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Pythagorean Fuzzy AHP Approach for Evaluating the Importance Level of Industry 4.0 Technologies in the Automotive Manufacturing Industry

Sinan Çıkmak[1]

[1.] *Business Administration Program, Vocational School of Social Sciences, Düzce University, Düzce, 81620, Türkiye*

Research Article

Abstract

To succeed in the rapidly advancing technological environment driven by Industry 4.0, automotive manufacturers need to swiftly embrace new technologies. Moreover, the ability to introduce innovations to the market more quickly and sustainably hinges on the integration of Industry 4.0 technologies. The automotive industry plays a crucial role in boosting the economy, generating a multiplier impact in Türkiye, much like it does in various countries around the world. Therefore, keeping a close eye on the digital transformation of the automotive industry is critical for establishing a cost-efficient, productive, and competitive market in a rapidly developing market. This study aims to indicate the importance level of Industry 4.0 technologies for automotive manufacturers operating in Türkiye. The Analytic Hierarchy Process (AHP) method based on Pythagorean fuzzy sets was employed to achieve this aim. Pythagorean fuzzy sets are a contemporary fuzzy approach that gives experts more freedom to express their judgments regarding uncertainty and ambiguity in decision-making problems. The study results reveal that the top three most important technologies in the automotive manufacturing industry are "simulation and modeling", "autonomous robots", and "big data and analytics", respectively. However, blockchain technology ranked lowest in terms of importance level. The proposed approach will serve as a guide for decision-makers in selecting the appropriate Industry 4.0 technology in the automotive industry.

Keywords: Automotive industry; Industry 4.0 technologies; Multi-criteria decision-making; Pythagorean fuzzy AHP

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Contact
* Corresponding author
Sinan Çıkmak
sinancikmak@duzce.edu.tr
Address: Business Administration Program, Vocational School of Social Sciences Düzce University, Düzce, Türkiye
Tel: +903805144892

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1. Introduction

Industry 4.0, promoted by the German government as part of its high-tech strategy, represents a future vision aimed at transforming the manufacturing value chain [1]. The adoption of Industry 4.0 technologies offers substantial advantages, including enhanced productivity and efficiency, improved knowledge sharing and collaboration, greater flexibility and adaptability, simplified regulatory compliance, better customer experiences, reduced costs, and increased revenues [2]. These benefits have captured the attention of academia, research organizations, businesses, and governments [3]. At the same time, this paradigm shift brings new opportunities that can disrupt traditional manufacturing approaches, significantly impacting major processes through the proliferation of digital technologies [4].

The emergence of Industry 4.0 and rapid advancements in new technologies have sparked significant interest among scholars and professionals across diverse industries [5]. This has resulted in a significant increase in the amount of literature examining the implications of these advancements. The growing body of research highlights the ongoing importance and impact of Industry 4.0 on both academic and practical applications. In this context, expanding sectoral and country-based studies on Industry 4.0 technologies will further enrich the literature.

Industry 4.0 encompasses a technology-driven transformation that seeks to revolutionize manufacturing and production systems across organizations, with a particular focus on the automotive industry [6]. Digital technologies are revolutionizing the automotive industry and disrupting traditional business models, leading to the emergence of new business opportunities related to Industry 4.0. As a result, companies must adapt to this new environment [7]. A study executed by KPMG in 2018 highlights the necessity for professionals to recognize and prioritize technologies of Industry 4.0 to attain a competitive edge. [8]. On the other hand, industrial companies are under significant pressure to digitize their plants and processes. However, with limited time and resources, careful selection of digital technologies becomes necessary, especially due to the novelty of the subject [9].

The automotive industry plays a crucial role in the economy, similar to its impact in various countries, by generating a substantial multiplier effect in Türkiye. Therefore, it is essential to continuously monitor digitalization in the automotive industry to achieve more efficient and competitive production [5]. This study presents an approach based on the Pythagorean fuzzy Analytic Hierarchy Process (AHP) method to determine the importance levels of Industry 4.0 technologies for automotive manufacturers operating in Türkiye. One of the advantages of using the AHP is its user-friendly nature. Pairwise comparisons allow users to easily weigh criteria [10]. Additionally, AHP is scalable, making it suitable for decision-making problems of various sizes within its hierarchical structure [11]. AHP is also a widely accepted technique for making subjective judgments about qualitative data [12]. Multi-criteria decision-making issues can be expanded using fuzzy sets to express the ambiguity and uncertainty of real-life situations, enabling decision-makers to attain more robust results [13]. Traditional AHP fails to account for uncertainties in evaluating criteria and alternatives, which can impact decision-making. To address this limitation, fuzzy AHP combines AHP with fuzzy logic for better handling of uncertainty and ambiguity [14]. The Pythagorean fuzzy AHP method combines Pythagorean fuzzy sets with the AHP to address uncertainty. This method was developed to enhance ordinary fuzzy AHP and achieve more consistent results [15]. Pythagorean fuzzy sets were first introduced by Yager [16] as an extension of intuitionistic fuzzy sets. Pythagorean fuzzy sets are a powerful tool for representing uncertain and imprecise information in decision-making [17,18] These sets allow decision-makers more autonomy in expressing uncertainties in multi-criteria decision-making [19].

Compared to previous studies, this article makes a significant contribution as it is the first study in which industry 4.0 technologies in the Turkish automotive industry are evaluated using the multi-criteria decision-making method. Additionally, the study introduces an original approach by using the AHP method based on Pythagorean fuzzy sets to eliminate ambiguity and uncertainty in expert opinions. With this proposed approach, it is aimed to provide a tool for companies operating in the automotive industry to determine the importance levels of industry 4.0 technologies that will provide a competitive advantage. Furthermore, it is expected that the results attained in the application section will yield valuable and actionable insights, enabling professionals working in the automotive industry to make informed decisions and enhance their practices.

The remainder of this study is structured as follows: Section 2 provides the literature review, followed by Section 3, which details the research methodology. Section 4 is dedicated to the application, and the findings are thoroughly discussed in Section 5. The study concludes with Section 6, which presents the conclusion along with the study's limitations and suggestions for further research.

2. Literature Review

2.1. Industry 4.0 and Automotive Industry

Industry 4.0, also known as the fourth industrial revolution, signifies the ongoing shift towards heightened automation and information interchange in manufacturing and technology. This transformation is particularly prominent within the automotive industry, which is poised to benefit substantially from these advancements [20]. The emergence of Industry 4.0 has garnered considerable attention within academic and industrial domains due to its potential to transform diverse aspects of business operations. This next phase of industrialization promises a multitude of advantages, including notable improvements in efficiency, faster production processes, heightened quality control, the ability to provide personalized products on a mass scale, and potential reductions in operational costs [1].

The automotive sector is being transformed by the integration of Industry 4.0 technologies, including augmented reality, the Internet of Things, artificial intelligence, and autonomous robots. These technologies impact not only industrial companies and suppliers but also the environment and workforce [21]. The vehicle production process, which involves a complex network of manufacturing stages and a long supply chain, stands to benefit immensely from these advancements. This entails the shaping of materials, production of spare parts, operations in welding, ordering of special components, painting, and the final assembly processes before vehicles are distributed in the market [22].

