

Retail Store Evaluation under Multiple Criteria in Thailand: A TOPSIS-Based Framework with Robustness Testing

Punn Natthapong Sangsuwan^{1*}

Abstract

The retail sector faces increasing complexity in evaluating store performance due to evolving market dynamics, competitive saturation, and digital disruption. To address these challenges, this study proposes a multi-criteria evaluation framework based on the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), enhanced with robustness testing. The framework integrates five dimensions—market potential, accessibility and visibility, competitive intensity, customer experience, and financial performance—to provide a comprehensive assessment of retail stores in Thailand. This study aims to develop and validate a structured, data-driven approach that assists retail managers in prioritizing investments and allocating resources under uncertainty. Five retail stores were analyzed using expert-derived weights, and two robustness tests ($\pm 10\%$ weight perturbation and Leave-One-Criterion-Out) confirmed the stability of the ranking. The results demonstrate that Store D consistently outperforms others, supported by strong accessibility, customer satisfaction, and financial indicators. The analysis also highlights clear differentiation between mid-tier and underperforming stores, offering managerial insights for resource allocation and strategic repositioning. The novelty of this research lies in extending MCDM applications to retail store evaluation with integrated robustness analysis in the Thai context. The findings contribute both theoretically, by enhancing methodological rigor, and practically, by providing an actionable decision-support tool for retail management.

Keywords: Retail management, Performance evaluation, Managerial decision-making

Introduction

The retail industry has become one of the most competitive sectors worldwide, shaped by rapid changes in consumer preferences, intensified market saturation, and continuous disruption from digital technologies (Ailawadi & Farris, 2017; Grewal et al., 2017). Retail managers must make complex decisions regarding where to expand, maintain, or divest store locations to sustain profitability and customer loyalty (Berman & Evans, 2018; Levy et al., 2019). Unlike purely financial decisions, retail store evaluation is inherently multi-dimensional, requiring consideration

¹ Lecturer, College of Innovative Business and Accountancy (CIBA), Dhurakij Pundit University, Thailand

* Corresponding Author e-mail: punnnatthapong.san@dpu.ac.th

of market potential, accessibility, competitive intensity, customer experience, and financial performance (Pan & Zinkhan, 2006; Brown & Burt, 1992).

In Thailand, the retail landscape has experienced a dramatic transformation. The expansion of modern trade formats, growing dominance of convenience stores, and rising competition from both domestic and international chains have redefined the competitive dynamics (Reardon & Timmer, 2014). Previous Thai studies have emphasized customer service, accessibility, and operational efficiency as key success drivers (Chaoprasert & Elsey, 2004; Ngaochay, 2011; Fongkam, 2015). However, systematic and integrated frameworks for retail store evaluation remain underdeveloped in the Thai context.

Multi-Criteria Decision-Making (MCDM) methods offer a promising approach to address this complexity. Tools such as the Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) have been widely applied in operations and supply chain management (Atthirawong & MacCarthy, 2002; Ho et al., 2010). Yet, their application in retail evaluation remains limited, and few studies incorporate robustness checks to validate results under uncertainty (Zolfani et al., 2013; Jangid et al., 2025).

The motivation for this study stems from the growing need for a structured, data-driven, and context-specific decision framework that enables retail managers in Thailand to make informed investment and location decisions under uncertainty. Traditional evaluation approaches in the Thai retail sector often rely primarily on experiential judgment or financial indicators, overlooking qualitative dimensions such as accessibility, customer experience, or competitive intensity. This gap highlights the need for a comprehensive analytical framework that systematically integrates both quantitative and qualitative dimensions into a unified decision-support model capable of producing transparent and robust results.

To address these gaps, this study proposes a TOPSIS-based framework for evaluating and ranking retail stores, enhanced with robustness testing through sensitivity analysis. Specifically, it seeks to answer three research questions:

- 1) How can multiple criteria, including market potential, accessibility, customer experience, competitive intensity, and financial performance, be systematically integrated into a unified framework for retail store evaluation in Thailand?
- 2) To what extent do store rankings derived using TOPSIS remain stable when subjected to sensitivity analyses such as weight perturbation and Leave-One-Criterion-Out (LOCO)?
- 3) What managerial insights can be drawn from the evaluation results to support retail investment decisions and resource allocation in the Thai market?

By addressing these questions, this study contributes both theoretically by extending MCDM applications in retail management through robustness testing (Hwang & Yoon, 1981; Chen & Hwang, 1992; Chen, 2000; Büyüközkan & Çifçi, 2012) and practically, by equipping Thai retail managers with an evidence-based decision-support tool for investment prioritization and risk management (Erbiyik et al., 2012; Fildes et al., 2022).

In summary, this study makes three major contributions.

- 1) It develops an integrated multi-criteria framework using the TOPSIS approach to comprehensively evaluate store performance across market, customer, competitive, and financial.
- 2) The proposed framework incorporates robustness testing (via sensitivity and LOCO analyses) to verify the stability and reliability of the evaluation results.
- 3) This study applies and validates this framework in Thailand's retail context, generating managerial implications for data-driven investment prioritization and resource allocation. These contributions collectively advance both methodological rigor and practical relevance in retail management research.

Literature Review

Retail Store Evaluation and Location Analysis

Retail store evaluation and location analysis have long been recognized as critical strategic decisions in retail management (Berman & Evans, 2018; Levy et al., 2019). Factors such as market demand, accessibility, customer demographics, and competitive intensity significantly influence store performance (Brown & Burt, 1992; Pan & Zinkhan, 2006; Theodoridis & Bennison, 2009). Accessibility and transportation facilities have been widely studied as determinants of store attractiveness (Teller & Reutterer, 2008), with some researchers also highlighting customer experience and service quality (Parasuraman et al., 1988).

In Thailand, empirical studies have emphasized similar issues. Ngaochay (2011) identified accessibility as a critical success factor for convenience stores in Bangkok, while Chaoprasert and Elsey (2004) found that service quality improvement significantly enhanced customer satisfaction in Thai retail banking. Fongkam (2015) highlighted the role of financial efficiency and location in shaping retail profitability. These findings suggest that while fragmented insights exist, a comprehensive framework that integrates all relevant dimensions remains lacking in the Thai retail context.

