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Exploring the Impact of Technology 4.0 Driven Practice on Warehousing Performance: A Hybrid Approach

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Abstract: Developing a promising technology that copes with the industrial warehousing environment requires special preparation. It includes infrastructure, equipment, resources, knowledge, efficiencies, and strategies for dealing with failures. This study examines Technology 4.0 driven warehouse practices and performance based on a thorough literature review. The study presents a unique proposition as it considers a two-fold fuzzy Delphi analysis to rank the Technology 4.0 driven practices using best-worst method (BWM) based on experts' responses. Warehouse performance measures are evaluated by the Combined Compromise Solution (CoCoSo) method. The results indicate the contributions of a 'Man-machines or robots for facilitating human'; 'Planning system for management'; 'Storage systems' as as leading practices contributing to 'improved inventory management', 'effective storage and distribution', and 'improved distribution and shipping or delivery process'. Using this study, researchers and managers will better understand how to adopt technology in warehouse management system.

Keywords: Technology 4.0; warehouse practices; warehousing performances; fuzzy Delphi method; hybrid method; BWM; CoCoSo; Saudi Arabia

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1. Introduction

The success of the Kingdom of Saudi Arabia's (KSA) National Development Logistic Program (NDLP) initiatives is contingent upon multi-layers of programs and stakeholder support from management, funding, education, and training of the workforce, development of more connected and digitally-enabled infrastructure, implementation of automated products, processes, and procedures. In today's demanding and competitive business world, warehousing organizations continuously evaluate and change to embrace automation in manufacturing to expand and be profitable [1]. Technologies such as Big Data, IoT (Internet of Things), Cloud Computing, A.I. (Artificial Intelligence), Blockchain, and RFID (Radio Frequency Identification) are playing a vital role in business transformation at a reduced cost to achieve sustainability in warehouse operations [2].

The surge in the industrial growth of the Kingdom of Saudi Arabia is likely to touch 25 billion by 2022 (https://earth.org/global_sustain/china-global-sustainability-index/, accessed on 20 September 2021), with capital investments of more than 106 billion USD (https://www.my.gov.sa/wps/portal/snp/aboutksa/digitaltransformation, accessed on 23 September 2021). This is an outcome of the National Development Logistic Program (NIDLP) proposed economic diversification strategy to position Saudi Arabia as a global hub for mining, energy, and logistics sector (https://www.my.gov.sa/wps/portal/snp/aboutksa/digitaltransformation, accessed on 23 September 2021). The vision of the Kingdom of Saudi Arabia (KSA) 2030 has also suffered a setback impacting the country's growth chart and progression plans. Despite this, the businesses and economy are likely to recover soon, requiring continuous and vigorous government and organizational efforts. Although developed countries have faced such challenges due to the pandemic, such issues are occurring in developing and emerging economies. Based on KSA vision 2030, the Saudi government has toiled to bring the fiscal stabilization, development of economic systems such as banking and economy, reforms in societies, culture, industry, healthcare, technology, and many more (https://www.my.gov.sa/wps/portal/snp/aboutksa/digitaltransformation, accessed on 23 September 2021). Transformations in their logistics industrial sector are a must for an effective contribution towards vision 2030 and to invite the interest of foreign investors. This requires organizations to improve the quality of their industrial warehousing sector [3], outputs, and performances. Supply chain efficiencies in the warehousing sector are an outcome of integrating technologies. All warehousing processes related to distribution and supply chains, right from procurement, production, distribution, logistics, and warehousing, have a high scope of improvement through automation. In a report, middle eastern retailers highlighted IoT and A.I. as crucial factors driving their growth (https://www.tortoisemedia.com/intelligence/global-ai/, accessed on 28 September 2021). The need for smart warehouses is considered one of the top drivers by 38% of retailers (https://www.tortoisemedia.com/intelligence/global-ai/, accessed on 28 September 2021). The retail sector in KSA has also shared similar views, promoting big data and IoT as essential to economic growth. In countries such as China and Saudi Arabia, companies invest more in foreign markets, but they are more restricted in the cross-border approach. The flow of cross-border data cannot be facilitated without a platform that is competitive (https://unctad.org/system/files/official-document/der2021_en.pdf, accessed on 29 September 2021). The list of countries in Table 1 shows how they invest in Artificial Intelligence to achieve their goals, growth in emerging economies, and sustainability index.

Table 1. Emerging economics and Technology 4.0.

Emerging Economies	Investment in Artificial Intelligence	Growth of Industry 4.0 in G20 [4]	Operating Environment for Implementation [5]	Global Sustainability Index
China	1st ($22 Billion) [4]	1	2	136 [1]
India	3rd ($2.5 Million) [6]	4	19	63 [2]
Saudi Arabia	2nd ($4 Billion) [4]	2	1	161 [3]

[1] https://earth.org/global_sustain/china-global-sustainability-index/, accessed on 1 October 2021; [2] https://earth.org/global_sustain/india-ranked-63rd-in-the-global-sustainability-index/, accessed on 1 October 2021; [3] https://earth.org/global_sustain/saudi-arabia-ranked-161st-in-the-global-sustainability-index/, accessed on 1 October 2021; [4] https://www.my.gov.sa/wps/portal/snp/aboutksa/digitaltransformation, accessed on 23 September 2021; [5] https://www.tortoisemedia.com/intelligence/global-ai/; [6] https://opengovasia.com/india-ranks-13-in-ai-tech/, accessed on 2 October 2021.

Implementing operating environments is ranked number one in Saudi Arabia; therefore, technology integration in warehouses is viable. However, much work needs to be carried out to explore how difficult it will be to implement, establish measurement standards, establish benchmarking practices, train employees, and most importantly, what effect it will have on the environment. These technologies remodel warehouses into new economic rhythms, social trends, and environmental patterns. Understanding the technological integrations is necessary to understand the readiness for the required performance metrics [4]. Instead, these digital technology models or facilities must integrate technology-enabled functions along the length of warehouse operations to receive maximum benefits. To stay relevant in the competitive business environment, these techno-laden facilities must be evaluated from their reliability, scale, quality, and cost perspective [1]. This is required to cope with the complexity of warehouse operations due to globalization and outsourced manufacturing breakthrough technologies; when integrated into warehouse operations, convert these ordinary facilities into robust, transformative, well-integrated networking systems and models. These models, in turn, can translate the value potential across a chain of portals and channels to yield expected revenues [5].

Furthermore, warehouses can enhance operational performance by evaluating technologically driven systems and data-driven system practices and integrations [6]. However, the following questions arise to gain an understanding of the issue. How do warehouses remain productive and sustainable while working with ever-changing technologies? What are the pull factors or enablers that support them? Is there a need to identify enablers by the warehousing organizations to understand their capabilities and limitations for such integration [7]? This study contributes to smart warehouses from a perspective of technological development and proposes a decision-making framework [8]. It is critical to bring innovative technologies to the grass-root level of industrial warehousing setups [3] so that organizations can holistically realize the benefits of integration. For organizations to meet the industry's needs, they need to be technologically savvy, have a technologically-enhanced workforce, and employ a labour force with the right skills. This study enriches the scientific knowledge related to smart warehouses from multiple perspectives: technology and stakeholders. Integrating innovative technologies into industrial warehouses setups will benefit from their implementation holistically. Technology-enabled warehouses, employees, and labour bases help align the organization's goals with the industry's needs. However, one must remember that the substitution of manual work by machines and the introduction of superior digital technology or digital initiatives at specific points will not deliver the expected returns. Therefore, researchers propose the following research questions to highlight the need for the research undertaken.

RQ1: How do Technology 4.0 driven warehouse practices contribute towards achieving performances?
RQ2: What will be the decision-making framework to help the warehousing industry achieve its operational goals?

Researchers have explored technology-driven practices based on the proposed research questions to gain more insight and clarity. The following section reviews the literature to identify prevailing Technology 4.0 driven practices, considering various aspects of warehouse operational performance. Using fuzzy Delphi, the selected Technology 4.0 driven practices and warehouse performance are re-evaluated in Section 3 for their appropriateness, based on an expert consensus. In Section 3, we discuss the proposed decision-making hybrid model based on BWM and CoCoSo, and in Section 4, we describe the case in detail. Section 5 provides results and discussions, and the final section includes the conclusion and future research.

