, within the service domains originally designated for Company A's operations. Company A's store 26 performs the best, as indicated in Figure 7a,d. Oppositely, the positive flows of stores 18 and 16 are the lowest of all, indicating low outranking capacity. Additionally, their negative flows are the highest derived, which denotes their outranked nature.

In the detailed analysis depicted in Figure 7, Company A's store 26 emerges as a notable focal point among its stores, showcasing the highest positive flow value Φ_i^+ of 0.180 (Figure 7a) and concurrently the lowest negative flow value Φ_i^- of 0.019 (Figure 7d). Table 2 illustrates the positive and negative preference flows derived by the GDSS PROMETHEE tool developed to assist CS analysis for each one of the stores of the company under investigation. This dual distinction underscores store 26′s unparalleled performance in comparison to its counterparts within the company's chain. The high value of the positive flow indicates the superiority of the alternative over all others, while a small value of the negative flow emphasizes its resistance to being outranked by other alternatives and vice versa.

Table 2. Positive Φ^+, Negative Φ^- and Net Φ^{net} flows of each company in Company's A service areas.

Store ID	Positive Flows			Negative Flows			Net Flows			Rankings		
	A	B	C	A	B	C	A	B	C	A	B	C
14	0.063	0.070	0.056	0.058	0.053	0.077	0.005	0.017	−0.022	2nd	1st	3rd
15	0.045	0.059	0.056	0.059	0.046	0.056	−0.014	0.013	0.000	3rd	1st	2nd
16	0.028	0.079	0.100	0.124	0.056	0.028	−0.096	0.024	0.072	3rd	2nd	1st
17	0.036	0.051	0.128	0.108	0.087	0.020	−0.072	−0.036	0.108	3rd	2nd	1st
18	0.016	0.064	0.320	0.242	0.154	0.004	−0.226	−0.090	0.316	3rd	2nd	1st
19	0.043	0.033	0.168	0.104	0.121	0.020	−0.060	−0.088	0.148	2nd	3rd	1st
20	0.057	0.054	0.089	0.075	0.078	0.047	−0.018	−0.025	0.043	2nd	3rd	1st
21	0.075	0.032	0.074	0.046	0.085	0.051	0.029	−0.053	0.023	1st	3rd	2nd
22	0.126	0.048	0.032	0.021	0.080	0.105	0.105	−0.032	−0.073	1st	2nd	3rd
23	0.076	0.038	0.048	0.022	0.114	0.079	0.096	−0.077	−0.019	1st	3rd	2nd
24	0.085	0.050	0.051	0.033	0.065	0.064	0.043	−0.028	−0.015	1st	3rd	2nd
25	0.180	0.014	0.086	0.039	0.069	0.079	0.046	−0.019	−0.028	1st	2nd	3rd
26	0.048	0.038	0.063	0.019	0.180	0.081	0.161	−0.166	0.005	1st	3rd	2nd
27	0.085	0.056	0.063	0.052	0.068	0.029	−0.004	−0.030	0.034	2nd	3rd	1st
28	0.078	0.044	0.099	0.040	0.079	0.086	0.045	−0.023	−0.022	1st	3rd	2nd
29	0.103	0.080	0.017	0.071	0.101	0.049	0.007	−0.057	0.050	2nd	3rd	1st
30	0.076	0.038	0.048	0.028	0.047	0.125	0.075	0.033	−0.108	1st	2nd	3rd

Conversely, the evaluation of Company B's performance in the same area, as discerned from the judgments of the same group of consumers, presents a contrasting scene. Figure 7b reveals the smallest positive flow value (0.014), indicative of the relatively low performance, while Figure 7e exposes the largest negative flow value (0.180), signifying a substantial degree of underperformance in service area 26. This collective evidence positions Company B as the one having the lowest performance among the three companies under consideration. Focusing on Company C, the outcomes delineated in Figure 7c illustrate a praiseworthy positive flow value (0.086) concomitant with a comparatively disadvantageous negative flow value (0.081), as depicted in Figure 7f. This portends that Company A's consumers in the 26th store service area recognize Company C as their second-best alternative, as it outranks, and it is not outranked by, Company B's store.

