**A knowledge-based experts’ system for evaluating digital supply chain readiness**

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**A knowledge-based experts’ system for evaluation of digital supply chain readiness**

**Abstract**

The digitalization of the supply chain (SC) enables companies to address customers' new requirements, the challenges of managing the SC and the expectations, and efficiency improvement. Although digital supply chain (DSC) is a buzzword, very few organizations and decision-makers understand the challenges of transforming from a traditional supply chain to a DSC. Therefore, the purpose of this paper is to develop and implement an integrated knowledge-based system (KBS) and evaluate the overall DSC readiness value (score) of an organization. DSC readiness factors are identified from an extensive literature review and validated by experts from academia and industry. The proposed KBS is based on Fuzzy – AHP that establishes a link between DSC readiness factors and their impact on performance and evaluates overall DSC readiness value (score). The proposed KBS has been validated in an Indian manufacturing company, and results show that the overall DSC readiness value (score) of the case company is 0.267. This paper will help organizations evaluate their current position in transforming from traditional supply chain to DSC and make a plan to achieve digitalization completely in their SC operations. Managers, practitioners, and decision-makers who are involved in digitalization can use our study’s findings as a starting point for aiding the transformation.

**Keywords:** Digital supply chain; readiness; digital transformation; Fuzzy - AHP; relationship; knowledge base system.

**Article Type:** Research paper

1. **Introduction**

Technological advancement, featured with digitalization , is transmuting the way organization operate in present times (Xu et al., 2018; Rajput and Singh, 2019). The use of digitalization is strikingly chaning the business models and creating new spheres of relationships of an organization (World Economic Forum, 2016). The way businesses are being influenced by technology so are customers. Due to awareness and ease of information accessibility through smart technologies, today’s customer is more knowledgeable than ever (Büyüközkan and Göçer, 2019). Organizations need to incorporate digitalization in their entire business models to fulfill ever-rising customer needs and cope with technological advancement. It is the adoption of technologies in operations or processes (Legner et al. 2017). More specifically, Wee et al. (2015) define digitalization as incorporating digital technologies in enabling, improving, and transforming business processes, activities, or functions. In addition to that, adopting digitalization in SC functions make SC more valuable, affordable, and easy to access (Hanifan, Sharma, and Newberry, 2014). Digitalization and advancement in technology will significantly change organizations' working environments (Ageron, Bentahar, and Gunasekaran, 2020). The entire organization process, such as finance, sales and marketing, maintenance, supply chain processes, will improve by increasing transparency and information sharing (Preindlet al., 2020).

The advent of technology also redefines the supply chain processes, making traditional processes redundant (Khan et al. 2021). New technologies such as the Internet of things (IoT), cloud computing (CC), big data analytic (BDA), artificial intelligence (AI), machine learning (ML), and cyber-physical system (CPS), etc. are forcing organizations to adopt digitalization in SC (Queiroz et al. 2019). The use of high-tech robots in assembly lines, the application of sensors at every stage of manufacturing, and big data in decision-making are significantly improving overall SC performance. Adopting SC digitization solutions can give organizations an advantage over competitors by way of improving customer serviceability, building better business relationships, and generating more revenue opportunities.

In literature, the definitions of DSC are fragmented and discussed from different perspectives. For example, Bhargava et al. (2013) defines DSC as a composed system of software, hardware, and networks that support and interacts with different SC activities such as plan, source, make, and deliver. Similarly, Rouse (2016) mentioned that DSC is based on web-enabled capabilities. According to DSC initiatives (2015), DSC captures, maximizes, and utilizes real-time information from various SC functions. This shows that DSC is not only limited to the adoption of emerging technologies but also related to how these technologies are utilized to increase SC transparency by making information available to all stakeholders, increase efficiency, effectiveness, and bring resilience in SC.

Digitalization and advancement of new technologies are already affecting all types and functions of SC (Korpela et al., 2017; Li et al., 2016; Srai et al., 2016). Several well-known consulting firms highlighted that the adoption of digitalization in SC is not a choice and essential for organizations to remain competitive in the market (Kearney, 2015; Hanifan, Sharma, and Newberry, 2014; Israelit et al. 2018; Boston Consulting Group, 2018; Mussomeli, Gish, and Laaper, 2016; Ernst & Young, 2016; Gezgin et al. 2017; Schrauf and Berttram, 2016; Roland Berger, 2016).

Due to the high speed of technology advancement and digitalization, SC professionals are wondering how to adopt this change and remain competitive (Hartley and Sawaya, 2019). Since the innovation in new technologies continues to multiply, a transformation from traditional to digital SC is essential for organizations to survive (Agarwal, Narain, and Ullah, 2019). In addition to that, literature evaluating DSC readiness is neither discussed in detail nor proposed any framework to evaluate overall DSC readiness. Therefore, this study addresses this gap and provides guidelines and support to managers and decision-makers in evaluating their DSC adoption stages/levels. However, many studies can be found in the literature on DSC and have proposed several frameworks. This study is the first to evaluate DSC readiness in an Indian organizational context to the best of our knowledge. This study will propose an integrated KBS that helps organizations evaluate their DSC readiness regarding a number or score. Figure 1 below shows our DSC readiness evaluation concept.

To be develop

DSC Readiness Factor (RF1)

DSC Readiness Factor (RF2)

DSC Readiness Factor (RF3)

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DSC Readiness Factor (RFn)

Knowledge Base System

(FIS – AHP)

Overall Organizations DSC Readiness

Value

Figure 1: DSC Readiness Evaluation Concept

The specific objectives of this study are as follows and are to:

1. Identify DSC readiness factors through literature review and academic experts
2. Validate the identified DSC readiness factors through academic experts and industrial decision-makers.
3. Develop a KBS that integrates knowledge from decision-makers and practitioners and aids the evaluation of overall organizational DSC readiness.

To achieve the objectives mentioned above and proposed KBS for DSC readiness evaluation, the remainder of the paper is organized as follows. Section 2 will provide the literature review followed by Section 3, presenting an overview of AHP and fuzzy inference system. Section 4 discusses the proposed methodology and implement the developed KBS in a case manufacturing company. Section 5 discusses the results and managerial implications, concludes the paper, and highlights future research direction and limitations in Section 6.

1. **Literature Review**
   1. **Supply Chain Management**

Supply chain management incorporates all procedures that change crude materials into conclusive items. It includes the dynamic streamlining of a business' stock side exercises to amplify client worth and a competitive advantage in the commercial center. Successful supply chain management requires cross-functional integration, and marketing must play a critical role. The challenge is to determine how to accomplish this integration (Lambert and Cooper, 2000).

Supply chain management is a process to ensure the smooth flow of any product, material, or service (Hugos, 2018). Supply chain management plays a key role in the business of organizations. Supply chain management includes all the steps from acquiring the basic raw material, processing, and delivering the final products to the end-user (Meredith and Shafer, 2019). An efficient and organized supply chain management provides a balance between the supply and demand of resources (Yu et al., 2018). It is an integral part of the business identifying the economic values, realizing the market, and improving its performance, giving an extra edge in this modern competitive digital era (Lambert and Enz, 2017). The advancement of communication has paved the way for supply chain management, and its demand has increased.

Supply chain management also plays an essential role in manufacturing (Barber et al., 2017). It affects the daily operations of manufacturing as well as its strategic aspects. It can affect various manufacturing processes like action plans required to initiate production activities, stocking of products, pricing and profits of the final product, utilization of company infrastructure, and means through which the organization interacts with its suppliers and customers (Schönsleben, 2019). Manufacturing organizations always require timely delivery of input raw material to be processed, and the final goods are produced in time. On-time supply of input raw material prevents raw material sourcing from alternate sources and avoids higher input cost and low profitability. An effective supply chain management controls the prices and offers its smooth supply (Taleizadeh and Noori-Daryan, 2016).

