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RESEARCH ARTICLE

A Hybrid Fuzzy DEMATEL–ELECTRE Framework for Evaluating the Impact of Industry 4.0 Technologies on Warehouse Management Strategy Outcomes

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ABSTRACT
Integrating Industry 4.0 (I4.0) technologies into warehouse management critically enhances strategic performance. However, existing studies often overlook the causal relationships between strategic outcomes and the transparency of technology prioritization. This study proposes a hybrid multi-criteria decision-making (MCDM) framework integrating Fuzzy DEMATEL to determine the relative weights of strategic outcomes, Fuzzy ELECTRE II to rank technologies, and SHAP-based Explainable Artificial Intelligence (XAI) to enhance model transparency and interpretability. The analysis relies on Delphi-based expert evaluations from 12 senior industrial engineers across three manufacturing firms. The results reveal that Cost Reduction (weight = 0.225), Operational Efficiency (0.097), and Inventory Management (0.115) are the most critical strategic outcomes. Artificial Intelligence, Internet of Things, and Big Data Analytics emerged as the top-ranked technologies based on ELECTRE II scores. SHAP analysis further identified Cost Reduction (SHAP value: +1.62), Customer Satisfaction (SHAP value: +0.50), and Real-time Data Processing (SHAP value: +0.40) as the primary drivers behind the technology rankings. The proposed framework offers a transparent, interpretable, and causally grounded decision-support model for aligning digital transformation investments with strategic warehouse performance objectives.

Keywords: Industry 4.0, Warehouse management, Fuzzy DEMATEL, Fuzzy ELECTRE, Explainable artificial intelligence

1. Introduction

In today's global and competitive market environment, warehouse management has evolved beyond simply storing and moving goods to become a strategic, technology-driven, and data-oriented function. By integrating physical and digital environments, Industry 4.0 (I4.0) technologies can transform warehouse operations into more flexible, rapid, error-free, and customer-centric systems. In this context, technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), Big Data Analytics (BD), Cloud Computing (CC), Cyber-Physical Systems (CPS), Additive Manufacturing (AM), Augmented Reality (AR), Digital Twins (DT), Blockchain (BC), and Robotics & Automation (RA) have significant direct and indirect impacts on warehouse strategy outcomes.

However, few studies in the current literature systematically and causally examine the influence of these technologies on warehouse performance strategies. Moreover, many existing decision-support models focus primarily on ranking, overlooking the relational depth among strategic factors. Therefore, this study aims to assess the impact of I4.0 technologies on eight key warehouse strategy outcomes using reliable multi-criteria decision-making (MCDM) methods.

In the first phase, the Fuzzy DEMATEL method is employed to identify the causal relationships among strategies and to calculate their relative importance. Then, based on these weights, the I4.0 technologies are ranked using the Fuzzy ELECTRE method. Furthermore, an Explainable Artificial Intelligence (XAI) approach is integrated into the framework to enhance model transparency and interpretability. The analysis is based on expert input from 12 senior industrial engineers in

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production, planning, logistics, and marketing departments across three manufacturing firms, gathered using the Delphi technique.

The primary contribution of this study is the development of an integrated, explainable, and scientifically grounded decision-support system that effectively aligns warehouse strategies with Industry 4.0 technologies.

2. Literature Review

The transformation of traditional warehouses into smart, responsive, and data-driven environments has become a central theme in supply chain innovation. I4.0 technologies enable this transformation by facilitating real-time monitoring, autonomous decision-making, and enhanced operational efficiency. Numerous studies have examined individual I4.0 technologies, such as IoT, AI, CPS, and Big Data, and their general contributions to logistics and manufacturing performance [1-3]. However, limited research has explored how these technologies directly influence specific warehouse management strategy outcomes (WMSOs) such as cost reduction, inventory accuracy, space utilization, and customer satisfaction.

The strategic outcomes addressed in this study were identified through a comprehensive review of recent literature examining the effects of digitalized warehouse systems and Industry 4.0 technologies. The literature highlights eight key strategic outcomes frequently emphasized and considered operationally significant in warehouse performance improvement. The descriptions of these outcomes, along with their supporting academic references, are presented in Table 1.

Table 1. Warehouse Management Strategy Outcomes (WMSOs).

Strategy Outcome	**Description**	**References**
Cost Reduction (CR)	Utilizing Warehouse Management Systems (WMS) enhances operational efficiency and minimizes errors, resulting in substantial cost savings.	[4][5]
Improved Operational Efficiency (IOE)	Intelligent WMS enhances automation and standardizes workflows, improving processing speed and overall efficiency.	[6][7]
Enhanced Inventory Management (EIM)	Technologies like RFID enable more accurate tracking and inventory management.	[8][9]
Higher Customer Satisfaction (HCS)	Efficient warehouse operations support faster order processing and delivery, boosting customer satisfaction.	[10]
Effective Space Utilization (ESU)	Advanced layout and storage strategies optimize warehouse space usage.	[11]
Error Reduction (ER)	Automation and smart technologies significantly reduce human errors in inventory operations.	[10][12]
Sustainability Initiatives (SI)	Practices such as using energy-efficient equipment lower energy consumption in warehouse operations.	[13]
Real-time Data Processing (RDP)	Modern WMS supports real-time data collection and analysis, improving decision-making.	[14]

