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## **APPLYING THE STEM APPROACH TO MULTI-CRITERIA DECISION-MAKING IN E-COMMERCE**

*In modern management, decision-making is no longer limited to one-objective problems. While managerial decisions used to be typically aimed at remedying a single specific objective in the past, this has increasingly become archaic. Today, managers must make complex decisions involving multiple, often competing targets in multiple domains. These targets may compete with each other or originate from different domains, which makes the process of decision-making much more intricate.*

*This paper presents both the theoretical foundations and actual application of the STEM (Step Method) approach to multi-criteria decision-making with particular focus on its use in the field of e-commerce. The STEM process is designed to examine goals objectively and find the best solutions for their accomplishment. The STEM process is based on the objective evaluation of multiple and conflicting objectives and finding a balanced solution with minimum deviations from the ideal target values. This is achieved through the minimization of the Chebyshev distance, which is a powerful tool in decision-making issues with multiple and incompatible objectives.*

*While multi-criteria decision-making techniques have gained popularity and have been applied in many areas like supply chain management, marketing strategies, and customer behavior analysis, their application in optimizing multiple performance indicators in the context of e-commerce platforms is still limited, especially in the context of the STEM approach with the application of the Chebyshev distance and actual performance data. This study aims to bridge this gap with a proposal for the application of the STEM approach in the context of e-commerce analytics.*

*A real-world application is presented with 24 months of actual data on e-commerce platforms, with the optimization of two performance indicators: sales and page views.*

**Keywords:** *multi-objective decision-making, e-commerce, STEM method, Chebyshev distance, decision-making*

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**INTRODUCTION.** Whenever several objectives must be optimized in a high-level decision-making scenario, the methods of single-objective optimization usually fail to provide well-balanced, practical solutions. Business analytics, for instance, involves optimizing sales, customer engagement, and other usually conflicting factors simultaneously, requiring a more flexible and holistic approach. Within such contexts, MCDM methods have emerged as necessary tools, aiding informed data-driven decisions by systematically considering a variety of objectives and constraints.

The underlying methodology of the research is stepwise optimization, which integrates the fundamental principles of MCDM with advanced mathematical modeling to find effective trade-offs among conflicting objectives. The approach determines the minimum and maximum achievable values of each objective and evaluates the weighted impact of each objective on the overall decision. This approach will help not only in determining the optimal solutions but also in estimating the relative importance of each objective, thus enhancing transparency and robustness while making decisions.

While multi-criteria decision-making techniques have been widely applied in fields such as supply chain management, marketing strategy, and customer behavior analysis, there are limited studies examining the applicability and implementation of these techniques for optimizing multiple performance measures in electronic commerce platforms. This represents a significant scientific gap in the research area, which this study aims to fulfill.

Included is the use of the Chebyshev distance for measuring deviations from target values in identifying solutions that minimize the worst-case deviation across objectives for a balanced optimization. Hierarchical clustering algorithms like Agglomerative Clustering help in grouping similar solutions and giving insights into deeper patterns within the data.

A real-world example of simultaneous optimization of product order sales and page views over 24 months is shown to illustrate the methodology. The methodology will point out which month has the best trade-off between the objectives and what drives that outcome, namely clicks, impressions, click-through rates, and ad spend.

Overall, the proposed approach shows an effective integration of mathematical optimization, distance metric, and clustering for solving challenging real-world multi-criteria decision problems. The research also adds to the literature on data-driven business optimization, as it provides a framework for managers to evaluate performance on multiple objectives in an e-commerce setting, thus filling existing gaps in the literature.

**LITERATURE REVIEW.** Multi-criteria decision-making is the name given to a set of techniques used in the selection and ranking of alternatives based on different conflicting criteria. Research has indicated the use of MCDM in most of the e-commerce processes, such as selecting suppliers, marketing, and customer interactions. For example, Wang et al. (2021) applied fuzzy hierarchy process analysis (FAHP) and VIKOR fuzzy methods to evaluate third-party logistics (3PL) providers, emphasizing the use of systemic decision models for supply chain decision making. The integration of fuzzy logic allows for accurate exploration of uncertainties, which is vital for companies that depend on reliable logistics (Wang et al., 2021).