Multi-Criteria Decision-Making (MCDM) in Management Research

MCDM has emerged as a widely used approach for solving complex decision problems involving multiple and often conflicting criteria (Chen & Hwang, 1992; Ho et al., 2010). Methods such as AHP, ANP, and TOPSIS have been applied extensively in supplier selection, sustainability evaluation, and logistics (Atthirawong & MacCarthy, 2002; Šijanec Zavrl et al., 2009; Büyüközkan & Çifçi, 2012). In particular, the TOPSIS is favored for its simplicity, computational efficiency, and intuitive appeal (Hwang & Yoon, 1981; Chen, 2000). Despite these advantages, the application of MCDM in retail evaluation remains limited. Existing studies often address isolated factors and rarely incorporate robustness testing to validate result stability (Zolfani et al., 2013; Deveci et al., 2017). In Thailand's emerging retail market, where competition is intensifying, MCDM provides managers with practical tools for complex decisions that blend quantitative and qualitative considerations (Erbayrak et al., 2012).

TOPSIS Application in Business and Retail Context

The TOPSIS approach has been applied across various domains, including supplier evaluation (Ho et al., 2010; Singh & Benyoucef, 2011), e-sourcing (Pandey, 2016), and energy systems (Šijanec Zavrl et al., 2009). In retail contexts, some studies have used the TOPSIS approach to assess shopping mall attractiveness and customer satisfaction (Erbiyik et al., 2012; Zolfani et al., 2013). However, these studies are often narrow in scope, focusing on limited sets of criteria or neglecting sensitivity analysis. This limits their utility for managerial decision-making, as results may shift when assumptions about weights or criteria change. Recent research has stressed the importance of incorporating robustness testing to strengthen managerial confidence (Jangid et al., 2025). In Thailand, however, there remains little empirical evidence on the application of the TOPSIS approach with sensitivity analysis in retail store evaluation, representing a significant gap in both the literature and practice. Beyond traditional evaluation approaches, recent digital transformation trends have further reshaped how retail decisions are analyzed and optimized.

Digital Transformation and Retail Analytics

In recent years, the retail industry has undergone a significant digital transformation, reshaping how managerial decisions are made and evaluated. Emerging technologies such as artificial intelligence (AI), the Internet of Things (IoT), and data analytics have provided retailers with unprecedented access to real-time customer, operational, and financial data. Studies by Singh and Hess (2020), Kumar et al. (2021), and Mostaghel et al. (2022) highlight how retail analytics enable managers to integrate customer behavior insights, transactional data, and spatial information into decision-making processes. These developments align with the global shift toward data-driven and evidence-based retail management, where analytical tools enhance forecasting accuracy, store performance monitoring, and investment decisions (Chopra & Meindl, 2023). Integrating such digital analytics within MCDM frameworks like the TOPSIS can further strengthen managerial decision-making by combining quantitative rigor with real-time business intelligence. This integration emphasizes that modern retail evaluation should not only rely on static performance indicators but also leverage dynamic data sources to enhance responsiveness and competitiveness. Consequently, the present study aligns with the contemporary movement toward digitalized, analytics-enabled retail management and extends traditional decision-making models into the digital era. These developments establish the conceptual foundation for integrating digital analytics within MCDM frameworks, as discussed in the following section.

Research Gap and Contribution

While recent studies emphasize the growing importance of digital transformation and analytics in retail management, research on an integrated decision-support framework that combines these advancements with MCDM methods remains limited, particularly in the Thai retail context. The literature review reveals three key gaps. Firstly, prior studies have examined isolated factors rather than integrating multiple dimensions into a comprehensive framework (Pan & Zinkhan, 2006; Teller & Reutterer, 2008). Secondly, while MCDM methods are well established in

operations and supply chain research, their application in retail evaluation for Thailand remains limited (Atthirawong & MacCarthy, 2002). Thirdly, existing retail applications involving the TOPSIS approach rarely include robustness testing, leaving the stability of the results under varying assumptions uncertain (Deveci et al., 2017). This study addresses these gaps by proposing an integrated TOPSIS framework with sensitivity analysis for retail store evaluation in Thailand. Theoretically, it extends MCDM to retail evaluation by incorporating robustness checks. Practically, it provides managers with reliable insights for investment prioritization and risk mitigation in Thailand's highly competitive retail sector. Table 1 presents a comparative review of the contributions, methods, and limitations.

Table 1 Comparative literature review

Author(s) and Year	Context	Criteria Scope					Method	Limitation	How This Study Addresses the Research Gaps
		Mkt.	Acc.	Comp.	Cust.	Fin.			
Hwang & Yoon (1981)	Method foundation	-	-	-	-	-	TOPSIS	No application context	Applies the TOPSIS in Thai retail with sensitivity
Parasuraman et al. (1988)	Service quality (SERVQUAL)	-	-	-	✓	-	Survey	Narrow focus on service	Integrates the customer with other factors
Büyükoçkan & Çifçi (2012)	E-sourcing	~	-	~	-	✓	TOPSIS	Lacks customer/market	Expands to all criteria
Liu et al. (2013)	Logistics site selection	✓	✓	~	-	~	TOPSIS	Logistics-focused	Applies to the Thai retail context
Zolfani et al. (2013)	Mall attractiveness	~	✓	~	✓	-	TOPSIS/ AHP	Limited scope; no robustness	Adds sensitivity analysis
Deveci et al. (2017)	Supplier selection	~	-	~	-	✓	TOPSIS/ ANP	Not retail-focused	Transfers MCDM to retail
Hernández & Bennison (2000)	Store attractiveness	-	✓	~	-	-	Location analysis	Emphasis on spatial factors	Combines spatial with only customer & financial
Fildes et al. (2022)	Retail performance	✓	-	-	-	~	Statistical	Focus on demand only	Integrates five dimensions

Note: ✓ is fully considered; ~ is partially considered; - is not considered.

Criteria shorthand: **Mkt** is Market Potential, **Acc** is Accessibility and Visibility, **Comp** is Competitive Intensity, **Cust** is Customer Experience, and **Fin** is Financial Performance.

Methodology

Population and Samples

The population of this study consists of retail stores operating in metropolitan Thailand, where market saturation and competitive intensity are most pronounced (Reardon & Timmer, 2014). Five retail stores (anonymized as Stores A–E) were purposively selected for analysis. The selection was based on similarity in product categories, scale of operations, and strategic relevance to the firm's portfolio, reflecting established approaches in retail location and evaluation research (Brown & Burt, 1992; Theodoridis & Bennison, 2009; Berman & Evans, 2018). While the sample size may be limited, this case-based approach is consistent with prior MCDM studies, which emphasize methodological demonstration and managerial insight rather than statistical generalization (Ho et al., 2010; Zolfani et al., 2013; Deveci et al., 2017).