* 1. **Digitalization and digital supply chain management**

Digitalization and digital supply chain management are newly coined terms in supply chain management. The procedure of digitalization influences nearly everything in the present business scenario, including supply chain management, and motivate the organizations to change their operations for the adoption of digitalization (MacCarthy et al. 2016). Ben-Daya, Hassini, and Bahroun, (2017) conducted a literature review on digital technology applications in SCM and described Industry 4.0 enablers and features in digitalized SCs as the core components for the digital connectivity and communication of the physical and digital elements in the SCs, thus, allowing real-time data storage, analysis, and sharing. The framework and digital parameters used in a study by Agrawal and Narain (2018) consist of six methods: Robotics, Big data, Unique identification, display innovation, Sensors and geo-location, and Cloud services, nanotech, and 3D printing. DSC is an intelligent, value-based, effective phenomenon to create income, regard to the organizations, and extend the possibilities with new technological and analytical methods. It does not distinguish among different manufacturing process based on their nature being digital or physical; however, it is a procedure to manage the SC processes by the use of extensive new technologies such as unmanned aerial vehicles, internet of things, cloud computing, etc. (Büyüközkan and Göçer, 2018).

The advancement of digitalization influences the economy and creates numerous opportunities. Digitalization is an essential tool for smooth business functions (Rajput and Singh, 2019). The advancement of technology and the adoption of digitalization have a significant impact on the manufacturing process, business models for products and services. Another important review on SCM and the latest technologies and trends in the Industry 4.0 revolution was presented by Menon and Shah (2019). Garay-Rondero et al. (2019) details the build and constituents of supply chain management to establish an organized model that blends the attributes and roles of supply chain management with the latest technological fashions of digitalization and automation progressive use of information and communication technologies for logistics global value chains.

Another study emphasizes the significance of emerging technologies such as the internet of things and blockchain for DSC advancement (Pundir et al., 2019). In a paper, a case study of pallet renting vendors is considered to exhibit the results of combining the technologies and associated improvement in its SC and asset management. The study of Agrawal, Narain, and Ullah, (2019) employed interpretive structural modeling (ISM) to establishes a hierarchy-based structural model to reflect the inter-dependence between the barriers of DSC. (Sahara et al., 2019) showed that supply chain integration, collaboration, coordination, strategy, technology & worker skills, and adaptability are among the significant factor categories that should be addressed to assess an organization's readiness to adopt a digital supply chain. Krykavskyy, Pokhylchenko and Hayvanovych, (2019) determined the effect of Digital Technologies in the cross-section of strategic and operational changes of the supply chain and clarified the readiness and capacity digital technologies for implementation in the enterprises activity as exemplified by the enterprises operating in Ukraine in various fields of activity. (Ivanov, Dolgui and Sokolov, 2019) find the impact of digitalization on SCM and its effect on the ripple effect control. (Hartley and Sawaya, 2019), robotic process automation (RPA), artificial intelligence (AI)/machine learning (ML), and blockchain can improve supply chain business processes. Pirola, Cimini and Pinto (2019) proposed a comprehensive assessment model suitable for evaluating small- and medium-size enterprises’ (SMEs) digital readiness levels.

Queiroz et al., (2019) proposed a framework for digital supply chain capabilities (DSCCs) with six main enabler technologies such as Internet of things (IoT), cloud computing (CC), big data analytic (BDA), artificial intelligence (AI), machine learning (ML), and cyber-physical system (CPS), etc. Recently, Nasiri et al., (2020) found that the digital transformation of companies based upon smart technologies can lead to improved relationship performance. Similalry, Ivanov and Dolgui (2020) proposed a digital SC twin framework for managing disruption risks and providing details about when and how to integrate data analytics to manage SC disruption risks. (Cimini, Pirola and Cavalieri, 2020) presented a framework that links the potentials of DSC implementations with the SC operation processes and highlighted the most suitable technologies to deploy them. (Gupta et al., 2020) explored the firm’s orientation in adopting Industry 4.0 and the digital supply chain. Focusing on Malaysian Small-Medium Enterprises (SMEs), Wong et al., (2020) investigated the effects of relative advantage, complexity, upper management support, cost, market dynamics, competitive pressure and regulatory support on blockchain adoption for operations and supply chain management among Preindl, Nikolopoulos and Litsiou, (2020) focused on the impact of ‘Industry 4.0ʹ and “Digital Transformation” on information sharing and decision making across the supply chain . Choudhury et al., (2021) used expert opinion and built the hierarchical structure using total interpretative structural modeling (TISM), which highlights the interdependencies between critical success factors (CSFs). Caiado et al., (2021) introduced a fuzzy rule-based maturity model, combined with a Monte Carlo simulation that evaluates how organizations integrate digital technologies in their operations. Dudukalov et al., (2021) enabled Russian and Thai retail supply chain administrators and market leaders (including policy makers) to share their expert opinion about the impact of digital transformation on supply chain performance and statistically evidenced presence of a relationship between digitalization, the Industry 4.0 technologies, and supply chain performance.

* 1. **Research Gap and Contribution of the Study**

Based on the above literature review, the following research gaps have been identified.

1. It has been highlighted by Büyüközkan and Göçer, (2018) that DSC literature is still in its early stage.
2. Literature related to the transformation of traditional SC into DSC is very limited and mainly focuses on adopting digital technologies in SC function (Richey et al., 2016; Srai and Lorentz, 2019; Kosmol, Reimann, and Kaufmann, 2019).
3. To evaluate the degree of DSC readiness of any organization, it is essential to determine the extent to which digital technologies such as IoT, CC, BDA, AI, ML, and CPS, etc., and digitalization have currently been used in an organization. What are the initiatives an organization is currently using?

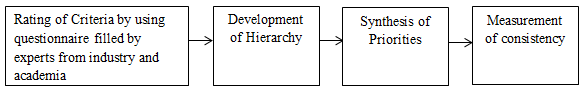
To address the abovementioned research gaps, we proposed KBS for DSC readiness evaluation for an organization.

1. **Overview of Analytical Hierarchical Process and Fuzzy Inference System**

It is important to illustrate AHP and fuzzy methods with an example to provide an overview of how AHP and fuzzy methods work. This will help understand the method and allow readers to get in-depth information about these well-known and widely used methods.

## 3.1 Analytical Hierarchal Process (AHP)

AHP is the most widely used MCDM method that considers both qualitative and quantitative criteria and ranks alternatives based on experts’ opinions. Experts’ opinion is based on pairwise comparison and includes both intangible and tangible criteria (Özkan, Başlıgil, and Şahin, 2011). Figure 2 shows the steps of implementing AHP.

Fig. 2. Analytical Hierarchy Process

In AHP, pairwise comparisons are made based on the nine-point intensity of standardized, as shown in Table 1.

Table 1 Importance scale of factors in pairwise comparison (Saaty, 1980)

|  |  |
| --- | --- |
| **Importance Scale** | **Importance description** |
| 1 | Equal importance of ‘I’ and ‘j’ |
| 3 | Week importance of ‘I’ and ‘j’ |
| 5 | Strong importance of ‘I’ and ‘j’ |
| 7 | Demonstrated importance of ‘I’ and ‘j’ |
| 9 | Absolute importance of ‘I’ and ‘j’ |
| 2,4,6,8 | Are intermediate values |

To understand the calculation of AHP, a detailed example with steps of manual calculation can be found in (Saaty, 1980; Saaty, 2008). AHP is a widely used method and its application can be found in several application areas (see: Khan, Dweiri, and Jain, 2016; Naim, Mahara, and Khan, (2020). Jain and Khan, 2017; Dweiri et al. 2016; Dweiri, Khan, and Almulla, 2018; Ishtiaq, Khan, and Haq, 2018; Khan and Hosany, 2016; Dweiri, Khan, and Jain, 2015).

## 3.2 Fuzzy Logic

A fuzzy logic system is the method used to convert nonlinear input data to scalar output data. General steps and architecture of a Fuzzy logic system are illustrated in Figure 3.