It is no secret that consumer behavior has always been in the spotlight, and it is the core for e-commerce researchers and marketers. So there are many studies trying to examine the influence of various factors on purchase decisions. For instance, Moore (2012) compared the relationship between customers and online clothing retailers. According to this author, fashion knowledge and product consideration have huge effects on decision-making. Obviously, it is consistent with the STEM approach, which considers a variety of factors when determining consumer preferences.

Dynamic pricing is another important topic in shaping consumer attitudes and behavior in e-commerce. Victor et al. (2018) identified a number of determinants that affect consumer reactions to pricing strategies, indicating the need for e-commerce businesses to align pricing models with customer demand Victor et al. (2018). Based on MCDM methods, retailers are able to analyze the implications of different pricing strategies and enhance competitive advantages.

There have been a number of studies that proposed frameworks for understanding the dynamics of decision-making in e-commerce. For example, (Kuntoğlu et al. 2020) introduced the critical review of indirect tool condition monitoring systems and decision-making methods in turning operations, which can be used analogously to assess e-commerce strategies (Kuntoğlu et al., 2020). Their conceptualization of decision-making strategies can guide e-commerce companies in assessing their operational efficiencies.

Moreover, Kurdi et al. (2022) examined the influence of online marketing channels on the buying behavior of consumers based on eWOM in Jordanian markets. Their research highlights the importance of integrating various marketing activities into decision-making to enable firms to prioritize their activities based on consumers' reviews and market trends (Kurdi et al., 2022).

While there are some useful observations in the literature regarding applying MCDM to e-commerce, there are still knowledge gaps. First, there is limited information on how different MCDM methods, i.e., STEM methods, can be effectively applied in specific e-commerce environments. Most studies have found specific issues, such as logistics or marketing strategy, in isolation, without considering their interdependence as a whole.

Furthermore, the evolution of consumer behavior in response to the emergence of new technologies, such as machine learning and artificial intelligence, on e-commerce sites has also not been comprehensively studied.

Future research should explore how these technologies can be utilized for enhancing MCDM models, providing more adaptive and responsive decision-making processes.

**METHODOLOGY.** Decision-making is the process of selecting the best alternative among presented alternatives using analytical, computational, or predictive techniques. For this purpose, all alternatives have to be analyzed in depth. Even if there are several objectives in the problem, studying each objective separately by going through its possible alternatives, criteria, and factors is also important. This is called Multi-criteria Decision Making (MCDM, Benayoun et al, 1971). In this study, MCDM is applied to evaluate performance trade-offs in an e-commerce environment.

The application of MCDM methods can be seen in various aspects, from daily life to organizational management processes, and even in problem-solving at the global level. MCDM can be applied in any field, and some of the characteristic features that are common in this method are diversity, conflicting criteria, incompatibility of units, and the presence of alternatives.

Criteria are of objective or attribute type depending upon their nature. Due to this reason, problems of MCDM are divided into two types:

1. Multi-objective Decision Making (MODM),
2. Multi-attribute decision making (MADM).

While MADM is applied when alternatives are predefined by the decision-maker, MODM, on the other hand, is applied when alternatives are generated with the aid of mathematical models.

In this study, the MODM technique was applied, as the problem involves the simultaneous optimization of multiple objective functions, **where monthly performance alternatives are generated through a mathematical optimization model rather than predefined choices.** Multi-objective Linear Programming (MOLP) is a formulation of the MODM problem, which seeks to optimize a number of linear objective functions simultaneously with a set of constraints.

Mathematically, a multi-objective problem can be expressed as follows:

$$(MODM) \begin{cases} \max f(x) \\ s. t. \quad x \in S \end{cases}$$

Where:

$f(x)$  is a set of  $n$  objective functions possibly in conflict with one another,  
 $x$  is an  $n$ -dimensional decision variable vector, such that  $x \in R^n$ .

In the case of **multi-objective linear programming**, the model can be written as:

$$(MODM) \begin{cases} \max f(x) = Cx \\ s. t. \quad x \in S = \{x \in R^n \mid Ax \leq b, x \geq 0\} \end{cases}$$

Where:

$C$  is a matrix of objective functions with dimensions  $k \times n$

$A$  is an  $m$  by  $n$  matrix of constraints,

$b$  is an  $m$  - vector,

$x$  is an  $n$  - vector of decision variables.