In a highly competitive global automotive market, manufacturers must leverage the technological advancements of Industry 4.0 to maintain and enhance their market positions [22]. The competition is growing fiercer, making it essential for companies to stand out through quality, efficiency, adaptability, and flexibility. Today's car buyers demand high-quality products that are customized to their needs and can seamlessly integrate into their daily routines. This increased demand for customization and technological sophistication has led to more complex manufacturing processes. To address these challenges, manufacturers need to enhance their strategies and modernize their infrastructure [22,23].

Industry 4.0 is anticipated to have a significant impact on the transformation of automotive production technologies. It aims to streamline processes, minimize human involvement, enhance efficiency, and elevate product quality. Digital technologies are revolutionizing the automotive industry, disrupting traditional business models, and creating new business opportunities. Consequently, companies must adapt to this new environment to stay competitive [7].

At its core, Industry 4.0 refers to the complete digitization and interconnection of business processes. This encompasses everything from developing new products to receiving and fulfilling customer orders, managing the production process, delivering products to consumers, and providing all necessary after-sales and accompanying services [24]. To successfully navigate the rapidly changing automotive industry under the Industry 4.0

paradigm, company boards and senior executives should identify which advanced innovations will have the most significant impact on the industry in the next decade. Although predicting the future with certainty is impossible, it is crucial for management to prioritize a thorough assessment of the necessary innovation capabilities and align with emerging industry trends [25].

2.2. Automotive Industry in Türkiye

The global automotive industry significantly contributes to national economies, drives technological advancements, and serves as a catalyst for the development of various sectors with which it interacts directly or indirectly [26]. The economic impact of the automotive industry worldwide is substantial. In 2020, it was valued at 4.5 trillion US dollars, accounting for about 5% of the global economy [27]. This industry will continue to be a significant part of the global economy, shaped by the development of new technologies and changes in consumer preferences [27].

Within the global context, the automotive sector plays a crucial role in the Turkish economy. Türkiye ranks as the world's 15th largest automobile producer, with a total of 1.5 million automobiles manufactured in 2022, contributing approximately $50 billion to the Turkish economy [28]. This achievement underscores Türkiye's growing capabilities and competitiveness in the global automotive landscape. Thanks to its high export volume and the employment opportunities it creates, Türkiye's automotive industry significantly impacts the country's economy. According to data published by the Turkish Exporters Assembly (TİM), the automotive industry accounted for 16% of total exports in the first five months of 2023, with a volume of 14.3 billion US dollars [29]. This highlights the sector's vital role in driving Türkiye's export economy and maintaining trade balances. Additionally, the sector is a significant employer, providing jobs for hundreds of thousands of people across the country. The industry's supply chain includes numerous small and medium-sized enterprises that benefit from strong demand for automotive components and services.

Table 1. An overview of Industry 4.0 technologies

Technology	Code	Definition
Additive manufacturing	TEC1	Additive manufacturing, often referred to as 3D printing, involves a process where objects are created by addin g material layer by layer to produce solid three-dimensional items [32]. This technology allows 3D printers to f abricate their own replacement parts and fulfill small order quantities, significantly lowering the cost of product ion per item [1].
Artificial intelligence	TEC2	Artificial intelligence encompasses a collection of technologies that allow machines and software to comprehen d, perceive, respond, and gain knowledge either through autonomous learning or enhanced human interaction [33].
Augmented reality	TEC3	Augmented reality represents an interactive environment grounded in reality, enhancing the user's real-world ex perience with computer-generated imagery, sounds, and additional effects [32]. Augmented reality plays a crucial role in the field of product design and development by reducing early-stage design mistakes, decreasing the n eed for multiple prototypes, and consequently saving organizations both time and financial resources. [34].
Autonomous robots	TEC4	Autonomous robot technology consists of advanced programmable machines that can automatically perform a se t of complex activities [1]. Robots that can imitate human activities prevent problems caused by human errors.
Big data and analytics	TEC5	Big data technology can be described as the conversion of massive and complex data sets into meaningful and workable data sets that can be processed by advanced computing technologies [1]. Big data has enormous pot ential to help reduce malfunction rates, enhance product quality, and increase output rates for a more efficient supply chain [34].
Blockchain	TEC6	Blockchain is a distributed database that uses new encryption and authentication technology as well as a netwo rk-wide consensus mechanism to maintain an ever-growing list of fully distributed and tamper-proof records [32].
Cloud technology	TEC7	A system for providing online storage services for all applications, programs, and data on a virtual server that does not require installation [4].
Cybersecurity	TEC8	Cyber security is the informatics measures taken to prevent the theft and attack of organizational information. I t is the prevention of unauthorized access to a private computer network [35]. As more devices connect to the internet and each other on a daily basis, the issue of cyber security becomes more important [36].
Industrial Internet of Things	TEC9	The Industrial Internet of Things refers to a network of physically connected objects that are capable of sensin g, monitoring, and interrelating within a supply chain [37]. It deals with systems of interconnected sensors and cloud technology that are designed to sense, analyze, store, and manage data in real-time [34].
Simulation and modelling	TEC10	Simulation is the replication of a real-world process or system in a virtual world, with the goal of simplifying and reducing the cost of system design, creation, testing, and live operation [4]. Simulation aids in the assessm ent of risks, inventory, implementation barriers, and the impact on the performance of various processes within an organization [34].

In 2023, the Turkish automotive industry, which exported $35 billion, was the leading producer of commercial vehicles in Europe [30]. Transitioning all road vehicles, especially automobiles, from relying on fossil fuels to being powered by hydrogen or electricity is a critical environmental goal. In 2016, Türkiye committed to the Paris Agreement and set an ambitious target to achieve net zero emissions by 2053 [29]. This commitment has spurred investments in research and development, particularly in electric and hybrid vehicle technologies, positioning Türkiye as a potential hub for sustainable automotive innovations. Positive expectations exist for the future of the automotive industry in Türkiye. The sector is expected to continue growing by adopting new technologies and venturing into new markets [27]. Government incentives and policies aimed at supporting automotive production, innovation, and exports will likely play a crucial role in sustaining this growth. Furthermore, collaborations with international automotive giants and strategic investments in smart manufacturing are anticipated to enhance the industry's efficiency and global competitiveness.

In conclusion, Türkiye's automotive industry is poised for a dynamic future, driven by innovation, sustainability, and strategic growth. Its contributions to the national economy and its role in the global automotive arena make it a critical industry for Türkiye's continued economic development and technological advancement.

2.3. Industry 4.0 Technologies

As part of its high-tech initiative, the German government has introduced a future vision called Industry 4.0. This initiative, based on information and communication technologies, promises increased production flexibility, real-time measurement and monitoring, high efficiency, and other benefits [1]. Industry 4.0 introduces new opportunities that can change the traditional business models of companies thanks to rapidly increasing number of digital technologies [4]. Industry 4.0 is fundamentally based on the rise of new technologies such as additive manufacturing, cloud computing, sensor technology, Internet of Things, and big data [31]. Therefore, it would not be incorrect to define Industry 4.0 as a collection of various advanced technologies.

Adoption of Industry 4.0 technologies can have potential impacts on diverse processes of production companies [4]. After the comprehensive literature review, Industry 4.0 technologies are listed and their short definitions are summarized in Table 1.