2. Literature Review

Automation orchestrates a gradient shift in warehouse setups by bringing down concrete walls and shifting the siloed and isolated mechanical functions to a centralized, transparent, technology-enabled, and integrated ecosystem [9]. It also offers a plethora of disruptive solutions capable of optimizing operations, streamlined logistics, and visibility across the value chain by leveraging the potential of machine learning and the integration of intelligence into the DNA of warehouse functions [2]. Furthermore, software-enabled digital processes allow prescriptive and predictive analytics for proactive forecasting and planning in logistics functions [10].

The inclination of organizations towards increased human-machine interactions transforms its configuration, which substantially influences its economic and environmental incentivization. Integrating innovative technologies in organizations usually brings a social change that can either alter their structures and operations to offer opportunities or pose challenges [2]. Hence, organizational readiness is vital to potentiate its interpretation of prevalent market trends, business, and environment to maximize returns [11]. Innovative technologies improve warehouse operations and allow regulated resource utilization [12] and inventory turnovers. It helps organizations manage the challenge related to managing delivery deadlines [13] according to significant fluctuation in customer order volume [14] and product returns. As a result, organizations tend to gain competitive advantage and customer satisfaction [15] and comply with their need to manage their resources.

Technology becomes integrated into a system based on its compatibility and characteristics, which could be routine, advanced, or breakthrough. Regular, sustainable performance in terms of effective resource utilization (reduced cost, operational efficiency, reliability, responsiveness, and flexibility) also defines its integration parameters [2]. If technology is expected to change the overall system completely and promises to deliver value, its integration becomes more accessible. Breakthrough technologies such as IoT or CPS (Cyber-Physical-System) [16,17] convert the manual operations of the warehouse of picking, deliveries, accounts into automated, well distributed, and paperless processes. Atzori et al. [3] argue that this saves resources, energy, and time and offers higher flexibility [18] in computation and energy capacity resource efficiency. Ready et al. [19] identified that role of IoT in warehouse operations is discussed in the context of inventory tracking, information sharing, and joint ordering; dispatching operations [20]; reducing TAT (turnaround time) [21]. Qiu et al. [22] find that IoT enables controlled manageability of inventory, handles data storage and management and security issues. Functions such as current inventory management, the anticipation of future orders, product safety, and durability by measuring the atmospheric conditions are managed using RIFD (radio frequency identification) and sensors [23]. Inter-machine co-operation between robotic systems reduces the burden of manual work by performing heavy and dangerous activities, thus reducing the risk of injuries [24]. The use of Robots for performing manual operations of lifting, organizing, and order picking [25] is often seen [26]. The use of A.I. offers voice recognition allowing machines to follow orders with minimal effort. The use of A.I. [27] and cloud computing allows automated storage and retrieval for easy access to stock availability in the warehouse [28]. Use of blockchain [29], big data analytics [30,31], and A.I. [20] is commonly seen in warehouse operations related to receiving [6,32], storage [6,33], more robust offering products such as raw materials, goods-in-process, finished products inventory holding, order picking [12,34], delivery, value-added-processing such as kitting, pricing, labelling, and product customization [35]. The integration of breakthrough and advanced technologies in the warehouse strengthens its ability to meet market challenges, respond to demand variations [36], staying flexible to handle peak throughputs at short notice during staff shortage [37]. Technical integrations in warehouse operations eventually lead to sustainability in terms of minimum errors, effective utilization of space [26], energy conservation, and reduced operational cost [38]. Due to increased demand, volume, velocity, and variety of data have multiplied; hence intelligent applications in the warehouse-like advanced analytics provide decisions [26,39] for competitive advantage [40].

On the contrary, social aspects of technology integration have not been discussed. It is mentioned in the works of some authors [4], but rarely has been discussed in detail. Nathaniel et al. [8] argue that technological integration complicates the equation of man and machine in warehouse operations. It causes stress because of fear of job insecurities; hence social aspects of technology integration must address the welfare of employees to provide them with a sense of job security through training. The following sub-section includes the discussions related to identified research gaps.

2.1. Article Selection

A comprehensive review of the literature on warehouses was undertaken to establish the scenario of 4.0 technologies in warehouses for smarter conversions. Initially, many articles were scanned, with papers in other languages being excluded. The expanding tendency of academics focused on smart warehouses and technological integrations demonstrate its significance in the growth and success of logistics 4.0. These tendencies pointed to the future direction of research and the current research work of the vast majority of scholars worldwide. This helps the researcher propose and identify the practices or enablers required to pursue the research directions. The next section of the paper will discuss the theoretical framework for the research undertaken.

2.2. Theoretical Foundation of Building Initiatives of Technology 4.0 Practices for Warehousing Performance

Wernerfelt [41] explains internal and external firm resources in his Resource-Based View (RBV). Firms control their internal resources, such as their financial, human, and technological infrastructure, while their customers, competitors, and suppliers are determined by industry attractiveness and structural autonomy. As a result of their internal resources, these companies have a competitive advantage and can better drive to attract their customers. In light of this, the author suggests that the current RBV contributes significantly to the firm performance that operates in a relatively dynamic and agile environment [40], as in the case of current research problems.

2.3. Research Gap

Researchers have made significant contributions to the warehousing management literature from various angles [42], but literature on warehouse sustainability concepts requires more attention [43]. Work on warehouse literature has been covered from technology adoption [44], relative advantage, financial rewards [5,45], cost reduction, and dealing with complexities [6,46], and from the human perspective [47]. However, these proposed results have only been theoretically presented and have not been empirically tested. Many authors have explored the research literature on sustainable performance in the warehouse context [48–51].

All works named herein shared theoretical discussions, but analytical implications of individual aspects of warehousing technology-driven practices along with expected outcomes need further exploration. Existing literature does not empirically verify if, how and for which types of warehouses technological integrations provide further improvement and opportunities. Hence this research intends to identify the decision-making framework between the technological practice and warehouse expected performance, please refer to Section 4. A detailed discussion of the hybrid methodology to answer the proposed research questions are given in the next section.

3. Research Framework for Hybrid Model

The three-phased methodology framework is used to achieve the objectives proposed, as shown in Figure 1. Using an integrated approach of literature survey and fuzzy Delphi, the first phase identified Technology 4.0 driven warehouses practices and performance measures for operational performance. In the second phase, Technology 4.0 driven practices are compared and ranked according to pairwise comparisons based on BWM. In the third phase, a hybrid method is used to evaluate the performance of warehouses through the adoption of technology-driven practices using CoCoSo.

3.1. Fuzzy Delphi

Delphi is a traditional method for determining a consensus among experts' opinions, but this consisted of several rounds of surveys, resulting in longer execution times and higher costs [52]. As a result of the experts' responses having various meanings, it is impossible to express their feedback in quantitative terms. As a result, the fuzzy Delphi method was developed to overcome these disadvantages by combining the fuzzy set theory with the traditional Delphi methodology [52]. Tseng et al. [53] have determined that using this method has benefited over Delphi methods as it reduces the number of survey rounds and saves time. Below are the detailed information about the steps involved in implementing the fuzzy Delphi method.