Research Instrument

Following the definition of the study population and sample selection, the research instrument consisted of a structured evaluation matrix with five main criteria and fifteen sub-criteria derived from previous literature and expert evaluation to systematically assess store performance (Parasuraman et al., 1988; Pan & Zinkhan, 2006; Teller & Reutterer, 2008). Each criterion presented in Figure 1 is operationalized into three measurable sub-criteria with defined measurement scales and directions (Benefit ↑ or Cost ↓), following established practices in MCDM and retail evaluation studies (Ho et al., 2010; Erbiyik et al., 2012; Fongkam, 2015).

Criteria	Sub-Criteria & Direction
 C₁: Market Potential	C₁₁: Peak footfall (persons/hour) Benefit ↑ C₁₂: Average household income in trade area (Baht/month) Benefit ↑ C₁₃: Population density (persons/km²) Benefit ↑
 C₂: Accessibility and Visibility	C₂₁: Walking distance to public transport (minutes) Cost ↓ C₂₂: Number of parking spaces Benefit ↑ C₂₃: Storefront visibility (meters) Benefit ↑
 C₃: Competitive Intensity	C₃₁: Number of competitors within 1 km Cost ↓ C₃₂: Distance to nearest major competitor (meters) Benefit ↑ C₃₃: Cannibalization within own chain (% overlap in sales) Cost ↓
 C₄: Customer Experience	C₄₁: SERVQUAL composite score (1–5) Benefit ↑ C₄₂: Net Promoter Score (NPS) Benefit ↑ C₄₃: Average waiting time during peak (minutes) Cost ↓
 C₅: Financial Performance	C₅₁: GMROI (%) Benefit ↑ C₅₂: Rent-to-sales ratio (%) Cost ↓ C₅₃: Payback period (months) Cost ↓

Figure 1 Criteria and sub-criteria with benefit and cost directions for retail evaluation

The selection of the five main criteria—market potential, accessibility and visibility, competitive intensity, customer experience, and financial performance—was guided by both theoretical foundations and managerial relevance. Foundational studies on retail location and service performance (Parasuraman et al., 1988; Pan & Zinkhan, 2006; Teller & Reutterer, 2008; Berman & Evans, 2018) provided theoretical justification for each dimension. These criteria were then refined through consultation with ten retail managers in Thailand, ensuring contextual relevance to the country’s market conditions and operational realities.

Furthermore, to ensure both theoretical rigor and practical relevance, a combination of literature-based and expert-derived approaches was adopted to enhance both construct validity and managerial applicability. The final set of weights was determined through expert judgment using consensus discussions, reflecting the strategic priorities commonly observed in the Thai retail sector, such as accessibility, service quality, and financial sustainability.

The TOPSIS approach was employed (Hwang & Yoon, 1981) because it combines methodological rigor with practical interpretability. Unlike pairwise comparison approaches such as the ANP, the TOPSIS does not require a large number of subjective judgments and can effectively handle both quantitative and qualitative indicators within a unified scale. Compared with VIKOR, which emphasizes compromise solutions, the TOPSIS directly measures each alternative’s geometric distance from the ideal and negative ideal solutions, an approach intuitively aligning with managerial decision-making in retail evaluation. Fuzzy MCDM variants were also considered during the conceptual phase; however, given the crisp nature of the available data and the objective of developing a transparent, replicable framework for practitioners, the classical TOPSIS model was deemed most appropriate.

Following the selection of criteria and validation of weighting consistency, the computational procedure of TOPSIS was implemented as follows:

Step 1: Constructing the Decision Matrix

$$X = [x_{ij}]_{m \times n} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}$$

Where m is the number of alternatives (retail stores), and n is the number of sub-criteria. This step organizes the raw data of each alternative (five retail stores) against the evaluation sub-criteria into a structured matrix for systematic comparison across stores.

Step 2: Normalization of the Matrix

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}}$$

Since criteria are measured in different units (e.g., Baht, percentages, Likert scales), normalization ensures fair comparison by converting all indicators into a common scale. This ensures comparability across different sub-criteria.

Step 3: Weighted Normalized Decision Matrix

$$V = \begin{bmatrix} r_{11}w_1 & r_{12}w_2 & \cdots & r_{1n}w_n \\ r_{21}w_1 & r_{22}w_2 & \cdots & r_{2n}w_n \\ \vdots & \vdots & \ddots & \vdots \\ r_{m1}w_1 & r_{m2}w_2 & \cdots & r_{mn}w_n \end{bmatrix}$$

Where w_{ij} represents the weight of the criterion j . Weights reflect managerial judgment regarding the relative importance of each criterion. For instance, if financial performance is considered more critical than accessibility, it is assigned a larger weight in this step. The weights were elicited from ten retail managers with expertise in operations, finance, and marketing, thereby ensuring consistency with managerial priorities in the Thai retail sector.

In addition, to enhance the credibility of expert-derived weights and reduce potential subjectivity, a reliability analysis was performed using Kendall's coefficient of concordance (w) (Kendall & Smith, 1939) to assess the degree of agreement among the ten participating managers. The coefficient is computed as:

$$W = \frac{12K}{a^2(b^3 - b)}$$

Where K is the sum of squared deviations of the average ranks for each criterion, a is the number of experts (10), and b is the number of sub-criteria evaluated (15). The resulting coefficient was tested for statistical significance using:

$$\chi^2 = a(b-1)W$$

The analysis indicated substantial agreement among experts ($W = 0.76$, $p < 0.01$), indicating strong concordance with the interpretation scale by Landis and Koch (1977). This result confirmed that the expert-derived weights were statistically consistent and provided a reliable foundation for subsequent TOPSIS analysis.

Step 4: Determining the Ideal and Negative Ideal Solutions

$$v_{ij}^+ = \begin{cases} \max_i v_{ij}, & j \in B \\ \min_i v_{ij}, & j \in C \end{cases} \Rightarrow A^+ = (v_1^+, v_2^+, \dots, v_n^+)$$

$$v_{ij}^- = \begin{cases} \min_i v_{ij}, & j \in B \\ \max_i v_{ij}, & j \in C \end{cases} \Rightarrow A^- = (v_1^-, v_2^-, \dots, v_n^-)$$

These equations establish benchmarks. The Positive Ideal Solution (PIS) represents the “best possible store,” while the Negative Ideal Solution (NIS) represents the “worst-case store.”

Step 5: Calculating Separation Measures

$$S_i^+ = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^+)^2}, \quad S_i^- = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^-)^2}$$

These calculations measure how far each store is from the ideal benchmark and how close it is to the worst benchmark. In business terms, this reflects the “performance gap” of each store.

Step 6: Closeness Coefficient and Ranking

$$C_i^* = \frac{S_i^-}{S_i^+ + S_i^-}$$

The closeness coefficient (C_i^*) shows each store’s relative closeness to the ideal profile. A higher value indicates stronger overall performance, guiding managers toward investment priorities.

