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# Digital Supplier Selection for a Garment Business Using Interval Type-2 Fuzzy TOPSIS

Ahmet Özek[1], Aytaç Yıldız[2]

[1] Marmara University, Faculty of Technology, İstanbul, Turkey;
[2] Bursa Technical University, Faculty of Engineering and Natural Sciences, Bursa, Turkey

**Corresponding Author:** Ahmet Özek, aozbek@marmara.edu.tr

**ABSTRACT**

The aim of this study was to use the interval type-2 fuzzy TOPSIS method to select the best supplier among a number of suppliers digitized by Industry 4.0 for a company operating in the garment industry. The interval type-2 fuzzy TOPSIS method involves an interval of type-2 fuzzy sets and can model uncertainties very well to solve fuzzy multi-criteria decision making problems. Alternatives were listed based on closeness indexes, and the best digital supplier was selected based on sensitivity analysis. This is the first study to use the model in question to select the best digital supplier for a company. We, therefore, believe that it will contribute to the literature. It is recommended that the model in question be used in other industries as well.

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**KEYWORDS**

Industry 4.0, Digital Supply Chain, Fuzzy TOPSIS, Garment Industry

## 1. INTRODUCTION

Revolution is a rapid, radical and noteworthy change in a certain area [1]. The Industrial Revolution was one of the most important revolutions in world history. The first phase of the Industrial Revolution was the First Industrial Revolution in the eighteenth century, in which human power was replaced by steam power resulting in a dramatic transformation in production. The second phase was the Second Industrial Revolution in the twentieth century which witnessed the integration of electricity into production, marking the onset of mass production. The third phase was the Third Industrial Revolution in which advanced automation systems were introduced to production in the 1970s. Today, we are on the verge of the fourth phase, which is the Fourth Industrial Revolution, involving smart factories that autonomously run entire production processes [2, 3].

The Industrial Revolution has provided limitless multiplication of goods and services [4]. Thus, enterprises and countries that quickly adapt to new industrial production concepts have achieved significant progress. Benefiting from the First Industrial Revolution very efficiently, western countries, the USA and Japan monopolized production for a long time and achieved high competitiveness while others generally turned into open markets [5, 6, 7]. However, developed countries have lost their competitive advantages to underdeveloped and developing countries in the early 2000s due to aging population and high labor costs etc. [8]. Developed countries such as the US, Germany and the United Kingdom had traditionally outsourced their production to developing countries. They have, however, been adversely affected by the global economic crisis in 2008, and therefore, started to reshore their production back [6, 9]. Germany was the first to execute it. In 2011, German Kagermann argued that the integration of sensors, embedded-connected systems, digitization and information-communication technologies into production promotes smart production, which can provide competitive advantage against low-cost manufacturing in Asia [7, 10, 11, 12]. The

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German National Science and Engineering Academy developed this idea and defined it as Industry 4.0 in 2013 [8]. Industry 4.0 is based on such technologies as smart robots, big data, internet of things (IoT), 3-D printing and cloud etc. [13, 14].

The Internet-based high automation in Industry 4.0 production connects machines, computers, suppliers and customers in real time [15, 16]. Thus, each machine is independently and autonomously involved in production, adapt themselves to new demands, monitor production processes, predict the current situation, analyze data, perform tasks by themselves, and report or solve possible operation and maintenance issues. Smart devices can be placed on production lines to minimize production costs or disruptions, artificial smart technologies can shorten decision-making processes, data can be shared with systems and related parties in real time, and interface can be used to interact with people [7, 9, 15, 16, 17].

In Industry 4.0, while production is fast and modular production principle, zero defective and high quality production is planned with flexible production lines [7, 15]. The expected advantages of Industry 4.0 are as follows: A decrease in production (10-30%), material, logistics (10-30%) and quality management (10-20%) and labor and investment costs; faster production, processing, delivery and launch of new products; more flexible business processes; higher sensitivity to customer demands; customized production; difficulty of imitation; high quality, competitiveness and efficiency (approx. 4.1% annually) [10, 18, 19]. Ovacı [6] maintains that enterprises that invest in Industry 4.0 can see a return on investment within three to five years. Dalenogare et al [10] concludes that Industry 4.0 will change the competition rules of production, the structure of industries and customer relations. Today, Industry 4.0 is used in automotive, telecommunication, health products, household appliances, electronics, machinery and textile/ garment sectors [6, 7].

The garment sector is a branch of industry which statistically analyzes the demand for clothing and meets that demand through mass production [20]. The garment sector emerged in developed European countries and North America which witnessed the Industrial Revolution. Those countries had monopolized the production of ready-to-wear garments for a long time. After the Second World War, Japan and the Far East countries turned to garment exports using cheap labor and transferring technology, which resulted in developed countries outsourcing their garment production to developing Asian countries [21]. They have also inspired developing countries such as Turkey to invest in the sector. This has led to the globalization of the sector, intensification of competition and reduction in profit margins [22]. In that environment, it became imperative for ready-to-wear companies wishing to dominate the market to create powerful and responsive supply chains to provide efficient operations and the best value to customers [23]. Although it is assumed that the mechanical mass production and labor-intensive structure of today's garment industry will prevent it from quickly adopting new technologies [24], ready-to-wear companies have already started to integrate such smart systems that provide decision and support such as Expert Systems (ES), Genetic Algorithms (GA), Artificial Neural Networks (ANN), Knowledge-Based Systems (KBS), Decision Support Systems (DSS), Fuzzy Logic Systems, Hybrid Systems into their supply chains to achieve competitive advantage [25]. They have also started to use artificial intelligence (AI), Internet of Things (IoT), 3D printing, wearable and soft engineering, intelligent logistics, nanotechnology, advanced materials, biotechnology, BPM (business process management), virtual reality (VR), augmented reality (AR), cyber-physical systems (CPS), cyber security, big data (BD), autonomous robots, cloud computing and simulation technologies, which constitute the basis of the Industrial Revolution 4.0, of which we are on the verge [26, 27, 28]. Those new technologies have digitized supply chains and increased the need for collaborating with digital suppliers.

With the development of information communication technologies, digitalization has spread to every field. In the future, digitalization is expected to become more widespread. Under these circumstances, it can be said that the adaptation time of the enterprises will determine their future success. This can be achieved through the digitization of the suppliers that directly affect the performance of the enterprises. In the apparel industry where information technologies are not used much, the importance of digitalization has been realized and digitalization has started. Accordingly, digital supplier selection is a new topic in the clothing sector as in many other sectors and there is not enough academic studies in this field.

The aim of this study was, therefore, to select a supplier that used Industry 4.0 technologies most effectively for a company operating in the garment industry. An Interval type-2 fuzzy TOPSIS (IT2F-TOPSIS) method, which is a multi-criteria decision making method modeling uncertainties accurately, was used.

Different from the T2F AHP method, the IT2F-TOPSIS method does not require pairwise comparison matrices, which makes calculations easier. Moreover, the IT2F-TOPSIS method yields more accurate results because it does not have a hierarchical structure.

The rest of the study is organized as follows; the second section of the study explained the digital supply chain. The third section briefly addressed the IT2F-TOPSIS method and presented the algorithm steps. The fourth section evaluated the alternative suppliers. The last section presented the findings of the research and made evaluations.