Table 2. Industry 4.0 (I4.0) Technologies

Technology	**Description**	**References**
Internet of Things (IoT)	IoT enables connectivity of devices and machines, facilitating real-time data sharing and analysis across operations.	[4][5]
Artificial Intelligence (AI)	AI drives automation and advanced data analytics, enhancing decision-making and efficiency within manufacturing processes.	[4][6]
Big Data Analytics (BD)	The ability to analyze vast amounts of data to gain insights that drive operational performance and strategic decisions.	[7][8]
Cloud Computing (CC)	Cloud platforms provide scalable resources and data storage solutions, enhancing collaboration and accessibility.	[9][10]
Robotics and Automation (RA)	Utilizing robotic systems to automate manufacturing tasks enhances precision and minimizes human error in production.	[4][11]
Augmented Reality (AR)	AR enhances real-world environments with digital information, aiding training and maintenance processes in industrial settings.	[5][12]
Additive Manufacturing (AM)	A technology that allows for the on-demand production of parts and products through layer-by-layer printing techniques.	[7][13]
Cyber-Physical Systems (CPS)	Integration of computation and physical processes, enabling real-time monitoring and control of industrial operations.	[14][15]
Blockchain Technology (BC)	Provides secure and transparent transaction tracking for supply chain management, improving traceability and trustworthiness.	[16][17]
Digital Twins (DT)	Virtual replicas of physical systems, enabling simulation and predictive analysis to optimize performance and maintenance.	[4][18]

Table 2 lists key I4.0 technologies, along with their descriptions and relevant academic references that support their significance.

Smart manufacturing studies [19], [20] suggest that I4.0 technologies must be aligned with long-term business strategies to deliver measurable value. Moreover, as the complexity of warehouse operations increases, there is a growing need for decision-making models that consider both the causality among strategic outcomes and the relative impact of emerging technologies. In this regard, MCDM approaches have been widely adopted. Among them, the Fuzzy DEMATEL method is frequently used to model cause–and–effect relationships among criteria under uncertainty [21], [22]. At the same time, Fuzzy ELECTRE has proven effective for ranking alternatives based on linguistic expert input [23], [24].

Despite these developments, previous research rarely combines both techniques or incorporates Explainable AI (XAI) to improve the interpretability of decision models. This study bridges that gap by integrating Fuzzy DEMATEL, Fuzzy ELECTRE, and SHAP-based explainability to assess and rank I4.0 technologies based on their influence on warehouse strategic goals, as informed by expert opinion and real-world industrial practices.

3. Methodology

This study proposes an integrated fuzzy MCDM model to evaluate the impact of I4.0 technologies on WMSOs systematically. The methodology comprises four main phases: (1) expert involvement and data collection, (2) determining the causal relationships among strategic outcomes, (3) ranking I4.0 technologies based on their influence on these strategies, and (4) explaining the model outputs using XAI techniques. Accordingly, Fuzzy DEMATEL, Fuzzy ELECTRE II, and SHAP-based XAI methods are sequentially applied. The overall methodology of the study is illustrated in Figure 1.

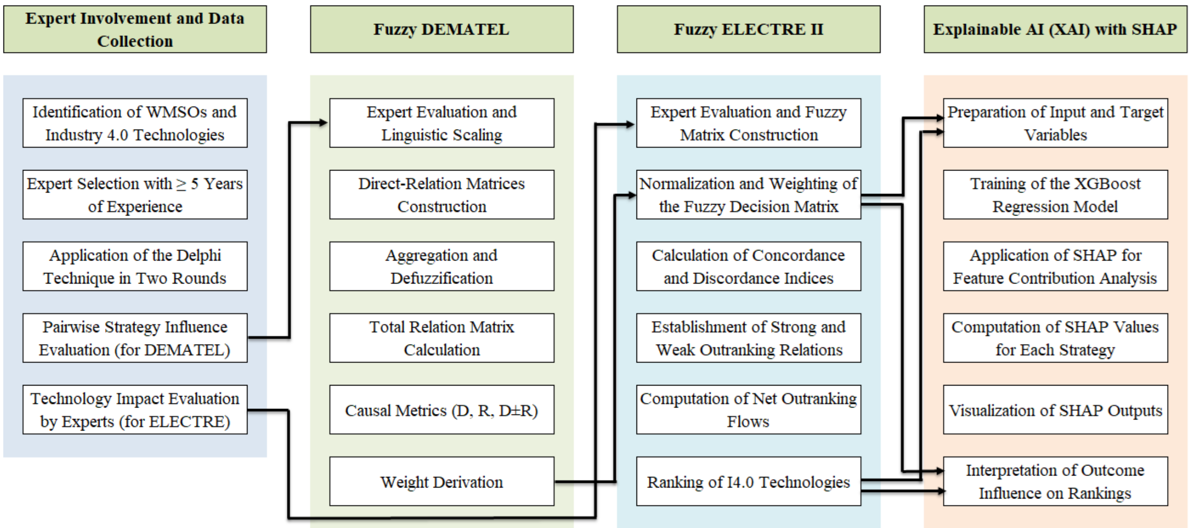

Figure 1. The Hybrid MCDM Framework

3.1. Expert Involvement and Data Collection

Data were collected from a panel of 12 senior industrial engineers from three different manufacturing companies. Experts were selected from the production, planning, logistics, procurement, and sales departments, each with a minimum of 5 years of professional experience. The Delphi technique was employed in two rounds to ensure consensus. Experts were asked to provide two types of evaluations:

i. the mutual influence levels among strategic outcomes (for Fuzzy DEMATEL),

ii. the degree of impact each I4.0 technology has on each strategy (for Fuzzy ELECTRE).

Evaluations were based on a five-point linguistic scale ranging from "very low (VL)" to "very high (VH)." The linguistic evaluations were transformed into fuzzy numerical values using predefined fuzzy triangular numbers, as shown in Table 3 for the Fuzzy DEMATEL and the Fuzzy ELECTRE methods.

The differing ranges of the triangular fuzzy numbers in Table 3 stem from the structural differences between the Fuzzy DEMATEL and Fuzzy ELECTRE II methods. While DEMATEL employs a [0–1] scale to represent the intensity of influence among criteria, ELECTRE II involves a comparative preference analysis between alternatives, typically requiring a broader numerical scale starting from 1. This distinction enables a more precise and discriminative calculation of concordance and discordance indices in the ELECTRE method.