Moreover, to assess the robustness of results, two sensitivity tests were integrated into the framework:

Weight perturbation ($\pm 10\%$): Each criterion’s weight was adjusted $\pm 10\%$, with other weights proportionally normalized. Rankings were recalculated to test stability.

Leave-One-Criterion-Out (LOCO): Each main criterion was excluded in turn to examine the impact on rankings.

These tests assure managers that the results are not overly sensitive to subjective judgments. Rankings remain credible even if managerial priorities shift or a dimension is overlooked.

Data Collection

Data were collected from three sources:

Market and demographic data: Household income, population density, and competitor presence (secondary sources).

Customer experience data: SERVQUAL-based (Parasuraman et al., 1988) survey (10 items, 5-point Likert scale) with 50 respondents per store, plus Net Promoter Score (NPS) and observed waiting times. In addition to the perceptual feedback obtained from SERVQUAL-based surveys, the proposed framework also recognizes the potential of incorporating behavioral analytics such as purchase frequency, transaction value, or loyalty program interactions. These

data points capture customers' revealed preferences and engagement intensity, complementing survey-based satisfaction measures.

Although behavioral data were not directly included in this study due to data access limitations, their integration would enhance the explanatory depth of the customer experience dimension and provide stronger predictive validity for retail decision-making. The incorporation of such behavioral metrics aligns with Thailand's growing adoption of digital CRM and loyalty systems, which are increasingly vital for data-driven performance evaluation.

Financial data: Rent-to-sales ratio, Gross Margin Return on Inventory (GMROI), and traffic conversion rate (internal store records).

Data were collected over two months, covering weekdays and weekends. Although inter-rater reliability was not formally tested, convergence among expert weights was achieved through iterative discussion. The complete dataset and corresponding weights are presented in Table 2.

Table 2 Decision matrix with criteria weights for retail store evaluation

Criteria and Main Weight	Sub-Criteria and Within Main Weight	Global Weight	Retail Store				
			A	B	C	D	E
C_1 (25%)	C_{11} (45%)	11.25%	422	312	259	510	191
	C_{12} (30%)	7.50%	58,342	41,287	36,412	65,198	34,379
	C_{13} (25%)	6.25%	13,876	9,462	12,084	17,245	8,137
C_2 (20%)	C_{21} (40%)	8.00%	6.3	4.1	9.4	5.2	11.7
	C_{22} (35%)	7.00%	19	35	12	28	8
	C_{23} (25%)	5.00%	8.4	10.9	7.2	12.7	5.6
C_3 (15%)	C_{31} (50%)	7.50%	8	6	11	5	9
	C_{32} (30%)	4.50%	698	1,198	452	1,503	603
	C_{33} (20%)	3.00%	7.3	3.2	11.8	4.1	17.6
C_4 (20%)	C_{41} (40%)	8.00%	4.12	4.28	3.72	4.49	3.36
	C_{42} (35%)	7.00%	22.4	34.6	8.3	41.7	5.2
	C_{43} (25%)	5.00%	4.6	2.4	6.1	3.1	7.4
C_5 (20%)	C_{51} (45%)	9.00%	209.7	261.5	159.2	289.8	140.6
	C_{52} (35%)	7.00%	13.7	9.3	15.6	10.6	17.1
	C_{53} (20%)	4.00%	14	11	19	12	21

Note: Global weight = (Main Weight) × (Within Main Weight).

Ethical Approval

All participants provided informed consent. Respondents were assured of anonymity, confidentiality, and the voluntary nature of participation. The study complied with Thailand's Personal Data Protection Act (PDPA) and was approved by an independent ethics review board.

Additionally, participants were informed that the collected data would be used strictly for academic purposes and stored securely to prevent unauthorized access.

Methodological Limitations

Three limitations are acknowledged:

Small sample size (five stores), suitable for methodological demonstration but limiting generalizability.

Use of expert-based weighting, which may involve subjectivity, although consensus was sought.

Context-specific nature of the Thai retail sector, which may not be generalizable to other markets without adaptation.

Despite these limitations, the methodological design provides a replicable foundation for future research aiming to validate or extend the proposed model using larger datasets, longitudinal data, or hybrid fuzzy–TOPSIS approaches, thereby strengthening its generalizability across different retail contexts.

Results

Normalized and Weighted Normalized Matrices

The first step involved normalizing the decision matrix to eliminate scale differences across criteria, followed by the application of managerial weights to reflect strategic priorities. Table 3 presents the normalized and weighted normalized values for the five retail stores across 15 sub-criteria.

Table 3 Normalized and weighted normalized matrices for retail store evaluation

Criteria	Sub-Criteria	Normalized					Weighted Normalized				
		A	B	C	D	E	A	B	C	D	E
C ₁	C ₁₁	0.528	0.391	0.324	0.638	0.239	0.059	0.044	0.036	0.072	0.027
	C ₁₂	0.536	0.379	0.334	0.599	0.316	0.040	0.028	0.025	0.045	0.024
	C ₁₃	0.493	0.336	0.429	0.613	0.289	0.031	0.021	0.027	0.038	0.018
C ₂	C ₂₁	0.359	0.233	0.535	0.296	0.666	0.029	0.019	0.043	0.024	0.053
	C ₂₂	0.368	0.687	0.244	0.552	0.166	0.026	0.048	0.017	0.039	0.012
	C ₂₃	0.403	0.523	0.346	0.610	0.269	0.020	0.026	0.017	0.030	0.013
C ₃	C ₃₁	0.458	0.333	0.584	0.284	0.508	0.034	0.025	0.044	0.021	0.038
	C ₃₂	0.320	0.550	0.207	0.690	0.277	0.014	0.025	0.009	0.031	0.012
	C ₃₃	0.317	0.139	0.513	0.178	0.765	0.010	0.004	0.015	0.005	0.023
C ₄	C ₄₁	0.459	0.477	0.414	0.500	0.374	0.037	0.038	0.033	0.040	0.030
	C ₄₂	0.377	0.582	0.140	0.701	0.087	0.026	0.041	0.010	0.049	0.006
	C ₄₃	0.406	0.212	0.538	0.273	0.653	0.020	0.011	0.027	0.014	0.033
C ₅	C ₅₁	0.427	0.532	0.324	0.590	0.286	0.038	0.048	0.029	0.053	0.026

Table 3 Normalized and weighted normalized matrices for retail store evaluation (Cont.)