3. Research Methodology

This section provides details about the research method of Pythagorean fuzzy AHP, which is being used to achieve the objectives of this research. First, it explains some preliminary information about Pythagorean fuzzy sets and their corresponding notations.

3.1. Pythagorean Fuzzy Sets

Yager [16] presented Pythagorean fuzzy sets as an extension of intuitionistic fuzzy sets. In Pythagorean fuzzy sets, unlike the intuitionistic fuzzy sets, the sum of the membership degree and non-membership degree determined by decision makers may be greater than 1, but the sum of their squares can be less than or equal to 1 [18,38,39]. The definitions below explain the general mathematical representation of Pythagorean fuzzy sets.

Definition 1. Let a set X be a universe of discourse. A Pythagorean fuzzy set P is an object having the form [40]:

$$\boldsymbol{P} = \{\langle \boldsymbol{x}, \boldsymbol{P}(\boldsymbol{\mu_P}(\boldsymbol{x}), \boldsymbol{v}(\boldsymbol{x}))\rangle \mid \boldsymbol{x} \in \boldsymbol{X}\} \tag{1}$$

where $\mu_P(x): X \mapsto [0,1]$ represent degree of membership and $v_P(x): X \mapsto [0,1]$ represent the degree of non-membership of the element $x \in X \ to \ P$, respectively, and, for every $x \in X$, it holds:

$$\boldsymbol{0} \le \boldsymbol{\mu_P}(\boldsymbol{x})^2 + \boldsymbol{v_P}(\boldsymbol{x})^2 \le \boldsymbol{1} \tag{2}$$

The degree of hesitancy condition is calculated as follows:

$$\boldsymbol{\pi_P}(\boldsymbol{x}) = \sqrt{\boldsymbol{1} - \boldsymbol{\mu_P^2}(\boldsymbol{x}) - \boldsymbol{v_P^2}(\boldsymbol{x})} \tag{3}$$

Definition 2. Let $\beta_1 = P(\mu_{\beta_1}, v_{\beta_1})$ and $\beta_2 = P(\mu_{\beta_2}, v_{\beta_2})$ be two Pythagorean fuzzy numbers, and $\lambda > 0$, the mathematical operations on these two Pythagorean fuzzy numbers are then shown as follows [40]:

Addition operator is formulated as:

$$\beta_1 \oplus \beta_2 = P\left(\sqrt{\mu_{\beta_1}^2 + \mu_{\beta_2}^2 - \mu_{\beta_1}^2\mu_{\beta_2}^2}, v_{\beta_1}v_{\beta_2}\right) \tag{4}$$

Multiplication operator is formulated as:

$$\boldsymbol{\beta_1} \otimes \boldsymbol{\beta_2} = \boldsymbol{P}(\boldsymbol{\mu_{\beta_1}\mu_{\beta_2}}, \sqrt{\boldsymbol{v_{\beta_1}^2} + \boldsymbol{v_{\beta_2}^2} - \boldsymbol{v_{\beta_1}^2 v_{\beta_2}^2}}) \tag{5}$$

Multiplication of a crisp value is formulated as:

$$\lambda\beta_1 = P\left(\sqrt{1 - \left(1 - \mu_{\beta_1}^2\right)^\lambda}, \left(v_{\beta_1}\right)^\lambda\right), \lambda > 0 \tag{6}$$

Power of a crisp value is computed as:

$$\beta_1^\lambda = P((\mu_{\beta_1})^\lambda, \sqrt{1 - (1 - v_{\beta_1}^2)^\lambda}), \lambda > 0 \tag{7}$$

Definition 3. Given two Pythagorean fuzzy numbers $\beta_1 = P(\mu_{\beta_1}, v_{\beta_1})$ and $\beta_2 = P(\mu_{\beta_2}, v_{\beta_2})$ a nature quasi-ordering on the Pythagorean fuzzy numbers is represented as follows [40]:

$$\boldsymbol{\beta_1} \ge \boldsymbol{\beta_2} \ \textit{if and only if} \ \boldsymbol{\mu_{\beta_1}} \ge \boldsymbol{\mu_{\beta_2}} \ \textit{and} \ \boldsymbol{v_{\beta_1}} \le \boldsymbol{v_{\beta_2}}$$

To compare the magnitudes of two given fuzzy Pythagorean numbers, the score function is given as follows:

$$\boldsymbol{s}(\boldsymbol{\beta_1}) = (\boldsymbol{\mu_{\beta_1}})^2 - (\boldsymbol{v_{\beta_1}})^2 \tag{8}$$

Definition 4. The following laws are determined to compare two Pythagorean fuzzy numbers based on the score functions offered above [40]:

i. If $s(\beta_1) < s(\beta_2)$, then $\beta_1 < \beta_2$

ii. If $s(\beta_1) > s(\beta_2)$, then $\beta_1 > \beta_2$

iii. If $s(\beta_1) = s(\beta_2)$, then $\beta_1 \sim \beta_2$

Definition 5. Let $\beta_i = P(\mu_i, v_i)$, $i = (1,2,\dots,n)$ be a group of Pythagorean fuzzy numbers. The aggregated value obtained using Pythagorean fuzzy weighted averaging is presented as follows:

$$PFWPA(\beta_1, \beta_2, \dots, \beta_n) = \left(\left(\sum_{i=1}^{n} w_i \mu_i^2 \right)^{\frac{1}{2}}, \left(\sum_{i=1}^{n} w_i v_i^2 \right)^{\frac{1}{2}} \right) \tag{9}$$

Where $w = (w_1, w_2, \dots, w_n)^T$ is the weight vector of β_i, $i = (1,2,\dots,n)$ with $w_i \in [0,1]$ and $\sum_{i=1}^{n} w_i = 1$. [38].

3.2. Pythagorean fuzzy AHP

In this research, the AHP method based on Pythagorean fuzzy sets was employed to determine the importance weights of Industry 4.0 technologies. The application steps of the Pythagorean fuzzy AHP method proposed by Ilbahar et al. [18] are presented as follows:

Step 1. The pairwise comparison matrix $A = (a_{ik})_{m \times m}$ is made based on Table 2 from the decision values provided by the experts with linguistic variables.

Table 2. Scale for interval-valued Pythagorean fuzzy AHP Method [18]

Linguistic term	Interval-valued Pythagorean fuzzy numbers			
	μ_L	μ_U	v_L	v_U
Certainly low important (CLI)	0.00	0.00	0.90	1.00
Very low important (VLI)	0.10	0.20	0.80	0.90
Low important (LI)	0.20	0.35	0.65	0.80
Below average important (BAI)	0.35	0.45	0.55	0.65
Average important (AI)	0.45	0.55	0.45	0.55
Above average important (AAI)	0.55	0.65	0.35	0.45
High important (HI)	0.65	0.80	0.20	0.35
Very high important (VHI)	0.80	0.90	0.10	0.20
Certainly high important (CHI)	0.90	1.00	0.00	0.00
Exactly equal (EE)	0.1965	0.1965	0.1965	0.1965

Step 2. The difference matrices $D = (d_{ik})_{m \times m}$ between the lower and upper values of the membership and non-membership functions are computed using Eqs. (10) and (11).

$$d_{ik_L} = \mu_{ik_L}^2 - v_{ik_U}^2 \tag{10}$$

$$d_{ik_U} = \mu_{ik_U}^2 - v_{ik_L}^2 \tag{11}$$

Step 3. Interval multiplicative matrix $S = (s_{ik})_{m \times m}$ is calculated using Eq. (12) and (13).