Figure 8 presents graphical representations of the overall net preference performance of each company in the service area domains associated with Company A. On the left side of Figure 8 is a visualization of Company A's rankings derived from the GDSS PROMETHEE Φ_i^{net} values. Moving to the middle and right sections of the figure, distinct maps show the performance evaluations of Company B and Company C in the service areas established for Company A. Among all the coffeehouses that belong to Company A, the one that stands out as the top performer is identified by having the highest Φ^{net} value, specifically recorded at 0.161 (Table 2). This performance is associated with the coffeehouse designated with the unique identifier 26, as visually depicted in the left section of Figure 8. The coffeehouse designated as store 18 emerges as a focal point for further investigation due to its status as the lowest-rated performer (−0.226).

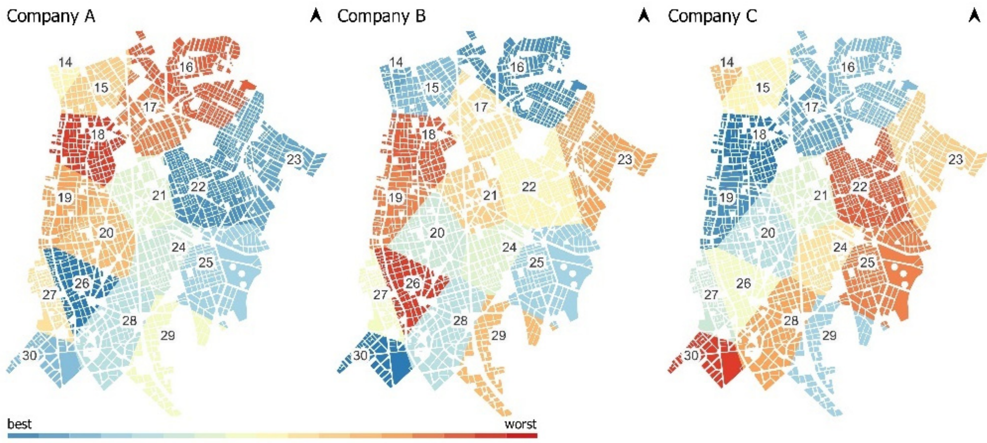


Figure 8. Φnet flows per service area for each competitive company.

Delving into the details presented in Figure 8, and particularly in the middle and right maps, it becomes apparent that in the specific service area pertaining to store 18, Company C exhibits the highest overall performance of 0.316. This observation implies that consumers prefer the coffeehouse affiliated with Company C over the other two competitors in the same vicinity. In the assessment of Company A's various stores, it is noteworthy that the store located in area 21, which is ranked in eighth position among Company A's stores, indicates a reference point that terminates Company A's superiority to both Φ_i^+, Φ_i^- and consequently Φ_i^{net} achieved performances. Figure 8 shows the Φ^{net} preference flows and the corresponding rankings, as estimated by the CS-GDSS PROMETHEE tool developed.

Hence, relying on the analysis of the net flows, it is discerned that within Company A's portfolio, a total of ten stores have positive outranking performance ($\Phi^{net} \geq 0$). Moreover, eight out of the seventeen stores surpass competitors in terms of ranking order, and five are ranked second, indicating a noteworthy overall performance. Conversely, the remaining six stores are ranked below their competitors. In the case of Company B, four of its stores have a positive Φ^{net}, among which only the stores in service areas 14 and 15 manage to receive the first ranking order. Similarly, Company C exhibits strong competition, with ten of its stores presenting an outranking profile ($\Phi^{net} > 0$) and seven presenting an outranked nature ($\Phi^{net} < 0$). However, the fact that Company C manages to obtain the first rank in seven areas and to register six positions in the second rank order shows that it is the strong competitor of Company A. The Φ^{net} estimations underscore the varied performance dynamics within each company's array of stores.