Table 3. Fuzzy Triangular Numbers Used in Fuzzy DEMATEL and Fuzzy ELECTRE

Linguistic Terms Symbol	Fuzzy DEMATEL	Fuzzy ELECTRE
Very low impact VL	(0.00, 0.10, 0.30)	(1.00, 1.00, 3.00)
Low impact L	(0.10, 0.30, 0.50)	(1.00, 3.00, 5.00)
Middle impact M	(0.30, 0.50, 0.70)	(3.00, 5.00, 7.00)
High impact H	(0.50, 0.70, 0.90)	(5.00, 7.00, 7.00)
Very high impact VH	(0.70, 0.90, 1.00)	(7.00, 9.00, 9.00)

3.2. Fuzzy DEMATEL Method

The Fuzzy DEMATEL method was employed in the first phase to identify the causal structure among the eight defined strategic warehouse outcomes. The linguistic evaluations were converted into triangular fuzzy numbers, and a direct-relation matrix was generated for each expert. These matrices were aggregated into a group decision matrix and defuzzified using the CFCS (Converting Fuzzy into Crisp Scores) method. The total relation matrix (T) was then computed. For each strategy [25]:

- D (Dispatching degree): total influence exerted on others,
- R (Receiving degree): total influence received from others,
- D+R (Prominence) and D–R (Causal classification) values were calculated.

Normalized prominence scores were used as criterion weights in the ELECTRE phase.

3.3. Fuzzy ELECTRE II for Technology Ranking

In the second phase, 10 I4.0 technologies were ranked using the Fuzzy ELECTRE II method based on their perceived impacts on the weighted strategic outcomes. Experts evaluated each technology-strategy pair using the VL–VH linguistic scale, and these evaluations were converted into fuzzy decision matrices. The steps involved [26]:

- normalization of the matrices and multiplication by the weights,
- calculation of concordance and discordance indices,
- determination of outranking relationships based on threshold values,
- computation of the net outranking flows for each technology served as the ranking scores.

The subsequent explainability analysis used these ranking scores as the target variable.

3.4. Explainable AI (XAI) with SHAP Analysis

The SHAP (SHapley Additive Explanations) method was applied to enhance the transparency and interpretability of the model. In this framework:

- Independent variables (X): weighted and normalized decision matrix (technologies × strategies),
- Dependent variable (y): net outranking scores from the ELECTRE II method.

An XGBoost-based regression model (XGBRegressor) was trained on this data. The XGBoost regression model was trained using default hyperparameters to establish a baseline understanding of the relationship between strategic outcomes and ELECTRE II scores. Specifically, the model employed a learning rate of 0.1, a maximum tree depth of 6, and 100 boosting iterations (n_estimators). The model also used the 'reg:squarederror' objective function to minimize prediction error. To ensure the robustness and generalizability of the model, a 5-fold cross-validation strategy was applied during training and testing. Using the TreeExplainer implementation of SHAP, the marginal contribution of each strategic outcome to the ranking of each technology was calculated. SHAP visualizations, including a bar chart, were generated to support the intuitive interpretation of the model's logic and provide decision-makers with a deeper understanding of the ranking mechanisms beyond numerical outputs.

4. Results and Discussion

This section presents a multi-layered evaluation of the influence of I4.0 technologies on warehouse management strategies, incorporating expert-driven causal analysis (Fuzzy DEMATEL), multi-criteria technology prioritization (Fuzzy ELECTRE II), and explainability analysis (SHAP).

4.1. Fuzzy DEMATEL Analysis of Strategic Relationships among WMSOs

A questionnaire was administered to the experts to identify the relationships between each pair of criteria. For each evaluation, they were asked: "To what extent does the component on the left influence the factor on the right?" The participants responded using a scale ranging from VL to VH (see Table 3). Table 4 presents the interaction matrix among strategy outcomes based on the linguistic evaluations provided by a single expert. These linguistic inputs were converted into triangular fuzzy numbers using a fuzzy linguistic scale. The initial direct relation matrix was constructed based on the fuzzy evaluations, and the crisp values of the WMSOs criteria were calculated. The total relation matrix is presented in Table 5, while Table 6 outlines the interaction effects among the factors. The final results of the DEMATEL analysis are shown in Table 7, and the interdependence and relational structure among the WMSOs are visualized in Figure 2.

As shown in Table 8, the Fuzzy DEMATEL analysis revealed the causal relationships and relative weights among warehouse management strategies. Cost Reduction (CR) emerged as the most influential strategic outcome with the highest weight (0.2252), indicating its central role as the most affected factor within the system. This finding is consistent with previous literature that emphasizes cost efficiency as a critical driver of warehouse performance and operational success in logistics settings [5], [27], [28]. The emphasis on CR indicates that organizations should adopt strategies aimed at minimizing costs while maintaining operational quality, a conclusion supported by studies advocating cost minimization as a core operational strategy in supply chain management [4]. Sustainability Initiatives (SI), Real-time Data Processing (RDP), and Error Reduction (ER) were identified as "Dispatcher" strategies due to their positive D–R values, signifying their role in influencing other outcomes. RDP (D–R: 4.18) and ER (D–R: 3.63) acted as strong causal drivers. This classification highlights the crucial roles of these strategies in facilitating other strategies, serving as catalysts for enhancing overall warehouse effectiveness. Previous research has underscored the importance of real-time data in enabling proactive decision-making and operational adjustments that enhance efficiency and effectiveness in warehouse management [29], [30].

In contrast, strategies such as Higher Customer Satisfaction (HCS), Enhanced Inventory Management (EIM), and Improved Operational Efficiency (IOE) were categorized as "Receivers," with moderate weights of 0.1564, 0.1150, and 0.0970, respectively. These findings emphasize the interaction between customer satisfaction and operational efficiency, a relationship acknowledged in the literature that connects customer-driven metrics to operational practices [31], [32]. The least impactful strategy was Effective Space Utilization (ESU), which weighted 0.0313. These results suggest that improving warehouse performance should prioritize cost reduction, which is significantly influenced by upstream strategies, such as RDP and SI.