Digital Supply Chain

A supply chain (SC) consists of suppliers, manufacturers, distributors and external resources and all processes involved in the production of software and components [29, 30]. It is a global system of complex interconnected networks that are widely distributed geographically [29]. Supply chain used to be a purely operational logistic function that once gave information to sales or production and focused on production lines and delivering products. Today, it has become an independent supply chain management (SCM) function managed by a separate unit in some companies [31]. SCM means having the right customers at the right place and time [30]. SCM operations involve systems that manage the flow of information, materials and services from suppliers to end consumers, and are important for business operations. They, therefore, have a significant impact on costs and profits [32]. However, intense competition in global markets reduces companies' capacity to use their supply chains to achieve workflow. SC managers are desirable for cheaper, better and faster product. However, traditional supply chains can be more costly, complex and vulnerable [30]. To overcome these challenges, there has been a paradigm shift towards what is today known as Industry 4.0, which has led to the automation and digitalization of supply chain functions including supply, production and distribution [30, 31, 32]. The digitization has significantly altered SCM behavior and led to the introduction of the concept of digital supply chain (DSC) [33].

DSC encourages companies to rethink their supply chain design to meet customer needs and expectations for the improvement of procurement and service quality [34]. It differs from traditional supply chains as the latter focus mainly on minimizing manufacturing, transport and logistics costs. DSC is a customer-centric platform model that uses and maximizes real-time data flowing from different sources and helps businesses collaborate by integrating the entire supply network [35, 36, 37].

DSC has an outstanding performance that makes customers very satisfied because it makes demand stimulation, simulation, matching, detection and management possible for the maximization of performance and minimization of risks and ensures timely delivery of products and quick and easy return at the end of their life cycle [35, 38, 39]. DSC and high digitized operations can increase annual productivity and revenues by 4.1% and 2.9%, respectively [40].

DSC operations consist of such technologies as autonomous robots, AR, additive manufacturing (AM), AI, high-tech sensors, cloud computing, IoT, autonomous vehicle, mobility and Big Data Analytics (BDA) as shown in Figure 1. [40, 41].

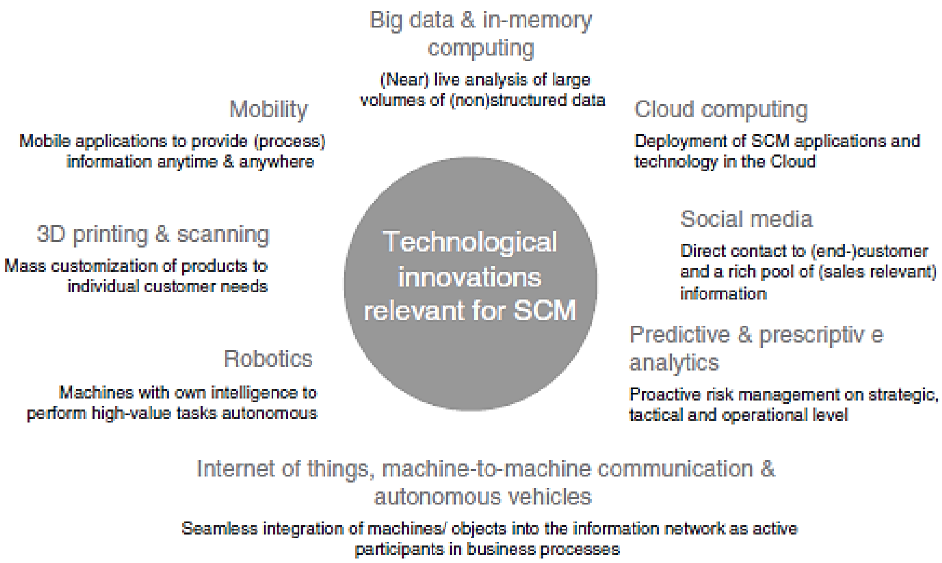


**Figure 1.** Innovations in supply chain management [37]

AM describes the use of 3D technologies in different stages of SC to achieve production flexibility, fast delivery, individualized product and less inventory [41]. It is a decentralized manufacturing technique that transforms the distribution network. It reduces the complexity and load of a product or supply chain, provides flexibility for the production of a variety of products and renders the supply chain more efficient. 3D printers help reduce the amount of stock throughout the supply chain and also simplify some manufacturing processes of technology (For example, a module can be printed using a single 3D operation instead of several components that require different supply chains) [42].

Driverless transportation systems (DTSs) minimize human errors, and thus, provide greater operational reliability and enhance storage and logistics efficiency and lower costs. DTSs can be used for decades and integrated with smart technologies that provide precise positioning, guidance, route optimization, machine diagnostics or real-time monitoring. These technologies can also support such warehouse operations as safer loading of goods, more efficient inventory management or faster collection cycles, and therefore, have a positive effect on SCM operations as well. These technologies also help operators with product delivery, storage and dispatch, reduce the number of accidents, enhance transportation visibility and help truck drivers [41].

Information technologies (ITs) play a critical role in the effective management of supply chains. They provide communication and data transfer and improve supply chain performance, and thus, integrate suppliers, processes and customers. One of the most significant developments in information technologies is IoT. The term IoT was coined in 1999 by Kevin Ashton. IoT is defined as the network of a series of physical and virtual objects connected through a network that enables communication, detection, interaction and data collection and exchange [30]. An increase in the number of IoT devices results in an increase in the number of participants and actors in supply chains. The peak of IoT is an output of supply chain systems characterized by low energy consumption and cost and sometimes long term and different levels of physical accessibility [29]. It helps to maximize the effectiveness of operations across supply chain partners [32], resulting in high transparency (supply chain visibility) and integrity control in supply chains (right products at the right time, place, quantity and cost) [43]. It also helps monitor the logistics operations where asset tracking or transit components are complex [32]

Today, a huge amount of data is being collected in various domains including technology-oriented data sources such as enterprise resource planning (ERP) systems, distributed manufacturing environments, orders and shipment logistics, social media, customer buying behavior, product life cycle operations, global positioning systems (GPS), radio frequency identification (RFID) technology, monitoring, mobile devices and surveillance cameras. Enterprises are, therefore, interested in large data sets characterized by 4V (volume, variety, velocity, and veracity). The bigger the data, the harder it is to manage and analyze it. Recent studies on BDA have developed tools and techniques to help make data-driven supply chain decisions [44]. BDA operations in SCM are used in procurement processes, dynamic vehicle routing, logistics, inventory management, order collection and storage [41].

Cloud computing (a.k.a. cloud) refers to the use of a remote server network to access shared resources such as data servers, storage, applications, and other services. Cloud computing allows supply chain users to store and process their data in a private cloud or on a third-party server, which makes the data easily accessible from almost anywhere. It also enables companies and individuals to minimize infrastructure and maintenance costs in information technology [45]. Digitization is also used to support routine resource acquisition activities such as procurement and assessment. Digital indirect procurement processes (maintenance or repair services, travel booking, office furniture or supplies) reduce uncoordinated procurement transactions [41].

Today, delivery of products can last for weeks or even months. To know where products are at any given time, they should be visible and transparent within supply chains, and therefore, they should be geographically positioned. RFID tags and GPS are used to track physical objects and send that information to a central data center. Those systems, which are fixed on products themselves or on transport units (e.g. containers), collect a large amount of data on weather, traffic, or telemetry of transportation vehicles [37].

Robots can be used in manufacturing, logistics, retail operations etc. Smart robots in retail or warehouse are used for cycle counting (also in supermarkets) or logistic and collection operations. Flying robots can be used to transport goods and packages to hard-to-reach areas. For example, Amazon conducted its first drone delivery test in the U.K. [41]. Many companies from different sectors are also investing in digitizing business operations and supply chains. For example, DHL, a large logistics service provider, follows trends that will affect the logistics industry in the future. DB Schenker, another logistics service provider, is investing in a digital mobility laboratory. Such airlines as THY, Lufthansa and Emirates with strong cargo operations are expanding paperless e-freight offers with data cleaning for customers. Monsanto, an agricultural company, is investing in sensor technology to digitize its agricultural operations. Amazon and Alibaba, global retailers, are investing in drones and robotics for product transportation and delivery [46].