Criteria	Sub-Criteria	Normalized					Weighted Normalized				
		A	B	C	D	E	A	B	C	D	E
	C_{52}	0.451	0.306	0.514	0.349	0.563	0.032	0.021	0.036	0.024	0.039
	C_{53}	0.394	0.303	0.536	0.336	0.594	0.016	0.012	0.021	0.013	0.024

Baseline Results of TOPSIS Evaluation

After applying the TOPSIS procedure, the baseline results indicating the relative performance of the five retail stores were obtained, as shown in Table 4. These values summarize each store's relative position against the ideal profile and provide a clear ranking for managerial consideration.

Table 4 Baseline TOPSIS results for retail store evaluation

Retail Store	PIS (S_i^+)	NIS (S_i^-)	Closeness Coefficient (C_i^*)	Rank
A	0.186	0.234	0.558	3
B	0.145	0.311	0.682	2
C	0.332	0.091	0.215	4
D	0.084	0.727	0.896	1
E	0.419	0.036	0.079	5

According to the results, Store D achieved the highest closeness coefficient, confirming its position as the most favorable location, while Store E ranked consistently lowest, reflecting its limited strategic potential. These results suggest that Store D should be prioritized for further investment and resource allocation. Stores B and A remain viable but require monitoring, while Stores C and E may necessitate strategic intervention such as operational restructuring, targeted marketing, or possible divestment.

Sensitivity Analysis: Weight Perturbation

To test robustness, the weight of each main criterion was perturbed by $\pm 10\%$, while other weights were proportionally adjusted. Table 5 presents the resulting rankings, all of which remained stable across scenarios.

Table 5 Sensitivity analysis results under $\pm 10\%$ weight perturbation

Retail Store	Baseline C_i^*	-10% Weight	+10% Weight	Rank Stability
A	0.558	0.545	0.566	Stable (Rank 3)
B	0.682	0.675	0.691	Stable (Rank 2)
C	0.215	0.224	0.209	Stable (Rank 4)
D	0.896	0.891	0.902	Stable (Rank 1)
E	0.079	0.082	0.077	Stable (Rank 5)

The stability indicates that the model is not highly sensitive to moderate weight changes, giving managers greater confidence in the reliability of the results. Even if managers alter their priorities, such as emphasizing financial outcomes over customer experience, the model consistently identifies Store D as the strongest candidate for investment. This robustness assures managers that strategic priorities can shift without undermining the credibility of the evaluation.

Sensitivity Analysis: Leave-One-Criterion-Out (LOCO)

A further robustness check was performed using the LOCO approach, with each criterion excluded in turn and the rankings recalculated. Table 6 shows the resulting outcomes.

Table 6 Sensitivity analysis results under LOCO

Retail Store	Baseline Rank	Criteria Excluding					Rank Stability
		C_1	C_2	C_3	C_4	C_5	
A	3	3	3	3	2	3	Mostly stable (2–3)
B	2	2	2	2	3	2	Mostly stable (2–3)
C	4	4	4	4	4	4	Stable (Rank 4)
D	1	1	1	1	1	1	Stable (Rank 1)
E	5	5	5	5	5	5	Stable (Rank 5)

The results confirmed that Store D consistently remained the top-ranked location, while Store E continued to be the least attractive. Stores A and B showed minor variations between the second and third ranks, but overall stability reinforced the reliability of the evaluation for managerial decision-making. This robustness provides assurance to managers that the model's conclusions are not driven by any single criterion. Even if financial or customer data are temporarily unavailable, the framework remains dependable. Similarly, when market conditions shift, such as sudden changes in rental costs or fluctuations in customer traffic, the model continues to provide reliable guidance.

To provide a comparative view of decision outcomes and demonstrate the consistency of the proposed framework, Figure 2 visualizes this stability across all baseline and sensitivity scenarios, clearly showing that Store D maintains its leading position while Store E persistently underperforms. Only minor rank shifts occur between Stores A and B, further underscoring the robustness of the proposed framework.

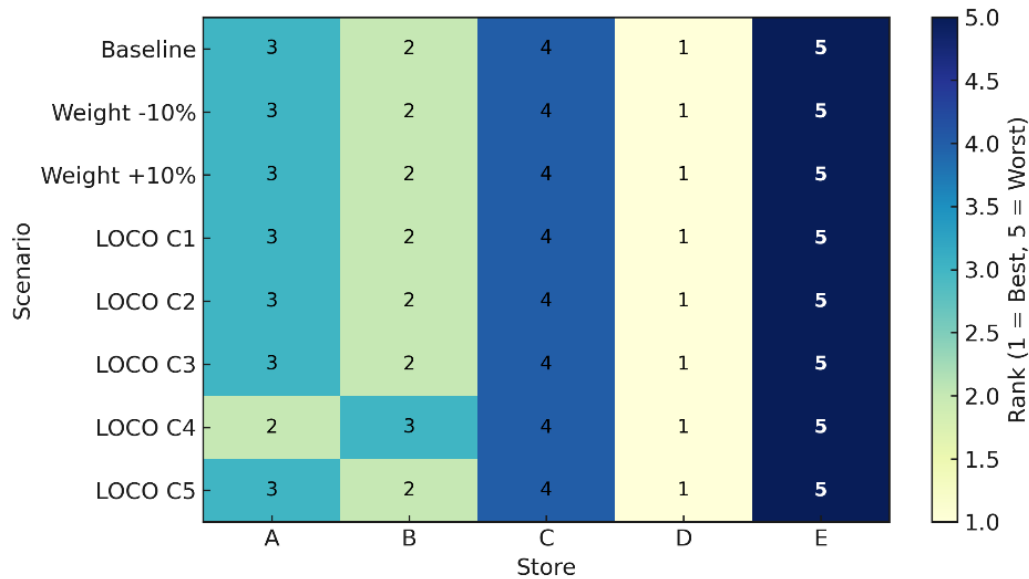


Figure 2 Stability of store rankings across baseline and sensitivity scenarios

In summary, the results provide consistent evidence that the proposed TOPSIS-based framework yields stable and reliable rankings across different evaluation scenarios. This robustness not only validates the methodological soundness of the approach but also strengthens its practical value for managerial decision-making, thereby setting the stage for the subsequent discussion.

Discussion and Conclusion

Building upon the quantitative results presented in the previous section, this discussion interprets the findings from theoretical, practical, and managerial perspectives. The results of this study provide strong evidence that MCDM frameworks, when applied systematically, can significantly enhance the quality of retail store evaluation. Using the TOPSIS approach, five retail stores were assessed across multiple dimensions: market potential, accessibility and visibility, competitive intensity, customer experience, and financial performance. The analysis produced a consistent ranking order, with Store D outperforming all others, while Store E persistently underperformed.