Figure 9 provides a visual representation of the companies distinguished by the highest Φ^{net} values, which serves as a noteworthy indicator of superior performance. Within the delineated service areas, focusing specifically on service areas 14 and 15, it is discerned that Company B claims the pinnacle with its third and fourth stores in terms of performance, registering Φ^{net} values of 0.017 and 0.13, respectively. In stark contrast, Company A trails with a Φ^{net} value of 0.005, and Company C exhibits a value of −0.022. Consequently, it becomes evident that these stores, affiliated with Company B, stand as a focal point for strategic attention. Elevating satisfaction ratings and surpassing competitors in this service area should be a paramount objective. It is evident that Company A's stores, specifically those designated as store 21 to store 26, together with those in areas 28 and 30, collectively showcase the most favorable Φ^{net} values when compared to their counterparts in the three competing companies. This overarching observation underscores the notable competitive advantage and commendable performance of Company A in the service areas evaluated.

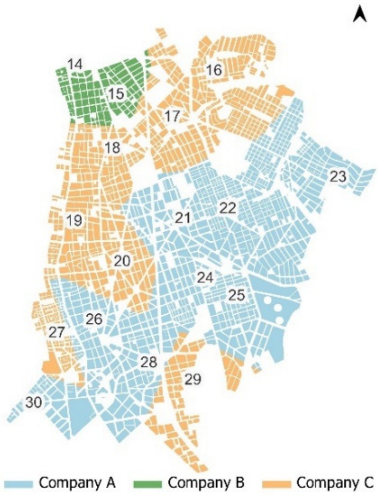


Figure 9. Dominant companies in the service areas formed according to Company A.

The scope of the analysis can be extensively expanded to explore consumer preferences with respect to the specified criteria. Table 3 provides a comprehensive overview by showing the average weight given to each criterion, by the consumers, across each service area. In particular, the consumers belonging to the service area of store 26 have explicitly emphasized the paramount importance of Criterion 4, attributing to it the highest average percentage of all respondents registered at 29.72. In addition, Criteria 1, 2, and 3 occupy intermediate positions in terms of importance, with weights of 17.01, 18.01, and 19.30, respectively. The analysis shows that Criterion 5 is the least important to consumers, with a weight of 15.96. Although Company C's store dominates Criterion 4 as its customers are very satisfied, at 75%, it suffers compared to Company A's store to Criteria 1 (4.2% vs. 58.3%), 2 (2.1% vs. 41.7%), and 3 (12.5% vs. 79.2%). As a result, Company A's store, which ranks first in this area, should sustain its high performance for Criteria 1, 2, and 3 and improve its performance for Criterion 4 to maintain its competitive advantage.

Table 3. Criterion weights' average (μ) and importance rankings per service area.

Store ID	Average Criteria Weights (%)					Criterion Importance Rankings				
	Cr. 1 [1]	Cr. 2 [2]	Cr. 3 [3]	Cr. 4 [4]	Cr. 5 [5]	Cr. 1	Cr. 2	Cr. 3	Cr. 4	Cr. 5
14	18.87	18.60	19.31	19.46	23.76	4	5	3	2	1
15	14.02	20.91	17.20	19.14	28.72	5	2	4	3	1
16	15.42	13.52	24.85	29.95	16.26	4	5	2	1	3
17	16.30	23.32	18.38	20.69	21.32	5	1	4	3	2
18	17.99	21.99	18.57	22.47	18.98	5	2	4	1	3
19	27.09	18.40	19.86	21.08	13.57	1	4	3	2	5
20	21.74	15.74	19.76	14.59	28.16	2	4	3	5	1
21	20.14	17.39	27.41	16.12	18.93	2	4	1	5	3
22	16.35	20.22	22.14	20.06	21.24	5	3	1	4	2
23	15.80	15.55	15.52	27.67	25.47	3	4	5	1	2
24	20.16	13.96	14.15	20.62	31.11	3	5	4	2	1
25	19.92	17.78	18.03	19.79	24.48	2	5	4	3	1
26	17.01	18.01	19.30	29.72	15.96	4	3	2	1	5
27	18.59	16.55	15.24	23.48	26.14	3	4	5	2	1
28	21.91	16.27	16.15	20.13	25.54	2	4	5	3	1
29	17.73	11.47	27.99	18.43	24.38	4	5	1	3	2
30	21.89	25.85	20.08	15.34	16.84	2	1	3	5	4

[1] Price criterion; [2] quality criterion; [3] delivery service criterion; [4] product availability and diversity criterion; [5] Ordering platforms criterion.