Type-2 fuzzy sets

Decision-making processes involve uncertainties, which are generally due to excessive number of decision making criteria, system behavior, and most importantly, decision-makers' preferences. Decision-makers make subjective and linguistic judgments, which do not yield accurate results. Uncertain set theory has been integrated in decision-making methods to deal with uncertain linguistic judgments. Although most of the methods use type-1 fuzzy sets (T1FSs) to model decision-makers' uncertain linguistic judgments, those sets are not suitable for modeling words [47] because words mean different things for different people.

Type-2 fuzzy sets (T2FSs) are used to overcome this problem because they treat uncertain linguistic judgments appropriately and have fuzzy membership functions, in which the degree of membership of each element belongs to a set. Thus, the modeling of an uncertainty is not limited to linguistic variables in T2FSs but also takes part in the definition of membership functions [48, 49]. The concept of T2FSs was first presented as an expanded and extended version of classical T1FSs [49]. T2FSs is used especially when a full membership function cannot be defined for a fuzzy set. Those sets are, therefore, very effective in overcoming uncertainties [47].

The membership functions of T1FSs are two-dimensional whereas those of T2FSs are three-dimensional. The new third dimension of T2FSs provides additional degrees of freedom and allows uncertainties to be modeled. Therefore, if T1FSs are considered to be a first degree approach to uncertainties in the real world, then type-2 fuzzy sets can be regarded as a quadratic approach to uncertainty. T2FSs are capable of performing well in the presence of noisy inputs and in case of uncertainty on linguistic data, the meanings of which may vary from expert to expert.

The membership functions of T1FSs are net sets. Therefore, when the meanings of criteria are ambiguous, evaluators have different views, resulting in a noisy evaluation environment. T1FSs, therefore, fail to provide effective decision support. In such cases, the problem can be modeled using T2FSs with membership functions of T1FSs [49]. As is known, linguistic information, usually from expert knowledge, does not provide information on the form of membership functions. In such cases, the effect of linguistic or numerical uncertainties can be mitigated by T2FSs as opposed to T1FSs. T2FSs involve more uncertainties and yield more accurate and robust results than T1FSs. Interval T2FSs are easier to calculate, and therefore, used by most applications. Interval T2FSs are used in real-world multi-criteria decision-making (MCDM) problems [50].

Interval type 2 fuzzy TOPSIS methodology

The fuzzy TOPSIS method developed by Hwang and Yoon (1981) is also widely used in MCDM problems. The fuzzy TOPSIS method is based on the concept that the chosen alternative should have the shortest distance from the positive-ideal solution and the longest distance from the negative-ideal solution. There are many studies using this method to solve MCDM problems. However, the fuzzy TOPSIS method is not always appropriate to represent uncertainties because it is based on T1FSs [51, 52].

Chen and Lee [53] expanded the classical TOPSIS method and developed the interval type-2 fuzzy TOPSIS method involving T2FSs to solve fuzzy multi-criteria decision-making problems. The IT2F-TOPSIS method uses T2FSs to solve fuzzy multi-criteria decision-making problems, and therefore, provides more rationality and flexibility to calculate the weights and values of criteria [54]. Some of the studies using the IT2F-TOPSIS method are as follows:

WASPAS and type-2 fuzzy TOPSIS method were used to select a car sharing station [49]. Interval type-2 AHP and TOPSIS methods were used to select an appropriate ship loader type in maritime transport [50]. IT2F-TOPSIS method was used to select a material [55], a new route from five different destinations for one airline [48] a green supplier [56], a supplier [51] and RFID for warehouses [52] and to assess supplier performance for an airline [57] and investment projects for development agencies [58].

The steps of the IT2F-TOPSIS method are as follows. Lee and Chen [54] presented the concept of ranking values of trapezoidal interval T2FSs. Let be an interval type-2 fuzzy set (Figure 2),

where

$$\tilde{\tilde{A}}_i = \left(\tilde{A}_i^U . \tilde{A}_i^{L,}\right) = ((a_{i1}^U, a_{i2}^U, a_{i3}^U, a_{i4}^U; H_1(\tilde{A}_i^U), H_2(\tilde{A}_i^L))).$$

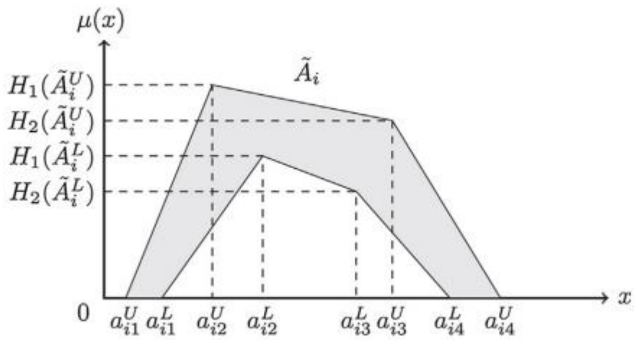


**Figure 2.** A trapezoidal IT2FSs [53]

The ranking value of the trapezoidal interval type-2 fuzzy set is defined as follows [54]:

$$\begin{aligned} Rank(\tilde{\tilde{A}}_i) = {} & M_1\left(\tilde{A}_i^U\right) + M_1\left(\tilde{A}_i^L\right) + M_2\left(\tilde{A}_i^U\right) + M_2\left(\tilde{A}_i^L\right) + M_3\left(\tilde{A}_i^U\right) + M_3\left(\tilde{A}_i^L\right) \\ & -\frac{1}{4}\left(S_1\left(\tilde{A}_i^U\right) + S_1\left(\tilde{A}_i^L\right) + S_2\left(\tilde{A}_i^U\right) + S_2\left(\tilde{A}_i^L\right) + S_3\left(\tilde{A}_i^U\right) + S_3\left(\tilde{A}_i^L\right) + S_4\left(\tilde{A}_i^U\right) + S_4\left(\tilde{A}_i^L\right)\right) + \\ & H_1\left(\tilde{A}_i^U\right) + H_1\left(\tilde{A}_i^L\right) + H_2\left(\tilde{A}_i^U\right) + H_2\left(\tilde{A}_i^L\right) \end{aligned} \tag{1}$$

Where $M_p(\tilde{A}_i^j)$ denotes the average of the elements $a_{ip}^j$ and $a_{i(p+1)}^j$, $M_p(\tilde{A}_i^j) = (a_{ip}^j + a_{i(p+1)}^j)/2,\ 1 \le p \le 3,\ S_q(\tilde{A}_i^j)$ denotes the standard deviation of the elements $a_{iq}^j$ and

$a^{j}_{i(q+1)}$, $S_q(\tilde{A}^j_i) = \sqrt{\frac{1}{2}\sum_{q}^{q+1}\left(a^j_{ik} - \frac{1}{2}\sum_{k=q}^{q+1} a^j_{ik}\right)^2}$, $1 \le q \le 3$, $S_4(\tilde{A}^j_i)$ denotes the standard deviation of the elements $a^j_{i1}, a^j_{i2}, a^j_{i3}, a^j_{i4}$, $S_4(\tilde{A}^j_i) = \sqrt{\frac{1}{4}\sum_{k=1}^{4}\left(a^j_{ik} - \frac{1}{4}\sum_{k=1}^{4} a^j_{ik}\right)^2}$,

$H_p(\tilde{A}^j_i)$ denotes the membership value of the element $a^j_{i(p+1)}$ in the trapezoidal membership function $\tilde{A}^j_i$, $1 \le p \le 2$, $j \in \{U, L\}$, and $1 \le i \le n$.