Table 4. Interaction Matrix Among Strategy Outcomes Based on Linguistic Evaluations Provided by A Single Expert

Strategy Outcome	**CR**	**ESU**	**EIM**	**ER**	**HCS**	**IOE**	**RDP**	**SI**
Cost Reduction (CR)	-	VH	VH	H	VH	H	M	M
Effective Space Utilization (ESU)	L	-	M	M	L	M	M	M
Enhanced Inventory Management (EIM)	L	M	-	H	VH	M	H	VH
Error Reduction (ER)	VL	VL	L	-	M	VL	H	M
Higher Customer Satisfaction (HCS)	L	VH	M	M	-	M	H	H
Improved Operational Efficiency (IOE)	L	VH	H	H	VH	-	H	M
Real-time Data Processing (RDP)	L	VL	VL	M	L	L	-	L
Sustainability Initiatives (SI)	L	VL	H	L	L	L	M	-

Table 5. The Total Relation Matrix

Strategy	**CR**	**ESU**	**EIM**	**ER**	**HCS**	**IOE**	**RDP**	**SI**
CR	-0.04956	2.81106	0.52889	-1.90219	-0.71362	0.63524	-4.02035	-1.72913
ESU	-0.26582	1.04241	-0.02069	-0.29029	-0.81962	0.18115	-0.80687	-0.44737
EIM	-0.45068	-0.84400	0.71042	-0.85639	0.05066	-0.44020	-0.74065	0.64438
ER	0.40036	-2.75149	-1.10412	2.17497	0.53649	-1.27857	2.69574	0.49085
HCS	-0.44283	1.23496	-0.18459	-1.04336	-0.23284	0.17841	-1.13542	-0.39681
IOE	-0.74188	1.16589	-0.62566	-0.24413	-0.32171	0.74795	-0.65493	-1.20304
RDP	0.60219	-0.83929	-1.55779	1.28518	-0.01334	-0.20185	2.12105	-1.07996
SI	-0.11455	-1.15872	1.37056	-1.59230	-0.28422	-0.31553	-1.32775	1.42333

Table 6. The Impact Relation Among Factors

Strategy	**CR**	**ESU**	**EIM**	**ER**	**HCS**	**IOE**	**RDP**	**SI**
CR	0	2.81106	0.52889	0	0	0.63524	0	0
ESU	0	1.04241	0	0	0	0.18115	0	0
EIM	0	0	0.71042	0	0.05066	0	0	0.64438
ER	0.40036	0	0	2.17497	0.53649	0	2.69574	0.49085
HCS	0	1.23496	0	0	0	0.17841	0	0
IOE	0	1.16589	0	0	0	0.74795	0	0
RDP	0.60219	0	0	1.28518	0	0	2.12105	0
SI	0	0	1.37056	0	0	0	0	1.42333
The threshold was set to 0.0, as the negative value (≈ -0.1908) calculated by taking the arithmetic mean of all values in the total relation matrix could not represent meaningful positive influences.								

Table 7. The Impact Relation Among Factors

Strategy	D (Influence)	R (Influenced)	D+R	D-R	Role	Weight	Rank
CR	-4.43967	-1.06278	-5.50245	-3.37689	Receiver	0.22529	1
ESU	-1.42709	0.66082	-0.76627	-2.08791	Receiver	0.03137	8
EIM	-1.92645	-0.88297	-2.80942	-1.04348	Receiver	0.11503	5
ER	1.16423	-2.46851	-1.30427	3.63274	Dispatcher	0.05340	7
HCS	-2.02247	-1.79821	-3.82068	-0.22427	Receiver	0.15643	3
IOE	-1.87751	-0.49339	-2.37090	-1.38412	Receiver	0.09707	6
RDP	0.31617	-3.86918	-3.55300	4.18535	Dispatcher	0.14547	4
SI	-1.99916	-2.29774	-4.29690	0.29858	Dispatcher	0.17593	2

The threshold was set to 0.0, as the negative value (≈ -0.1908) calculated by taking the arithmetic mean of all values in the total relation matrix could not represent meaningful positive influences.