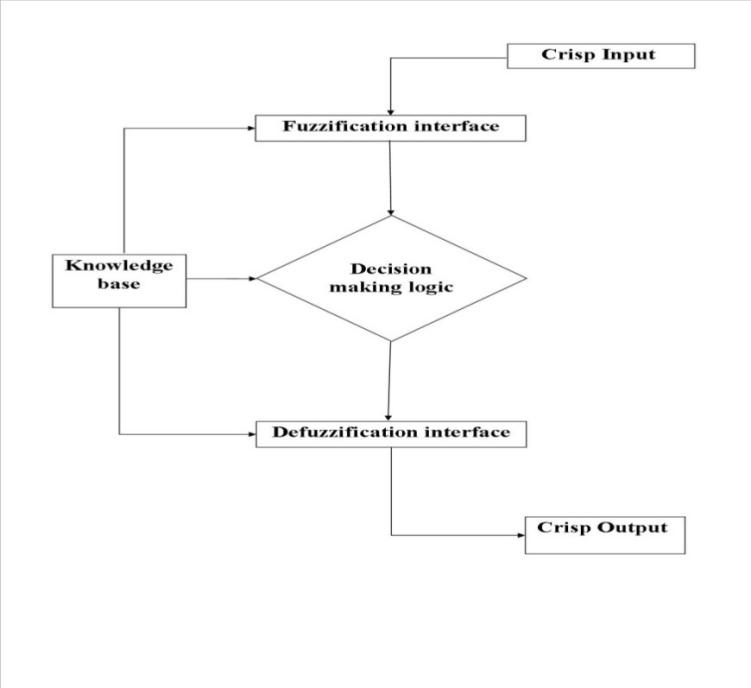


Fig. 3. Fuzzy Logic System

Sources: (Dweiri & Kablan, 2006; Khan, Dweiri, & Chaabane, 2016)

* The fuzzification inference calculates the values of the input variables on their membership function to determine the degree of belonging, so the crisp values will be converted to fuzzy values.
* The knowledge- base is based on decision-makers and experts' knowledge of considered application areas and decision rules that establish a relationship between inputs and outputs results. The membership function is according to experts' experience and knowledge of the system.
* If-Then rules are established to decide the relationship between inputs and outputs.
* The defuzzification inference converts a fuzzy output into a crisp output (Dweiri & Kablan, 2006).

### 3.2.1 Fuzzy Logic Algorithm

The following steps should be followed to solve any fuzzy problem.

#### Step 1: Define Linguistic Terms and Variables

First, we have to define the linguistic variables for inputs and outputs variables and their values are in words or sentences from a natural human language instead of traditional numeric values (Zadeh, 1965; Zadeh, 1988). For example, let height (h) be the linguistic variable, representing the students' height. To qualify the height, terms such as “short” and “tall” are used in real life. These are the linguistic values of height. Then, H (h) = {too-small, small, medium tall, tall} can be the set of breakdowns for the linguistic variable height. Each member of this breakdown is called a linguistic term and can cover a portion of the overall values of the height.

#### Step2: Construct the membership function

Fuzzification and defuzzification steps cannot be possible without selecting and constructing a membership function. It maps the non-fuzzy input values to the fuzzy linguistic terms and vice versa (Zadeh, 1965; Zadeh, 1988). There are many kinds of available membership functions used in different Fuzzy sets, including trapezoidal, linear, triangular, and Gaussian, etc. However, the most commonly used membership function is Triangular. Selection of membership function shape is solely dependent on experts' and decision-maker's knowledge and system experience. In this example, a trapezoidal function form was used, as presented in Figure 4.

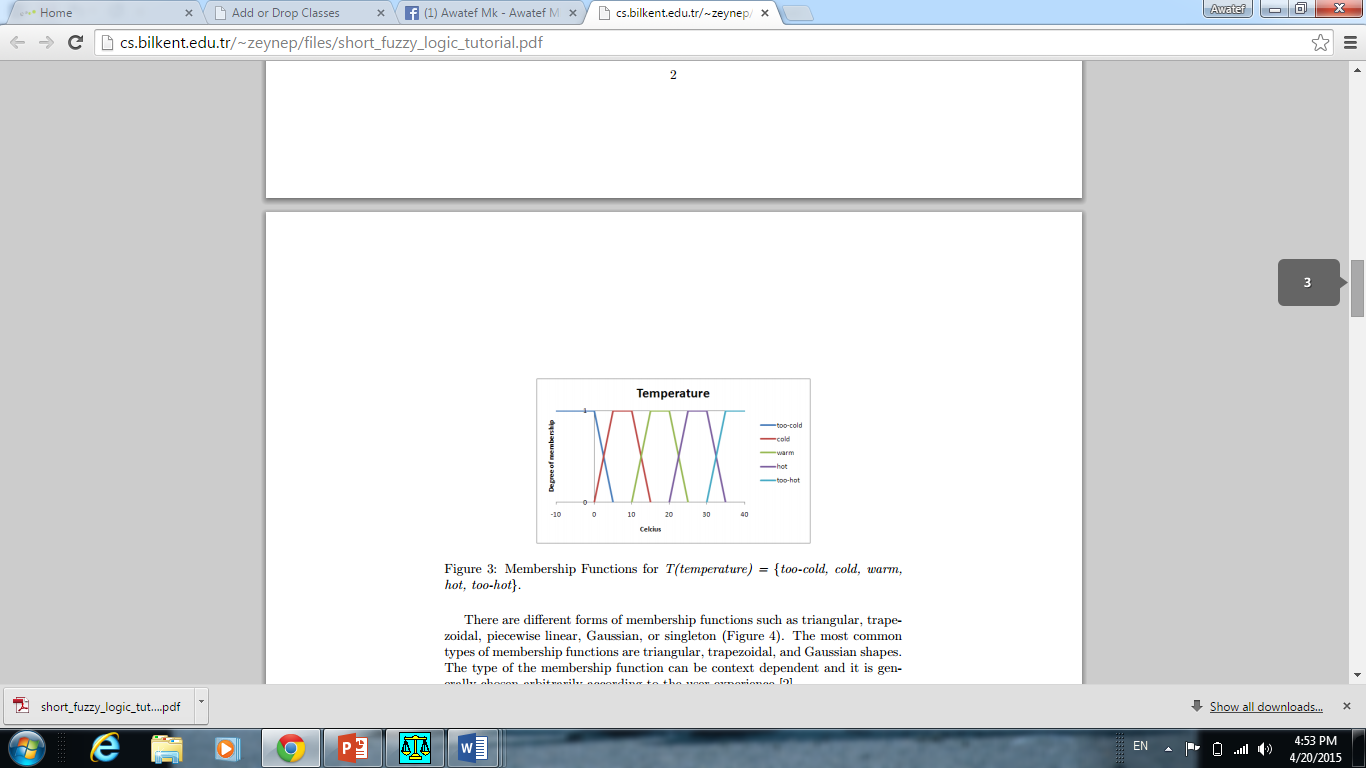


Fig. 4. Membership function for temperature (Klir and Yuan, 1996)

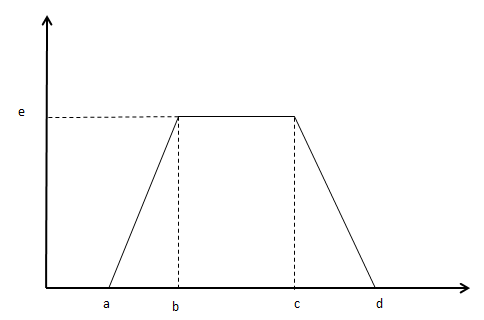
For constructing a trapezoidal membership function manually, as shown in figure 5, the range of the membership function is divided into 5 points a,b,c,d, and e.

Fig. 5. Trapezoidal membership function (Klir and Yuan, 1996)

Equation 8 has to be solved to design the membership function (Klir and Yuan, 1996).

(8)

#### Step 3: Construct the rule base

In order to control the output variables, a rule base has been constructed. A fuzzy rule is a simple IF-THEN rule with a condition and a conclusion. The following rules are a sample of air condition system rules.

If (Temperature is cold or too- cold) AND (target is warm), then the command is heated.

If (Temperature is hot or too- hot) AND (target is warm), then the command is cool.

If (Temperature is warm) AND (target is warm), then the command is no change.

#### Step 4: Convert the output data to crisp values (Defuzzification).

The final step in the fuzzy inference system is defuzzification. After the inference step, the overall results are in fuzzy values, so the defuzzification process must be completed to obtain final crisp outputs. The defuzzification process depends on the output variable membership function. For example, assume that we have the result in Figure 8 at the end of the inference. In figure 6, fuzzy results are mentioned in the shaded area, and with the help of this, we will be able to get the crisp value.