In Eq. (1), the summation of $M_1(\tilde{A}^U_i), M_1(\tilde{A}^L_i), M_2(\tilde{A}^U_i), M_2(\tilde{A}^L_i), M_3(\tilde{A}^U_i), M_3(\tilde{A}^L_i), H_1(\tilde{A}^U_i), H_1(\tilde{A}^L_i), H_2(\tilde{A}^U_i)$ and $H_2(\tilde{A}^L_i)$ are referred to as the basic ranking score, where we deduct the average of $S_1(\tilde{A}^U_i), S_1(\tilde{A}^L_i), S_2(\tilde{A}^U_i), S_2(\tilde{A}^L_i), S_3(\tilde{A}^U_i), S_3(\tilde{A}^L_i), S_4(\tilde{A}^U_i)$ and $S_4(\tilde{A}^L_i)$ from the basic ranking score to give the dispersive interval type-2 fuzzy set a penalty, where $1 \le i \le n$.

Assume that there is a set $X$ of alternatives, where $X = \{x_1, x_2, \ldots, x_n\}$, and that there is a set $F$ of attributes, where $F = \{f_1, f_2, \ldots, f_m\}$. Assume that there are $k$ decision-makers $D_1, D_2, \ldots$, and $D_k$. The set $F$ of attributes can be divided into two sets $F_1$ and $F_2$, where $F_1$ denotes the set of benefit attributes while $F_2$ denotes the set of cost attributes, $F_1 \cap F_2 = \phi$, and $F_1 \cup F_2 = F$. The proposed method is now presented as follows:

***Step 1:*** Construct the decision matrix $Y_p$ of the *pth* decision-maker and construct the average decision matrix $\overline{Y}$, respectively, as follows:

$$Y_p = (\tilde{f}^p_{ij})_{mxn} = \begin{array}{c} \\ f_1 \\ f_2 \\ \vdots \\ f_m \end{array}\begin{array}{c} \begin{array}{cccc} x_1 & x_2 & \cdots & x_n \end{array} \\ \begin{bmatrix} \approx{f}^p_{11} & \approx{f}^p_{12} & \cdots & \approx{f}^p_{13} \\ \approx{f}^p_{21} & \approx{f}^p_{22} & \cdots & \approx{f}^p_{23} \\ \vdots & \vdots & \vdots & \vdots \\ \approx{f}^p_{31} & \approx{f}^p_{m1} & \cdots & \approx{f}^p_{mn} \end{bmatrix} \end{array} \tag{2}$$

$$\overline{Y} = \left(\overset{\approx}{f}_{ij}\right)_{mxn}, \tag{3}$$

where, $(\overset{\approx}{f}_{ij}) = \left(\frac{\overset{\approx}{f}^1_{ij} \oplus \overset{\approx}{f}^2_{ij} \oplus \ldots. \oplus \overset{\approx}{f}^k_{ij}}{k}\right)$, $\overset{\approx}{f}_{ij}$ is an interval type-2 fuzzy set, $1 \le i \le m, 1 \le j \le n, 1 \le p \le k$, and k denotes the number of decision-makers.

***Step 2:*** Construct the weighing matrix $W_p$ of the attributes of the pth decision-maker and construct the average weighing matrix $\overline{W}$, respectively, as follows:

$$W_p = (\overset{\approx}{w}^p_i)_{1xm} = \left[\overset{\approx}{w}^p_1 \quad \overset{\approx}{w}^p_2 \quad \cdots \overset{\approx}{w}^p_m\right], \tag{4}$$

$$\overline{W} = (\overset{\approx}{w}_i)_{1xm}, \tag{5}$$

where $\overset{\approx}{w}_i = \left(\frac{\overset{\approx}{w}^1_i \oplus \overset{\approx}{w}^2_i \oplus \ldots. \oplus \overset{\approx}{w}^k_i}{k}\right)$, $\overset{\approx}{w}_i$ is an interval type-2 fuzzy set, $1 \le i \le m, 1 \le p \le k$, and $k$ denotes the number of decision-makers.

***Step 3:*** Construct the weighted decision matrix $\overline{Y}_w$,

$$\overline{Y}_w = (\overset{\approx}{v}_{ij})_{mxn} = \begin{array}{c} \\ f_1 \\ f_2 \\ \vdots \\ f_m \end{array}\begin{array}{c} \begin{array}{cccc} x_1 & x_2 & \cdots & x_n \end{array} \\ \begin{bmatrix} \overset{\approx}{v}_{11} & \overset{\approx}{v}_{12} & \cdots & \overset{\approx}{v}_{13} \\ \overset{\approx}{v}_{21} & \overset{\approx}{v}_{22} & \cdots & \overset{\approx}{v}_{23} \\ \vdots & \vdots & \vdots & \vdots \\ \overset{\approx}{v}_{m1} & \overset{\approx}{v}_{m2} & \cdots & \overset{\approx}{v}_{mn} \end{bmatrix} \end{array}, \tag{6}$$

where $\overset{\approx}{v}_{ij} = \overset{\approx}{w}_i \otimes \overset{\approx}{f}_{ij}$, $1 \le i \le m$, and $1 \le j \le n$.

***Step 4:*** Based on equation (1), calculate the ranking value $Rank(\overset{\approx}{v}_{ij})$ of the interval type-2 fuzzy set $\overset{\approx}{v}_{ij}$, where $1 \le j \le n$. Construct the ranking weighted decision matrix $\overline{Y}^*_w$,

$$\overline{Y}^*_w = \left(Rank(\overset{\approx}{v}_{11})\right)_{mxn}, \tag{7}$$

where $1 \le i \le m$, and $1 \le j \le n$.

**Step 5:** Determine the positive ideal solution $x^{+} = \left(v_1^{+}, v_2^{+}, \ldots\ldots v_m^{+}\right)$ and the negative-ideal solution $x^{-} = \left(v_1^{-}, v_2^{-}, \ldots\ldots v_m^{-}\right)$, where

$$v_i^{+} = \begin{cases} \max\limits_{1\le j\le n}\{rank(\tilde{\tilde{v}}_{ij})\}, & if\ \ f_i \in F_1 \\ \min\limits_{1\le j\le n}\{rank(\tilde{\tilde{v}}_{ij})\}, & if\ \ f_i \in F_2 \end{cases} \quad (8)$$

and

$$v_i^{-} = \begin{cases} \min\limits_{1\le j\le n}\{rank(\tilde{\tilde{v}}_{ij})\}, & if\ \ f_i \in F_1 \\ \max\limits_{1\le j\le n}\{rank(\tilde{\tilde{v}}_{ij})\}, & if\ \ f_i \in F_2 \end{cases} \quad (9)$$

where $F_1$ denotes the set of benefit attributes, $F_2$ denotes the set of cost attributes, and $1 \le i \le m$

**Step 6:** Calculate the distance $d^{+}(x_j)$ between each alternative $x_j$ and the positive ideal solution (PIS) $x^{+}$ as follows:

$$d^{+}(x_j) = \sqrt{\sum_{i=1}^{m} (Rank(\tilde{\tilde{v}}_{ij}) - v_i^{+})^2} \quad (10)$$

where $1 \le j \le n.$ Calculate the distance $d^{-}(x_j)$ between each alternative $x_j$ and the negative-ideal solution (NIS) $x^{-}$, as follows:

$$d^{-}(x_j) = \sqrt{\sum_{i=1}^{m} (Rank(\tilde{\tilde{v}}_{ij}) - v_i^{+})^2} \quad (11)$$

where $1 \le j \le n.$

**Step 7:** Calculate the relative degree of closeness $C(x_j)$ of $x_j$ with respect to the positive ideal solution $x^{+}$, as follows:

$$C(x_j) = \frac{d^{-}(x_j)}{d^{-}(x_j) + d^{+}(x_j)}, \quad (12)$$

where $1 \le j \le n.$

**Step 8:** Rank the values of $C(x_j)$ in a descending sequence, where $1 \le j \le n.$ The larger the value of $C(x_j)$, the higher the preference of the alternative $x_j$, where $1 \le j \le n.$

## 2. MATERIAL AND METHOD

### 2.1 Material and Method

The aim of this study was to select the best supplier among a number of suppliers for a company that has been operating in the Turkish garment industry and selling women's, men's, children's and baby clothes under its own brand in over 1000 stores in over 40 countries for 30 years. The company makes very little of the products that it sells. But instead, they are manufactured by domestic and foreign apparel manufacturers. The company has a very large supply network that maintains its production structure and wants to select the best supplier (digital supplier) using Industry 4.0 technologies to overcome the problems of communication and supply chain management. To this end, IT2F-TOPSIS method, which is a multi-criteria decision making method, was used. The literature review in Section 2 (Digital Supply Chain) was used to determine the criteria for digital supplier selection. The company experts (IT specialist, supply chain manager, quality manager, sales-marketing manager) were also consulted for their opinions. Alternative digital suppliers were determined by the company, and a hierarchical selection model was developed given in Figure 3.