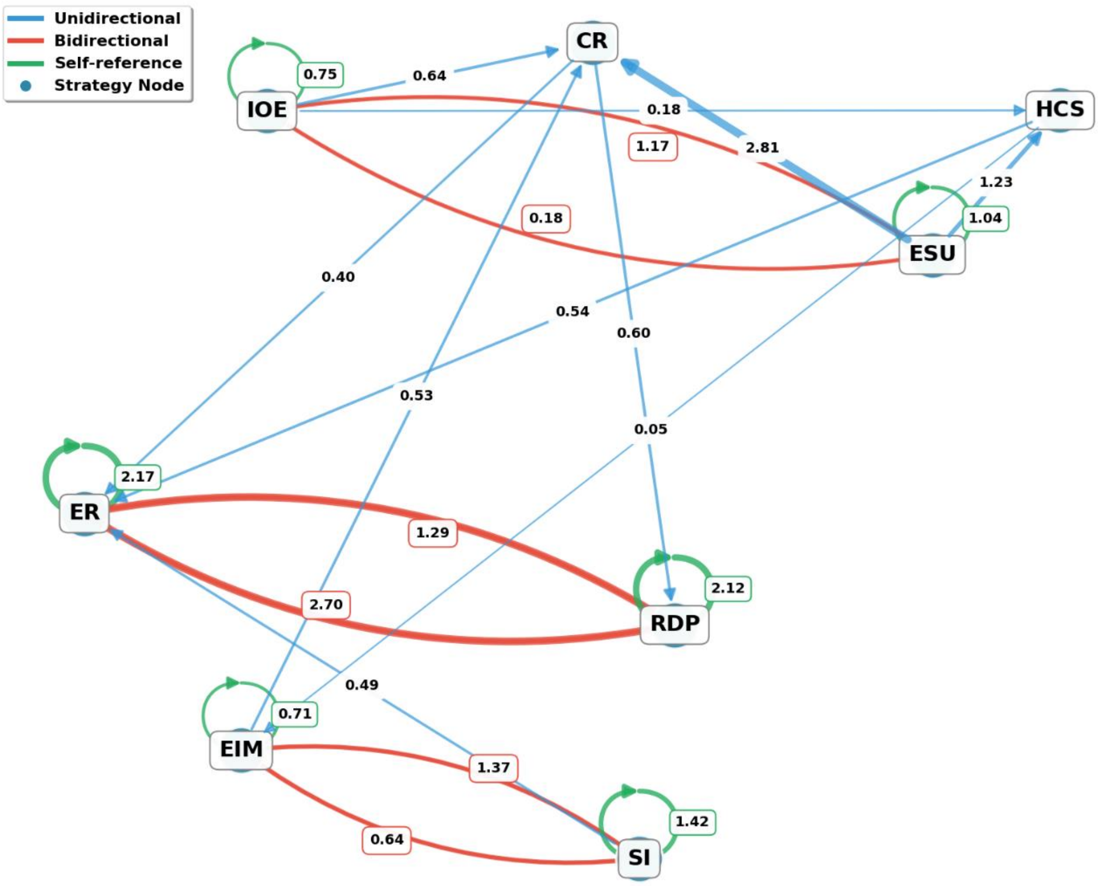

Figure 2. Interrelationships Among WMSOs.

4.2. Fuzzy ELECTRE II-Based Ranking of I4.0 Technologies for WMSOs

Using the weighted strategic outcomes obtained from the DEMATEL analysis, the Fuzzy ELECTRE II method was applied to rank ten I4.0 technologies. This approach enables the identification of the most influential factors contributing to the overall differentiation among the technologies, thereby providing a foundation for developing and implementing effective improvement strategies.

Table 8 presents a sample of the input data collected from one domain expert who evaluated the alternatives. The Concordance Matrix and Discordance Matrix are provided in Tables 9 and 10, respectively. The resulting ELECTRE II Strong Preference Relation is shown in Table 11, while the Weak Preference Relation is illustrated in Table 12.

Finally, the overall ranking of I4.0 technologies—based on strong and weak preference relations—is visualized in Figure 3, along with their respective ELECTRE II scores. According to the results, Artificial Intelligence (AI) achieved the highest rank, followed by the Internet of Things (IoT), Big Data Analytics (BD), and Digital Twins (DT). Artificial Intelligence (AI) emerged as the top-ranked technology, primarily due to its very high contributions to inventory management and operational efficiency. AI's ability to automate complex decision-making processes and forecast demand patterns supports more agile and efficient operations, which are critical in dynamic supply chain environments [33], [34]. The Internet of Things (IoT), ranking second, effectively reduced costs and enhanced real-time data processing. IoT enables seamless machine-to-machine communication and real-time monitoring, making it a cornerstone of responsive warehouse systems [34], [35].

Table 8. Sample Expert Input Matrix for The Evaluation of I4.0 Technologies Against WMSOs

	AI	AM	AR	BC	BD	CC	CPS	DT	IoT	RA
AI	0	1	1	1	0.88497	1	1	0.85453	0.59786	0.74334
AM	0.03137	0	0.66764	0.66764	0.03137	0.42509	0.14640	0.03137	0	0
AR	0	0.68994	0	0.59878	0	0.11503	0.11503	0	0	0
BC	0	0.80020	0.88497	0	0	0.22529	0	0.17593	0	0.17593
BD	0.69309	1	1	1	0	1	1	0.75745	0.29096	0.59286
CC	0.35278	1	1	1	0.60628	0	0.72131	0.36374	0.17593	0.47783
CPS	0.43259	1	1	1	0.73950	0.85453	0	0.64243	0.17593	0.47783
DT	0.61424	1	1	1	0.70904	0.82407	0.82407	0	0.35757	0.68994
IoT	1	1	1	1	0.88497	1	1	1	0	1
RA	0.52217	1	1	1	0.56357	0.67860	0.82407	0.85453	0.52217	0

Table 9. Concordance Matrix

	AI	AM	AR	BC	BD	CC	CPS	DT	IoT	RA
AI	0	1	1	1	0.88497	1	1	0.85453	0.59786	0.74334
AM	0.03137	0	0.66764	0.66764	0.03137	0.42509	0.14640	0.03137	0	0
AR	0	0.68994	0	0.59878	0	0.11503	0.11503	0	0	0
BC	0	0.80020	0.88497	0	0	0.22529	0	0.17593	0	0.17593
BD	0.69309	1	1	1	0	1	1	0.75745	0.29096	0.59286
CC	0.35278	1	1	1	0.60628	0	0.72131	0.36374	0.17593	0.47783
CPS	0.43259	1	1	1	0.73950	0.85453	0	0.64243	0.17593	0.47783
DT	0.61424	1	1	1	0.70904	0.82407	0.82407	0	0.35757	0.68994
IoT	1	1	1	1	0.88497	1	1	1	0	1
RA	0.52217	1	1	1	0.56357	0.67860	0.82407	0.85453	0.52217	0

Table 10. Discordance Matrix

	AI	AM	AR	BC	BD	CC	CPS	DT	IoT	RA
AI	0	0.92965	0.75000	0.48429	0.17359	0.37500	0.24214	0.34862	0.25000	0.34862
AM	0.92965	0	0.37500	0.58103	0.92965	0.92965	0.92965	0.64571	0.92965	0.62500
AR	0.75	0.37500	0	0.37500	0.75000	0.69724	0.75000	0.75000	1	1
BC	0.48429	0.58103	0.37500	0	0.51058	0.48429	0.37500	0.64571	0.64571	0.62500
BD	0.17359	0.92965	0.75000	0.51058	0	0.37500	0.31911	0.34862	0.25000	0.34862
CC	0.37500	0.92965	0.69724	0.48429	0.37500	0	0.37500	0.37500	0.62500	0.62500
CPS	0.24214	0.92965	0.75000	0.37500	0.31911	0.37500	0	0.40357	0.40357	0.34862
DT	0.34862	0.64571	0.75000	0.64571	0.34862	0.37500	0.40357	0	0.34862	0.40357
IoT	0.25000	0.92965	1	0.64571	0.25000	0.62500	0.40357	0.34862	0	0.40357
RA	0.34862	0.62500	1	0.62500	0.34862	0.62500	0.34862	0.40357	0.40357	0