To reach an overall optimal solution, it is necessary to consider the following key concepts:

**Feasible solution:** This is the smaller subset of all present alternatives that comply with the given constraints. It defines the set of possible or acceptable alternatives.

**Most-preferred solution:** This represents the ideal objective values against which feasible solutions are compared within the decision-making framework. The main work of the STEM method is to measure the "distance" between the feasible and the preferred solution. To that end, a weight vector  $\theta$  is set, where:

$$\sum_{i=1}^k \theta_i = 1 \text{ and } \theta_i \geq 0.$$

These are the weights used to compute the weighted Chebyshev indices, which are a measure of how far away from the optimum a feasible one is, taking into account the relative importance of each objective.

$$\|f^x - f(x)\|_{\infty}^{\theta} = \max_{i=1, \dots, k} \{\theta_i | f_i^* - f_i(x) |\}$$

The STEM (Izadikhah et al, 2012) method is implemented in the following sequential steps:

### **Step 1: Optimization of Each Objective Function Separately**

This process begins by optimizing each objective function separately to locate its maximum, which can be attained. For each function  $f_i(x)$ , the following problem is solved:

$$f_i^+ = \max f_i(x)$$

where  $x$  is the set of optimal solutions. These optimal values are formulated in a matrix, the maximum possible under each objective.

### **Step 2: Determination of Minimum Values for Each Objective**

The second step is to define the smallest possible value of each objective:

$$f_i^- = \min f_i(x)$$

This creates a second matrix defining the unwanted or least desirable boundaries of each objective function.

### **Step 3: Determination of Weights based on Maximum Values**

In this step, the relative importance or influence of each objective function is quantitatively approximated using the maximum value matrix. The process approximates the relative effect  $\pi_i$  by calculating the difference in maximum and minimum values for each objective and how much it influences the decision-making process.

These values are used to find weight coefficients  $\lambda'_i$ , which describes how important each objective is within the broader decision-making space.

#### **Step 4: Calculation of Weights from Minimum Values**

Following the same procedure, but now with the minimum (worst-case) value matrix, a second relative impact  $\pi_i$  and weights  $\lambda'_i$  set are calculated. This provides more information about the impacts on the system of each objective's lower bound.

#### **Step 5: Solution Comparison and Selection**

In the last phase, every possible solution is assessed by computing a performance index  $Z$ , which indicates the largest deviation of the solution from ideal objective values, based on the weights determined earlier. The solution with the lowest value of  $Z$  is the most balanced since it minimizes the worst-case difference across all objectives.

In this study, the STEM method has been used in the context of e-commerce decision-making, where there is a need to optimize a number of objective functions that characterize the performance of a business. The objective functions used in this study were:

Maximize Order product sale:  $Y_1$

Maximize Page View:  $Y_2$

The objective functions were derived from a number of web analytics and digital marketing variables, such as Sessions, Impressions, Click-Through Rate, Cost Per Click, Average Sales per Order Item, and Clicks. The data used in this study were collected over 24 months and then used with the STEM method to identify the most efficient performance period of the business.

**ANALYSIS.** The STEM technique was employed for the analysis of 24 months of e-commerce data, and the objective was to maximize product sales ( $Y_1$ ) and page views ( $Y_2$ ). This was done through stepwise optimization and the Chebyshev distance criterion, which enables the determination of the most balanced month for the objectives. The indicators under study are as follows:

For product sales ( $Y_1$ ): Sessions ( $X_1$ ), Impressions ( $X_2$ ), Click-Through Rate ( $X_3$ ), Cost Per Click ( $X_4$ ), Average Sales per Order Item ( $X_5$ ), Clicks ( $X_6$ ).

For page views ( $Y_2$ ): Average Sales per Order Item ( $X_1$ ), Sessions ( $X_1$ ), Clicks ( $X_3$ ), Cost Per Click ( $X_4$ ), Click-Through Rate ( $X_5$ ), Impressions ( $X_6$ ).