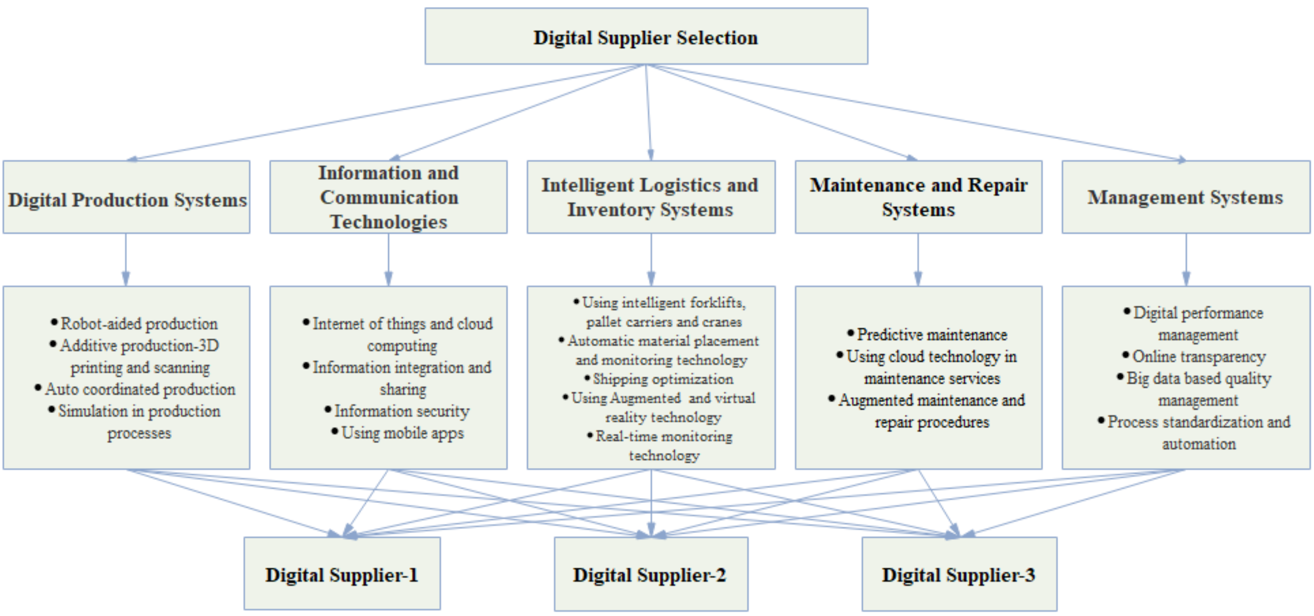


**Figure 3.** Hierarchical model for the selection of the best digital supplier

In order to evaluate the suppliers and the criteria, a team of 5 persons working in the purchasing, quality and production departments of the company was organized. They are university graduates and have been working in the company for at least 5 years. In addition to their expertise, the team also has extensive knowledge in digital technologies. A team of five people consisting of the company's own experts and experts in digital technologies were formed. Based on the team's feedback, the selection criteria and alternatives were evaluated according to the above-described steps of the IT2F-TOPSIS method.

Step 1: The criteria used in the selection of DS were assessed using the linguistic terms in Table 1 based on the team's feedback, and the resulting weight matrix is given in Table 2.

**Table 1.** Linguistic terms and interval T2FSs

| Linguistic terms | Interval T2FSs |
| --- | --- |
| Very Low (VL) | ((0, 0, 0, 0.1; 1, 1), (0, 0, 0, 0.05; 0.9, 0.9)) |
| Low (L) | ((0, 0.1, 0.1, 0.3; 1, 1), (0.05, 0.1, 0.1, 0.2; 0.9, 0.9)) |
| Medium Low (ML) | ((0.1, 0.3, 0.3, 0.5; 1, 1), (0.2, 0.3, 0.3, 0.4; 0.9, 0.9)) |
| Medium (M) | ((0.3, 0.5, 0.5, 0.7; 1, 1), (0.4, 0.5, 0.5, 0.6; 0.9, 0.9)) |
| Medium High (MH) | ((0.5, 0.7, 0.7, 0.9; 1, 1), (0.6, 0.7, 0.7, 0.8; 0.9, 0.9)) |
| High (H) | ((0.7, 0.9, 0.9, 1; 1, 1), (0.8, 0.9, 0.9, 0.95; 0.9, 0.9)) |
| Very High (VH) | ((0.9, 1, 1, 1; 1, 1), (0.95, 1, 1, 1; 0.9, 0.9)) |

**Table 2.** Linguistic assessment of digital supplier selection criteria and weight matrix

| Criteria | Linguistic terms | IT2FSs |
| --- | --- | --- |
| Digital Production Systems (DPS) | | ((0.68,0.78,0.78,0.9,1,1) (0.69,0.78,0.78,0.84,0.9,0.9)) |
| Robot- aided production (RAP) | H | ((0.7, 0.9, 0.9, 1; 1, 1), (0.8, 0.9, 0.9, 0.95; 0.9, 0.9)) |
| Additive production-3D printing and scanning (AP) | M | ((0.3, 0.5, 0.5, 0.7; 1, 1), (0.4, 0.5, 0.5, 0.6; 0.9, 0.9)) |
| Auto coordinated production (ACP) | VH | ((0.9, 1, 1, 1; 1, 1), (0.95, 1, 1, 1; 0.9, 0.9)) |
| Simulation in production processes (SPP) | MH | ((0.5, 0.7, 0.7, 0.9; 1, 1), (0.6, 0.7, 0.7, 0.8; 0.9, 0.9)) |
| Information and Communication Technologies (ICT) | | ((0.8,0.95,0.95,1,1,1) (0.88,0.95,0.95,0.98,0.9,0.9)) |
| Internet of things and cloud computing (ICC) | H | ((0.7, 0.9, 0.9, 1; 1, 1), (0.8, 0.9, 0.9, 0.95; 0.9, 0.9)) |
| Information integration and sharing (IIS) | VH | ((0.9, 1, 1, 1; 1, 1), (0.95, 1, 1, 1; 0.9, 0.9)) |
| Information security (IS) | VH | ((0.9, 1, 1, 1; 1, 1), (0.95, 1, 1, 1; 0.9, 0.9)) |
| Using mobile apps (UMA) | H | ((0.7, 0.9, 0.9, 1; 1, 1), (0.8, 0.9, 0.9, 0.95; 0.9, 0.9)) |
| Intelligent Logistics and Inventory Systems (ILIS) | | ((0.74,0.9,0.9,0.98,1,1) (0.82,0.9,0.9,0.94,0.9,0.9)) |
| Using intelligent forklifts, pallet carriers and cranes (IFC) | H | ((0.7, 0.9, 0.9, 1; 1, 1), (0.8, 0.9, 0.9, 0.95; 0.9, 0.9)) |
| Automatic material placement and monitoring technology (AMP) | H | ((0.7, 0.9, 0.9, 1; 1, 1), (0.8, 0.9, 0.9, 0.95; 0.9, 0.9)) |
| Shipping optimization (SO) | VH | ((0.9, 1, 1, 1; 1, 1), (0.95, 1, 1, 1; 0.9, 0.9)) |
| Using Augmented and virtual reality technology (AVR) | MH | ((0.5, 0.7, 0.7, 0.9; 1, 1), (0.6, 0.7, 0.7, 0.8; 0.9, 0.9)) |
| Real-time monitoring technology (RTM) | VH | ((0.9, 1, 1, 1; 1, 1), (0.95, 1, 1, 1; 0.9, 0.9)) |
| Maintenance and Repair Systems (MRS) | | ((0.5,0.7,0.7,0.9,1,1) (0.6,0.7,0.7,0.8,0.9,0.9)) |
| Predictive maintenance (PM) | MH | ((0.5, 0.7, 0.7, 0.9; 1, 1), (0.6, 0.7, 0.7, 0.8; 0.9, 0.9)) |
| Using cloud technology in maintenance services (CTM) | MH | ((0.5, 0.7, 0.7, 0.9; 1, 1), (0.6, 0.7, 0.7, 0.8; 0.9, 0.9)) |
| Augmented maintenance and repair operations (AMR) | MH | ((0.5, 0.7, 0.7, 0.9; 1, 1), (0.6, 0.7, 0.7, 0.8; 0.9, 0.9)) |
| Management Systems (MS) | | ((0.75,0.72,0.72,0.78,0.8,0.8) (0.66,0.72,0.72,0.75,0.72,0.72)) |
| Digital performance management (DPM) | VH | ((0.9, 1, 1, 1; 1, 1), (0.95, 1, 1, 1; 0.9, 0.9)) |
| Online transparency (OT) | H | ((0.7, 0.9, 0.9, 1; 1, 1), (0.8, 0.9, 0.9, 0.95; 0.9, 0.9)) |
| Big data based quality management (BQM) | MH | ((0.5, 0.7, 0.7, 0.9; 1, 1), (0.6, 0.7, 0.7, 0.8; 0.9, 0.9)) |
| Process standardization and automation (PSA) | VH | ((0.9, 1, 1, 1; 1, 1), (0.95, 1, 1, 1; 0.9, 0.9)) |