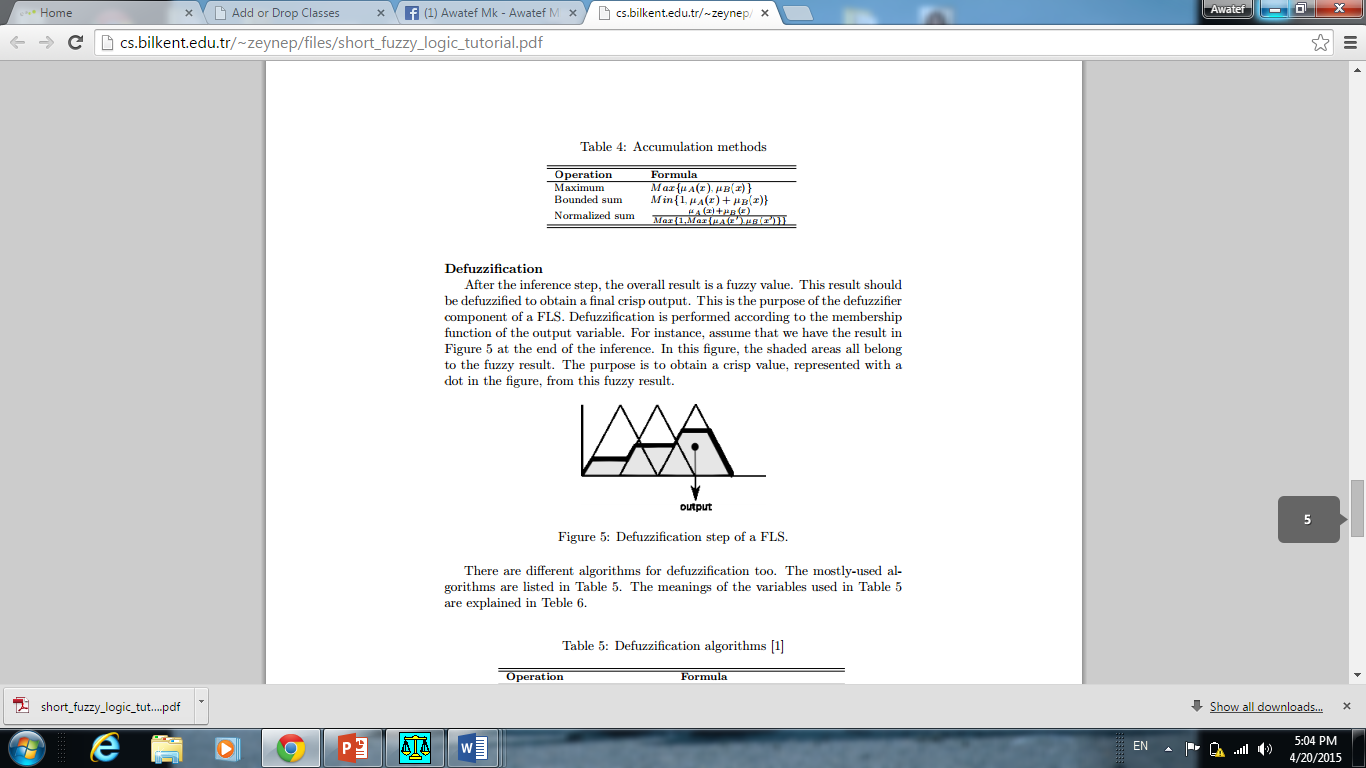


Fig. 6. Defuzzification of the fuzzy logic (Klir and Yuan, 1996)

To get the crisp value center of gravity, equation 9 is used

(9)

The meanings of the variables used in equation 10 are explained in Table 2.

Table 2 Variables of equation 9

|  |  |
| --- | --- |
| **Variable** | **Meaning** |
|  | Result of Defuzzification |
|  | Output Variables |
|  | Membership Function after Accumulation |
|  | lower Limit for Defuzzification |
|  | Upper Limit for Defuzzification |

### 3.2.2 Fuzzy set operations

The most used operations for OR and AND operators are max and min, respectively as shown in Table 3. For complement (NOT) operation, the given below Equation 10 is used for fuzzy sets

Table 3 Fuzzy set operations

|  |  |
| --- | --- |
| OR (Union) | AND (Intersection) |
|  |  |

The inference is the process in which all evaluated results of each rule will be combined to achieve the final result. There are many ways in which we can combine the results of individual rules. Table 4 contains possible accumulation methods that are used to combine the results of individual rules. The maximum algorithm is generally used for accumulation (Klir and Yuan, 1995).

Table 4 Accumulation methods (Klir and Yuan, 1996)

|  |  |
| --- | --- |
| **Operation** | **Formula** |
| Maximum |  |
| Bounded sum |  |
| Normalized sum |  |

A fuzzy inference system and its integration with other multi-criteria decision-making methods can be found in several applications, such as in supplier selection and order allocation (Kaviani et al. 2020); a knowledge-based system for overall supply chain performance evaluation (Khan, Chaabane, and Dweiri, 2019); in supplier sustainability performance evaluation and selection (Khan et al. 2018); and in supplier performance evaluation and improvement (Rehman et al. 2018).

An important approach of operation research is MCDM (Multi-criteria decision-making), which is widely used in various decision-making fields. The ranking problems can be solved using various MCDM methods (Triantaphyllou, 2000). With the availability of a large input dataset and uncertainty, Multi-Attribute Utility Theory (MAUT) can be applied to incorporate preferences. Analytic Hierarchy Process (AHP) having a hierarchal structure is an effective decision-making approach for less data-intensive applications. But, sometimes inconsistencies between judgment and ranking criteria arises due to interdependence between criteria and alternatives (Ceballos, Lamata and Pelta, 2016). Another approach namely Best-Worst Method (BWM) provides solution to overcome the problem of inconsistency. This method require a lesser pairwise comparison (Mohammadi and Rezaei, 2020). An approach that requires less maintenance for enhancing performance over time and adopting environment changes is Case-Based Reasoning (CBR) and does not need intensive data. In order to deal with multiple inputs and outputs for Data Envelopment Analysis (DEA) can be used. There is a disadvantage of this method in that it requires precise information of all input and outputs. This problem of imprecise information of input can be dealt by using the Fuzzy Set Theory. Therefore, to address these limitations, we choose FIS and AHP to propose our KBS.

Several optimization methods based on linear programming, non-linear programming etc., have been used in different applications. However, FIS based KBS is more feasible and efficient. For example, Amjadian and Gharaei (2021), proposed mixed-integer nonlinear programming (MINLP) and bi-objective optimization method to design and optimize close loop supply chain. This method has several dis-advantages as compared to our proposed FIS-AHP method. Firstly, it cannot take account of the nonlinear effect. Secondly, there is a risk of high-dimensionality of the problem. Lastly, it cannot combine both qualitative and quantitative inputs and incorporates experts' knowledge and experience. On the other hand, FIS and AHP based KBS can handle both qualitative and quantitative inputs and take nonlinear effects. Moreover, it incorporates experts knowledge and experience in developing rule base. In terms of number of iterations and optimality error, infeasibility, and complementarity, FIS based KBS requires very less iterations and provide feasible and multi and cross factors complementarity.

For deep reviews of other solution methods, readers can benefit by having view of such methods like simulation-based optimization approach (Sayyadi and Awasthi, 2018; Giri and Masanta, 2020); interval-valued fuzzy sets and possibilistic statistical reference point systems (Rabbani et al. 2019); fuzzy axiomatic design (Awasthi and Omrani, 2019); outer approximation with equality relaxation and augmented penalty algorithm (Gharaei et al. 2019; Amjadian and Gharaei, 2021); robust possibilistic approach (Rabbani et al. 2020); game theoretic model (Yin, Nishi, and Zhang, 2016); generalised cross decomposition (Gharaei et al. 2019), generalised outer approximation (Shekarabi et al. 2019) and generalized benders decomposition (Gharaei et al. 2020).