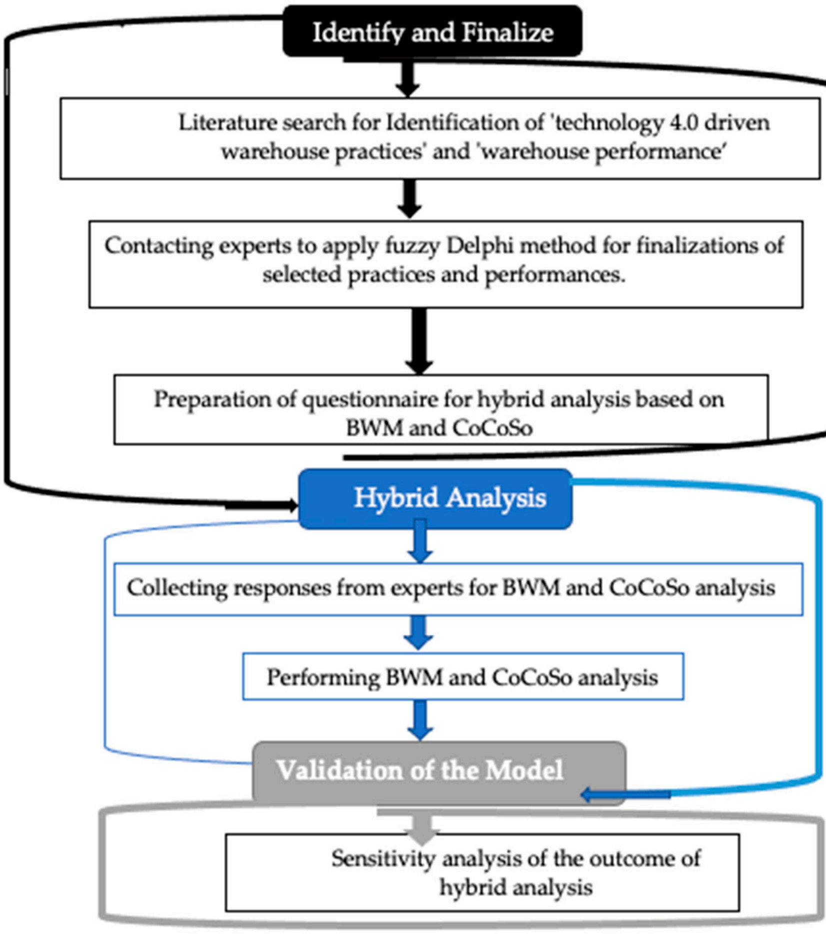

Figure 1. Steps of decision-making framework.

Step 1. Identify the factors/criterion

This step starts with a literature survey and expert interviews to identify the reasonable factors/criteria related to the problem of the study.

Step 2. Collecting the opinions of expert group

A questionnaire survey is conducted to collect expert opinions about Technology 4.0 driven warehouse practices and warehousing performance. A five-point Likert scale is used to gather expert opinions, which is given in tabular in the paper by Ishikawa et al. [52] (See Table 2).

Table 2. Linguistic scale and their associated TFNs.

Scale	Level of Significance	Triangular Fuzzy Number
1	Very low	(0.1, 0.1, 0.3)
2	Low	(0.1, 0.3, 0.5)
3	Medium	(0.3, 0.5, 0.7)
4	High	(0.5, 0.7, 0.9)
5	Very high	(0.7, 0.9, 0.9)

Step 3. Setting up of the triangular fuzzy numbers

A linguistic scale is used to transform the experts' inputs into TFNs. The observations in the inputs are used to find maximum and minimum by using the TFNs. The consensus of the group of the experts is calculated by geometric mean (M_A), by using the following procedure:

Let the value of evaluation for the significance of jth element given by ith expert from the 'n' expert is; $\widetilde{w}_{ij} = \left(l_{ij}, m_{ij}, u_{ij}\right)$, i = 1, 2, ... n and j = 1, 2, ... m. Then fuzzy weighting $\widetilde{w}_j$ of jth element is:

$$\begin{aligned} \widetilde{w}_j &= \left(l_j, m_j, u_j\right) \\ l_j &= min_i\left(l_{ij}\right) \\ m_j &= \sqrt[n]{\textstyle\prod_i^n m_{ij}} \\ u_j &= max_i\left(u_{ij}\right) \end{aligned} \tag{1}$$

where w_{ij} signifies that ith expert's evaluation for Technology 4.0 driven warehouse practices j, l_j characterize the lowest appraisal values of Technology 4.0 driven warehouse practices j, m_j indicate the geometric mean of all the expert assessment values for element j, and u_j is experts' highest assessment value for criterion j. Same process is repeated for the warehousing performance indicators.

Step 4. Defuzzification of the TFNs

TFNs, in this step, are converted into crisp number (S_i) of Technology 4.0 driven warehouse practices and warehousing performance using Equation (2) based on centre of gravity method.

$$Sj = \left(\frac{l_j + m_j + u_j}{3}\right) \tag{2}$$

Step 5. Finalisation of the Technology 4.0 driven warehouse practices and **warehousing performance**

Lastly, Technology 4.0 driven warehouse practices and warehousing performance are finalized using the fuzzy Delphi method. The obtained weights' significance of Technology 4.0 driven warehouse practices and warehousing performance are compared with a threshold value (λ) as follows:

The practice/performance i is considered, if $S_i \geq \lambda$, else i is not considered.

3.2. BWM Method

The Best Worst Method in decision-making frameworks is used to determine the prioritizing factors. Given the relatively low number of pairwise comparisons among the factors (in this study, Technology 4.0-driven warehousing practices) and less mathematical complexity, the academic community has widely applied the BWM method. Ali et al. [54] applied it to find out the decision-making framework for Drone integration in various companies by using the opinion of eight experts; Chen and Ming [55] have used it as a method of development to select smart product-service modules with six experts responses. A further advantage of the BWM is that it effectively handles inconsistencies that may arise from pairwise comparisons. The purpose of this method is to evaluate the effectiveness of Technology 4.0 driven practices by comparing them to the best and worst Technology 4.0 driven practices. As a result, the best TDP practices are preferred over the other TDP practices, and the worst TDP practices are preferred over the other TDP practices when a comparison is made, usually using a 9-point scale (1–9). The description of the stepwise procedure for applying the BWM method is given below:

Step 1. Identification of Technology 4.0 driven warehouse practices

This step identifies the major Technology 4.0 driven warehouse practices ("n" number of Technology 4.0 driven warehouse practices: TDP_1, TDP_2, TDP_3, ... TDPn) by examining the literature and applying the fuzzy Delphi.

Step 2. Determine the best and worst Technology 4.0 driven warehouse practices

The experts will select the best and worst from the finalized Technology 4.0 driven warehouse practices. The best and worst Technology 4.0 driven warehouse practices are denoted as c_B, and c_W, respectively.

Step 3. Perform the reference comparison with Technology 4.0 driven warehouse practices

Expert input is used to determine the best Technology 4.0 driven warehouse practices based on a 9-point scale, and it is represented by the A_B vector as follows:

$$A_B = (a_{B1}, a_{B2}, \ldots, a_{Bn})$$

where A_B the Best-to-Others (BO) vectors, a_{Bj} denotes the preference of the best Technology 4.0 driven warehouse practices B over the best Technology 4.0 driven warehouse practices j and $a_{BB} = 1$.

Step 4. Perform the reference comparisons with worst Technology 4.0 driven warehouse practices

The predominance of the other Technology 4.0 driven warehouse practices is calculated through expert input using a 9-point scale and represented by A_W vector as follows:

$$A_W = (a_{1W}, a_{2W}, \ldots, a_{nW})^T$$

where A_w the Others-to-Worst (OW) vector, a_{jw} refers the preference of the Technology 4.0 driven warehouse practices j over the worst Technology 4.0 driven warehouse practices W and $a_{ww} = 1$.

Step 5. Determine the optimal weights

The optimal weight for each Technology 4.0 driven warehouse practices is the one where, for each pair w_B/w_j and w_j/w_W, it should have $w_B/w_j = a_{Bj}$ and $wj/w_W = a_{jW}$. To satisfy these conditions for all j, maximum absolute differences are minimized of the set $\{|w_B - a_{Bj}w_j|, |w_j - a_{jW}w_W|\}$. This problem can be represented as following model:

$$\min \max \{|w_B - a_{Bj}w_j|, |w_j - a_{jW}w_W|\}.$$

Subject to:

$$\sum_j w_j = 1$$
$$w_j \geq 0\,;\, j \tag{3}$$

Model (1) can be converted as following linear problem.

$$\begin{aligned} &\min \xi^L \\ &\text{s.t.} \\ &\left|\frac{w_B}{w_j} - a_{Bj}\right| \leq \ \xi^L \text{ for all j} \\ &\left|\frac{w_j}{w_W} - a_{jW}\right| \leq \ \xi^L \text{ for all j} \\ &\sum_j w_j = 1 \\ &w_j \geq 0 \text{ for all j} \end{aligned} \tag{4}$$

The optimal weights of each Technology 4.0 driven warehouse practices $(w_1^*, w_2^*, \ w_3^* \ldots w_n^*)$ and optimal value of ξ^L was obtained by solving the linear problem by Equation (4). The value of the consistency ratio is compared. Consistency of the comparison depends on the value of ξ^L, a value closer to 0 indicates higher consistency and the value less than 0.1 is recommended by Rezaei [56].