$$s_{ik_L} = \sqrt{1000^{d_{ik_L}}} \tag{12}$$

$$s_{ik_U} = \sqrt{1000^{d_{ik_L}}} \tag{13}$$

Step 4. The determinacy value $\tau = (\tau_{ik})_{m \times m}$ is determined using Eq. (14):

$$\tau_{ik} = 1 - (\mu_{ik_U}^2 - \mu_{ik_L}^2) - (v_{ik_U}^2 - v_{ik_L}^2) \tag{14}$$

Step 5. The determinacy degrees are multiplied with $S = (s_{ik})_{m \times m}$ matrix for computed the matrix of weights, $T = (t_{ik})_{m \times m}$ before normalization using Eq. (15):

$$t_{ik} = \left(\frac{s_{ik_L} + s_{ik_U}}{2} \right) \tau_{ik} \tag{15}$$

Step 6. The normalized priority weights w_i is calculated using Eq. (16):

$$w_i = \frac{\sum_{k=1}^{m} t_{ik}}{\sum_{i=1}^{m} \sum_{k=1}^{m} t_{ik}} \tag{16}$$

4. Application

In the application phase of the research, data were obtained from five experts, all of whom hold engineering degrees and work in leading companies within the Turkish automotive industry. These companies, recognized as pioneers in automotive manufacturing, have been kept anonymous for confidentiality purposes. The first expert serves as a quality manager at an automotive manufacturing company, leveraging extensive experience in quality assurance. The second expert is a process preparation engineer, contributing expertise in optimizing manufacturing processes within an automotive production setting. The third expert works as a process planning engineer at a company specializing in the production of buses and defense vehicles, focusing on workflow optimization and production planning. The fourth expert holds the position of financial coordinator, providing strategic insights into financial management within the sector. Lastly, the fifth expert is the IT & digital transformation director at a firm producing buses and defense vehicles, driving digital innovation and technological advancements. The combined expertise of these professionals, with their diverse roles and over a decade of experience each, ensures a comprehensive and multidimensional evaluation of Industry 4.0 technologies. Their input was instrumental in grounding the study's findings on a solid foundation of practical and managerial insights.

Table 3. Pairwise comparisons of experts for Industry 4.0 technologies

	TEC1	TEC2	TEC3	TEC4	TEC5	TEC6	TEC7	TEC8	TEC9	TEC10
TEC1	EE,EE,EE,EE,EE	LI,VHI,VLI,AAI,VLI	AAI,AI,BAI,LI,LI	VLI,LI,EE,LI,LI	VLI,HI,VLI,VLI,AI	VLI,VHI,VHI,HI,HI	LI,HI,LI,LI,HI	VHI,VHI,CLI,AI,HI	AAI,HI,AAI,BAI,AI	LI,BAI,EE,VLI,BAI
TEC2	HI,VLI,VHI,BAI,VHI	EE,EE,EE,EE,EE	VHI,BAI,AAI,VLI,AI	EE,VLI,AI,VLI,AI	EE,AI,BAI,CLI,AI	AI,AAI,CHI,AI,HI	AI,AAI,AAI,VLI,HI	AAI,AI,BAI,EE,HI	VHI,AAI,AAI,LI,EE	VLI,VLI,AAI,CLI,EE
TEC3	BAI,AI,AAI,HI,HI	VLI,AI,BAI,VHI,AI	EE,EE,EE,EE,EE	VLI,VHI,BAI,AI,EE	BAI,HI,EE,AI,AI	BAI,VHI,VHI,VHI,AI	LI,HI,LI,EE,AAI	AAI,VHI,LI,HI,AAI	AI,AAI,HI,AAI,BAI	CLI,BAI,AI,BAI,EE
TEC4	VHI,HI,EE,HI,HI	EE,BAI,AI,VHI,AI	VHI,VLI,AAI,AI,EE	EE,EE,EE,EE,EE	EE,AAI,AI,BAI,VHI	EE,HI,HI,VHI,VHI	AI,AI,BAI,EE,VHI	CHI,HI,CLI,VHI,VHI	AAI,BAI,AAI,AAI,AI	BAI,LI,EE,EE,AI
TEC5	VHI,LI,VHI,VHI,AI	EE,LI,AAI,CHI,AI	AAI,LI,EE,AI,AI	EE,BAI,AI,AAI,VLI	EE,EE,EE,EE,EE	EE,VHI,VHI,CHI,EE	AI,AAI,EE,AI,AI	CHI,VHI,CLI,VHI,AI	AAI,BAI,HI,AAI,BAI	BAI,VLI,AAI,EE,BAI
TEC6	VHI,VLI,VLI,HI,LI	AI,VLI,CLI,AI,LI	AAI,VLI,VLI,VLI,AI	EE,LI,LI,VLI,VLI	EE,VLI,VLI,CLI,EE	EE,EE,EE,EE,EE	AI,LI,VLI,CLI,LI	CHI,AI,CLI,AI,LI	HI,BAI,BAI,LI,LI	VLI,CLI,VLI,CLI,LI
TEC7	HI,LI,HI,HI,LI	AI,LI,AAI,VHI,LI	HI,LI,HI,EE,BAI	AI,AI,AAI,EE,VLI	AI,BAI,EE,AI,AI	AI,HI,VHI,CHI,HI	EE,EE,EE,EE,EE	AAI,HI,BAI,CHI,AAI	VHI,BAI,HI,AAI,BAI	VLI,LI,AAI,AI,LI
TEC8	VLI,VLI,CHI,AI,LI	BAI,LI,AAI,EE,LI	BAI,VLI,HI,LI,BAI	CLI,LI,CHI,VLI,VLI	CLI,VLI,CHI,VLI,AI	CLI,AI,CHI,AI,HI	BAI,LI,AAI,CLI,BAI	EE,EE,EE,EE,EE	AI,HI,CHI,LI,AI	VLI,VLI,HI,VLI,AI
TEC9	BAI,LI,BAI,AAI,AI	VLI,LI,BAI,HI,EE	AI,BAI,LI,BAI,AAI	BAI,AAI,BAI,BAI,AI	BAI,AAI,LI,BAI,AAI	LI,AAI,AAI,HI,HI	VLI,AAI,LI,BAI,AAI	AI,LI,CLI,HI,AI	EE,EE,EE,EE,EE	CLI,BAI,BAI,BAI,EE
TEC10	CHI,AAI,EE,VHI,AAI	VHI,VHI,BAI,CHI,EE	CHI,AAI,AI,AAI,EE	AAI,HI,LI,EE,AI	AAI,CHI,BAI,EE,AAI	VHI,HI,VHI,CHI,HI	VHI,HI,BAI,AI,HI	VHI,VHI,BAI,VHI,AI	CHI,AAI,AAI,AAI,EE	EE,EE,EE,EE,EE