Using these indicators, two objective functions are created to forecast sales and page views. The optimization process then proceeds with the STEM/Chebyshev method<sup>1</sup>, where the stepwise optimization of the individual objective functions and the Chebyshev distance criterion are used to find the solution closest to the ideal one.

Maximize the order product sales.

$$Y_1 = 5.55 + 4.15 \cdot x_1 - 5.04 \cdot x_2 - 2776.45 \cdot x_3 - 13.87 \cdot x_4 + 116.90 \cdot x_5 - 119.41 \cdot x_6$$

<sup>1</sup> According to the STEM method (Step 1).

Maximize Page View

$$Y_2 = 0.82 + 1.52 \cdot x_1 + 17.96 \cdot x_2 - 0.14 \cdot x_3 - 1.54 \cdot x_4 - 0.35 \cdot x_5 - 1.58 \cdot x_6$$

We are to determine the values of  $Y_1$  and  $Y_2$  for each month and identify which month is optimal based on the objective functions. Since we have 24 months of data, we do the following:

1. Calculate  $Y_1$  and  $Y_2$  for each month.
2. Calculate  $d_1$  and  $d_2$  for each month in terms of standard deviations.
3. Calculate the  $Z$  values for each month
4. Select the month with the lowest  $Z$  value.<sup>2</sup>

For 24 months, we will have 24 solutions, and the best month will be the one with the lowest  $Z$  value. After determining the maximum values of  $Y_1$  and  $Y_2$ , we have:

$$Y_{1max} = 11690.79 \text{ (month 7)}$$

$$Y_{2max} = 12,263.93 \text{ (month 7)}$$

Thus, month 7 will contain the highest values of the  $Y_1$  and  $Y_2$  targets, which we should accept as optimal values. We then compute the Chebyshev criterion  $D$  for each month using those maximum values.

$$D_i = \max (Y_1^{max} - Y_{1i}, Y_2^{max} - Y_{2i}),$$

where

$Y_1^{max}, Y_2^{max}$  are the best possible values,

$Y_{1i}, Y_{2i}$ , are the actual indicators for the  $i$  month

For example, for month 7:

$$D_7 = \max (Y_1^{max} - Y_{17}, Y_2^{max} - Y_{27}), \text{ where}$$

$$D_7 = \max (11690.79 - 10983.39, 12263.93 - 12263.93)$$

$$D_7 = \max (707.43, 0) = 707.43$$

Or for month 6:

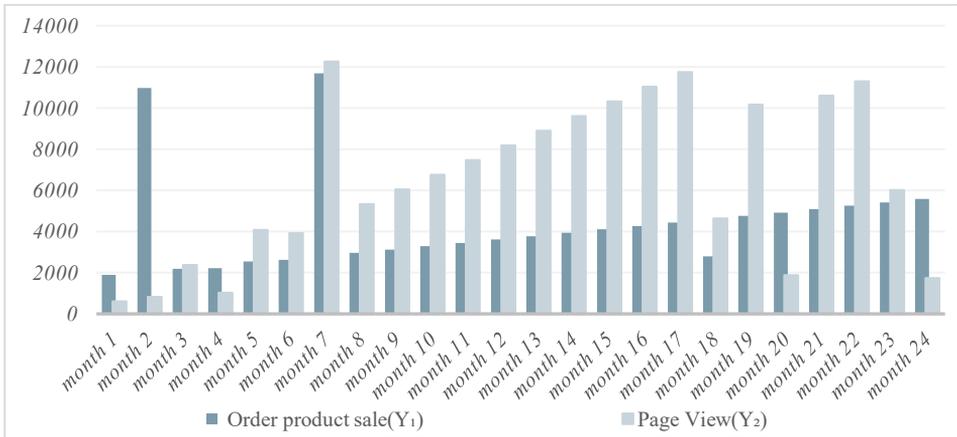
$$D_6 = \max (Y_1^{max} - Y_{16}, Y_2^{max} - Y_{26}), \text{ where}$$

$$D_6 = \max (11690.79 - 8566.97, 12263.93 - 2420.83)$$

$$D_6 = \max (3123.82, 9843.10) = 9843.10$$

The same procedure is applied to the remaining months, and the resulting vector is the Chebyshev distance for the respective objective function. From the matrix, we can see which months are most similar to one another (i.e., at least distance) and which months are relatively different. That is, the months can be divided in terms of similarity.