3.3. Combined Compromise Solution (CoCoSo)

The CoCoSo method has recently been developed by Yazdani et al. [57], and it is one of the most effective MCDM techniques currently available. By combining an additive weighting model with an exponential weighting model, this method produces an overall result. Based on an evaluation against the criteria (in this study, Technology 4.0 driven warehouse practices), this method ranks the alternatives of warehouse performance measures. There have been rapid increases in the popularity of the CoCoSo approach within the supply chain field and related research fields.

Yazdani et al. [58] developed a decision model based on DEA and R-FUCOM in conjunction with R-CoCoSo to select logistics centres within autonomous communities of Spain. The framework for selecting medical waste treatment technologies was developed by Liu et al. [59] based on Pythagorean fuzzy CoCoSo. Below presents details regarding the steps of the CoCoSo procedure.

Step 1. The initial decision-making matrix related to the selected criteria/practices is prepared by using Table 3's linguistic terms, as follows

$$X_{ij} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix};\ i = 1,2,\ldots n,\ j = 1,2,\ldots m \tag{5}$$

Table 3. Linguistic scale and their associated TFNs.

Linguistic Scale	Crisp Value
Very Low (VL)	1
Low (L)	2
Medium (M)	3
High (H)	4
Very High (VH)	5

The matrix $[X]_{m\times n}$ shows the initial decision-making matrix which include the m-number of alternative/performance and n-evaluation criteria/practices. Hence, "x_{ij}" represents the selection of the ith "warehouse performances" by adopting the jth Technology 4.0 driven warehouse practices.

Step 2. The normalization of the initial decision-making matrix is carried out by using Equations (6) and (7) below (please refer Zeleny, [60]):

For benefit criteria,

$$r_{ij} = \frac{x_{ij} - \min\limits_i x_{ij}}{\max\limits_i x_{ij} - \min\limits_i x_{ij}}; \tag{6}$$

For non-benefit/cost criteria,

$$r_{ij} = \frac{\max\limits_i x_{ij} - x_{ij}}{\max\limits_i x_{ij} - \min\limits_i x_{ij}}; \tag{7}$$

Step 3. The weighted comparability sequence (S_i) of each alternative and power weight of comparability sequences (P_i) of each alternative is calculated using the Equations (8) and (9), respectively.

$$S_i = \sum\nolimits_{j=1}^{n} (w_j r_{ij}) \tag{8}$$

$$P_i = \prod\nolimits_{j=1}^{n} (r_{ij})^{w_j} \tag{9}$$

Step 4. Relative weights of each alternative is calculated using the three aggregation approaches, which are provided by Equations (10)–(12),

$$k_{ia} = \frac{S_i + P_i}{\sum_{i=1}^{m}(P_i + S_i)}; \tag{10}$$

The Equation (10) shows the arithmetic mean of sums of scores, weighted sum measure (S_i), and weight power measure (P_i),

$$k_{ib} = \frac{S_i}{\min_i S_i} + \frac{P_i}{\min_i P_i} \tag{11}$$

The Equation (11) is used to have a sum of relative scores of weighted comparability sequence (S_i) and power weighted comparability sequence (P_i) compared to the best.

$$k_{ic} = \frac{\lambda(S_i) + (1-\lambda)(P_i)}{(\lambda \max_i S_i + (1-\lambda)\max_i P_i)} \tag{12}$$

The Equation (12) signifies the balanced compromise of weighted comparability sequence (S_i) and power weighted comparability sequence (P_i) score. The value of the parameter λ is mostly taken as 0.5. However, it might be different as recommended by the team's requirements.

Step 5. Based on the value of k_i, the weights of the alternatives are calculated by Equation (13).

$$k_i = (k_{ia}k_{ib}k_{ic})^{\frac{1}{3}} + \frac{1}{3}(k_{ia} + k_{ib} + k_{ic}) \tag{13}$$

The alternatives are ranked based on the value of k_i, that is, the alternative with a significant value of k_i is ranked higher than those without.

After discussing the hybrid methodology based on the fuzzy Delphi, BWM, and CoCoSo, the next section includes the case application of the warehousing sector.

4. Case Study

4.1. Case Companies Information

The warehousing sector displays better growth with technological developments in the Makkah region. The level of automation is increasing, which changes the way warehousing operations are carried out to gain a competitive advantage. Technology is being embraced by the government, resulting in the implementation of omnichannel networks and the improvement of the supply chain network. These changes are reflected in the structural changes and storage facilities. A shift, therefore, in the industry toward leveraging technology has led to increased efficiency for the warehousing sector. The warehouses selected have all been converted to smart warehouses using a combination of system-based and data-driven strategies for conversion. Their subdomain functions are focused on inventory management, order-picking and batch-handling, warehouse operations, cyber-physical systems, warehouse management, and operating labour.

4.2. Background of Experts

A range of experts was contacted from the warehousing organization. They were involved in supply chain planning, efficiencies improvements, warehouse maintenance, management operations, inventory management, procurements of raw materials, and vendor management related to technology and equipment were contacted. A careful selection process was followed for the experts' selection. A panel of Experts constituted had a minimum of 10 and a maximum of 25 years of experience with bachelor's and master's in Industrial and Production Engineering; Business Management, and Supply Chain Management.

4.3. Finalization of Technology 4.0 Driven Practices and Warehousing Performance

Based on the literature review and fuzzy Delphi, a twofold approach is proposed for developing a decision-making model for Technology 4.0 warehouse practices and their performance in warehousing. A literature search enabled the researchers to identify 11 Technology 4.0 driven warehouse practices and 14 warehouse operation performance measures.

A semi-structured questionnaire was then developed to finalize the identified practices and performance measures. The experts were contacted for two rounds of responsive feedback. In the first round, responses were collected to finalize the 'practices' and their corresponding performances. Regular onsite and virtual meetings, in this regard, were held. The experts use a linguistic scale (shown in Table 2) for their preferred responses for the selection of 'practices' and their corresponding performances. Once the responses are gathered, it is transformed into TFN by using Table A1. In this research, decision-making for linguistic groups is based on individual semantics and consensus reaching. Out of 13 practices, nine Technology 4.0 driven warehouse practices were considered most effective for the study, along with 13 warehousing performances out of 15 (see Table 4). The De-fuzzy value of a Technology 4.0 practice and the performance of warehousing is considered significant when it is greater than 0.7; otherwise, it is dropped from further consideration (Chang et al. [61] and Khan et al. [62]). A final questionnaire was prepared to gather feedback on TDS practices and warehouse performance, as proposed in Table 4.

Table 4. Identification of the Technology 4.0 driven practices and warehouse performances.

TDP Practices	Min	Geometric Mean	Max	De-Fuzzy	Decision
Man-machines or robots for facilitating human	0.5	0.793725	0.9	0.731242	Accept
Tracking and stock level monitoring models	0.5	0.813926	0.9	0.737975	Accept
Planning systems for management	0.5	0.774026	0.9	0.724675	Accept
Navigation algorithm and sensing systems	0.5	0.813926	0.9	0.737975	Accept
Fair Acceptance	0.1	0.329723	0.7	0.376574	Reject
Visualization and application models	0.5	0.813926	0.9	0.737975	Accept
Simulation models for inbound transportation management-AGV	0.5	0.793725	0.9	0.731242	Accept
Managing optimization, controlling, monitoring, and planning stages	0.5	0.754816	0.9	0.718272	Accept
Decision making models for Inventory status	0.5	0.813926	0.9	0.737975	Accept
System for facilitating	0.1	0.278554	0.7	0.359518	Reject
Human efforts	0.1	0.20345	0.7	0.334483	Reject
Order quality and responsiveness	0.5	0.813926	0.9	0.737975	Accept
Inventory status updates, risk, and investment minimization	0.1	0.278554	0.7	0.359518	Reject
Storage systems	0.5	0.813926	0.9	0.737975	Accept
Warehousing Performance	**Min**	**Geometric Mean**	**Max**	**De-Fuzzy**	**Decision**
Improved inventory management	0.5	0.793725	0.9	0.731242	Accept
Improve human skills	0.1	0.278554	0.7	0.359518	Reject
Effective storage management	0.5	0.793725	0.9	0.731242	Accept
Better adoption of digital technology	0.1	0.278554	0.7	0.359518	Reject
Improved resource planning and utilization	0.5	0.793725	0.9	0.731242	Accept