Table 4. Aggregated pairwise comparison matrix of Industry 4.0 technologies

	TEC1	TEC2	TEC3	TEC4	TEC5	TEC6	TEC7	TEC8	TEC9	TEC10
TEC1	(0.197,0.197,0.197,0.197)	(0.35,0.46,0.54,0.65)	(0.35,0.47,0.53,0.65)	(0.179,0.289,0.589,0.699)	(0.28,0.39,0.61,0.72)	(0.6,0.72,0.28,0.4)	(0.38,0.53,0.47,0.62)	(0.54,0.63,0.35,0.46)	(0.51,0.62,0.38,0.49)	(0.239,0.329,0.549,0.639)
TEC2	(0.54,0.65,0.35,0.46)	(0.197,0.197,0.197,0.197)	(0.45,0.55,0.45,0.55)	(0.259,0.339,0.539,0.619)	(0.289,0.349,0.509,0.589)	(0.6,0.71,0.29,0.38)	(0.46,0.57,0.43,0.54)	(0.439,0.529,0.349,0.439)	(0.459,0.549,0.329,0.419)	(0.189,0.249,0.609,0.689)
TEC3	(0.53,0.65,0.35,0.47)	(0.43,0.53,0.47,0.57)	(0.197,0.197,0.197,0.197)	(0.379,0.459,0.419,0.499)	(0.419,0.509,0.369,0.459)	(0.64,0.74,0.26,0.36)	(0.359,0.469,0.409,0.519)	(0.55,0.67,0.33,0.45)	(0.51,0.62,0.38,0.49)	(0.269,0.329,0.529,0.609)
TEC4	(0.589,0.699,0.179,0.289)	(0.449,0.529,0.349,0.429)	(0.419,0.499,0.379,0.459)	(0.197,0.197,0.197,0.197)	(0.469,0.549,0.329,0.409)	(0.619,0.719,0.159,0.259)	(0.449,0.529,0.349,0.429)	(0.63,0.72,0.26,0.35)	(0.49,0.59,0.41,0.51)	(0.279,0.349,0.409,0.479)
TEC5	(0.61,0.72,0.28,0.39)	(0.459,0.549,0.329,0.399)	(0.369,0.459,0.419,0.509)	(0.329,0.409,0.469,0.549)	(0.197,0.197,0.197,0.197)	(0.579,0.639,0.119,0.159)	(0.419,0.499,0.379,0.459)	(0.59,0.67,0.31,0.39)	(0.49,0.6,0.4,0.51)	(0.309,0.389,0.489,0.569)
TEC6	(0.37,0.49,0.51,0.63)	(0.24,0.33,0.65,0.76)	(0.26,0.36,0.64,0.74)	(0.159,0.259,0.619,0.719)	(0.119,0.159,0.579,0.639)	(0.197,0.197,0.197,0.197)	(0.19,0.29,0.69,0.81)	(0.4,0.49,0.49,0.58)	(0.35,0.48,0.52,0.65)	(0.08,0.15,0.81,0.92)
TEC7	(0.47,0.62,0.38,0.53)	(0.44,0.56,0.44,0.56)	(0.409,0.519,0.359,0.469)	(0.349,0.429,0.449,0.529)	(0.379,0.459,0.419,0.499)	(0.69,0.81,0.19,0.29)	(0.197,0.197,0.197,0.197)	(0.6,0.71,0.29,0.38)	(0.54,0.65,0.35,0.46)	(0.3,0.42,0.58,0.7)
TEC8	(0.35,0.46,0.54,0.63)	(0.299,0.399,0.479,0.579)	(0.33,0.45,0.55,0.67)	(0.26,0.35,0.63,0.72)	(0.31,0.39,0.59,0.67)	(0.49,0.58,0.4,0.49)	(0.29,0.38,0.6,0.71)	(0.197,0.197,0.197,0.197)	(0.53,0.65,0.35,0.45)	(0.28,0.39,0.61,0.72)
TEC9	(0.38,0.49,0.51,0.62)	(0.299,0.399,0.479,0.579)	(0.38,0.49,0.51,0.62)	(0.41,0.51,0.49,0.59)	(0.4,0.51,0.49,0.6)	(0.52,0.65,0.35,0.48)	(0.35,0.46,0.54,0.65)	(0.35,0.45,0.53,0.65)	(0.197,0.197,0.197,0.197)	(0.249,0.309,0.549,0.629)
TEC10	(0.599,0.679,0.199,0.259)	(0.609,0.689,0.189,0.249)	(0.529,0.609,0.269,0.329)	(0.409,0.509,0.369,0.469)	(0.509,0.589,0.289,0.349)	(0.76,0.88,0.12,0.22)	(0.58,0.7,0.3,0.42)	(0.64,0.74,0.26,0.36)	(0.549,0.629,0.249,0.309)	(0.197,0.197,0.197,0.197)

During the preliminary phase of the data collection process, the experts received a detailed explanation of the study's objectives and the significance of their participation. They were informed about the specific focus on the application of industry 4.0 technologies within the automotive sector and were then requested to share their insights and evaluations on this subject matter. This initial interaction enabled us to gain a comprehensive understanding of the expertise and practical experience possessed by the interviewed experts in the domains of digital transformation and the automotive industry. Following this, the experts were further engaged in a detailed process, being asked to assess pairwise comparisons of industry 4.0 technologies by responding to a carefully constructed questionnaire, thus providing a structured framework for their assessments and insights.

The Pythagorean fuzzy AHP calculation steps applied by utilizing the experts' evaluation data are given below:

Step 1: Each of the five experts was asked to assess their pairwise comparisons for Industry 4.0 technologies using the linguistic scale provided in Table 2. Thus, pairwise comparison matrices for Industry 4.0 technologies are constructed, as shown in Table 3. Then, the linguistic variables are converted into corresponding interval-valued Pythagorean fuzzy numbers. Furthermore, a consistency check was performed to ensure the experts' judgments in the pairwise comparison matrix was meaningful. Since the experts' ratings differed, their opinions needed to be combined to create a compromised pairwise comparison matrix. Thus, the aggregated pairwise comparison matrix for the Industry 4.0 technologies was calculated using Eq. (9), as shown in Table 4.