The superior performance of Store D can be attributed to its strategic advantages across multiple dimensions, particularly in terms of accessibility, market exposure, and customer satisfaction. Located in a high-traffic area with excellent visibility, it offers an optimized product mix that aligns with local demand and consistently achieves the highest customer satisfaction and NPS among all stores. Furthermore, Store D exhibits strong financial indicators, including the highest traffic conversion rate and stable gross margin return, confirming the robustness of its superior position under both baseline and perturbed conditions.

Stores A and B occupy a competitive middle tier, performing moderately well across most criteria. Both stores benefit from good accessibility and stable market potential, but achieve only average customer satisfaction and financial returns. Store A demonstrates strong service quality

yet lacks sufficient visibility and foot traffic, whereas Store B shows operational efficiency but faces intense local competition. In contrast, Stores C and E form the lower-performing group, reflecting more fundamental strategic and locational weaknesses. Store C maintains a balanced performance without major deficiencies; however, its moderate market exposure and limited differentiation constrain its competitiveness. Store E persistently underperforms due to weak accessibility, poor customer engagement, and below-average financial outcomes. From a managerial perspective, these findings imply that while mid-tier stores (A and B) may benefit from tactical improvements such as enhanced brand visibility and localized marketing, underperforming stores (C and E) require structural or locational interventions to achieve sustainable recovery.

This study adopts a case-based design involving five retail stores in metropolitan Thailand to demonstrate the proposed framework. While the limited sample size constrains statistical generalization, it aligns with the methodological aim of illustrating the framework's applicability rather than generating population-level inference. The stability of the rankings across sensitivity analyses reinforces the internal validity of the findings. Future research may further validate this framework by expanding the sample to include different formats, regions, and time periods, thereby enhancing external validity and scalability assessment.

Although this research focuses on five stores in metropolitan Bangkok, the framework is designed to be scalable and adaptable to broader contexts. The selection of stores within a single urban region ensures methodological control by minimizing external variation. However, extending the framework to other provinces or alternative retail formats such as community malls, specialty stores, or hybrid online-offline outlets could yield different weighting effects. For instance, in smaller towns, accessibility and market potential may play a lesser role, whereas customer experience and product mix could become more critical determinants of performance. Future applications should therefore validate ranking stability across store types and regions to confirm generalizability at the national level.

Theoretical Contributions

This study advances the literature on retail evaluation in three important ways:

Integration of multiple dimensions: Previous studies often emphasize isolated factors such as demand (Fildes et al., 2022), accessibility (Hernández & Bennison, 2000), or service quality (Parasuraman et al., 1988). By consolidating market, customer, competitive, and financial perspectives, this study demonstrates a holistic framework for retail evaluation.

Extension of MCDM into retail management: While MCDM methods such as TOPSIS have been widely applied in logistics, supplier selection, and sustainability assessments (Ho et al., 2010; Deveci et al., 2017), their application to retail evaluation remains limited. This study contributes by adapting and validating the TOPSIS approach for the retail domain.

Inclusion of robustness testing: Sensitivity analyses using $\pm 10\%$ weight perturbation and LOCO methods reveal that rankings remain highly stable. This enhances methodological rigor by ensuring that results are not overly dependent on subjective weighting

or single dimensions, an aspect often missing in retail-focused studies (Erbiyik et al., 2012, Zolfani et al., 2013).

Practical Insights into the Thai Retail Context

The results also hold direct managerial relevance, especially in Thailand's rapidly evolving retail landscape. For practitioners, this implies that Store D should be prioritized for investment, expansion, or strategic resource allocation, as it consistently emerges as the strongest location. Stores A and B provide moderate opportunities, and therefore, managers should consider tailored strategies such as localized promotions, service improvements, or targeted marketing to strengthen their competitive standing. Store C demonstrates stability but lacks the potential for significant growth, suggesting that managers may need to reposition its market offering or adjust operational focus. Store E's persistent underperformance across all scenarios signals limited viability, warranting managerial action in the form of significant restructuring or, if unfeasible, divestment.

These findings align with prior Thai studies emphasizing the importance of accessibility (Ngaochay, 2011), customer service innovation (Chaoprasert & Elsey, 2004), and operational efficiency (Fongkam, 2015) as key drivers of retail success. By systematically integrating these perspectives with financial metrics, the present study equips Thai retail managers with a structured and actionable decision-support framework for prioritizing investments and mitigating risks.

Furthermore, this study contributes to a broader understanding of data-driven decision-making within Thailand's retail sector. The proposed framework enables managers across both local chains and multinational retailers to objectively evaluate store performance, optimize resource allocation, and strengthen competitiveness. Such integration of MCDM and TOPSIS methods reflects the growing need for systematic, technology-assisted evaluation in Thailand's increasingly competitive retail market.

In operational terms, managers can apply the framework to three key areas:

- 1) Investment prioritization, to identify high-potential stores for expansion;
- 2) Performance monitoring, for early detection of underperforming locations; and
- 3) Strategic resource allocation, to optimize capital deployment and risk management.

Building on these managerial insights, actionable strategies can be derived from the ranking and sensitivity results. For underperforming stores such as Store E, managers may consider layout redesigns, product mix adjustments, or staff retraining to address service weaknesses. Mid-tier stores (A and B) should focus on customer engagement and localized marketing to sustain competitiveness, while Store C could pursue niche differentiation or partnerships with local suppliers. For the top-performing Store D, management should maintain its strengths through service consistency, optimizing inventory turnover, and model replication in demographically similar areas. The sensitivity analysis further provides a foundation for contingency planning: if priorities such as financial performance or accessibility change, managers can proactively reallocate resources to preserve overall network efficiency.

These recommendations ensure that the proposed framework not only identifies performance gaps but also supports continuous improvement and strategic adaptability, two critical capabilities in Thailand's fast-evolving, data-driven retail ecosystem.

Conclusion

In conclusion, this study demonstrates that the TOPSIS approach, when combined with sensitivity analysis, provides a robust and practical framework for retail store evaluation. Theoretical contributions include extending MCDM methods to the retail sector and validating their robustness under uncertainty. Practical contributions lie in offering retail managers in Thailand an evidence-based tool to prioritize investments, allocate resources, and manage risks in an increasingly competitive environment. For managers in Thailand's retail sector, this study concludes that robust MCDM frameworks such as the TOPSIS approach with sensitivity analysis can reliably guide expansion priorities, optimize resource allocation, and strengthen strategic risk management.