Table 4. *Cont.*

Improved distribution and shipping or delivery process	0.5	0.793725	0.9	0.731242	Accept
Increased return on investment	0.5	0.793725	0.9	0.731242	Accept
Decrease in non-value-added activities	0.5	0.793725	0.9	0.731242	Accept
Improved information integration and sharing	0.5	0.793725	0.9	0.731242	Accept
Improved benchmarking standards	0.5	0.793725	0.9	0.731242	Accept
Improved C.E. based smart culture	0.1	0.278554	0.7	0.359518	Reject
Improved capacity/space utilization-availability/usage	0.5	0.793725	0.9	0.731242	Accept
Reduced operational cost	0.5	0.793725	0.9	0.731242	Accept
Reduced downtime	0.5	0.793725	0.9	0.731242	Accept
Reduced TAT for delivery performance	0.5	0.813926	0.9	0.737975	Accept

4.4. Prioritization of Technology 4.0 Driven Warehouse

The questionnaire was prepared to collect the expert's responses for the Technology 4.0 driven warehouse practices (TDP) presented in Table 5 below. Technology 4.0 driven warehouse practices (TDP) are identified by each expert with the help of a questionnaire.

Table 5. Technology 4.0 driven practices.

Practices	Description	Authored by
Planning systems for management	Optimization, control, monitoring, and planning of point-of-sale data, inventory information, customer projections, and planned orders for high-volume distribution.	[63]
Man-machines or robots for facilitating human	Automated Mobile Robots (AMR) using sensors are needed in warehouses to facilitate/manage human efforts and interventions.	[27]
Order quality and responsiveness	By integrating Technology4.0 into inventory management, inventories can be reduced, order fulfilment can be increased, order processing time is reduced, and orders will be fulfilled correctly the first time. This will reduce customer inquiries, simplify customer support, and increase customer satisfaction.	[11,14]
Visualization and application models	Intelligent agents are used to define complex operations, managing speed and accuracy to deliver the products.	[64]
Tracking and stock level monitoring models	Adopting assessment models that update automatically whenever products get delivered, sold, lost, or destroyed. This is to eliminate inefficiencies and have the correctness.	[38,65]
Decision-making models for Inventory status	For warehouses to be able to update inventory status, minimize Risk, and investment, decision support models are needed.	[65]
Simulation models for inbound transportation management-AGV	The key steps of the inbound receiving process are handled by Automated Guided Vehicle (AGV), which is built on a simulation framework.	[15]

Table 5. *Cont.*

Practices	Description	Authored by
Storage systems: Automated Storage and retrieval (AS/RS)	The automated storage and retrieval (AS/RS) system has been developed to achieve capacity utilization, standardized and accurate picking operations, and cost reduction. This system uses a computerized control system to automatically retrieve and place the products.	[17,65]
Navigation algorithm and sensing systems	Magnetic positioning and RFID indoor positioning systems are helpful for integrating industrial trucks and lift trucks in the operations.	[43]

The experts use Saaty's nine-point scale (1–9) to select the best TDP practices over the other TDP practices, and the same process is repeated for choosing the other TDP practices over the worst practices.

Table 6 exhibits all the experts' optimal weights calculated by the BWM's optimization model 2 (Equation (4)). Further, average weight is found for each practice (TDP) and shown in Table 7 and their ranks. Researchers suggested that the average consistency ratio (C.R.) needs to be less than 0.10 to have consistent and reliable results based on the experts' data. Table 6 has the values of the consistency ratio of each expert, and Table 7 contains the average consistency ratio, which is <0.10; thus, the criteria is achieved in our case.

Table 6. Best and worst Technology 4.0 driven warehouse practices along with the optimal weights from each expert.

Best	**TDP1**	**TDP1**	**TDP2**	**TDP8**	**TDP2**	**TDP2**	**TDP8**	**TDP8**	**TDP1**	**TDP1**
Worst	**TDP7**	**TDP9**	**TDP9**	**TDP9**	**TDP7**	**TDP5**	**TDP5**	**TDP7**	**TDP5**	**TDP5**
TDP1	0.25	0.26	0.17	0.17	0.17	0.17	0.08	0.29	0.30	0.11
TDP2	0.16	0.17	0.28	0.17	0.29	0.29	0.19	0.19	0.19	0.33
TDP3	0.11	0.11	0.11	0.11	0.11	0.11	0.08	0.07	0.08	0.08
TDP4	0.11	0.11	0.09	0.08	0.09	0.09	0.10	0.09	0.10	0.11
TDP5	0.05	0.06	0.06	0.06	0.06	0.03	0.03	0.03	0.03	0.03
TDP6	0.08	0.09	0.09	0.08	0.09	0.09	0.06	0.06	0.06	0.07
TDP7	0.03	0.06	0.06	0.06	0.03	0.06	0.06	0.05	0.06	0.07
TDP8	0.16	0.11	0.11	0.25	0.11	0.11	0.30	0.12	0.13	0.14
TDP9	0.05	0.03	0.03	0.02	0.05	0.06	0.10	0.09	0.05	0.05
CR	0.07	0.08	0.06	0.09	0.05	0.05	0.08	0.08	0.08	0.09

Table 7. Weight and rank Technology 4.0 driven warehouse practices.

Technology 4.0 Driven Warehouse Practices (TDP)	**Weights**	**Rank**
Planning system for management (TDP1)	0.197	2
Man-machines or robots for facilitating human (TDP2)	0.226	1
Order quality and responsiveness (TDP3)	0.099	4
Visualization and application models (TDP4)	0.095	5
Tracking and stock level monitoring models (TDP5)	0.044	9
Decision-making models for Inventory status (TDP6)	0.077	6
Simulation models for inbound transportation management and AGV (TDP7)	0.053	7
Storage systems (TDP8)	0.156	3
Navigation algorithm and sensing systems (TDP9)	0.053	8
Average Consistency Ratio (CR) = 0.0735		

4.5. Prioritization of Warehousing Performance Measures

The last part of the questionnaire includes warehouse performance as indicated below in Table 8. Each expert used a linguistic decision matrix, as shown in Table 3, to evaluate warehousing performances using Technology 4.0 driven practices as an evaluation criterion.

The linguistic terms are transformed with the crisp values (using Table 3) for all the ten experts' responses.

Table 8. Warehousing performances.

Practices	Description	Authored by
Improved distribution and shipping or delivery process (WOP1)	As soon as new orders are placed, the automated process starts with picking items from inventory, packing boxes, and making sure packages reach their destinations. This improves efficiency.	[14,33]
Increased return on investment (WOP2)	Streamlining the process with technology ensures better ROI.	[28,36]
Improved benchmarking standards (WOP3)	Based on the current best practices, AI/ML helps to generate actions and drive improvements in warehouse operations.	[43,63]
Reduced operational cost (WOP4)	Due to integrated A.I./ML-based processes receiving, storing, order picking, inspection, packaging, dispatching, delivery, kitting, pricing, labeling, and product customization have less costs.	[14,38]
Improved information integration and sharing (WOP5)	With a technology-driven process, all the data is consolidated in one place, and the digital performance management for product location, quaintly on hold, etc., is supported by IIoT.	[65]
Reduce reverse logistics (WOP6)	In warehouses, return and reverse logistics are very important. Smart systems enable identification, implementation, and tracking.	[54]
Reduced downtime and GoLive (WOP7)	Robotic process automation, ERP, Digital work instructions, augmented reality-based operator assistance, and basic retrofit automation for loading, conveyors etc., are accelerated adoption irrespective of existing technology infrastructure.	[16,17]
Improved resource planning and utilization (WOP8)	Utilizing technology 4.0 driven resource planning allows for demand-driven planning for human deployment, increasing productivity and efficiency on various work stations and maximizing space utilization.	[2,10,63]
Decrease in non-value-added activities (WOP9)	Machine monitoring system connected to the IIoT (Industrial Internet of Things) is the best way to capitalize on the value-added warehousing system. It helps to reduce the yield losses by collecting real-time operator feedback and connecting them from anywhere which improves administrative functions.	[65]
Effective storage management (WOP10)	Storing items in a class based on the fixed items are considered best. Optimum number of boundaries of storages and volume are considered for random and class-based storage. However, travel time is fairly insensitive to the number of storage classes.	[65]
Reduced TAT for delivery performance (WOP11)	Warehouses are having differential speed of adoption with advantage to those with existing technology infrastructure such as Operator training using virtual reality, advanced analytics (AI/ML) for operations, automation of plant/warehouse logistics (AGV etc.)	[21]
Improved inventory management (WOP12)	Control and safeguarding of the inventory is an essential task for a successful warehouse for better business in terms of cost, turnover and accuracy by using AI/ML, big data and cloud computing.	[39]
Improved capacity/space utilization-availability/usage (WOP13)	Technology-driven system specially simulation, ERP etc., help to direct put away to manage the space discriminately, allow the material handling. It relatively provides the most economical means of storage in terms of equipment cost, use of space, damage to material, handling labour and operational safety utilization.	[10,33]

The average of all matrices is calculated and presented in Table 9.