Table 5. The difference matrix of Industry 4.0 technologies

	TEC1	TEC2	TEC3	TEC4	TEC5	TEC6	TEC7	TEC8	TEC9	TEC10
TEC1	(0,0)	(-0.3,-0.08)	(-0.3,-0.06)	(-0.457,-0.264)	(-0.44,-0.22)	(0.2,0.44)	(-0.24,0.06)	(0.08,0.274)	(0.02,0.24)	(-0.351,-0.193)
TEC2	(0.08,0.3)	(0,0)	(-0.1,0.1)	(-0.316,-0.176)	(-0.264,-0.137)	(0.216,0.42)	(-0.08,0.14)	(0,0.158)	(0.035,0.193)	(-0.439,-0.309)
TEC3	(0.06,0.3)	(-0.14,0.06)	(0,0)	(-0.105,0.035)	(-0.035,0.123)	(0.28,0.48)	(-0.141,0.053)	(0.1,0.34)	(0.02,0.24)	(-0.299,-0.172)
TEC4	(0.264,0.457)	(0.018,0.158)	(-0.035,0.105)	(0,0)	(0.053,0.193)	(0.316,0.492)	(0.018,0.158)	(0.274,0.451)	(-0.02,0.18)	(-0.151,-0.045)
TEC5	(0.22,0.44)	(0.211,0.302)	(-0.123,0.035)	(-0.193,-0.053)	(0,0)	(0.31,0.394)	(-0.035,0.105)	(0.196,0.353)	(-0.02,0.2)	(-0.228,-0.088)
TEC6	(-0.26,-0.02)	(-0.578,-0.423)	(-0.48,-0.28)	(-0.492,-0.316)	(-0.394,-0.31)	(0,0)	(-0.62,-0.392)	(-0.176,0)	(-0.3,-0.04)	(-0.84,-0.634)
TEC7	(-0.06,0.24)	(-0.12,0.12)	(-0.053,0.141)	(-0.158,-0.018)	(-0.105,0.035)	(0.392,0.62)	(0,0)	(0.216,0.42)	(0.08,0.3)	(-0.4,-0.16)
TEC8	(-0.274,-0.08)	(-0.246,-0.07)	(-0.34,-0.1)	(-0.451,-0.274)	(-0.353,-0.196)	(0,0.176)	(-0.42,-0.216)	(0,0)	(0.078,0.3)	(-0.44,-0.22)
TEC9	(-0.24,-0.02)	(-0.246,-0.07)	(-0.24,-0.02)	(-0.18,0.02)	(-0.2,0.02)	(0.04,0.3)	(-0.3,-0.08)	(-0.3,-0.078)	(0,0)	(-0.334,-0.206)
TEC10	(0.292,0.422)	(0.371,0.475)	(0.172,0.299)	(-0.053,0.123)	(0.137,0.264)	(0.529,0.76)	(0.16,0.4)	(0.28,0.48)	(0.206,0.334)	(0,0)

Table 6. The interval multiplicative matrix of Industry 4.0 technologies

	TEC1	TEC2	TEC3	TEC4	TEC5	TEC6	TEC7	TEC8	TEC9	TEC10
TEC1	(1,1)	(0.355,0.759)	(0.355,0.813)	(0.206,0.402)	(0.219,0.468)	(1.995,4.571)	(0.437,1.23)	(1.318,2.58)	(1.072,2.291)	(0.297,0.513)
TEC2	(1.318,2.818)	(1,1)	(0.708,1.413)	(0.335,0.545)	(0.402,0.622)	(2.106,4.266)	(0.759,1.622)	(1,1.727)	(1.129,1.95)	(0.219,0.344)
TEC3	(1.23,2.818)	(0.617,1.23)	(1,1)	(0.695,1.129)	(0.886,1.529)	(2.63,5.248)	(0.615,1.2)	(1.413,3.236)	(1.072,2.291)	(0.356,0.553)
TEC4	(2.485,4.845)	(1.063,1.727)	(0.886,1.439)	(1,1)	(1.2,1.95)	(2.982,5.47)	(1.063,1.727)	(2.58,4.745)	(0.933,1.862)	(0.593,0.855)
TEC5	(2.138,4.571)	(2.072,2.835)	(0.654,1.129)	(0.513,0.834)	(1,1)	(2.914,3.896)	(0.886,1.439)	(1.968,3.382)	(0.933,1.995)	(0.454,0.738)
TEC6	(0.407,0.933)	(0.136,0.232)	(0.191,0.38)	(0.183,0.335)	(0.257,0.343)	(1,1)	(0.117,0.258)	(0.544,1)	(0.355,0.871)	(0.055,0.112)
TEC7	(0.813,2.291)	(0.661,1.514)	(0.834,1.625)	(0.579,0.941)	(0.695,1.129)	(3.873,8.511)	(1,1)	(2.106,4.266)	(1.318,2.818)	(0.251,0.575)
TEC8	(0.388,0.759)	(0.428,0.784)	(0.309,0.708)	(0.211,0.388)	(0.296,0.508)	(1,1.839)	(0.234,0.475)	(1,1)	(1.311,2.818)	(0.219,0.468)
TEC9	(0.437,0.933)	(0.428,0.784)	(0.437,0.933)	(0.537,1.072)	(0.501,1.072)	(1.148,2.818)	(0.355,0.759)	(0.355,0.763)	(1,1)	(0.316,0.491)
TEC10	(2.741,4.291)	(3.605,5.161)	(1.81,2.806)	(0.834,1.529)	(1.607,2.485)	(6.22,13.804)	(1.738,3.981)	(2.63,5.248)	(2.037,3.168)	(1,1)

Table 7. The determinacy value matrix of Industry 4.0 technologies

	TEC1	TEC2	TEC3	TEC4	TEC5	TEC6	TEC7	TEC8	TEC9	TEC10
TEC1	1.000	0.780	0.760	0.807	0.780	0.760	0.700	0.806	0.780	0.842
TEC2	0.780	1.000	0.800	0.859	0.874	0.796	0.780	0.842	0.842	0.870
TEC3	0.760	0.800	1.000	0.859	0.842	0.800	0.807	0.760	0.780	0.873
TEC4	0.807	0.859	0.859	1.000	0.859	0.824	0.859	0.824	0.800	0.894
TEC5	0.780	0.909	0.842	0.859	1.000	0.916	0.859	0.843	0.780	0.859
TEC6	0.760	0.845	0.800	0.824	0.916	1.000	0.772	0.824	0.740	0.794
TEC7	0.700	0.760	0.807	0.859	0.859	0.772	1.000	0.796	0.780	0.760
TEC8	0.806	0.824	0.760	0.824	0.843	0.824	0.796	1.000	0.778	0.780
TEC9	0.780	0.824	0.780	0.800	0.780	0.740	0.780	0.778	1.000	0.872
TEC10	0.870	0.896	0.873	0.824	0.874	0.769	0.760	0.800	0.872	1.000

Table 8. Matrix of weights for Industry 4.0 technologies prior to normalization

	TEC1	TEC2	TEC3	TEC4	TEC5	TEC6	TEC7	TEC8	TEC9	TEC10
TEC1	1.000	0.434	0.444	0.246	0.268	2.495	0.583	1.570	1.311	0.341
TEC2	1.613	1.000	0.848	0.378	0.448	2.535	0.928	1.148	1.296	0.245
TEC3	1.538	0.739	1.000	0.784	1.017	3.151	0.732	1.766	1.311	0.397
TEC4	2.957	1.199	0.999	1.000	1.353	3.483	1.199	3.016	1.118	0.647
TEC5	2.616	2.231	0.750	0.579	1.000	3.118	0.999	2.256	1.142	0.512
TEC6	0.509	0.156	0.228	0.214	0.275	1.000	0.145	0.636	0.454	0.066
TEC7	1.086	0.826	0.992	0.653	0.784	4.780	1.000	2.535	1.613	0.314
TEC8	0.462	0.500	0.386	0.246	0.339	1.169	0.282	1.000	1.607	0.268
TEC9	0.534	0.500	0.534	0.643	0.613	1.468	0.434	0.435	1.000	0.352
TEC10	3.060	3.927	2.015	0.974	1.788	7.701	2.173	3.151	2.270	1.000