The arithmetic mean of the weights of the sub-criteria was determined to calculate the weights of the main criteria [59].

Step 2: Three alternative digital suppliers were assessed using the linguistic terms (Table 1) again based on the team's feedback, and the resulting decision matrix is given in Table 3.

Step 3: After linguistic evaluation of alternative digital suppliers, these linguistic evaluations are converted to their corresponding Interval T2FSs on the scale in Table 1, which developed by Lee and Chen [54] and used in the interval type-2 fuzzy TOPSIS method. The converted matrix is given in Table 4.

After the decision matrix was developed, $\tilde{\tilde{f}}_{ij}$ values were calculated using equation (3), and the fuzzy decision matrix was obtained as illustrated in Table 5.

**Table 3.** Linguistic assessment of alternative digital suppliers and decision matrix

| Main Criteria | Sub-Criteria | Alternatives Digital Suppliers | | |
|---|---|---|---|---|
| | | DS-1 | DS-2 | DS-3 |
| DPS | RAP | L | L | M |
| | AP | VL | VL | VL |
| | ACP | L | L | MH |
| | SPP | L | L | M |
| ICT | ICC | ML | ML | M |
| | IIS | ML | ML | MH |
| | IS | ML | M | H |
| | UMA | ML | MH | H |
| ILIS | IFC | ML | MH | H |
| | AMP | ML | ML | H |
| | SO | L | M | H |
| | AVR | VL | L | L |
| | RTM | L | M | MH |
| MRS | PM | L | ML | ML |
| | CTM | VL | L | ML |
| | AMR | VL | VL | ML |
| MS | DPM | L | ML | H |
| | OT | L | ML | H |
| | BQM | L | ML | MH |
| | PSA | ML | M | H |