Table 9. Initial decision matrix.

Performance Measures	TDP1	TDP2	TDP3	TDP4	TDP5	TDP6	TDP7	TDP8	TDP9
WOP1	3.3	3.4	3.2	2.4	3.4	2.8	3	3.1	2.5
WOP2	4	3.3	3.5	2.3	2.4	2.1	1.9	2.3	2.3
WOP3	2	4.6	3.7	2.3	2	2.2	2.5	1.7	1.7
WOP4	3.6	3.2	3.3	2.4	3.9	3.4	3.4	3.9	3.9
WOP5	3.3	4.7	3.8	2.3	2	2.8	2.6	1.7	1.7
WOP6	2.1	3.1	3.4	2.8	3.2	3.6	2.8	2.5	2.5
WOP7	3.4	3.2	3.4	2.7	2.6	4	3.6	2.4	2.4
WOP8	2.3	3.3	2.5	2.1	2.7	3.2	3.1	2.1	2.1
WOP9	3.1	2.8	2.8	2.3	4	3.6	3.2	4.2	4.2
WOP10	3.3	3.4	3.9	2.4	3.4	3.6	4	2.9	2.9
WOP11	3.2	3.5	3.7	3.2	3.5	3.3	3.3	2.7	2.7
WOP12	3.7	3.7	3.4	3.7	2.9	3.6	3.4	3.7	3.7
WOP13	2.5	4.1	3.3	2.4	2.7	3.9	3.5	3.8	3.8

Next, the normalised matrix is obtained by using Equations (6) and (7) and shown in Table 10. Table 11 presents a weighted comparability sequence and their summation (Sj) for each warehousing performance calculated using Equation (8).

Table 10. Normalized decision matrix.

Performance Measures	TDP1	TDP2	TDP3	TDP4	TDP5	TDP6	TDP7	TDP8	TDP9
WOP1	0.65	0.32	0.50	0.19	0.70	0.37	0.52	0.56	0.32
WOP2	1.00	0.26	0.71	0.13	0.20	0.00	0.00	0.24	0.24
WOP3	0.00	0.95	0.86	0.13	0.00	0.05	0.29	0.00	0.00
WOP4	0.80	0.21	0.57	0.19	0.95	0.68	0.71	0.88	0.88
WOP5	0.65	1.00	0.93	0.13	0.00	0.37	0.33	0.00	0.00
WOP6	0.05	0.16	0.64	0.44	0.60	0.79	0.43	0.32	0.32
WOP7	0.70	0.21	0.64	0.38	0.30	1.00	0.81	0.28	0.28
WOP8	0.15	0.26	0.00	0.00	0.35	0.58	0.57	0.16	0.16
WOP9	0.55	0.00	0.21	0.13	1.00	0.79	0.62	1.00	1.00
WOP10	0.65	0.32	1.00	0.19	0.70	0.79	1.00	0.48	0.48
WOP11	0.60	0.37	0.86	0.69	0.75	0.63	0.67	0.40	0.40
WOP12	0.85	0.47	0.64	1.00	0.45	0.79	0.71	0.80	0.80
WOP13	0.25	0.68	0.57	0.19	0.35	0.95	0.76	0.84	0.84

Table 11. Weighted comparability sequence matrix.

Performance Measures	TDP1	TDP2	TDP3	TDP4	TDP5	TDP6	TDP7	TDP8	TDP9
WOP1	0.13	0.07	0.05	0.02	0.03	0.03	0.03	0.09	0.02
WOP2	0.20	0.06	0.07	0.01	0.01	0.00	0.00	0.04	0.01
WOP3	0.00	0.21	0.08	0.01	0.00	0.00	0.02	0.00	0.00
WOP4	0.16	0.05	0.06	0.02	0.04	0.05	0.04	0.14	0.05
WOP5	0.13	0.23	0.09	0.01	0.00	0.03	0.02	0.00	0.00
WOP6	0.01	0.04	0.06	0.04	0.03	0.06	0.02	0.05	0.02
WOP7	0.14	0.05	0.06	0.04	0.01	0.08	0.04	0.04	0.01
WOP8	0.03	0.06	0.00	0.00	0.02	0.04	0.03	0.03	0.01
WOP9	0.11	0.00	0.02	0.01	0.04	0.06	0.03	0.16	0.05
WOP10	0.13	0.07	0.10	0.02	0.03	0.06	0.05	0.08	0.03
WOP11	0.12	0.08	0.08	0.07	0.03	0.05	0.04	0.06	0.02
WOP12	0.17	0.11	0.06	0.10	0.02	0.06	0.04	0.13	0.04
WOP13	0.05	0.15	0.06	0.02	0.02	0.07	0.04	0.13	0.04

The power-weighted comparability sequence and their summation (P_i) is computed by using Equation (9) and is shown in Table 12 for each warehousing performance are computed using Equation (9) and shown in Table 13 for each warehousing performance.

CoCoSo method is based on three aggregation methods to compute the relative weights (k_{ia}, k_{ib}, k_{ic}) of warehousing performance by using the Equations (10)–(12). These relative weights are applied to determine the final weights (as shown by K column) by using Equation (13) is shown in Table 12. Final ranks are found based on 'K' weights for the warehousing performances and are shown in Table 13.

Table 12. Exponentially comparability sequence matrix.

Performance Measures	TDP1	TDP2	TDP3	TDP4	TDP5	TDP6	TDP7	TDP8	TDP9
WOP1	0.919	0.771	0.934	0.853	0.984	0.926	0.966	0.913	0.941
WOP2	1.000	0.740	0.967	0.820	0.931	0.000	0.000	0.800	0.927
WOP3	0.000	0.988	0.985	0.820	0.000	0.798	0.936	0.000	0.000
WOP4	0.957	0.703	0.946	0.853	0.998	0.971	0.982	0.980	0.993
WOP5	0.919	1.000	0.993	0.820	0.000	0.926	0.943	0.000	0.000
WOP6	0.554	0.659	0.957	0.924	0.978	0.982	0.956	0.837	0.941
WOP7	0.932	0.703	0.957	0.911	0.948	1.000	0.989	0.820	0.935
WOP8	0.688	0.740	0.000	0.000	0.955	0.959	0.971	0.751	0.907
WOP9	0.889	0.000	0.859	0.820	1.000	0.982	0.975	1.000	1.000
WOP10	0.919	0.771	1.000	0.853	0.984	0.982	1.000	0.892	0.962
WOP11	0.904	0.798	0.985	0.965	0.987	0.965	0.979	0.867	0.953
WOP12	0.968	0.845	0.957	1.000	0.965	0.982	0.982	0.966	0.988
WOP13	0.761	0.918	0.946	0.853	0.955	0.996	0.986	0.973	0.991

Table 13. Relative weights, final weigh and raking of warehousing performance measures.