## 3.3 Importance of combining AHP and Fuzzy Logic

The fuzzy analytic hierarchy process (AHP) proves to be a very useful methodology for multiple criteria decision-making in fuzzy environments. The vast majority of the applications use a crisp point estimate method such as the extent analysis or the fuzzy preference programming (FPP) based nonlinear method for fuzzy AHP priority derivation (Wang and Chin, 2011). In fuzzy logic, the importance of each criterion gets influenced by the level of decomposition in the hierarchical model. Fuzzy logic cannot measure the level of consistency in the judgments provided by a decision-maker. On the other hand, the analytic hierarchy process (AHP) cannot capture human judgments' subjectivity (or fuzziness) as the verbal assessments are converted into crisp values. The fuzzy analytic hierarchy process is a merger of the two methods, Fuzzy logic and the Analytic Hierarchy Process (AHP), which inherits the advantages of both and, therefore, addresses the problems mentioned above (Ishizaka 2014) . In recent years the use of combining fuzzy and AHP method can be seen in many application areas like GIS application ( Chabok et al. 2020), Optimal selection of Iron and Steel wastewater treatment technology (Mahjouri et al, 2017), Reservoir heterogeneity (wang et al. 2017), Identification of soil erosion-susceptible areas (Saha et al, 2019),. Landfill site selection (Şener and Şener 2020 ) and many more.

1. **Research methodology**

This study will identify and validate the DSC readiness factors and DSC capabilities from the literature. Identified DSC readiness factors are essential for DSC readiness evaluation and measure the capability to transform from traditional SC into DSC. Based on identified DSC readiness factors, integrated KBS will be developed. Figure 7 below shows a step-by-step methodology.

Literature review

Experts’ discussion / opinion

DSC readiness factor identification and validation

Step 4: Identification of survey company and academic experts

Step 5: Face to face interview

Step 1: Literature screening

Step 2: Keyword selection

Step 3: Inclusion and exclusion criteria

Knowledge Base System Development (FIS – AHP)

Step 6: DSC Readiness Factors Weights (AHP)

Step 7: Define Linguistic Variables for FIS

Step 8: Construct Membership function

Step 9: Construct and Validate the Rule Base

Step 10: Conversion of Output into Crips Value

Experts’ discussion / opinion

Overall DSC readiness evaluation

Figure 7: Proposed research methodology

* 1. **Digital supply chain readiness factors identification and validation**

The first objective of this study is to identify the DSC readiness factor from the literature. We have adopted a structured literature review technique to search literature relevant to our study objectives. We rely only on the Scopus database as it has been used in several literature review papers and is recommended and trusted by several authors (Chicksand et al., 2012). Therefore, we only searched in the Scopus database to find DSC readiness factors and digital SC capabilities.

We used different keywords and their combination to identify the most relevant and close to our objective of this study. Keywords such as “*digitalization*”, “*DSC*”, “*SC and digitalization*”, “*IoT and SC*”, “*DSC readiness*”, “*readiness factors*”, “*DSC capabilities*” were used. During the initial search phase, we found that several articles that contained digitalization did not discuss their impact on overall SC and DSC readiness.

Inclusion and exclusion criteria in any literature search play a significant role in the research outcome. In this study, we excluded those articles that are not relevant and in line with the objectives sets in section 1. In addition to that, we did not consider articles that were not peer-reviewed and working papers. Furthermore, book chapters, conference proceedings, and graduate thesis were excluded. We considered articles that are published in a peer-reviewed journal and relevant to our study objectives.

We started the screening process by first reading the abstract and conclusion of the articles. We then eliminated articles that do not cover digitalization and DSC. We also included only those articles that discussed the impact of technology advancement and its application in SC. In addition to that, we included articles that considered the role of advanced technology, such as IoT, CC, BDA, AI, ML, and CPS, etc., in different SC functions.

To validate the identified DSC readiness factors from the literature, we developed a simple questionnaire (see appendix 1) and send it to experts from both academia and industry. The survey for validation of DSC readiness factors was conducted in the Indian manufacturing industry.

After the identification of industries that are suitable for our study’s objectives, we contacted senior managers and decision-makers who have more than 10 years of experience and familiar with the new technology trends. In addition to that, all selected participating managers are involved directly and indirectly in initiatives and decisions related to SC, and strategic decision-making related to DSC, overall SC management, and digitalization. The same set of managers were used in developing KBS to evaluate overall DSC readiness. A survey was prepared to validate the identified DSC readiness factors, and responses were collected during a face-to-face interview. At the start of the interview, the survey's objectives were explained, and we clarified any doubt of the respondent while completing the questionnaire. A total of 21 responses out of 43 were received (i.e. 49 %). It took more than 6 weeks to collect all the responses. The demographics summary of experts is shown in table 5 below.

Table 5: Demographics summary of experts

|  |  |  |
| --- | --- | --- |
| **Characterstics** | **Number of Respondents** | **Percentage of Samples(%)** |
| **Gender** |  |  |
| Male | 18 | 85.71 |
| Female | 3 | 14.29 |
|  |  |  |
| **Age** |  |  |
| 20-25 | 2 | 9.52 |
| 26-30 | 5 | 23.81 |
| 31-35 | 5 | 23.81 |
| 36-40 | 3 | 14.29 |
| 41-45 | 3 | 14.29 |
| >45 | 3 | 14.29 |
|  |  |  |
| **Designation Level** |  |  |
| Middle Manager | 10 | 47.62 |
| Manager | 3 | 14.29 |
| Senior Manager | 4 | 19.05 |
| Others | 4 | 19.05 |
|  |  |  |
| **Years of Experience** |  |  |
| 1-5 | 5 | 23.81 |
| 6-10 | 7 | 33.33 |
| 11-15 | 3 | 14.29 |
| 16-20 | 4 | 19.05 |
| >20 | 2 | 9.52 |

Experts who responded to the survey belong to the manufacturing sector of the case company. The concerned experts are engaged in different departments like engineering, operations, IT, planning, finance, maintenance, stores, purchase, etc. A total of 21 experts participated in the validation process to identify DSC readiness factors. Table 6 below shows the identified and validated DSC readiness factors derived from Queiroz et al. (2019) and experts and its description.

Table 6: Identified and validated DSC readiness factors

|  |  |  |  |
| --- | --- | --- | --- |
| **DSC Readiness Factors** | **Notation** | **Description** | **Reference** |
| Information and communication technology (ICT) policies | RF1 | The ICT policies of an organization define the adoption and integration of new technologies in its processes. | Scuotto et al. (2017); Giotopoulos et al. (20170; Bibri and Krogstie (2017);  Trentesaux et al. (2016) |
| Worker IT skills | RF2 | It is defined as how the workforce is capable to adopt change in their way of doing tasks after adopting new technology in the process. | Gunasekaran et al. (2017),  Waibel et al., (2017) |
| Supplier-buyer relationship | RF3 | It is defined as the first tier supplier capability to adopt new technology and allow integration. | Jääskeläinen and Thitz, (2018);  Chen (2019) |
| Relationship with customer | RF4 | It is defined as how much and up to what extent an organization integrates with the customer and shares information and transparent in their process | Li et al. (2016);  Zhong et al. (2017) |
| Use of smart technologies in WH | RF5 | It is defined as the WH capable to adopt new technologies or are already using technologies such as QR codes, RFID tags, etc. | Masoni et al., (2017); Kibira et al. (2016) |
| Use of smart technologies in logistics | RF6 | To get real-time information is a logistics service provider or in-house logistics capable to adopt new technology in inbound and outbound logistics. | Stock and Seliger, (2016) |
| Use of smart technologies in production | RF7 | Smart manufacturing practices are currently in use or are organizations capable to adopt new technologies in their manufacturing process. | Savarino et al., (2018) |
| IT network infrastructure | RF7 | IT infrastructure is capable to give support to the technologies used by the organization. | Wang et al., (2016) |
| \*Training policy | RF8 | Organization plan/policy to send managers and workforce for training related to new technologies | - |

\*Added by experts

* 1. **Knowledge Base System Development**

Since our KBS is based on fuzzy - AHP, as mentioned and discussed in section 3, we will implement and followed the same steps of AHP and fuzzy in KBS development. AHP will help us to calculate the importance weights of identified DSC readiness factors. To do that, we developed a survey (see appendix 1) and asked the same experts (industrial and academic) who validated the identified DSC readiness factor to perform a pair-wise comparison on Saaty’s scale, as mentioned in Table 1. We combined experts’ judgments and their pair-wise comparison by taken an average, and this is shown in Table 7 below. We used MS Excel to get the importance weights of the DSC readiness factor. The results of DSC readiness factors are shown in Table 8 below.