5. Discussion

5.1. Internal and External Benchmarking Analysis

Using the proposed framework based on the CRITIC and GDSS PROMETHEE methods, a benchmarking analysis is performed in two directions. The first is an internal benchmarking assessment, where each store is assigned to a quartile based on the Φ^{net} values estimated for the company's stores only. Such an analysis for Company A's stores indicates that branches 22, 23, 26, and 30 belong to the first quartile (Q1). Additionally, stores 21, 24, 25, and 28 are labeled as Q2, while stores 14, 15, 27, 29 and stores 16, 17, 18, 19, 20 belong to the third (Q3) and fourth (Q4) quartile, respectively (Figure 10I).

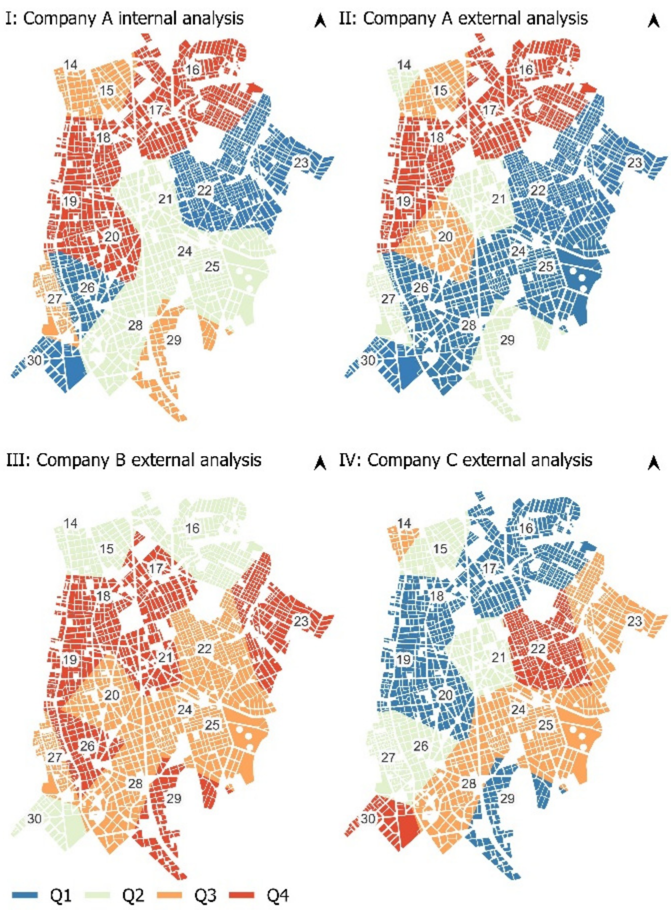


Figure 10. Internal (**I**) and external (**II**–**IV**) benchmarking analysis mappings.

The second consists of an external benchmarking assessment, in which the estimated performances for each company and for every service area are assigned to a quartile, taking into consideration the total of the estimated Φ^{net} preference flows. The analysis aims to generate benchmarking performance mappings that illustrate the examined alternative companies' quartile classifications. Such maps are numberless and allow for faster review of the analysis results, while they also enable the efficient identification of threats and opportunities. The external analysis for the coffeehouse companies examined is illustrated in Figure 10II–IV for each one of them.

