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Demand and Supply Risk: Sustainability Manufacturing Industries of Turkey Based on Artificial Intelligence

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مخاطر العرض والطلب: استدامة الصناعات التحويلية في تركيا القائمة على الذكاء الاصطناعي

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Abstract:
The aim of this paper is to investigate the influence of artificial intelligence (AI) on improving the sustainability performance of supply chains in the manufacturing sectors of Turkey. The paper took a quantitative approach, with a sample size of 350 manufacturing entities. It combined both qualitative and quantitative approaches. Statistical tools were employed to analyse the data and identify patterns and linkages. The results highlighted the significant impact of AI in reducing supply chain risks, stressing its crucial role in managing demand. Moreover, the research emphasized that incorporating artificial intelligence (AI) into company operations goes beyond only technological progress and instead becomes a crucial necessity for enhancing resilience and sustainability. The paper implies that firms can derive significant advantages by incorporating AI technology to effectively manage unpredictable demand, optimize inventories, and improve overall sustainability. Nevertheless, the study's focus on Turkey's manufacturing industries implies the necessity for more extensive research, including other sectors and areas. To summarize, AI has great potential to transform supply chain risk management, which might have a major impact on the future of manufacturing in Turkey and potentially worldwide.

Keywords: Supply Chain Risk Management, Artificial Intelligence (AI), Sustainability Performance, Manufacturing Industries, Demand Management.

الملخص
الهدف من هذه الورقة هو دراسة تأثير الذكاء الاصطناعي (AI) على تحسين أداء الاستدامة لسلاسل الدعم في قطاعات التصنيع في تركيا. في هده الورقة تأخذ الكمية، حيث بلغ حجم العينة 350 كيانًا صناعيًا. لقد جمعت بين النهج النوعي والكمي. وتم استخدام الأدوات الإحصائية لتحليل البيانات وتحديد الأنماط والروابط. وأبرزت نتائج تأثير الذكاء الاصطناعي في الحد من مخاطر سلسلة الدعم، مؤكدة على دوره الحاسم في إدارة الطلب. علاوة على ذلك، أكد البحث على أن دمج الذكاء الاصطناعي في عمليات الشركة يستخدم التقدم التكنولوجي فحسب، بل يصبح بدلاً من ذلك ضرورة حاسمة لتعزيز المرونة والاستدامة. وتشير الورقة إلى أن الشركات يمكن أن تستمد مزايا كبيرة من خلال دمج تكنولوجيا الذكاء الاصطناعي لإدارة الطلب غير المتوقع بشكل فعال، وتحسين المخزونات، وتحسين الاستدامة الشاملة. ومع ذلك، فإن تركيز الدراسة على الصناعات التحويلية في تركيا يعني ضمناً ضرورة إجراء أبحاث أكثر شمولاً، بما في ذلك القطاعات والمجالات الأخرى. لتلخيص ذلك، يتمتع الذكاء الاصطناعي بإمكانات كبيرة لتحويل إدارة مخاطر سلسلة التوريد، الأمر الذي قد يكون له تأثير كبير على مستقبل التصنيع في تركيا وربما في جميع أنحاء العالم.

الكلمات المفتاحية: إدارة مخاطر سلسلة التوريد، الذكاء الاصطناعي، أداء الاستدامة، الصناعات التحويلية، إدارة الطلب.

1: Introduction

Contemporary businesses strive for global competitiveness by using supply chain management, acknowledging the significant impact that events in one global sector might have on other regions [7]. For example, a crisis in one place has a broader impact beyond that particular area, as its repercussions reverberate throughout global supply chains [1]. Research has indicated that emergencies increase uncertainty, leading to increased risks in several areas. Efficient supply chain management (SCM) prioritizes the smooth and economical transportation of items across all phases [3]. Due to the uncertain and unpredictable occurrence of disasters, fluctuations in demand, and changes in policies, companies frequently struggle with possible disruptions in an increasingly unstable environment [4]. Disruptions to supply networks inevitably affect their consistency, aims, and profitability [5]. Therefore, it is crucial for enterprises to consistently identify, evaluate, control, and oversee these risks [4]. Despite the long historical background of SCRM, it continues to face obstacles, particularly in the aftermath of global catastrophes such as the pandemic [6]. Prior studies have placed significant attention on disturbances such as environmental disasters [3]. According to modern literature, there is a new area of research that focuses on using artificial intelligence to make it easier to predict these unexpected events [7]. Artificial intelligence improves the ability of the supply chain to withstand and recover from sudden interruptions by enabling continuous monitoring and reducing the negative consequences [8]. AI has the capacity to boost problem-solving by increasing speed, accuracy, and the variety of inputs available, surpassing existing techniques [9]. Scholars have characterized design as a crucial decision-making process that is integral to creativity [10]. The necessity of AI-driven innovations in developing robust supply chains, which include aspects such as information sharing and processing, has been recognized as crucial for managing supply chain risks [10]. The latest technical progress highlights the diverse uses of AI, particularly in areas such as supply chain management [11]. Industries are progressively transitioning their approaches: moving from being responsive to being proactive, from relying on manual processes to automated ones, and from using forecasting to employing predictive analytics in operations [12] The widespread presence and growing importance of AI in the business world necessitate further research on the subject. Modern SCRM heavily relies on techniques such as machine learning, deep learning, and natural language processing [13]. Therefore, incorporating AI approaches into SCRM can play a crucial role in ensuring the continuous advancement of enterprises in the face of uncertainty [14]. Specifically, supply chain management (SCM) emerges as a crucial recipient of the revolutionary capabilities of artificial intelligence (AI). This study aims to clarify the impact of artificial intelligence on supply chain risk management and its consequences for the effectiveness of the manufacturing industry.