Table 7: AHP Pairwise Comparison (average) from all experts

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **RF1** | **RF2** | **RF3** | **RF4** | **RF5** | **RF6** | **RF7** | **RF8** |
| **RF1** |  | 1 | 1/8 | 1 | 1/8 | 1/5 | 1/9 | 1/9 |
| **RF2** |  |  | 2 | 1 | 1 | 1/6 | 1/4 | 1/9 |
| **RF3** |  |  |  | 1 | 1 | 1 | 1/9 | 1/8 |
| **RF4** |  |  |  |  | 1/8 | 1/4 | 1/9 | 1/8 |
| **RF5** |  |  |  |  |  | 3 | 1/5 | ¼ |
| **RF6** |  |  |  |  |  |  | 1/9 | 1/9 |
| **RF7** |  |  |  |  |  |  |  | 1 |
| **RF8** |  |  |  |  |  |  |  |  |

Table 8: DSC Readiness Factors Importance Weights

|  |  |
| --- | --- |
| **DSC Readiness Factor** | **Importance Weights** |
| RF1 | 0.022 |
| RF2 | 0.047 |
| RF3 | 0.058 |
| RF4 | 0.028 |
| RF5 | 0.106 |
| RF6 | 0.080 |
| RF7 | 0.326 |
| RF8 | 0.331 |

Once we had the weights of DSC readiness factors, we then defined the linguistic variables for the fuzzy inference system (FIS). In this step, we defined the input and output variables for FIS. The input variables are the importance weights of the DSC readiness factors as mentioned in Table 6 above. In addition, we defined DSC readiness factors with the linguistic terms of Low (L), Medium (M), and High (H). Similarly, the output variable, which is the score of DSC readiness, is described by linguistic terms Low (L), Medium (M), and High (H).

After defining the input variables, we then constructed the membership function. The fuzzy set F in U can be represented as a set of ordered pairs of a generic element I and its degree of membership function as equation 11.

F=

The probability that belongs to F is the membership function.

If A and B are two fuzzy subsets of and if is the degree of membership function of in and is the degree of membership function of in then the fuzzy union set and fuzzy intersection set are defined according to equations 12 & 13 (Dweiri, & Kablan, 2005).

(),())|

(),())|

After discussion with the expert and scanning the literature review, three triangular membership functions, L, M, and H, were used as inputs for all DSC readiness factors and output (score), as shown in figure 8 below.

**µ (X)**

Low (L)

Medium (M)

High (H)

1

0

M &H

L &M

**X**

Fig. 8: Membership function for DSC readiness factors and output (score)

This linguistic scale and its equivalent to fuzzy numbers on a numeric scale 0-1 are shown in Table 9 below.

Table 9: Linguistic Terms for DSC Readiness Factors Inputs and Output

|  |  |
| --- | --- |
| Low (L) | (0，0.25，0.50) |
| Medium (M) | (0.25，0.50，0.75) |
| High (H) | (0.50，0.75，1.0) |

Once the membership function has been developed, the rules are constructed and validated. The same experts in DSC readiness factors validation and AHP pair-wise comparison were asked to develop the fuzzy if-then rules. We developed a simple survey (see appendix 3) and gave it to the experts. Summary of the final if-then fuzzy rules was calculated based on the most frequent answer of the experts and shown in appendix 4. Below Table 10 shows the sample of rules used in KBS.

Table 10: Fuzzy if-then Rules (Sample)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **DSC Readiness Score** | | | |
|  | **RF1 Wt.** | | |
| **RF1 Value** | **L** | **M** | **H** |
| **L** | M | H | H |
| **M** | L | M | M |
| **H** | L | L | L |

The above-mentioned rules will be interpreted as follows:

*If RF1 value is “L” and its weights is “M”, then the DSC readiness score will be “H”*

*If RF1 value is “M” and its weights is “L”, then the DSC readiness score will be “L”*

*If RF1 value is “H” and its weights is “H”, then the DSC readiness score will be “H”*

The last step is converting output data into Crips value in which the DSC readiness score is achieved. Here we will use the same membership functions and linguistic terms as mentioned in above Figure 8 and Table 9. Now our KBS system is ready to take input and evaluate the overall DSC readiness score.

* 1. **Data analysis and results**
     1. **Case study**

To implement our developed KBS, we choose an Indian manufacturing company. The company under consideration is an industrial organization dealing in power plant components. The case company manufactures large-size castings and forgings various steels like alloy steels, creep-resistant steel, and supercritical grade steel. The case company is a pioneer organization and powering ahead in making India's heaviest castings and forgings. The company produces steel products to the tune of 10,000 metric tonnes (MT) per year. It is ISO-50001, ISO-9001, ISO-14001, and OHSAS-18001 certified company. The workforce of the company is around 1500, including top management, working executive, and other direct workforces. The company performs all its processes starting from engineering, design, manufacture, and supply through its manpower and is well versed in all engineering equipment. It also comprises of strong vendor base throughout the country and ancillary units nearby to its location.

The case company is planning to transform its traditional way of managing its SC to DSC. In order to do this, they want to evaluate their current capabilities and set a long-term strategy to fully transform their traditional SC to DSC. Our proposed KBS will help them identify their level of adoption of digitalization in their SC and underperforming DSC readiness factors for improvement. The case company is one of the companies whose experts were participated in DSC readiness factor validation, AHP pair-wise comparison, and rule base development. In addition, one of the authors is working in the considered case company. Therefore, we did not face any problem in getting DSC readiness factor values. Due to confidentiality, the case company gave us DSC readiness factors value in terms of percentage or between 0 to 1. Table 11 below shows the DSC readiness factors value that we received from the case company.

Table 11: DSC Readiness Factor Value of Case Company

|  |  |  |  |
| --- | --- | --- | --- |
| **DSC Readiness Factor** | **Value** | **DSC Readiness Factor** | **Value** |
| RF1 | 0.781 | RF5 | 0.826 |
| RF2 | 0.881 | RF6 | 0.794 |
| RF3 | 0.965 | RF7 | 0.807 |
| RF4 | 0.739 | RF8 | 0.902 |

Once we got the values from the case company, we used Matlab fuzzy input analyzer and implemented our KBS in it. Matlab has a built-in system and performs all the steps as mentioned in section 3 and figure 8. We have created a membership function for input (value) and output (score) and rule base (fuzzy if-then) rules in the system. A total of 72 rules was used. Figure 9 below shows the proposed KBS.

RF1 Value and Weight

RF2 Value and Weight

**Knowledge Base System**

**(FIS – AHP)**

RF3 Value and Weight

RF4 Value and Weight

**Overall DSC Readiness Value (Score)**

RF5 Value and Weight

RF6 Value and Weight

RF7 Value and Weight

RF8 Value and Weight

Figure 9: Proposed KBS

Now our KBS is ready to take inputs and evaluate the overall DSC readiness value (score). We entered the DSC factor (RF1, RF2, . . . RF8) values from what the case company provided as shown in Table 11 and its weight was calculated using AHP from Table 8. Figure 10 below shows the final results of KBS.

RF1 Value = 0.781 Weight = 0.022

RF2 Value = 0.881 Weight = 0.047

**Knowledge Base System**

**(FIS – AHP)**

**Total 72 Rules**

RF3 Value = 0.965 Weight = 0.058

RF4 Value = 0.739 Weight = 0.028

**Overall DSC Readiness Value (Score) = 0.267**

RF5 Value = 0.826 Weight = 0.106

RF6 Value = 0.794 Weight = 0.080

RF7 Value = 0.807 Weight = 0.326

RF8 Value = 0.902 Weight = 0.331

Figure 10: Implemented KBS

Above mentioned DSC readiness value is calculated as 0.267 based on data provided by the case company.