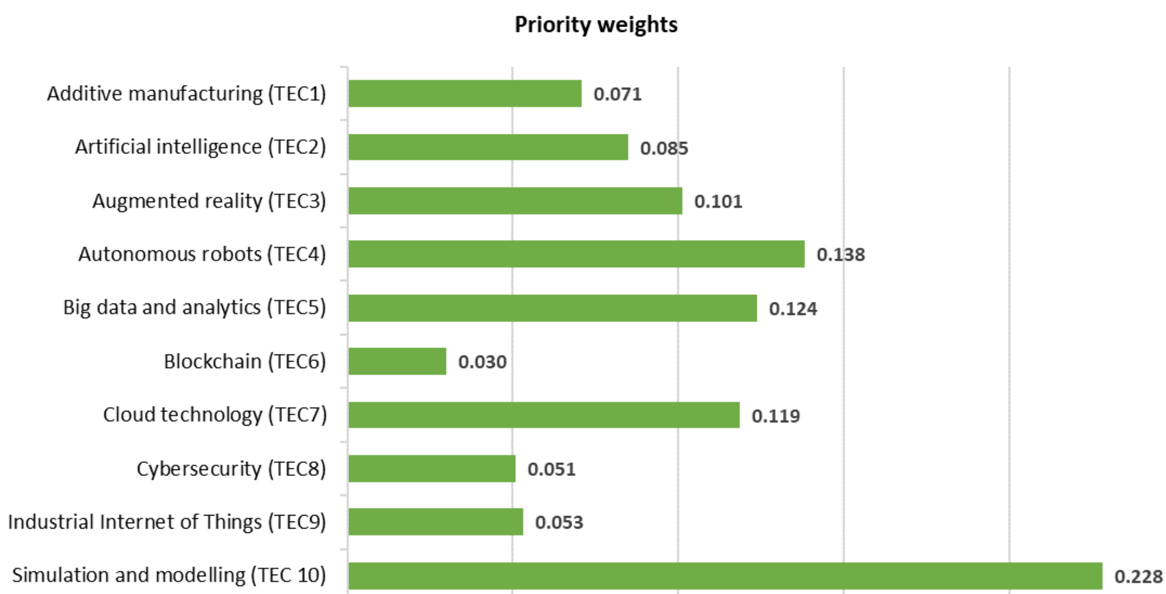

Figure 1. Priority weights of Industry 4.0 technologies

Step 2: The difference matrix of Industry 4.0 technologies $D = (d_{ik})_{m\times m}$ between the lower and upper values of membership and non-membership functions was computed using Eqs. (10) and (11), as indicated in Table 5.

Step 3: The interval multiplicative matrix $S = (s_{ik})_{m\times m}$ calculated using Eqs. (12) and (13) is provided in Table 6.

Step 4: As shown in Table 7, the determinacy value matrix was calculated using Eq. 14.

Step 5: Table 8 shows the matrix of weights $T = (t_{ik})_{m\times m}$ before normalization computed based on Eq. (15) in this step.

Step 6: Finally, the normalized priority weights of Industry 4.0 technologies are calculated using Eq. (16) and presented in Figure 1.

5. Discussion of the Results

In this research, AHP approach, renowned for being among the leading methods for multi-criteria decision-making, was applied in combination with Pythagorean fuzzy sets in order to rank the technologies of Industry 4.0 by their significance within the automotive industry. The results show the importance weight of Industry 4.0 technologies that are effective in the automotive industry, as seen in Figure 1.

The results received from the Pythagorean fuzzy AHP method indicate that simulation and modeling (TEC10) technology hold the highest level of importance, with a weight value of 0.228. The progress of the automotive industry has been greatly influenced by the evolution of simulation technology. This technology enables manufacturers to create and test vehicle designs without the need for physical prototypes. By constructing virtual models, designers can assess the performance of product components in simulated real-world scenarios [41]. Moreover, the use of simulation and modeling technology in automotive production is not limited to product design. It can also enhance the efficiency and effectiveness of production processes. For instance, automotive manufacturers can simulate line flows to identify bottlenecks or challenges and then optimize them.

Thanks to the implementation of simulation, there is a reduction in both the costs and the time required for product development [41]. The holistic approach improves the quality and performance of the final product and streamlines the entire production process, leading to increased productivity and reduced operational costs. Therefore, the integration of advanced simulation technologies is essential for continuous innovation and efficiency in the automotive industry.

The second most important technology was autonomous robots (TEC4), with a weight value of 0.138. Similarly, a study conducted on the utilizing level of Industry 4.0 technologies in manufacturing businesses in the automotive industry operating in Slovakia and the Czech Republic revealed a high frequency of industrial robot usage [42]. One of the initial industries to extensively utilize robots is the automotive sector [43]. A recent study reveals that the global automotive robot market will grow by over 10% between 2020 and 2026, from $9 billion to $16 billion, nearly three times faster than vehicle production in a similar time frame [43].

The integration of robotics into manufacturing was once a recent concept, but it has now become the primary objective for almost all sectors in the manufacturing industry [44]. Although robotics is utilized in various industries, statistical data indicates that the automotive industry remains the primary recipient, accounting for 28% of overall robotics usage [44,45]. Due to recent technological advancements and the rapid growth of AI, robots have become increasingly prevalent in the automobile manufacturing sector. These specially programmed robots can perform a wide variety of hazardous and labor-intensive tasks without the need for human intervention. Their use in different operating mechanisms has increased significantly, allowing for maintaining high standards of quality and output [44].

Incorporating advanced robotic technology into the production phase of an industrial process enhances the overall efficiency and productivity of manufacturing operations [44]. Industrial robots are a crucial technology for digitization and the advent of smart manufacturing [45]. Thus, the ongoing evolution and integration of robotics in the automotive industry highlight their indispensable role in modern manufacturing processes.

Big data and analytics (TEC5) were ranked as the third most important technology, with a weight value of 0.124. Big data and analytics systems are capable of processing large volumes of data and providing different methods of analysis. This capability allows for the early identification of potential faults and the development of appropriate counteractive actions through early signal detection, as well as better management of the data [46]. The significance of data is growing across all aspects of the automotive industry, from vehicle development to production and service operations, as well as in connected vehicle-focused online services. Connected, mobile, Internet of Things devices and machines are producing vast amounts of sensor data [47]. As a result, big data analytics technology plays a crucial role in processing and analyzing this data, extracting insights and information that enhance processes and decision-making.

The use of big data analytics has transformed the way vehicle design and manufacturing processes are carried out. Manufacturers can now optimize production processes by analyzing large amounts of data from different sources. This has led to improved efficiency and reduced waste [48]. Another important benefit is predictive maintenance, where data collected from machines and production lines can predict potential equipment failures, helping to minimize downtime and reduce maintenance costs [49]. Continuous learning from large manufacturing data facilitates the system's ability to self-learn, self-optimize, and self-regulate [50]. Thus, big data analytics not only helps quick decision-making but also contributes to long-term strategic planning and operational improvements in the automotive industry.

Cloud technology (TEC7) had the fourth highest importance level, with a weight value of 0.119. Cloud computing has significantly reshaped the operational landscape for companies in recent years. By leveraging remote servers located on the internet to save, analyze, and process data, cloud computing has revolutionized the way companies handle their information and applications. This shift has enabled businesses to access scalable and flexible resources, streamline their operations, and enhance collaboration and productivity [51]. Moreover, cloud computing positively impacts companies by increasing their revenue and helping them achieve their goals [52].

In the automotive industry, cloud computing allows manufacturers to flexibly adjust IT resources based on fluctuating workloads, helping them quickly adapt to changing market demands. Additionally, cloud computing contributes to resource optimization, cost reduction, revenue increase, improved CRM strategies, and more effective delivery of service [53].