Table 11. ELECTRE II Strong Preference Relation

	AI	AM	AR	BC	BD	CC	CPS	DT	IoT	RA
AI	0	0	0	1	1	1	1	1	1	1
AM	0	0	1	0	0	0	0	0	0	0
AR	0	1	0	1	0	0	0	0	0	0
BC	0	0	1	0	0	0	0	0	0	0
BD	1	0	0	0	0	1	1	1	0	1
CC	0	0	0	1	1	0	1	0	0	0
CPS	0	0	0	1	1	1	0	1	0	0
DT	1	0	0	0	1	1	1	0	0	1
IoT	1	0	0	0	1	0	1	1	0	1
RA	0	0	0	0	1	0	1	1	0	0

Table 12. ELECTRE II Weak Preference Relation

	AI	AM	AR	BC	BD	CC	CPS	DT	IoT	RA
AI	0	1	1	1	1	1	1	1	1	1
AM	0	0	1	1	0	0	0	0	0	0
AR	0	1	0	1	0	0	0	0	0	0
BC	0	1	1	0	0	0	0	0	0	0
BD	1	1	1	1	0	1	1	1	0	1
CC	0	1	1	1	1	0	1	0	0	0
CPS	0	1	1	1	1	1	0	1	0	0
DT	1	1	1	1	1	1	1	0	0	1
IoT	1	1	1	1	1	1	1	1	0	1
RA	0	1	1	1	1	1	1	1	0	0

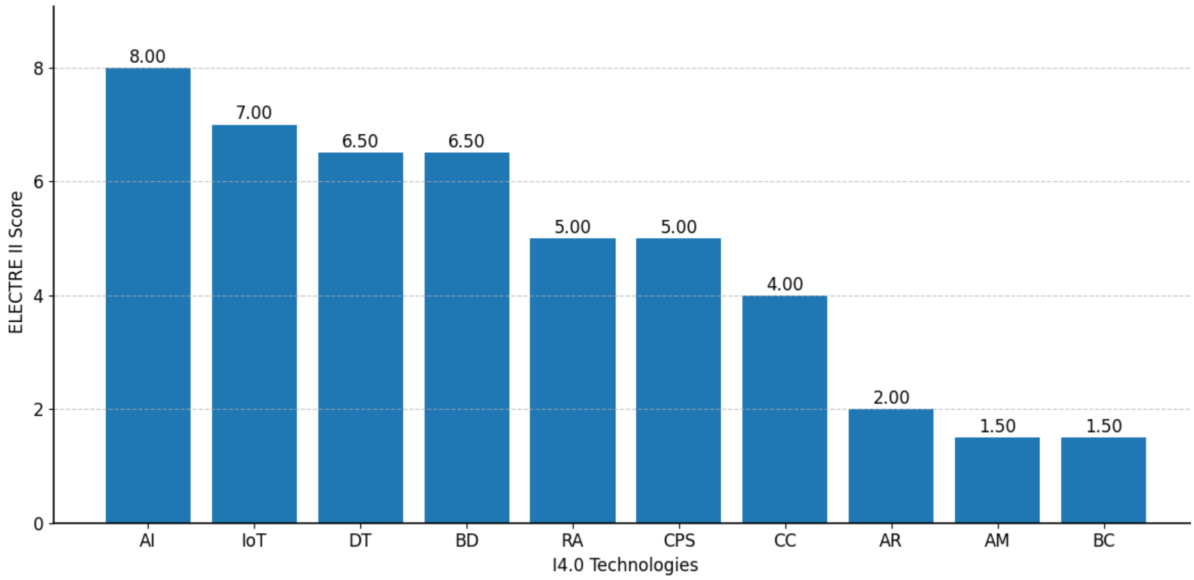

Figure 3. I4.0 Technologies Ranking.

A weighted and normalized average fuzzy decision matrix was used to evaluate the performance of I4.0 technologies in relation to each WMSO. The results of this assessment are presented in Table 13 and Figure 4, which illustrate the relative relationships and differentiation indices among the technologies in terms of strategic outcomes. In particular, Figure 4 (Heatmap of I4.0 Technologies vs WMSOs) provides a visual representation of the strategic relevance of each technology, highlighting areas of dominance and underperformance.

According to the data in Table 13, IoT and RA technologies exhibit the highest performance relative to CR, each achieving a score of 0.22529. These are followed by AI, BD, DT, and CPS, demonstrating a moderate contribution level with scores of 0.18924. In contrast, AM, BC, and CC show lower levels of impact, each scoring 0.13517, while AR ranks the lowest with a score of 0.08110. These findings indicate that while certain I4.0 technologies play a central role in cost reduction, others contribute to this objective only to a limited extent.