* 1. **Sensitivity Analysis**

Section 4.2 and section 4.3 show the development and implementation of the proposed KBS to evaluate the overall DSC readiness value (score). To capture the effect of changes on inputs (readiness factor value and weight) on overall DSC readiness value (score), we have generated two scenarios which are as follows:

* *Scenario 1*: In this scenario, we consider the impact of readiness factor (RF1, RF2, . . . RF8) value and varies from their initial values up to 0.95, and the overall DSC readiness value (score) changes from 0.267 to 0.250. This shows that our proposed KBS is sensitive to input value (RF1, RF2, . . . RF8) and shows its impact on overall DSC readiness value (score).
* *Scenario 2*: In this scenario, we change the reediness factor RF7 value from 0.807 to 0.90, and the overall DSC readiness value (score) changes from 0.267 to 0.273. This also means that this factor has an impact on overall readiness value (score).

Figure 11 and figure 12 below show the generated scenario.

RF1 Value = 0.95 Weight = 0.022

RF2 Value = 0.95 Weight = 0.047

**Knowledge Base System**

**(FIS – AHP)**

**Total 72 Rules**

RF3 Value = 0.95 Weight = 0.058

RF4 Value = 0.95 Weight = 0.028

**Overall DSC Readiness Value (Score) = 0.250**

RF5 Value = 0.95 Weight = 0.106

RF6 Value = 0.95 0.95 Weight = 0.080

RF7 Value = 0.95 Weight = 0.326

RF8 Value = 0.95 Weight = 0.331

Figure 11: Scenario 1

RF1 Value = 0.781 Weight = 0.022

RF2 Value = 0.881 Weight = 0.047

**Knowledge Base System**

**(FIS – AHP)**

**Total 72 Rules**

RF3 Value = 0.965 Weight = 0.058

RF4 Value = 0.739 Weight = 0.028

**Overall DSC Readiness Value (Score) = 0.273**

RF5 Value = 0.826 Weight = 0.106

RF6 Value = 0.794 Weight = 0.080

RF7 Value = 0.90 Weight = 0.326

RF8 Value = 0.902 Weight = 0.331

Figure 12: Scenario 2

1. **Discussion of results and implications**

The KBS for DSC readiness evaluation model provides a framework for the adoption and incorporation of the DSC factors within the current SCM to aid the transitioning into a digitalized SCM. This approach is shown in a multi-DSC factor interconnected framework with the following managerial implications.

**5. 1 Discussion of Results**

The results of the study can be found in Table 8 and Figure 10. From Table 8, it is observed that, the importance weights of the DSC readiness factors are ranked in the following order RF8 > RF7 > RF5 > RF6 > RF3 > RF2 > RF4 > RF1 having weights 0.331, 0.326, 0.106, 0.080, 0.058, 0.047, 0.028, 0.022 respectively. The most important readiness factor is training and policy, which is rightly so as without proper training to the workforce, it is difficult for organizations to transform their traditional SC to DSC. The second most important readiness factor is the IT network infrastructure. It is essential for organizations to have an up-to-date network system that integrates the entire organization operates efficiently and effectively. Our study results also show that without proper and updated IT network infrastructure, organizations will not be able to fully adopt digitalization in their supply chain management.

Sensitivity analysis was also performed to see the impact of input value on overall DSC readiness performance (score). The result shows that if we change the readiness factor RF1, RF2, and RF8 to 0.95, then overall readiness performance (score) will change from 0.267 to 0.250. This shows that maximizing the readiness value to the maximum will not necessarily improve the overall performance. Similarly, we changed the readiness factor RF7 value from 0.807 to 0.90, and the overall DSC readiness value (score) varies from 0.267 to 0.273. This shows that the organization needs to put more effort into this factor to improve overall DSC readiness performance (score).

Warehousing plays a significant role in the success of any organization's SC and impacts overall SC performance (Khan, Dweiri, and Chaabane, 2016). In line with this, our study's third most important factor is highlighting the importance of smart technologies and integrated systems in managing warehousing management. Similarly, adopting up-to-date technology, RFID, etc., improves overall logistics performance and vital for overall SC success (Jain and Khan, 2017; Jain and Khan, 2016). Our fourth most important readiness factor is the use of smart technologies in logistics. To achieve overall digitalization and complete transformation to DSC, other readiness factors such as supplier-buyer relationship, enhancement of IT skills among workers, relationship with customers, and ICT policies are also essential.

**5.2 Practical implications**

In order to set long-term strategies and achieve long-term goals, organizations need to plan and always lead the market. In addition to that, the vast experience of decision-makers and managers is key to utilize in setting strategies and setting long-term goals. Incorporating experts’ knowledge in decision-making is mandatory nowadays, and organizations must find a way to incorporate their knowledge in effective decision-making. To do so, an expert-based KBS is convenient to achieve this goal. Our proposed KBS shows how a manager's and decision maker’s knowledge can be integrated into evaluating overall DSC readiness performance (score). This study consulted with 21 experts who have vast experience in developing the KBS and the overall score of the considered case company is 0.267.

Our proposed KBS will help decision-makers and managers of Indian manufacturing companies in evaluating the current capabilities of adopting digitalization in their supply chain operations. This will also help them plan and focus more on paying more attention to the under-performed readiness factor. Our proposed KBS allows managers and decision-makers to perform sensitivity analysis. This will help them to have visibility of their decisions related to readiness in adopting digitalization and their impact before implementing it. In addition to that, this will also allow them to take necessary corrective actions effectively and efficiently. Due to limited resources, most of the managers and decision makers pay attention to few readiness factors without considering the importance of each readiness factor. This ignored readiness factor may or may not have a significant impact on overall DSC readiness.

**5.3 Academic implications**

This study contributes to the literature in several ways. First, this study contributes to understanding the readiness of organizations toward adopting DSCs via an Indian manufacturing company context. It extends the literature by adding the element of readiness to the adoption of DSCs. Second, this study identifies a list of factors that constitute a framework of organizations' readiness for adopting DSCs. This framework can serve as a theoretical framework for researchers to further investigate organizational readiness or their current position in transforming from traditional SCs to DSCs. Finally, the focus of the study and its evaluation of readiness in an Indian manufacturing organizational context adds additional perspective. It extends previous studies that only focus on DSCs adoption evaluation and show the level of readiness of organizations for transitioning to DSCs.

**5.4****Managerial Implications**

This study developed a KBS to aid in evaluating DSC readiness at an organizational level By analyzing the traditional SC of a case organization aids in ascertaining the level of their readiness to switch towards DSCs. The results indicated the actual situation and the future challenges posed by the organization for transitioning toward DSC. The findings of this study provide a comprehensive and in-depth understanding of decision-makers and managers in the efficient and effective adoption of digitalization in their SC. This study can specifically be helpful to the managers and decision-makers of the manufacturing sector of developing countries like India, which is one of the biggest markets in the world. Our proposed KBS helps managers and decision-makers in a smooth transition from traditional to DSC.

In an environment where everyone is competing based on their SC, it is extremely difficult for decision-makers and managers to devote resources to every aspect of their SC. Thus, the ranking of various DSC reediness factors using AHP will help them to firstly focus more on the top-ranking factor. Thus, the results obtained from our proposed KBS make it easier for decision-makers and managers to adopt digitalization in their SC to focus more on training policy and IT network infrastructure. By focusing on these top two DSC readiness factors, an organization can easily migrate to digitalization. Sensitivity analysis also helps managers and decision-makers to see the impact of their decision on overall DSC readiness performance (score) by changing readiness factor values. Our proposed KBS helps an organization know about their readiness factors score for moving in towards DSC and identifying bottlenecks in achieving their targets. Developed KBS will also be helpful for organizations to understand their SC complexity with respect to impact on performance through which proactive decision-making will take place.

1. **Conclusion and future research directions**

**6.1 Conclusions**

In this era of technological advancement, organizations need to switch towards digitalization to compete and survive in the market. Digitalization has helped evolve a new ecosystem where smart systems are helping organizations compete more fiercely with their competitors. There is a growing demand to provide customer demand-related data across the SC and product delivery and service-related data for enhanced visibility and traceability. DSC integration thus becomes imperative to meet these demands. Organizations need to be ready to digitalize their SCs by adopting various innovations and technologies like blockchain, artificial intelligence, and smart production systems for better traceability of their products throughout the SC. Although they are essential and beneficial for the digitalization of the SC, these innovative technologies are often complex and expensive to adopt. Developing countries especially face specific challenges for the adoption of these innovative technologies for digitalization. The case organization is trying to transform its traditional SC to the digital one to benefit from technological advancements over its competitors and thus perform better in an increasingly competitive market.