**Table 4.** Converting the evaluation of alternatives into interval type-2 fuzzy numbers

| Main Criteria | Sub-Criteria | Alternatives Digital Suppliers | | |
|---|---|---|---|---|
| | | DS-1 | DS-2 | DS-3 |
| DPS | RAP | ((0, 0.1, 0.1, 0.3; 1, 1), (0.05, 0.1, 0.1, 0.2; 0.9, 0.9)) | ((0, 0.1, 0.1, 0.3; 1, 1), (0.05, 0.1, 0.1, 0.2; 0.9, 0.9)) | ((0.3, 0.5, 0.5, 0.7; 1, 1), (0.4, 0.5, 0.5, 0.6; 0.9, 0.9)) |
| | AP | ((0, 0, 0, 0.1; 1, 1), (0, 0, 0, 0.05; 0.9, 0.9)) | ((0, 0, 0, 0.1; 1, 1), (0, 0, 0, 0.05; 0.9, 0.9)) | ((0, 0, 0, 0.1; 1, 1), (0, 0, 0, 0.05; 0.9, 0.9)) |
| | ACP | ((0, 0.1, 0.1, 0.3; 1, 1), (0.05, 0.1, 0.1, 0.2; 0.9, 0.9)) | ((0, 0.1, 0.1, 0.3; 1, 1), (0.05, 0.1, 0.1, 0.2; 0.9, 0.9)) | ((0.5, 0.7, 0.7, 0.9; 1, 1), (0.6, 0.7, 0.7, 0.8; 0.9, 0.9)) |
| | SPP | ((0, 0.1, 0.1, 0.3; 1, 1), (0.05, 0.1, 0.1, 0.2; 0.9, 0.9)) | ((0, 0.1, 0.1, 0.3; 1, 1), (0.05, 0.1, 0.1, 0.2; 0.9, 0.9)) | ((0.3, 0.5, 0.5, 0.7; 1, 1), (0.4, 0.5, 0.5, 0.6; 0.9, 0.9)) |
| ICT | ICC | ((0.1, 0.3, 0.3, 0.5; 1, 1), (0.2, 0.3, 0.3, 0.4; 0.9, 0.9)) | ((0.1, 0.3, 0.3, 0.5; 1, 1), (0.2, 0.3, 0.3, 0.4; 0.9, 0.9)) | ((0.3, 0.5, 0.5, 0.7; 1, 1), (0.4, 0.5, 0.5, 0.6; 0.9, 0.9)) |
| | IIS | ((0.1, 0.3, 0.3, 0.5; 1, 1), (0.2, 0.3, 0.3, 0.4; 0.9, 0.9)) | ((0.1, 0.3, 0.3, 0.5; 1, 1), (0.2, 0.3, 0.3, 0.4; 0.9, 0.9)) | ((0.5, 0.7, 0.7, 0.9; 1, 1), (0.6, 0.7, 0.7, 0.8; 0.9, 0.9)) |
| | IS | ((0.1, 0.3, 0.3, 0.5; 1, 1), (0.2, 0.3, 0.3, 0.4; 0.9, 0.9)) | ((0.3, 0.5, 0.5, 0.7; 1, 1), (0.4, 0.5, 0.5, 0.6; 0.9, 0.9)) | ((0.7, 0.9, 0.9, 1; 1, 1), (0.8, 0.9, 0.9, 0.95; 0.9, 0.9)) |
| | UMA | ((0.1, 0.3, 0.3, 0.5; 1, 1), (0.2, 0.3, 0.3, 0.4; 0.9, 0.9)) | ((0.5, 0.7, 0.7, 0.9; 1, 1), (0.6, 0.7, 0.7, 0.8; 0.9, 0.9)) | ((0.7, 0.9, 0.9, 1; 1, 1), (0.8, 0.9, 0.9, 0.95; 0.9, 0.9)) |
| ILIS | IFC | ((0.1, 0.3, 0.3, 0.5; 1, 1), (0.2, 0.3, 0.3, 0.4; 0.9, 0.9)) | ((0.5, 0.7, 0.7, 0.9; 1, 1), (0.6, 0.7, 0.7, 0.8; 0.9, 0.9)) | ((0.7, 0.9, 0.9, 1; 1, 1), (0.8, 0.9, 0.9, 0.95; 0.9, 0.9)) |
| | AMP | ((0.1, 0.3, 0.3, 0.5; 1, 1), (0.2, 0.3, 0.3, 0.4; 0.9, 0.9)) | ((0.1, 0.3, 0.3, 0.5; 1, 1), (0.2, 0.3, 0.3, 0.4; 0.9, 0.9)) | ((0.7, 0.9, 0.9, 1; 1, 1), (0.8, 0.9, 0.9, 0.95; 0.9, 0.9)) |
| | SO | ((0, 0.1, 0.1, 0.3; 1, 1), (0.05, 0.1, 0.1, 0.2; 0.9, 0.9)) | ((0.3, 0.5, 0.5, 0.7; 1, 1), (0.4, 0.5, 0.5, 0.6; 0.9, 0.9)) | ((0.7, 0.9, 0.9, 1; 1, 1), (0.8, 0.9, 0.9, 0.95; 0.9, 0.9)) |
| | AVR | ((0, 0, 0, 0.1; 1, 1), (0, 0, 0, 0.05; 0.9, 0.9)) | ((0, 0.1, 0.1, 0.3; 1, 1), (0.05, 0.1, 0.1, 0.2; 0.9, 0.9)) | ((0, 0.1, 0.1, 0.3; 1, 1), (0.05, 0.1, 0.1, 0.2; 0.9, 0.9)) |
| | RTM | ((0, 0.1, 0.1, 0.3; 1, 1), (0.05, 0.1, 0.1, 0.2; 0.9, 0.9)) | ((0.3, 0.5, 0.5, 0.7; 1, 1), (0.4, 0.5, 0.5, 0.6; 0.9, 0.9)) | ((0.5, 0.7, 0.7, 0.9; 1, 1), (0.6, 0.7, 0.7, 0.8; 0.9, 0.9)) |
| MRS | PM | ((0, 0.1, 0.1, 0.3; 1, 1), (0.05, 0.1, 0.1, 0.2; 0.9, 0.9)) | ((0.1, 0.3, 0.3, 0.5; 1, 1), (0.2, 0.3, 0.3, 0.4; 0.9, 0.9)) | ((0.1, 0.3, 0.3, 0.5; 1, 1), (0.2, 0.3, 0.3, 0.4; 0.9, 0.9)) |
| | CTM | ((0, 0, 0, 0.1; 1, 1), (0, 0, 0, 0.05; 0.9, 0.9)) | ((0, 0.1, 0.1, 0.3; 1, 1), (0.05, 0.1, 0.1, 0.2; 0.9, 0.9)) | ((0.1, 0.3, 0.3, 0.5; 1, 1), (0.2, 0.3, 0.3, 0.4; 0.9, 0.9)) |
| | AMR | ((0, 0, 0, 0.1; 1, 1), (0, 0, 0, 0.05; 0.9, 0.9)) | ((0, 0, 0, 0.1; 1, 1), (0, 0, 0, 0.05; 0.9, 0.9)) | ((0.1, 0.3, 0.3, 0.5; 1, 1), (0.2, 0.3, 0.3, 0.4; 0.9, 0.9)) |
| MS | DPM | ((0, 0.1, 0.1, 0.3; 1, 1), (0.05, 0.1, 0.1, 0.2; 0.9, 0.9)) | ((0.1, 0.3, 0.3, 0.5; 1, 1), (0.2, 0.3, 0.3, 0.4; 0.9, 0.9)) | ((0.7, 0.9, 0.9, 1; 1, 1), (0.8, 0.9, 0.9, 0.95; 0.9, 0.9)) |
| | OT | ((0, 0.1, 0.1, 0.3; 1, 1), (0.05, 0.1, 0.1, 0.2; 0.9, 0.9)) | ((0.1, 0.3, 0.3, 0.5; 1, 1), (0.2, 0.3, 0.3, 0.4; 0.9, 0.9)) | ((0.7, 0.9, 0.9, 1; 1, 1), (0.8, 0.9, 0.9, 0.95; 0.9, 0.9)) |
| | BQM | ((0, 0.1, 0.1, 0.3; 1, 1), (0.05, 0.1, 0.1, 0.2; 0.9, 0.9)) | ((0.1, 0.3, 0.3, 0.5; 1, 1), (0.2, 0.3, 0.3, 0.4; 0.9, 0.9)) | ((0.5, 0.7, 0.7, 0.9; 1, 1), (0.6, 0.7, 0.7, 0.8; 0.9, 0.9)) |
| | PSA | ((0.1, 0.3, 0.3, 0.5; 1, 1), (0.2, 0.3, 0.3, 0.4; 0.9, 0.9)) | ((0.3, 0.5, 0.5, 0.7; 1, 1), (0.4, 0.5, 0.5, 0.6; 0.9, 0.9)) | ((0.7, 0.9, 0.9, 1; 1, 1), (0.8, 0.9, 0.9, 0.95; 0.9, 0.9)) |

**Table 5.** Fuzzy decision matrix

| Main Criteria | Alternatives Digital Suppliers | | |
|---|---|---|---|
| | DS-1 | DS-2 | DS-3 |
| DPS | (0,0.08,0.08,0.25,1,1)<br>(0.04,0.08,0.08,0.16,0.9,0.9) | (0,0.08,0.08,0.25,1,1)<br>(0.04,0.08,0.08,0.16,0.9,0.9) | (0.3,0.4,0.4,0.53,1,1)<br>(0.35,0.4,0.4,0.46,0.9,0.9) |
| ICT | (0.1,0.3,0.3,0.5,1,1)<br>(0.2,0.3,0.3,0.4,0.9,0.9) | (0.25,0.45,0.45,0.65,1,1)<br>(0.35,0.45,0.45,0.55,0.9,0.9) | (0.55,0.75,0.75,0.9,1,1)<br>(0.65,0.75,0.75,0.83,0.9,0.9) |
| ILIS | (0.04,0.16,0.16,0.34,1,1)<br>(0.1,0.16,0.16,0.25,0.9,0.9) | (0.24,0.42,0.42,0.62,1,1)<br>(0.33,0.42,0.42,0.52,0.9,0.9) | (0.52,0.7,0.7,0.84,1,1)<br>(0.61,0.7,0.7,0.77,0.9,0.9) |
| MRS | (0.23,0.3,0.3,0.4,1,1)<br>(0.27,0.3,0.3,0.35,0.9,0.9) | (0.03,0.13,0.13,0.3,1,1)<br>(0.08,0.13,0.13,0.22,0.9,0.9) | (0.1,0.3,0.3,0.5,1,1)<br>(0.2,0.3,0.3,0.4,0.9,0.9) |
| MS | (0.03,0.15,0.15,0.35,1,1)<br>(0.09,0.15,0.15,0.25,0.9,0.9) | (0.15,0.35,0.35,0.55,1,1)<br>(0.25,0.35,0.35,0.45,0.9,0.9) | (0.65,0.85,0.85,0.98,1,1)<br>(0.75,0.85,0.85,0.91,0.9,0.9) |

Step 4: Then, a weighted fuzzy decision matrix given in Table 6 was obtained using equation (6).