Table 13. The Weighted Normalized Average Fuzzy Decision Matrix

	CR	ESU	EIM	ER	HCS	IOE	RDP	SI
AI	0.18924	0.02241	0.09662	0.05340	0.15643	0.09707	0.12220	0.17593
AM	0.13517	0.02241	0.06902	0.02289	0.05632	0.03495	0.05237	0.04189
AR	0.08110	0.01345	0.06902	0.01271	0.09386	0.03495	0.05237	0.07540
BC	0.13517	0.01345	0.04141	0.01271	0.09386	0.03495	0.05237	0.12566
BD	0.18924	0.02241	0.11503	0.03814	0.13140	0.08154	0.12220	0.17593
CC	0.13517	0.02241	0.06902	0.02289	0.13140	0.08154	0.12220	0.17593
CPS	0.18924	0.02241	0.06902	0.03814	0.13140	0.08154	0.08728	0.17593
DT	0.18924	0.02241	0.09662	0.03814	0.13140	0.09707	0.14547	0.12566
IoT	0.22529	0.03137	0.09662	0.05340	0.15643	0.09707	0.14547	0.17593
RA	0.22529	0.03137	0.09662	0.05340	0.13140	0.09707	0.08728	0.12566

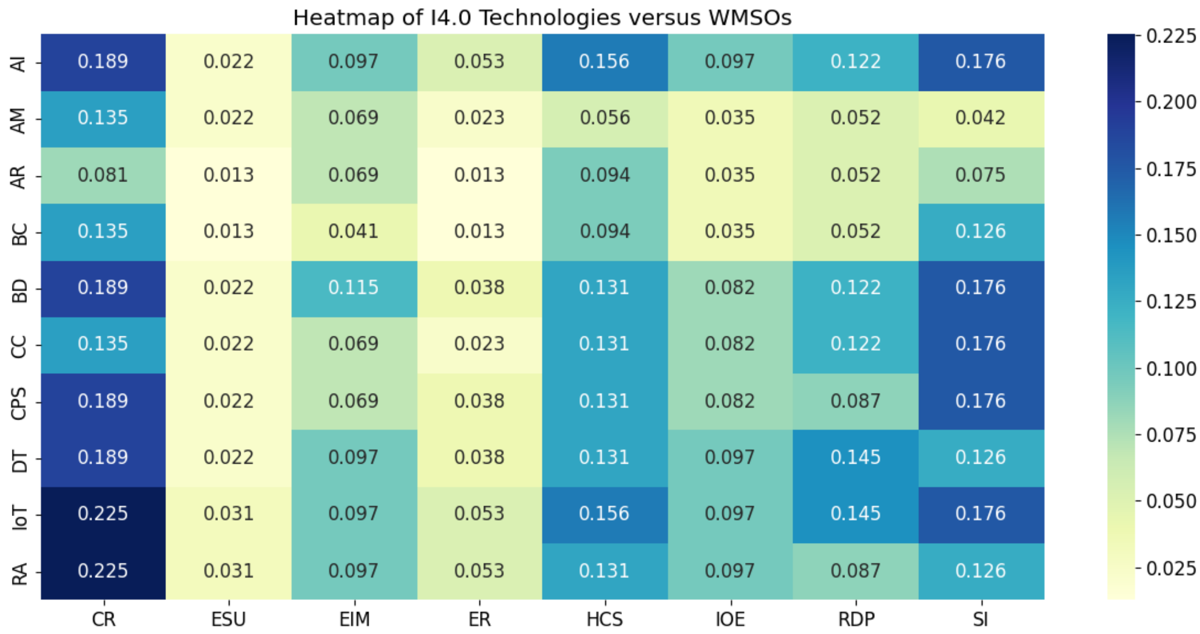

Figure 4. Heatmap of I4.0 Technologies versus WMSOs

As shown in Table 14, the Fuzzy ELECTRE II analysis results reveal that different I4.0 technologies dominate distinct WMSOs, with no single technology ranking highest across all strategic dimensions. IoT consistently ranks among the top performers in critical areas, including CR, ESU, ER, HCS, IOE, RDP, and SI. Likewise, RA frequently ranks alongside IoT across multiple outcomes. AI and BD technologies stand out in EIM, HCS, and SI strategies, while DT is particularly effective in data-intensive objectives such as RDP and IOE. In contrast, technologies like AR, AM, and BC generally have a lower influence across most WMSOs. These findings underscore the need for a strategy-specific approach in technology prioritization. IoT, AI, BD, DT, and RA are the most impactful and versatile technologies supporting warehouse transformation initiatives.

Table 14. The Weighted Normalized Average Fuzzy Decision Matrix

Strategy	Top Technologies	Top Score	Second Technologies	Second Score
CR	IoT, RA	0,22529	AI, BD, CPS, DT	0,18924
ESU	IoT, RA	0,03137	AI, AM, BD, CC, CPS, DT	0,02241
EIM	BD	0,11503	AI, DT, IoT, RA	0,09662
ER	AI, IoT, RA	0,05340	BD, CPS, DT	0,03814
HCS	AI, IoT	0,15643	BD, CC, CPS, DT, RA	0,13140
IOE	AI, DT, IoT, RA	0,09707	BD, CC, CPS	0,08154
RDP	DT, IoT	0,14547	AI, BD, CC	0,12220
SI	AI, BD, CC, CPS, IoT	0,17593	BC, DT, RA	0,12566

4.3. Explainability Analysis Using SHAP

The SHAP-based explainability analysis was conducted to reveal the underlying decision logic behind the ELECTRE II-based technology rankings. An XGBoost regression model was trained using the weighted decision matrix as input and the ELECTRE scores as the target variable. The results showed that Cost Reduction (CR) was by far the most influential criterion, with a SHAP value of +1.62, followed by Higher Customer Satisfaction (HCS) (+0.5) and Real-time Data Processing (RDP) (+0.4) (see Figure 5). These three outcomes emerged as the primary drivers of the technology rankings. Accordingly, top-performing technologies, such as Artificial Intelligence (AI) and the Internet of Things (IoT), achieved high scores in these strategies. For instance, IoT scored particularly high in Cost Reduction (CR = 0.225), Higher Customer Satisfaction (HCS = 0.156), and Real-time Data Processing (RDP = 0.145), as reported in Table 13. These alignments between SHAP values and normalized performance scores demonstrate the consistency between model explainability and expert-based evaluations.

In contrast, outcomes such as Sustainability Initiatives (SI), Enhanced Inventory Management (EIM), Improved Operational Efficiency (IOE), Error Reduction (ER), and Effective Space Utilization (ESU), despite having relatively high values for some technologies, showed minimal contribution in the SHAP analysis due to low variance across alternatives. This indicates that SHAP is sensitive to the absolute value of a strategic outcome and how differentiating that outcome is among the technologies. As a result, the findings emphasize that decision-makers should focus on the magnitude of strategy scores and their discriminatory power across technological options.