Beyond its immediate implications, the findings reinforce the growing significance of multi-criteria decision models in retail management. The results are consistent with prior studies emphasizing accessibility, service quality, and operational efficiency as key determinants of retail success (Ngaochay, 2011; Chaoprasert & Elsey, 2004; Fongkam, 2015). However, this study extends existing knowledge by integrating these determinants within a unified, data-driven MCDM framework, validated through robustness testing. Unlike earlier applications of the TOPSIS approach that focus on static or single-dimensional analyses (Erbiyik et al., 2012; Zolfani et al., 2013), the present research demonstrates that incorporating sensitivity analysis enhances the stability of results and managerial confidence.

Ultimately, this integration advances methodological rigor and practical relevance, providing a replicable model for future studies across other emerging retail contexts. Future research may further extend this framework by incorporating behavioral analytics or fuzzy-based extensions to enhance its adaptability to dynamic, data-rich retail environments.

Implications

Theoretical Contributions

This study offers several theoretical contributions:

Advancing MCDM research in retail: By applying TOPSIS to retail store evaluation, this study extends the methodological scope of MCDM beyond its traditional domains of logistics and supplier selection.

Integration of multi-dimensional criteria: The inclusion of market, customer, competitive, and financial dimensions within a single framework contributes to the growing body of research advocating holistic evaluation in business decision-making and aligns with calls for integrated retail evaluation frameworks (Pan & Zinkhan, 2006; Teller & Reutterer, 2008).

Incorporation of robustness analysis: By integrating weight perturbation and LOCO sensitivity tests, this research demonstrates the importance of methodological rigor, ensuring that MCDM applications produce reliable outcomes under uncertainty. Collectively, these contributions advance both the methodological and substantive boundaries of MCDM research.

Managerial Implications

The findings also generate practical insights for retail managers, particularly in Thailand:

Investment prioritization: Store D consistently ranks as the top location, making it the most viable candidate for expansion, increased resource allocation, or strategic partnerships.

Balanced portfolio management: Stores A and B form a competitive middle tier, where managers may deploy selective strategies such as location-specific promotions, service upgrades, or operational improvements to enhance performance.

Risk assessment: Store C's stable but limited performance highlights the need for repositioning or niche-market strategies, while Store E's persistent underperformance suggests that corrective measures or divestment may be required.

Decision confidence: The robustness of results across sensitivity analyses reassures managers that rankings remain reliable even when priorities or assumptions shift, thereby reducing uncertainty in strategic decision-making. Overall, the proposed framework equips managers with a structured decision-support toolkit, transforming abstract evaluation results into actionable guidance for investment, portfolio management, and risk mitigation in Thailand's retail sector.

Limitations and Suggestions for Future Research

Limitations

Although this study makes valuable contributions, several limitations should be acknowledged.

1) The analysis is conducted on five retail stores in metropolitan Thailand. While appropriate for demonstrating the methodology, this limited scope affects sample representativeness and reduces the ability to generalize findings across other retail formats or geographic regions. Expanding the sample could provide a more comprehensive understanding of retail dynamics.

2) The weighting of criteria relies on expert judgment. While this approach reflects managerial priorities, it may introduce survey bias or subjective influence despite the high inter-rater agreement validated by Kendall's coefficient of concordance ($W = 0.76, p < 0.01$). Broader surveys, anonymous rating methods, or data-driven techniques for deriving weights could help reduce bias and enhance reliability.

3) The context of the study is specific to Thailand's retail sector. Although the findings are relevant to other emerging markets, differences in consumer behavior, competitive structures,

and regulatory environments mean that caution is required when applying the results to mature economies.

4) The evaluation represents a static assessment, capturing performance at a single point in time. Retail environments are highly dynamic, and longitudinal or real-time studies would allow researchers to observe how store rankings evolve in response to shifting market conditions or technological changes.

5) The methodological approach, while robust, is limited to the TOPSIS approach with sensitivity analysis. Comparative studies that apply alternative methods such as AHP, VIKOR, fuzzy MCDM, or hybrid models incorporating machine learning could enrich insights and validate the robustness of the findings.

Suggestions for Future Research

1) Expand datasets to include larger and more diverse retail networks across regions and store formats.

2) Incorporate customer behavioral data (e.g., loyalty programs, purchase histories) alongside managerial evaluations for more granular insights.

3) Explore hybrid decision-making models that combine MCDM with optimization or predictive analytics for forward-looking evaluations.

4) Conduct cross-country comparative studies to examine whether robustness holds in varied retail ecosystems.

5) Future research could also explore the integration of fuzzy or probabilistic extensions of the TOPSIS approach to accommodate data ambiguity and behavioral dynamics in retail analytics, thereby enhancing adaptability and realism in decision-making under uncertainty.

Acknowledgment

The authors gratefully acknowledge the support of the College of Innovative Business and Accountancy (CIBA), Dhurakij Pundit University.

References

- Ailawadi, K. L., & Farris, P. W. (2017). Managing multi- and omni-channel distribution: Metrics and research directions. *Journal of Retailing*, 93(1), 120-135.
<https://doi.org/10.1016/j.jretai.2016.12.003>
- Atthirawong, W., & MacCarthy, B. (2002). An application of the analytical hierarchy process to international location decision-making. *Proceedings of the 7th Annual Cambridge International Manufacturing Symposium: Restructuring Global Manufacturing* (pp. 1-18). University of Cambridge, Institute for Manufacturing. Retrieved from
<https://www.researchgate.net/publication/242551654>
- Berman, B., & Evans, J. R. (2018). *Retail management: A strategic approach* (13th ed.). Pearson.