Augmented reality (TEC3) ranked fifth in terms of importance, with a weight of 0.101. One of the cornerstones of Industry 4.0 is the Augmented Reality technology, which offers benefits for various tasks such as maintenance, assembly, and inspection [54]. Augmented reality is a powerful technological tool that holds the potential to significantly enhance various aspects of production and manufacturing. It can play a crucial role in improving manufacturing processes, aiding in maintenance activities, streamlining assembly processes, and providing effective on-the-job training for employees [55]. With its ability to overlay digital information onto real-world environments, augmented reality can help optimize workflows, reduce errors, and improve overall efficiency across a wide range of industrial activities [56]. Augmented reality contributes to various aspects of the automotive industry, including maintenance, repair, diagnostics, inspection, and training [57]. Critical assembly operations can be performed more effectively using devices equipped with augmented reality technology, which will be accessible to operators in factory environments. Specifically, the utilization of augmented reality glasses enables operators to visualize the position of each part on the assembly line and view logistics and production information within their field of view. This facilitates minimal errors and provides for better quality control [54,56].

Artificial intelligence (TEC2) in the automotive sector was ranked sixth among Industry 4.0 technologies, with a weight value of 0.085. The dawn of Industry 4.0 is creating new opportunities for manufacturing companies to enhance their operational efficiency and competitiveness through the use of Artificial Intelligence applications [58]. One industry that is poised for significant transformation with the implementation of advanced artificial intelligence systems is the automotive industry [59]. Integrating artificial intelligence into the automotive sector will significantly aid in lowering expenses across various operational stages, including design and production. Artificial Intelligence can contribute to cost reduction in numerous areas by enhancing manufacturing workflows, bettering supply chain management, and pinpointing possible vehicle problems [60]. The use of Artificial Intelligence in the automotive industry is not restricted to the manufacturing facility or production line. There is great potential for applying artificial intelligence in design work, various after-sales services, and within the automobile itself [59]. Artificial intelligence is used in some cars to provide driver assistance through advanced technology. Autonomous vehicles, the next generation of cars with self-learning and self-driving capabilities, represent the most advanced application of artificial intelligence in the automotive industry [60].

According to the analysis results, the ranking of the remaining technologies according to their importance level is as follows: additive manufacturing (TEC1) ranked seventh, industrial internet of things (TEC9) ranked eighth, and cybersecurity (TEC8) technologies ranked ninth. Lastly, blockchain (TEC6) technology was placed in the tenth and last position in terms of importance. The automotive industry is at different maturity levels in developing Industry 4.0 technologies and concepts [21], leading to differing levels of importance for these technologies. For instance, current additive manufacturing technologies are not yet suitable for mass production within the automotive sector. In contrast, robotic systems play a crucial role in automotive production processes, and manufacturers are actively developing these systems to address the specific needs of the industry [5]. Similarly, blockchain technology has garnered significantly less attention in the automotive industry compared to other sectors, such as the financial industry [61]. The application of blockchain technology in the automotive field is still in its nascent stages, with only a few project-based implementations to date [62]. This shows that although blockchain, like some other industry 4.0 technologies, has potential, its integration and adoption in the automotive industry are still developing.

6. Conclusions, Limitations and Further Research

This study aimed to evaluate the importance levels of Industry 4.0 technologies for automotive manufacturers operating in Türkiye using the Pythagorean fuzzy AHP method by addressing a gap in the literature. The study revealed that the top five most important Industry 4.0 technologies in the Turkish automotive sector are simulation and modeling, autonomous robots, big data and analytics, cloud technology, and augmented reality, in that order. On the other hand, blockchain technology, cybersecurity, and additive manufacturing were ranked relatively as the less critical technologies.

The analysis results show that simulation and modeling technology are the most important. Similarly, Sonntag et al. [21] highlighted in their study that simulation and modeling are essential technologies of Industry 4.0 in the automotive industry. Simulation and modeling enable the creation and testing of virtual prototypes, which in turn lead to reduced costs and shorter development times. Automotive manufacturers can use simulations to identify and address production bottlenecks, streamline operations, and optimize resource allocation, leading to improved efficiency and reduced production times. Additionally, Pardhı et al. [63] demonstrated how detailed simulation models of vehicle dynamics and powertrain systems can replicate real-world performance under diverse conditions, enabling manufacturers to test innovative propulsion technologies and optimize system designs early in the development process. Autonomous robots, which are ranked second, are now an integral part of automotive production. They significantly enhance productivity and quality while reducing operational risks. The increasing complexity of production processes and the growing demand for customization have driven manufacturers to adopt flexible and adaptive technologies in the automotive sector. Čech et al. [64] emphasize the critical role of autonomous mobile robots in addressing these challenges. The rise of big data and analytics, the third most important technology, enables the processing and analysis of vast amounts of data. This technology supports predictive maintenance and real-time decision-making, optimizing production processes and reducing costs. As highlighted by Beier et al. [65], big data and analytics offers significant potential for improving corporate operational efficiencies within the automotive industry. By leveraging real-time data and predictive analytics, automotive companies can optimize resource utilization. Cloud technology ranked fourth, has revolutionized the operational landscape for companies by using remote servers to store, manage, and process data. This shift allows businesses to access scalable and flexible resources, streamline operations, and enhance collaboration and productivity. Cieśla and Ulewicz [66] highlight that cloud-based systems in the automotive industry significantly enhance real-time data accessibility and decision-making by enabling seamless communication among stakeholders. This fosters improved quality control and operational efficiency, especially in dynamic and distributed manufacturing environments. In the field of automotive manufacturing industry, augmented reality, ranked fifth, holds the impressive potential to integrate digital information into real-world environments. By doing so, it facilitates more efficient workflows and reduces errors across various aspects of production, maintenance, and training.

Despite their potential, certain technologies such as additive manufacturing, Industrial Internet of Things, cybersecurity, and blockchain are at different levels of maturity and adoption in the automotive industry. Additive manufacturing shows promise but is not yet suitable for mass production. Industrial Internet of Things and cybersecurity are essential for digitizing manufacturing processes, but they require further development to address industry-specific challenges. Although still in its early stages, blockchain technology has the potential to improve transparency and security in supply chains, but it has not yet gained widespread attention and implementation. In conclusion, this study offers a valuable framework for decision-makers in the automotive sector to effectively prioritize and integrate Industry 4.0 technologies. By understanding the relative importance of these technologies, companies can make informed decisions to improve their operational efficiency and competitiveness in a rapidly evolving market.

This study also has some limitations. Specifically, there is a geographical constraint, as the research was solely conducted in the automotive sector in Türkiye. Therefore, the results may only be relevant to the national context. However, this situation presents an opportunity to replicate this study across automotive industries in different countries to observe if the findings hold true or how they differ. Another limitation of the research is that it is limited to companies in the automotive manufacturing industry. With a new study, Industry 4.0 technologies can be examined to include second and third-tier companies, distributors, vendors, and customers. For future studies, the proposed methodology can be tested in other sectors that have potential for applying Industry 4.0 technologies. Additionally, other multi-criteria decision-making methods that integrate various types of fuzzy sets, such as hesitant fuzzy sets and neutrosophic sets, can be considered as alternatives for future studies.

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Conflict of Interest Statement

The author declares that there is no conflict of interest in the study.

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