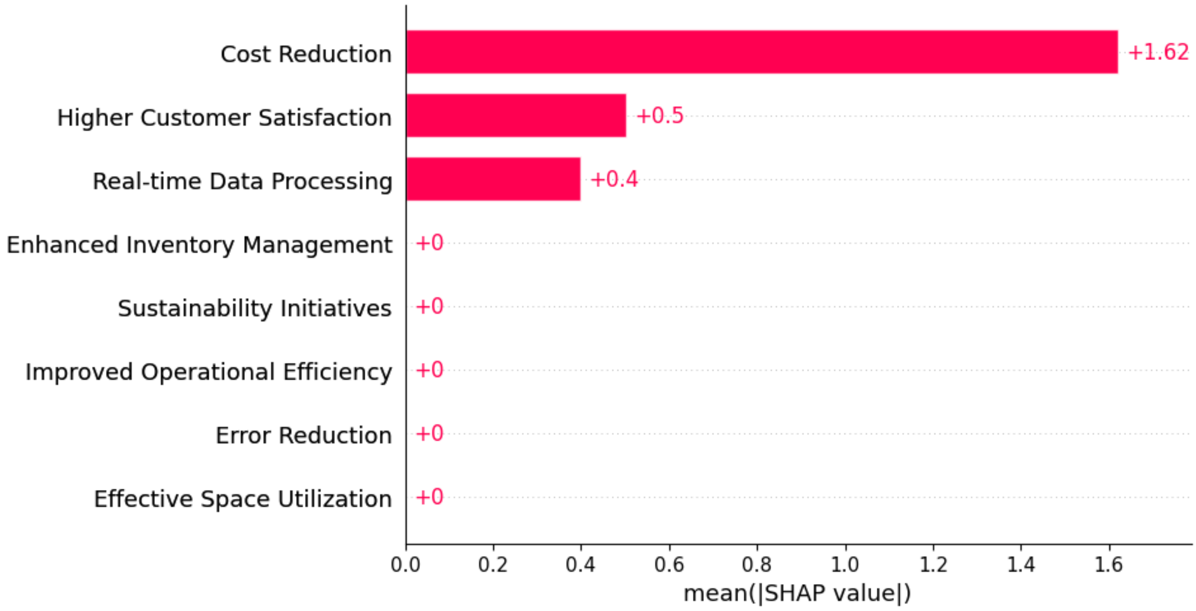

Figure 5. The SHAP Bar Chart

5. Conclusion

This study proposes a hybrid fuzzy MCDM framework that integrates Fuzzy DEMATEL, Fuzzy ELECTRE II, and SHAP-based explainability to evaluate the strategic impacts of Industry 4.0 technologies on warehouse management strategy outcomes (WMSOs). The model combines causal analysis with explainability, offering a transparent and interpretable decision-support system for industrial digital transformation.

The analysis revealed that Cost Reduction (CR) is the most critical outcome in the strategic network, while Real-time Data Processing (RDP), Sustainability Initiatives (SI), and Error Reduction (ER) act as key causal drivers. Through Fuzzy ELECTRE II, Artificial Intelligence (AI), Internet of Things (IoT), and Big Data Analytics (BD) were identified as the top-ranking technologies. SHAP analysis further confirmed the consistency of these results by highlighting CR, Higher Customer Satisfaction (HCS), and RDP as the most influential drivers of technology prioritization.

From a managerial perspective, these findings suggest that technologies such as AI and IoT should be prioritized for warehouse investments to enhance cost efficiency, provide real-time visibility, and improve customer responsiveness. Other technologies, including CPS and AM, have demonstrated strong contributions within specific strategies, such as process stability and customization, underscoring their niche yet valuable roles.

Furthermore, the proposed model offers practical utility for decision-makers such as warehouse managers and digital transformation leaders. By quantifying the strategic impact of various Industry 4.0 technologies, the framework helps prioritize investments based on specific warehouse performance goals. For instance, a warehouse decision-maker aiming to improve customer satisfaction and reduce operational costs can use the model’s outputs to select technologies—such as IoT or AI—that demonstrate the most significant contributions to these objectives. In future studies, we intend to supplement the framework with a simulated or real-world application to further demonstrate its practical implementation.

In conclusion, this study fills a notable gap by providing a causally grounded and explainable methodology for aligning I4.0 technology investments with warehouse performance goals. The scope can be expanded in future studies by involving more industrial participants. Additionally, a case study demonstrating the application of the model in a real-world warehouse management scenario could be included to illustrate its practical relevance better. Furthermore, the proposed decision-support framework need not be limited to warehouse management. It can also be applied to other operational domains of the supply chain, such as production planning, supplier selection, maintenance management, quality control, energy efficiency, and sustainability. These areas are highly susceptible to transformation through the capabilities of I4.0 technologies—such as real-time data processing, predictive analytics, autonomous systems, and resource optimization—and offer substantial potential for strategic performance improvement. Accordingly, future studies that extend the model's applicability to broader manufacturing and logistics contexts could enhance its generalizability and provide a more comprehensive understanding of how I4.0 investments contribute to strategic success across the entire value chain.

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Authors Contributions

This study was conducted by Ahmet Kala and Cem Özkurt, who contributed to all stages of the study, including conception and design, data collection, data analysis and interpretation, manuscript drafting, technical support, critical review of the content, and literature review. Bilal Emre Yahyaoğlu contributed to data collection, data analysis and interpretation, and literature review, assisting in the development of the study. All authors reviewed and approved the final version of the manuscript.

Conflict of Interest Notice

There is no conflict of interest to declare

Ethical Approval

This study did not involve any personal or sensitive data. It was based solely on expert opinions collected through the Delphi technique. Therefore, formal ethics committee approval was not required.

Availability of data and material

Not applicable

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