Performance Measures	K_a	Ranking	K_b	Ranking	K_c	Ranking	K	Final Ranking
WOP1	0.085	7	3.967	7	0.925	7	2.336	7
WOP2	0.064	10	3.238	11	0.702	10	1.862	11
WOP3	0.047	13	2.550	12	0.518	13	1.436	13
WOP4	0.088	2	4.655	2	0.958	2	2.632	2
WOP5	0.060	12	3.605	9	0.651	12	1.958	10
WOP6	0.079	8	3.261	10	0.866	8	2.009	9
WOP7	0.085	6	4.050	6	0.925	6	2.369	6
WOP8	0.060	11	2.319	13	0.660	11	1.465	12
WOP9	0.078	9	3.959	8	0.855	9	2.273	8
WOP10	0.087	5	4.485	4	0.952	5	2.561	4
WOP11	0.087	4	4.453	5	0.955	4	2.551	5
WOP12	0.092	1	5.293	1	1.000	1	2.913	1
WOP13	0.088	3	4.590	3	0.956	3	2.605	3

5. Results and Discussion

The strategic challenges faced by the industrial setups to integrate Technology 4.0 driven warehouses practices for improved industrial outputs are yet to be achieved. However, our findings suggest that Man-machines or robots for facilitating human ≻ Planning system for management ≻ Storage systems ≻ Order quality and responsiveness ≻ Visualization and application models ≻ Decision-making models for inventory status ≻ Simulation models for inbound transportation management and AGV ≻ Navigation algorithm and sensing systems ≻ Tracking and stock level monitoring models.

The main goal of a warehouse is to obtain all these requirements after removing or reducing non-value-added tasks by the man-machine interactions (ranked as 1st). This reduces downtime in the warehouse and is considered the most effective practice by smart warehouses. For example, robots are used for doing night patrols and collecting mundane data. They can hear sounds such as footsteps or smell harmful air quality with extreme sensing. Robots are powerful and efficient. They are expected to deliver higher quality results by benchmarking standards.

In technologically driven warehouses, the planning system is considered the 2nd most effective method for storing and managing inventory. Management planning systems optimize, control, monitor, and plan various high volume distribution and shipping stages, such as point of sales data, stock, on-hand data, forecasts, and reorders [12].

The storage system rating, at 3, for capacity utilization and cost reduction is low. However, customized warehouses of varying sizes, free zones and non-free zones of locations [66], convenient locations near major logistics hubs, and onsite labour and staff accommodations have not proven as effective as it is expected.

The 4th highest ranked practice is helping the warehouse to increase its competitiveness by setting a cut-off time for next-day deliveries. Warehouses can calculate staging, demurrage, labour, and stock costs using cloud data. As a result of automation, overhead expenses, driving costs, and operating costs are reduced. Reduced energy consumption, less waste, and fewer emissions reduce overhead, driving costs, and operational costs [67].

A visual representation (ranked as 5) provides an overview of shelves in the warehouse, simulated cart movement, and a variety of picking list statistics. We know that optimization models are required to track products and keep stock levels accurately. These models (ranked at 6) are compatible with minimum stock levels, stock reviews, JIT policies, reorder lead times, economic order quantities, and batch control. By using modern computerised technology, the utilization and availability of space can be maintained more efficiently and quickly. In the simulation, computer models (ranked at 7) are used to understand and improve an entire warehouse system in order to achieve the desired results in virtual settings. In terms of investment rate and return, 'Navigation algorithm and sensing systems for effective equipment utilization' are the 8th ranked. As a result of a lack of advanced analytics, it isn't easy to share machine operating parameters such as average speed, cycle time, product output, etc., to the cloud for further processing. As a result, the cloud will not be able to integrate data for valuable real-time insights. By using an inventory tracking system (ranked as 9), a warehouse tracks the movement of raw materials and finished goods to meet customer demand. By a tracking system, inventory is easily visualized at every step of the order process, including shipping, receiving, storing, and fulfilling orders and returning, exchanging, and providing warranty services. Warehouse organisations use cloud and mobile solutions to track inventory in real-time to reduce costs, analyse trends in the supply chain, minimize reverse logistics and increase revenue. With it, warehouses update, select groups of items, implement quality control and batch tracking and integrate their systems with other warehouses. In RFID tags, unique identification numbers enable remote reading and are used to identify items.

The research findings and future directions are summarized in the next section. The research findings and future directions are summarized in the next section.

Sensitivity Analysis

MCDM analyses are prone to error, and the result obtained by these analyses could be influenced by the imprecision of the data, the vagueness of the data, and the subjective opinions of the analysts. Various studies have shown that a small variation in criterion weights can affect the ranking [56]. As a result, it is vital to verify the robustness of the ranking algorithm. A sensitivity analysis is carried out to test the reliability of the results [62].

During the sensitivity analysis, the weights of Sustainable Practices are varied based on the highest weighted categories. In order to generate nine tests of Technology 4.0 practices (Test 1 to Test 9), researchers varied the weight of the highest weighted practice, TDP2 in our case, from 0.1 to 0.9, with increments of 0.1. As a result of the change in TDP2 weight, a corresponding change is also apparent in other Technology 4.0 driven practices weights. See Appendix A Table A1 and Figure 2. This resulted in a difference in the ranking of the warehouse performance as a result of the weight changes in different tests. Using the CoCoSo method, the results of 9 different tests of warehouse performance are shown in Table A2 and Figure 3. Based on Figures 2 and 3, it is evident that most of the Technology 4.0 driven practices and warehouse performance indicators remain the same and are hardly affected in all the tests executed. Accordingly, it is concluded that the proposed hybrid method is sufficiently reliable, robust, and stable to obtain the desired results.

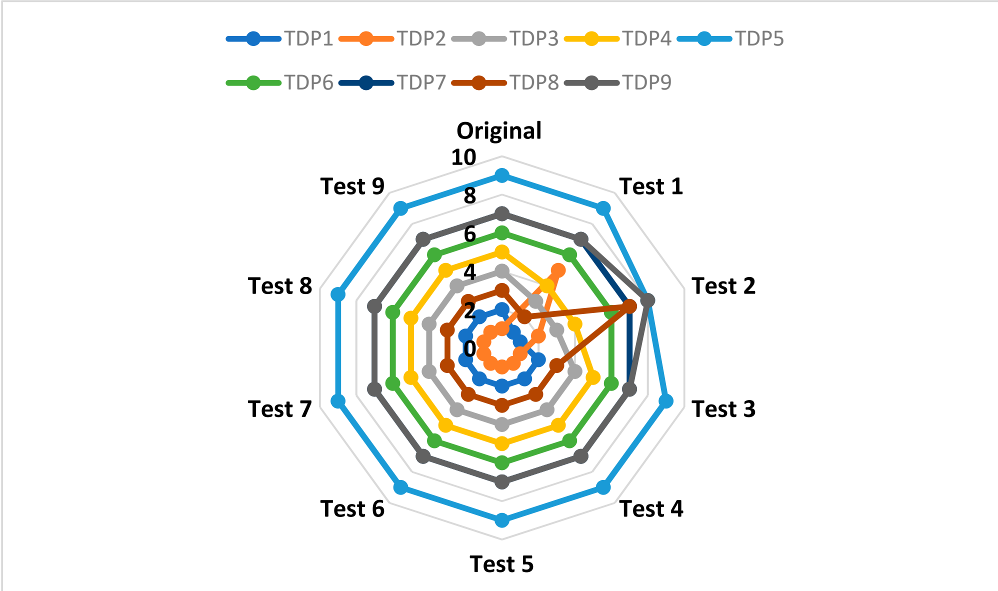

Figure 2. The illustrative ranking of Technology 4.0 driven practices in nine tests.