This study identifies various factors that are supportive of the DSC readiness of the organizations. As discussed, organizations in developing countries often face challenges in the digitalization of their SC. One of the most prominent among these is the lack of skilled workforce and managers for adopting digitalization. From the current case, organizations need to plan for policies for systematic and phase-wise training of the employees in the latest innovative technologies so that organizations can move forward in the digitalization of their SCs. There is no single factor that can prepare organizations for the complete digitalization of the SC.

Along with the skilled workforce, infrastructure support for the adoption of these technologies is also essential. IT infrastructure and the adoption of smart technologies like RFID and robotic systems in warehouses will significantly benefit organizations in their goals of transformation to digitalization. This study develops a knowledge-based framework for assessing the digital readiness of the organizations and thus paves the way for other organizations also for their effective and smooth transition.

**6.2 Limitations and future scope**

This study can be developed further in the future to overcome a few limitations that this study has. This study employs a multi-criteria decision-making approach relying on expert opinion for obtaining the results. Although the results are based on experts who have specific years of experience in this field, the study can still be further developed by statistically validating the framework using a statistical approach like Structural Equation Modelling with a larger data set. The final framework consists of nine factors for assessing the digital readiness of the organizations. Future studies can develop a hierarchical model having multiple criteria and sub-criteria for determining digital readiness. Further, future studies can use an integrative approach combining two methodologies for first ranking the factors of digital readiness and then evaluating the performance of each organization on these factors so that a comparison of the digital readiness of multiple organizations can be made simultaneously.

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**Appendix 1: Survey**

We are conducting a research to develop a knowledge base system to evaluate overall digital supply chain (DSC) reediness. The purpose of this survey is to perform pair-wise comparison for Analytical Hierarchal Process (AHP). Your response will help us in finding the importance weights of identified DSC readiness factors. The survey will take around 8 to 10 minutes and your responses are completely anonymous. We really appreciate your time.

|  |  |
| --- | --- |
| **Section 1** | Demographic Data Collection |

|  |  |  |  |
| --- | --- | --- | --- |
|  | Male |  | Female |

1. Your Gender?
2. Your Age?

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | 20-25 |  | 26-30 |  | 31-35 |  | 36-40 |  | 41-45 |  | >45 |

1. Your Designation Level?

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Middle Manager |  | Manager |  | Senior Manger |  | Director |  | Others |

1. Since when are you attached with this profession?

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | 1-5 yrs. |  | 6-10 yrs. |  | 11-15 yrs. |  | * 1. yrs. |  | >20 yrs. |

|  |  |
| --- | --- |
| **Section 2** | In this section, eight identified DSC readiness factors will be rated |

|  |  |  |
| --- | --- | --- |
| **DSC Readiness Factors** | **Notation** | **Description** |
| Information and communication technology (ICT) policies | RF1 | It defines as ICT policies of an organization to adopt and integrate new technologies in their processes. |
| Worker IT skills | RF2 | It defines that how the workforce (white collar and blue collar) capable to adopt change in their way of doing task after adopting new technology in process. |
| Supplier-buyer relationship | RF3 | It defines that first tier supplier capabilities to adopt new technology and allow integration. |
| Relationship with customer | RF4 | It defines how much and up to what extend organization integrates with customer and share information and transparent in their process |
| Use of smart technologies in WH | RF5 | It defines that is WH capable to adopt new technologies or they are already using such technologies such as QR codes, RFID tags etc. |
| Use of smart technologies in logistics | RF6 | In order to get real time information, is logistics service provider or I house logistics is capable to adopt new technology in inbound and outbound logistics. |
| Use of smart technologies in production | RF7 | Smart manufacturing practices are currently in use or are organization capable to adopt new technologies in their manufacturing process. |
| IT network infrastructure | RF7 | In order to get maximum benefit of new technology, is organization IT infrastructure is capable to give support. |
| Trainings | RF8 | Organization plan to send managers and workforce for training related to new technologies |

Please answer the following questions by choosing a number to rate the importance of a criteria on the scale provided.

* By choosing 1 you declare an ***equal rating*** between the factors.
* The lowest rating you can choose is 2 which indicate a ***low importance*** of the criteria on the side you chose the number for.
* The highest rating you can choose is 9 which indicate a ***high importance*** of the criteria on the side you chose the number for.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **RF1** | 9 | 8 | 7 | 6 | 5 | 4 | 3 | 2 | **1** | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | **RF2** |
| **RF1** | 9 | 8 | 7 | 6 | 5 | 4 | 3 | 2 | **1** | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | **RF3** |
| **RF1** | 9 | 8 | 7 | 6 | 5 | 4 | 3 | 2 | **1** | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | **RF4** |
| **RF1** | 9 | 8 | 7 | 6 | 5 | 4 | 3 | 2 | **1** | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | **RF5** |
| **RF1** | 9 | 8 | 7 | 6 | 5 | 4 | 3 | 2 | **1** | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | **RF6** |
| **RF1** | 9 | 8 | 7 | 6 | 5 | 4 | 3 | 2 | **1** | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | **RF7** |
| **RF1** | 9 | 8 | 7 | 6 | 5 | 4 | 3 | 2 | **1** | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | **RF8** |
| **RF2** | 9 | 8 | 7 | 6 | 5 | 4 | 3 | 2 | **1** | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | **RF3** |
| **RF2** | 9 | 8 | 7 | 6 | 5 | 4 | 3 | 2 | **1** | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | **RF4** |
| **RF2** | 9 | 8 | 7 | 6 | 5 | 4 | 3 | 2 | **1** | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | **RF5** |
| **RF2** | 9 | 8 | 7 | 6 | 5 | 4 | 3 | 2 | **1** | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | **RF6** |
| **RF2** | 9 | 8 | 7 | 6 | 5 | 4 | 3 | 2 | **1** | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | **RF7** |
| **RF2** | 9 | 8 | 7 | 6 | 5 | 4 | 3 | 2 | **1** | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | **RF8** |
| **RF3** | 9 | 8 | 7 | 6 | 5 | 4 | 3 | 2 | **1** | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | **RF4** |
| **RF3** | 9 | 8 | 7 | 6 | 5 | 4 | 3 | 2 | **1** | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | **RF5** |
| **RF3** | 9 | 8 | 7 | 6 | 5 | 4 | 3 | 2 | **1** | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | **RF6** |
| **RF3** | 9 | 8 | 7 | 6 | 5 | 4 | 3 | 2 | **1** | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | **RF7** |
| **RF3** | 9 | 8 | 7 | 6 | 5 | 4 | 3 | 2 | **1** | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | **RF8** |
| **RF4** | 9 | 8 | 7 | 6 | 5 | 4 | 3 | 2 | **1** | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | **RF5** |
| **RF4** | 9 | 8 | 7 | 6 | 5 | 4 | 3 | 2 | **1** | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | **RF6** |
| **RF4** | 9 | 8 | 7 | 6 | 5 | 4 | 3 | 2 | **1** | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | **RF7** |
| **RF4** | 9 | 8 | 7 | 6 | 5 | 4 | 3 | 2 | **1** | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | **RF8** |
| **RF5** | 9 | 8 | 7 | 6 | 5 | 4 | 3 | 2 | **1** | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | **RF6** |
| **RF5** | 9 | 8 | 7 | 6 | 5 | 4 | 3 | 2 | **1** | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | **RF7** |
| **RF5** | 9 | 8 | 7 | 6 | 5 | 4 | 3 | 2 | **1** | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | **RF8** |
| **RF6** | 9 | 8 | 7 | 6 | 5 | 4 | 3 | 2 | **1** | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | **RF7** |
| **RF6** | 9 | 8 | 7 | 6 | 5 | 4 | 3 | 2 | **1** | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | **RF8** |
| **RF7** | 9 | 8 | 7 | 6 | 5 | 4 | 3 | 2 | **1** | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | **RF8** |

*Thank You Very Much for Participating in Our Survey*