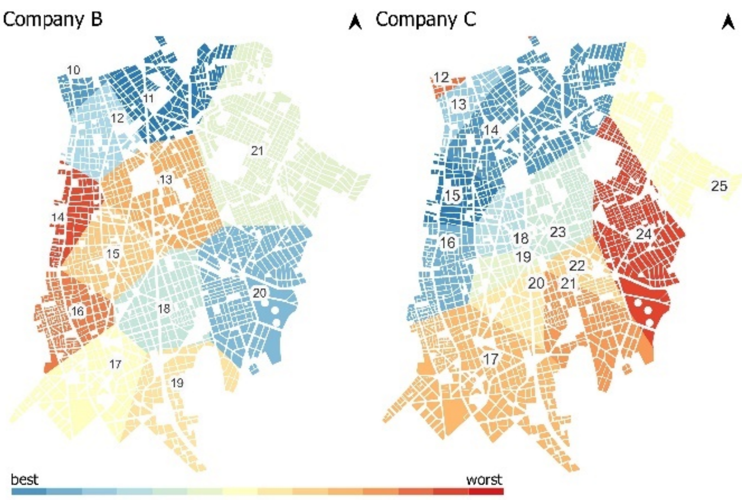
With respect to Company A, it is observed that it receives performance for the first and highest quartile (Q1) in seven of its service areas (22, 23, 24, 25, 26, 28 and 30). Stores in areas 22, 23 24, 25, 28 have secured their position as their performance is classified in the Q1 quartile, while their competitors belong to Q3 or Q4. In areas 14, 21, 27 and 29, its stores are classified as Q2. For the first area mentioned previously, the company holds the same classification as Company B (threat); however, improvements will open a window of opportunity, as none of the competitors are ranked in Q1.

On the other hand, Company A lags behind Company C in service areas 16, 17, 18, 19 and 20. Company B is also rated as Q4 in service areas 17, 18 and 19, indicating space where improvements can yield significant results. Stores 15 and 20 are classified as Q3. As there is no Q1 competitor dominating areas 14, 15, 21 and 27, improvements in the performance of Company A's stores can significantly strengthen their position. Undoubtedly, Company A's underperformance (Q4) in service areas 16 to 19 indicates that the stores in these areas are under pressure. These service areas are dominated by Company C's store performance (Q1).

5.2. Extending the Analysis to the Competitor's Service Areas

The questionnaire survey conducted for Company A also includes consumer preferences for the three competing coffeehouse chains (Companies B and C). Thus, the analysis can be extended to include the performance of the competitors considering their service areas. This approach uses competitor store location data to create service areas for each of the competing coffee chains. Subsequently, consumer responses are then effectively reassigned and reallocated to the derived service areas. In this way, the CS analysis is carried out in a manner similar to the respective study company, with the aim of mapping the consumer preferences of the original study company to the service areas of the competitive stores.

Within the study area of Thessaloniki, Company B claims ownership of twelve stores, while Company C has a total of fourteen stores. Figure 11 illustrates the rankings determined by the Φ^{net} flows that correspond to the rival companies' store service areas. The leading store for Company B, as determined by net flows, is store 11. It is worth noting that this store's service area almost overlaps with that of Company A's stores 15, 16, 17. Despite this geographical proximity, Company A's stores rank lower than Company B's best-performing store (Figure 11a). Company C's store with the highest performance, as determined by consumer preferences, is store 15 (Figure 11b). Store 15 is in close proximity to Company A's stores 18 and 19, and consumers in these service areas have expressed a preference for Company C's stores. For Company B, store 14 stands out as the one with the least favorable performance, while for Company C store 24, does the same.



(**a**) (**b**)

Figure 11. Rankings obtained with respect to competitor's store service areas for (**a**) Company B and (**b**) Company C.

Based on the values obtained from the Φ^{net}, it can be seen which company excels in each of the service areas designed for the analysis of each competing coffeehouse chain. Considering the service areas configured for Company B, it is derived that its outranking capacity is restricted to the influence area of store 10. For the remaining eleven service areas, Company B is outranked by Company A in six cases and by Company C in five

(Figure 12a). Additionally, the same analysis performed for Company C, as shown in Figure 12b, indicating that Company C excels in four cases, while Company A's stores perform better in six service areas.

(**a**) (**b**)

Figure 12. Dominant companies in the service areas formed for (**a**) Company B and (**b**) Company C.