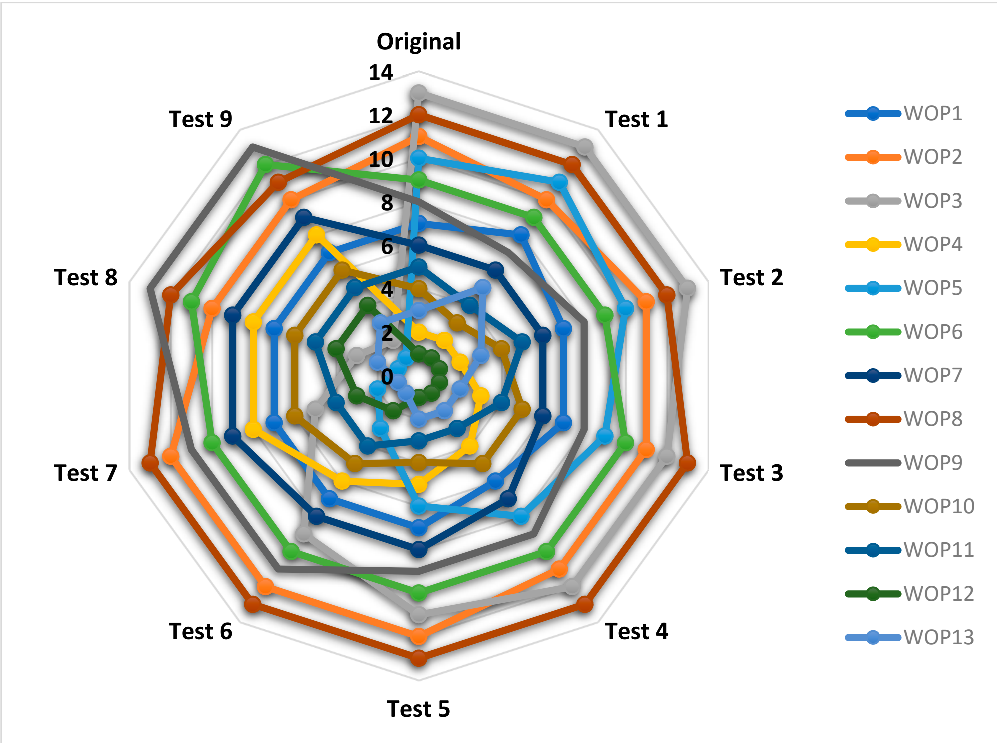

Figure 3. The illustrative ranking of warehouse performances in nine tests.

6. Conclusions and Future Research Directions

The study covers the warehousing scenario in the Mecca region, identifying and mapping the practices compared to national and international benchmarked practices. After consulting experts, the decision-making framework is proposed for shortlisting, finalizing, and ranking the practices and performance data. Linguistic scale ratings were used to capture the diversity, subjectivity and imprecision inherent in the human responses.

Through technology, people around the world can connect, and by connecting those at the grassroots level, new knowledge related to the latest prevalent practices can be integrated.

Through the collective efforts of government support and the strength of all industrial sectors, the logistics sector has carried out well compared to global standards. To remain competitive, it must solidify the productive and manufacturing core.

Research findings provide insights to businesses in understanding the implications of different technologies such as IoT, A.I., Big Data, and Blockchain to improve warehouse functions and ultimately increase business and supply chain resilience.

6.1. Managerial Implications

This research is a stepping stone, especially for novice or newly built organizations or those who plan to understand the automation scenario thoroughly. It provides managers with important feedback that can help them embrace change by understanding the impact of various technology-driven practices. It offers insight to organizations competing at international levels on how to improve their practices by benchmarking them against benchmarks, thus enabling the warehousing industry to contribute to the vision of 2030 effectively. Study findings are relevant to a wide range of businesses as the practices chosen are universal and easily applied to any organizations. More contributions are needed to adapt, practice, and perform sustainability from a developing country perspective.

6.2. Research Implications

This study helps researchers grasp the significance and implications of the study and how it can be incorporated into their research to expand their research scope. Researchers consider this study as a continuation of the one conducted by Yavas and Ozen [10], which discussed essential logistics for Industry 4.0 and their relevance to future implications and transformations related to Industry 4.0. In their work, Ali et al. [68] use theory-based SEM evaluation hybrid Machine learning Models for sustainable practices; hence, the same can be used for Industry 4.0 through AI/ML methods for the warehousing sector. Researchers can identify the sectors that benefit from the research results, especially those expected to boost the Kingdom's economy, how this benefit will be gained, and what requirements each sector must meet. The researcher can use other scales to measure the expert's response to Delphi and CoCoSo methods. Further research can consider the group decision-making consensus method for the non-cooperative behaviour management of personalized individual semantics. This study can be tested by using other multi-attribute decision-making models such as one proposed by Medic et al. [69] are, the Fuzzy Analytical Hierarchy procedure, and PROMETHEE.

6.3. Limitation

In the study, established organizations are considered in well-developed industrial corridors. The main drawback of the MCDM analysis is the generalisation of the results. The result of this study could be applied only to organizations working in these areas [70]. The other areas might have other challenge. As a result, this study could be tested with organisations representing different operational areas and milestones to have an entirely different point of view on a given smart and sustainable warehouse [71].

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Appendix A

Table A1. Technology 4.0 driven practices weight and ranks for sensitivity analysis in various test.

	Original	Test 1		Test 2		Test 3		Test 4		Test 5		Test 6		Test 7		Test 8		Test 9	
TDP1	0.20	0.23	1	0.20	1	0.18	2	0.15	2	0.13	2	0.10	2	0.08	2	0.05	2	0.03	2
TDP2	0.23	0.10	5	0.20	2	0.30	1	0.40	1	0.50	1	0.60	1	0.70	1	0.80	1	0.90	1
TDP3	0.10	0.12	3	0.10	3	0.09	4	0.08	4	0.06	4	0.05	4	0.04	4	0.03	4	0.01	4
TDP4	0.10	0.11	4	0.10	4	0.09	5	0.07	5	0.06	5	0.05	5	0.04	5	0.02	5	0.01	5
TDP5	0.04	0.05	9	0.05	8	0.04	9	0.03	9	0.03	9	0.02	9	0.02	9	0.01	9	0.01	9
TDP6	0.08	0.09	6	0.08	6	0.07	6	0.06	6	0.05	6	0.04	6	0.03	6	0.02	6	0.01	6
TDP7	0.05	0.06	7	0.05	7	0.05	7	0.04	7	0.03	7	0.03	7	0.02	7	0.01	7	0.01	7
TDP8	0.16	0.18	2	0.16	7	0.14	3	0.12	3	0.10	3	0.08	3	0.06	3	0.04	3	0.02	3
TDP9	0.05	0.06	7	0.05	8	0.05	7	0.04	7	0.03	7	0.03	7	0.02	7	0.01	7	0.01	7

Table A2. Warehouse performance weight and ranks for sensitivity analysis in various test.

	Original		Test 1		Test 2		Test 3		Test 4		Test 5		Test 6		Test 7		Test 8		Test 9	
WOP1	2.34	7	2.42	8	2.35	7	2.29	7	2.22	6	2.16	7	2.10	7	2.22	7	2.53	7	3.47	7
WOP2	1.86	11	1.95	10	1.88	11	1.82	11	1.76	11	1.70	12	1.65	12	1.75	12	2.01	10	2.78	10
WOP3	1.44	13	1.25	13	1.40	13	1.54	12	1.67	12	1.79	11	1.91	9	2.32	5	3.25	3	5.93	2
WOP4	2.63	2	2.82	2	2.67	2	2.53	3	2.39	4	2.27	5	2.14	6	2.19	8	2.39	8	3.01	8
WOP5	1.96	10	1.83	11	1.93	10	2.03	9	2.12	8	2.21	6	2.29	3	2.72	2	3.70	1	6.53	1
WOP6	2.01	9	2.10	9	2.03	9	1.96	10	1.90	10	1.84	10	1.79	10	1.84	10	2.00	11	2.49	12
WOP7	2.37	6	2.51	6	2.40	6	2.29	6	2.20	7	2.11	8	2.02	8	2.08	9	2.28	9	2.91	9
WOP8	1.47	12	1.47	12	1.47	12	1.46	13	1.46	13	1.46	13	1.46	13	1.57	13	1.84	12	2.63	11
WOP9	2.27	8	2.45	7	2.31	8	2.17	8	2.04	9	1.91	9	1.78	11	1.75	11	1.74	13	1.73	13
WOP10	2.56	4	2.69	3	2.59	4	2.49	5	2.39	5	2.30	4	2.21	5	2.32	6	2.62	6	3.55	6
WOP11	2.55	5	2.66	4	2.57	5	2.49	4	2.41	3	2.33	3	2.26	4	2.39	4	2.75	5	3.83	5
WOP12	2.91	1	3.06	1	2.94	1	2.83	1	2.73	1	2.63	1	2.53	2	2.69	3	3.15	4	4.52	4
WOP13	2.60	3	2.611	5	2.61	3	2.60	2	2.60	2	2.59	2	2.58	1	2.86	1	3.54	2	5.52	3

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