- Brown, S., & Burt, S. (1992). Retail location theory: Evolution and evaluation. *The International Review of Retail, Distribution and Consumer Research*, 2(2), 185-229.
<https://doi.org/10.1080/09593969300000014>
- Büyüközkan, G., & Çifçi, G. (2012). A novel hybrid MCDM approach based on fuzzy DEMATEL, ANP, and TOPSIS to evaluate green suppliers. *Expert Systems with Applications*, 39(3), 3000-3011. <https://doi.org/10.1016/j.eswa.2011.08.162>
- Chaoprasert, C., & Elsey, B. (2004). Service quality improvement in Thai retail banking and its management implications. *ABAC Journal*, 24.
- Chen, C. T. (2000). Extensions of the TOPSIS for group decision-making under fuzzy environment. *Fuzzy Sets and Systems*, 114(1), 1-9. [https://doi.org/10.1016/S0165-0114\(97\)00377-1](https://doi.org/10.1016/S0165-0114(97)00377-1)
- Chen, S. J., & Hwang, C. L. (1992). *Fuzzy multiple attribute decision making: Methods and applications*. Springer.
- Chopra, S., & Meindl, P. (2023). *Supply chain management: Strategy, planning, and operation* (8th ed.). Pearson Education.
- Deveci, M., Demirel, N. Ç., & Ahmetoğlu, E. (2017). Airline new route selection based on interval type-2 fuzzy MCDM: A case study of new route between Turkey-North American region destinations. *Journal of Air Transport Management*, 59, 83-99.
<https://doi.org/10.1016/j.jairtraman.2016.11.013>
- Erbıyık, H., Özcan, S., & Karaboğa, K. (2012). Retail store location selection problem with multiple analytical hierarchy process of decision making: an application in Turkey. *Procedia – Social and Behavioral Sciences*, 58, 1405-1414.
<https://doi.org/10.1016/j.sbspro.2012.09.1125>
- Fildes, R., Ma, S., & Kolassa, S. (2022). Retail forecasting: Research and practice. *International Journal of Forecasting*, 38(4), 1283-1318. <https://doi.org/10.1016/j.ijforecast.2019.06.004>
- Fongkam, P. (2015). Factors affecting traditional retail stores competitiveness in Chiang Mai, Thailand. *Journal of Economics, Business and Management*, 3(2), 198-202.
<https://doi.org/10.7763/JOEBM.2015.V3.198>
- Grewal, D., Roggeveen, A. L., & Nordfält, J. (2017). The future of retailing. *Journal of Retailing*, 93(1), 1-6. <https://doi.org/10.1016/j.jretai.2016.12.008>
- Ho, W., Xu, X., & Dey, P. K. (2010). Multi-criteria decision making approaches for supplier evaluation and selection: A literature review. *European Journal of Operational Research*, 202(1), 16-24. <https://doi.org/10.1016/j.ejor.2009.05.009>
- Hwang, C. L., & Yoon, K. (1981). *Multiple attribute decision making: Methods and applications-A state-of-the-art survey*. Springer-Verlag.
- Jangid, P., Kumar, T., Jahnvi, Dhanuk, K., & Sharma, M. K. (2025). A stability and robustness analysis of multi-criteria decision methods in logistics. *Decision Analytics Journal*, 16, Article 100618. <https://doi.org/10.1016/j.dajour.2025.100618>
- Kendall, M. G., & Smith, B. B. (1939). The problem of m rankings. *The Annals of Mathematical Statistics*, 10(3), 275-287. <https://doi.org/10.1214/aoms/1177732186>

- Kumar, V., & Venkatesan, R. (2021). Transformation of metrics and analytics in retailing: The way forward. *Journal of Retailing*, 97(4), 496-506. <https://doi.org/10.1016/j.jretai.2021.11.004>
- Landis, J. R., & Koch, G. G. (1977). The measurement of observer agreement for categorical data. *Biometrics*, 33(1), 159-174. <https://doi.org/10.2307/2529310>
- Levy, M., Weitz, B. A., & Grewal, D. (2019). *Retailing management* (10th ed.). McGraw-Hill Education.
- Lin, Y. H., Lee, P. C., & Ting, H. I. (2008). Dynamic multi-attribute decision making model with grey number evaluations. *Expert Systems with Applications*, 35(4), 1638-1644. <https://doi.org/10.1016/j.eswa.2007.08.064>
- Liu, H., Ke, W., Wei, K. K., & Hua, Z. (2013). The impact of IT capabilities on firm performance: The mediating roles of absorptive capacity and supply chain agility. *Decision Support Systems*, 54(3), 1452-1462. <https://doi.org/10.1016/j.dss.2012.12.016>
- Mostaghel, R., Oghazi, P., Parida, V., & Sohrabpour, V. (2022). Digitalization driven retail business model innovation: Evaluation of past and avenues for future research trends. *Journal of Business Research*, 146, 134-145. <https://doi.org/10.1016/j.jbusres.2022.03.072>
- Ngaochay, T. (2011). Paths to success for 7-Eleven in Thailand. *Information Management and Business Review*, 3(1), 1-7. <https://doi.org/10.22610/imbr.v3i1.910>
- Pan, Y., & Zinkhan, G. M. (2006). Determinants of retail patronage: A meta-analytical perspective. *Journal of Retailing*, 82(3), 229-243. <https://doi.org/10.1016/j.jretai.2005.11.008>
- Pandey, M. (2016). Evaluating the service quality of airports in Thailand using fuzzy multi-criteria decision making method. *Journal of Air Transport Management*, 57, 241-249. <https://doi.org/10.1016/j.jairtraman.2016.08.014>
- Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1988). SERVQUAL: A multiple-item scale for measuring consumer perceptions of service quality. *Journal of Retailing*, 64(1), 12-40. Retrieved from https://www.researchgate.net/publication/200827786_SERVQUAL_A_Multiple-item_Scale_for_Measuring_Consumer_Perceptions_of_Service_Quality
- Reardon, T., Timmer, C. P., & Minten, B. (2012). Supermarket revolution in Asia and emerging development strategies to include small farmers. *Proceedings of the National Academy of Sciences*, 109(31), 12332-12337. <https://doi.org/10.1073/pnas.1003160108>
- Singh, A., Klarner, P., & Hess, T. (2020). How do chief digital officers pursue digital transformation activities? The role of organization design parameters. *Long Range Planning*, 53(3). <https://doi.org/10.1016/j.lrp.2019.07.001>
- Singh, R. K., & Benyoucef, L. (2011). A fuzzy TOPSIS based approach for e-sourcing. *Engineering Applications of Artificial Intelligence*, 24(6), 1018-1025. <https://doi.org/10.1016/j.engappai.2010.09.006>
- Šijanec Zavrl, M., Žarnić, R., & Šelih, J. (2009). Multicriterial sustainability assessment of residential buildings. *Technological and Economic Development of Economy*, 15(4), 612-630. <https://doi.org/10.3846/1392-8619.2009.15.612-630>

- Teller, C., & Reutterer, T. (2008). The evolving concept of retail attractiveness: What makes retail agglomerations attractive when customers shop at them? *Journal of Retailing and Consumer Services*, 15(3), 127-143. <https://doi.org/10.1016/j.jretconser.2007.03.003>
- Theodoridis, C., & Bennison, D. (2009). Complexity theory and retail location strategy. *The International Review of Retail, Distribution and Consumer Research*, 19(4), 389-403. <https://doi.org/10.1080/09593960903331386>
- Zolfani, S. H., Aghdaie, M. H., Derakhti, A., Zavadskas, E. K., & Morshed Varzandeh, M. H. (2013). Decision making on business issues with foresight perspective; an application of new hybrid MCDM model in shopping mall locating. *Expert Systems with Applications*, 40(17), 7111-7121. <https://doi.org/10.1016/j.eswa.2013.06.040>