6. Conclusions

In the era of dynamic market landscapes, CS research has become a critical tool for retail organizations. This study explores the profound importance of CS research coupled with benchmarking analysis to improve retail store performance and understand the performance of a company's competitors. Companies can benefit from the results obtained to enrich their understanding regarding performance estimation and to identify potential opportunities for future investments. By delving into these specifics, it becomes possible to tailor promotional campaigns for the products, crafting customized strategies that align with the distinct characteristics of each service area. The proposed framework provides a performance analysis of the company under study inside the service areas of its stores, assisting both internal analysis and external benchmarking analysis. Internals analysis mappings highlight the best (Q1) and the worst (Q4) stores in terms of CS as well as those that have opportunity potential (Q3) and those at risk (Q3). Such an analysis allows administration officers to identify stores that receive lower performances and to investigate improvement actions. These actions should be in line with improvements to the most important criteria. The intensity of the improvement actions can be decided using dominance analysis and external benchmarking analysis mappings where the most competitive rival can be obtained. Large deviations in the estimated preference flows indicate the amount of effort that should be made to gain better rankings. The analysis is further extended when investigating the performance of competitors, as the locations of their stores are also known. It can also be used to assist consumer preference analysis in the service areas of its competitors, aiming to highlight areas of dominance or competitive pressure.

CS is influenced by many factors; thus, it can further be considered a multi-criteria problem, as the satisfaction dimensions can be seen as the analysis criteria. In addition, consumer preferences drawn from the company's clientele can be used to calculate satisfaction. Since the number of consumers is large, the problem can be treated as a group decision problem. The proposed framework suggests the CS-GDSS PROMETHEE method, as it provides, in addition to a ranking, the degree of superiority of the stores by estimating preference flows. As the PROMETHEE method does not support criteria weighting procedures, the framework introduces an integration with the CRITIC method. The main advantage of adopting the CRITIC method for eliciting weights is that the weights are extracted directly from the consumers' preferences decision matrix without burdening the questionnaire with additional questions and ensures a unified criterion weight elicitation environment.

PROMETHE spatial analysis tool integration is not just a strategic choice but an essential component for sustaining and thriving in the competitive retail environment. The spatial extension of the method provides a geomarketing tool that assists marketers in taking more efficient decisions. The main advantage of the proposed framework is that it embodies preferential variations in terms of criteria importance and preference flow estimations. However, future research should enable decision model variation development per service area. In that manner, the analysis will gain flexibility, with emphasis given to the criteria under consideration for each store evaluation performance estimation. Product differentiation provided by a company can overcome distance-related attractiveness limitations. Therefore, the proposed framework is designed to address CS benchmarking analysis among companies of the same magnitude. In the current analysis, the surveyed companies offer almost the same range of products, and this is the main reason for not including other smaller and more neighborhood-oriented coffeehouses in the analysis. Moreover, it is expected that consumers' preferences will change over time. Thus, the analysis should be periodically implemented to enable spatiotemporal characteristic monitoring. An updated version of the computational tool in the future could support such an analysis. Although the process of exploring the potential reasons for the varying importance of the criteria is beyond the scope of the current work, it is a valuable direction for future research. Finally, it should be noted that even though the PROMETHEE method is a well-known approach in operations research, in many cases, assistance should be provided during the results interpretation phase. In that direction, quartile analysis simplifies the result readability by non-expert users.

Approaches utilized to investigate CS implemented out of the spatial context provide results that do not take into account the location characteristics of consumers. The proposed framework is the first in the relevant literature to provide a decision flowchart that combines GIS functionalities and MCDA methods. It establishes an evaluation model that assists the comparative analysis of multistore companies based on consumer perceptions and, thus, extends the traditional CS studies from a global to a local-oriented perspective. Technically, this is achieved by assessing the impact of individual stores within a retail chain based on CS and extends the scope of field studies to the spatial context. This extended investigation is crucial to elucidate the relationships that define how consumers perceive and evaluate each specific store within the entire chain. A more insightful understanding of the performance of the chain's stores can be gained by delving into the different aspects of the consumer experience in the various service areas covered by the company.

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