<sup>2</sup> The calculation was performed according to the STEM method described above.



**Figure 1. Chebyshev Distance Values for 24-Month Performance**

For example, months with similar results can be brought together into one cluster to explore them further. Agglomerative Clustering (hierarchical clustering technique) has been applied in an attempt to cluster the months. It is used to group objects based on their similarity to each other. Agglomerative clustering is a bottom-up clustering approach in which each object is first assigned to its own cluster, and the clusters are merged until a desired objective is achieved (e.g., the number of clusters or the minimum distance between clusters).

After applying the method, we see that month 7 has the smallest D value, which means that it is closest to the optimal values of the two objective functions.

As mentioned, the Chebyshev criterion determines how much the value of a given month deviates from the optimal values of the two objective functions  $Y_1$  and  $Y_2$ . It turns out that month 7 is the month that has the smallest deviation from the optimal values of the two objective functions. Therefore:

- According to the Chebyshev optimization method, month 7 is the best.
- Other months are less optimal as regards values, i.e., they do not reach the same value as regards sales, as well as the number of views.

Having already arrived at the best alternative month—here the 7th month—it also becomes important to learn about the values of the variables ( $x$ 's) for which the 7th month would be the optimum. These are:

1. Sessions ( $X_1$ ) = 1830.34
2. Impressions ( $X_2$ ) = 58.79
3. Click-Thru Rate ( $X_3$ ) = 0.24
4. Cost Per Click ( $X_4$ ) = 2.5
5. Average Sales per Order Item ( $X_5$ ) = 18.5
6. Cliles ( $X_6$ ) = 1.72

Having the above numbers, we are provided with a notion of what contributed to the successful outcome, both in sales and visit increase. The first trend was that Sessions ( $X_1$ ) and Impressions ( $X_2$ ) were high, thus contributing to the website's improvement. Additionally, a high CPC (Cost Per Click) indicates that the ad budget was enormously large, which must have provided targeted

visits. The increase in Click-Thru Rate ( $X_3$ ) and Clicks ( $X_6$ ) further indicates increased ad effectiveness and engagement.

**CONCLUSION.** Decision-making is a complex process regulated by numerous disciplines, including technological improvements, financial returns, social accountability, and management concerns. Resolving these multi-dimensional problems with the help of effective analysis requires the application of modern and dynamic methods, among which are MODM, STEM, and the method of Chebyshev distance.

The MODM method allows to easily select balanced solutions based on multiple criteria and constraints simultaneously. The STEM method, applied in stages, provides a consistent and comprehensive solution to problems through step-by-step identification of potential risks and benefits. The Chebyshev distance method, in turn, promotes objectivity in decision-making by defining the maximum discrepancies between alternatives, which is extremely important for selecting the optimal solution.

In the course of analysis by the STEM multi-objective optimization method with the utilization of the Chebyshev distance metric, it was discovered that the 7th month of the year yielded the most balanced outcome between two performance measures: product sales volume ( $Y_1$ ) and page views ( $Y_2$ ). The month attained the optimal values of the two objectives, but also realized the minimum deviation from their ideal values among any other month. The major reason for the high performance in month 7 was due to the increased Sessions ( $X_1$ ), Impressions ( $X_2$ ), Clicks ( $X_6$ ), and the high Click-Through Rate ( $X_3$ ), along with the high Cost Per Click ( $X_4$ ).

The study highlighted that in multi-objective problems, performance evaluation against a single objective may be insufficient. It is necessary to consider the interaction between more than one objective and to aim for balanced solutions. From this perspective, the STEM approach, supported by the Chebyshev method, provided a clear and comprehensive appraisal.

Thus, the ideal combination of these approaches facilitates not just broad analysis of complex problems but also setting well-weighed, considered, and lasting effective choices in different spheres—from technology to business management, while at the same time providing managers with useful and informed guidance on what certain variables imply in terms of overall e-commerce performance. Through the application of the STEM method, managers can make direct associations between analytical results and business decisions, including advertising budgeting, click-through rate optimization, and session engagement, thus making informed strategic decisions that improve both sales and customer interaction metrics.

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