**Table 6.** Weighted fuzzy decision matrix

| Main Criteria | Alternatives Digital Suppliers | | |
|---|---|---|---|
| | DS-1 | DS-2 | DS-3 |
| DPS | (0,0.06,0.06,0.23,1,1)<br>(0.03,0.06,0.06,0.14,0.81,0.81) | (0,0.06,0.06,0.23,1,1)<br>(0.03,0.06,0.06,0.14,0.81,0.81) | (0.18,0.31,0.31,0.47,1,1)<br>(0.24,0.31,0.31,0.39,0.81,0.81) |
| ICT | (0.08,0.29,0.29,0.5,1,1)<br>(0.18,0.29,0.29,0.39,0.81,0.81) | (0.2,0.43,0.43,0.65,1,1)<br>(0.31,0.43,0.43,0.54,0.81,0.81) | (0.44,0.71,0.71,0.9,1,1)<br>(0.57,0.71,0.71,0.8,0.81,0.81) |
| ILIS | (0.03,0.14,0.14,0.33,1,1)<br>(0.08,0.14,0.14,0.24,0.81,0.81) | (0.18,0.38,0.38,0.61,1,1)<br>(0.27,0.38,0.38,0.49,0.81,0.81) | (0.38,0.63,0.63,0.82,1,1)<br>(0.5,0.63,0.63,0.72,0.81,0.81) |
| MRS | (0.12,0.21,0.21,0.36,1,1)<br>(0.16,0.21,0.21,0.28,0.81,0.81) | (0.02,0.09,0.09,0.27,1,1)<br>(0.05,0.09,0.09,0.17,0.81,0.81) | (0.05,0.21,0.21,0.45,1,1)<br>(0.12,0.21,0.21,0.32,0.81,0.81) |
| MS | (0.02,0.11,0.11,0.27,0.8,0.8)<br>(0.06,0.11,0.11,0.19,0.65,0.65) | (0.11,0.25,0.25,0.43,0.8,0.8)<br>(0.17,0.25,0.25,0.34,0.65,0.65) | (0.49,0.61,0.61,0.76,0.8,0.8)<br>(0.5,0.61,0.61,0.68,0.65,0.65) |

Step 5: A ranked weighted decision matrix (Table 7) was calculated using equation (1).

**Table 7.** Ranked weighted decision matrix

| Main Criteria | Alternatives Digital Suppliers | | |
|---|---|---|---|
| | DS-1 | DS-2 | DS-3 |
| DPS | 3.97 | 3.97 | 5.41 |
| ICT | 5.20 | 6.03 | 7.68 |
| ILIS | 4.44 | 5.77 | 7.21 |
| MRS | 4.84 | 4.17 | 4.80 |
| MS | 4.24 | 5.05 | 6.46 |

***Steps 6:*** Positive and negative ideal solutions (Table 8) were calculated using equations (8) and (9).

***Table 8.*** PIS and NIS

| Main Criteria | Positive ideal solution | Negative ideal solution |
|---|---|---|
| DPS | 5.41 | 3.97 |
| ICT | 7.68 | 5.20 |
| ILIS | 4.44 | 7.21 |
| MRS | 4.84 | 4.17 |
| MS | 6.46 | 4.24 |

Step 7: The distance of each alternative to the positive ($d^+$) and negative ($d^-$) ideal solutions was calculated using equations (10) and (11). Closeness indexes $C(x_i)$ were calculated using equation (12) and shown in Table 9.

**Table 9.** Distance of each alternative to PIS and NIS and closeness indexes

| Alternatives Digital Suppliers | d+ | d- | $C(x_i)$ | Ranking |
|---|---|---|---|---|
| DS-1 | 3.625 | 2.857 | 0.441 | 2 |
| DS-2 | 2.997 | 1.856 | 0.383 | 3 |
| DS-3 | 2.777 | 3.68 | 0.570 | 1 |

According to the closeness indexes, the preferred order of alternative digital suppliers were ranked as DS-3, DS-1 and DS-2. Afterwards, a sensitivity analysis was performed depending on the scenarios given in Table 10 to determine whether the ranking of alternatives would be different according to different criteria weights. The results are given in Figure 4.

**Table 10.** Combinations of scenarios with different criteria weights

| Scenarios | Combinations |
|---|---|
| Scenario 1 | Current |
| Scenario 2 | DPS Very Low, The Rest current |
| Scenario 3 | ICT Very Low, The Rest current |
| Scenario 4 | ILIS Very Low, The Rest current |
| Scenario 5 | MRS Low, The Rest current |
| Scenario 6 | MS Very Low, The Rest current |
| Scenario 7 | DPS Very High, The Rest current |
| Scenario 8 | ICT Very High, The Rest current |
| Scenario 9 | ILIS Very High, The Rest current |
| Scenario 10 | MRS Very High, The Rest current |
| Scenario 11 | MS Very High, The Rest current |

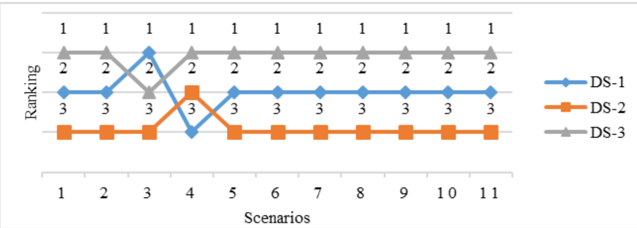


**Figure 4.** Changes in sensitivity analysis results

The sensitivity analysis results show that DS-3 is the best digital supplier in all scenarios, except for Scenario 3, where the weight of criterion ICT was changed. This result indicates that the IT2F-TOPSIS results are sensitive and that supplier DS-3 is the most suitable digital supplier.

## 3. RESULTS AND DISCUSSION

In recent years, companies have been using competitive strategies to survive in the market, to meet the changing needs of their customers and to ensure sustainable development in the business world. They adopt Industry 4.0 technologies such as autonomous robots, 3D printing, IoT, BDA, cloud computing, augmented reality, cyber physical systems and simulation in order to create an innovative business environment. These technologies have fundamentally changed business processes and models and SCM. Consequently, the traditional supply chain has been transformed into DSC, which has started to improve the overall performance of companies.

The use of digital smart systems in DSC renders supply chains more transparent and efficient. Real-time analysis and evaluation in DSC helps companies make better and faster decisions to meet customer needs. It also reduces costs and risks and helps companies make their supply chain management more efficient and useful than before.

DSC will be much more effective in the next two and three years. The expected advantages of DSC are up to a 30% reduction in operating costs, a 75% less loss on sale and up to 75% reduction in inventory. Parent companies, therefore, want to work with suppliers that use digital technologies in all their activities.

The aim of this study was to determine the supplier using digital technologies most effectively among a number of suppliers of a company operating in the garment sector in Turkey and working with numerous domestic and foreign suppliers. Supplier selection involves numerous criteria. The IT2F-TOPSIS was, therefore, the method of choice in this study because it is an MCDM method that analyzes uncertainties better than IT1FSs. The best DS was chosen as a result of the evaluations made according to the application steps of the method. As a result, the benefits of the company in the case of working with this selected supplier are listed below:

- Information flow between the supplier and the company will be manageable, resulting in more workflow and collaborations.
- Integration between the supplier and the company will make purchasing processes more predictable and resulting in optimum stock control, and thus, low inventory costs.
- The company and the supplier will have more mutual data collection opportunities and analyze data to find solutions to various problems.
- Preventive maintenance activities carried out by the supplier will increase the efficiency of the lines, enabling the company to meet demands without delay.
- In conclusion, Industry 4.0 technologies will increase the flexibility, quality and efficiency of suppliers and reduce their costs and improve their decision-making processes. In this way, companies will be able to make customized products, design virtual clothing, meet customer demands more rapidly and launch new products and services more frequently. This improvement will move companies towards better levels of performance in terms of quality, flexibility and cost.

Finally, the study is the first study in the literature to determine a DS. The sensitivity analysis results show that the selection model and method are sensitive. Therefore, companies that wish to select and assess the best supplier among their suppliers that use industry 4.0 technologies can use the selection model and method proposed in this study.

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