2: Related Work

The dynamic and fast-changing global economic environment has presented manufacturing industries worldwide with unprecedented challenges and opportunities. Turkey, due to its advantageous geographical position connecting Europe and Asia, is no different. The manufacturing sector of the nation has had significant growth and increased importance in the last decades [15]. As the sector grew, the complexities of managing supply chains also increased, highlighting the importance of strong supply chain risk management (SCRM). SCRM is crucial for manufacturing companies since it immediately influences operational efficiency, cost-effectiveness, and customer satisfaction. The focus on supply chain risk management (SCRM) has grown in importance due to the rising frequency of unforeseen global events such as trade wars, natural catastrophes, and health crises [16] In the Turkish manufacturing industry, it is vital to comprehend and address these risks in order to maintain reliable supply chain performance and sustainability. Amidst this context, the widespread adoption of digital technology, particularly artificial intelligence (AI), presents a revolutionary remedy. Artificial intelligence (AI), due to its capacity to analyse extensive quantities of data, forecast outcomes, and automate intricate procedures, has the potential to completely transform supply chain relationship management (SCRM) [17]. Throughout the years, AI applications have spread into other industries, enhancing productivity and encouraging new ideas. The manufacturing sector can benefit from AI by using its abilities to properly forecast demand, optimize supply channels, streamline internal operations, and promote environmental sustainability. The chronic difficulty of demand unpredictability frequently leads to inefficiencies in inventory management and consequent revenue loss. Manufacturing organizations have the ability to better synchronize their output with market demands by utilizing the predictive analytics capabilities of AI [18]. AI can monitor real-time global developments on the supply front, accurately predicting potential interruptions and recommending the best sourcing solutions. Moreover, within the realm of internal production processes, the implementation of AI has the potential to significantly alter the status quo. Automated procedures, continuous monitoring of machinery, and anticipatory maintenance have the potential to greatly improve operational effectiveness [19]. Lastly, given global climate change, it is crucial to prioritize the implementation of sustainable and eco-friendly manufacturing practices. AI-powered solutions can assist firms in minimizing waste, optimizing energy usage, and ensuring that their operations comply with global sustainability requirements [20].The integration of artificial intelligence (AI) in supply chain risk management (SCRM) presents a possible road for Turkey's manufacturing industry to achieve global competitiveness and resilience.

This collaboration has the potential to greatly advance the industry, guaranteeing its long-term viability and strength in a rapidly evolving global landscape

3: Identification of Gaps in The Existing Literature, Leading to The Current Research Hypotheses

A deep dive into the prevailing academic discourses on the intersections of Artificial Intelligence (AI), supply chain risk management, and manufacturing provides rich insights. However, upon meticulous examination, certain lacunae emerge, particularly in the context of Turkey's manufacturing industries, which have led to the formulation of the present research hypotheses. A majority of the extant studies have addressed the advantages of AI in enhancing operational efficiency, predictive analytics, and process optimization across various industrial domains [21]. However, the nuances of how AI directly impacts the multifaceted risks within the supply chain, especially in a specific socio-economic and industrial context like Turkey's, remain relatively uncharted.

H1 posits that AI has a favourable impact on the demand risk and performance of Turkey's manufacturing entities. While AI's role in demand forecasting through data analytics is widely acknowledged [17], the extant literature often presents a generic overview. The unique socio-economic dynamics and market behaviours inherent to Turkey's consumers and industrial buyers necessitate a more localized and granular exploration. This gap in understanding the specific impact of AI on demand risk within the Turkish manufacturing milieu underpins the need for the first hypothesis.

H2, which addresses the supply risks, the current body of research often centres on global supply chain dynamics, emphasizing multinational corporations [22] Turkey, with its distinct geopolitical position and economic relationships, grapples with a unique set of supply risks. The role of AI in mitigating these challenges, by perhaps enhancing supplier relationship management or optimizing logistics in real-time within the Turkish context, remains to be explored in depth. While the confluence of AI and supply chain management has seen substantial academic deliberation, there's a discernible regional and risk-specific gap in the literature, particularly concerning Turkey's manufacturing landscape. This paper, through its articulated hypotheses, endeavours to bridge these gaps, contributing not just to the academic corpus but also offering pragmatic insights for Turkey's manufacturing stakeholders.

3.1:Conceptual Framework

Based on the study's hypotheses, the conceptual model can be presented as follow:

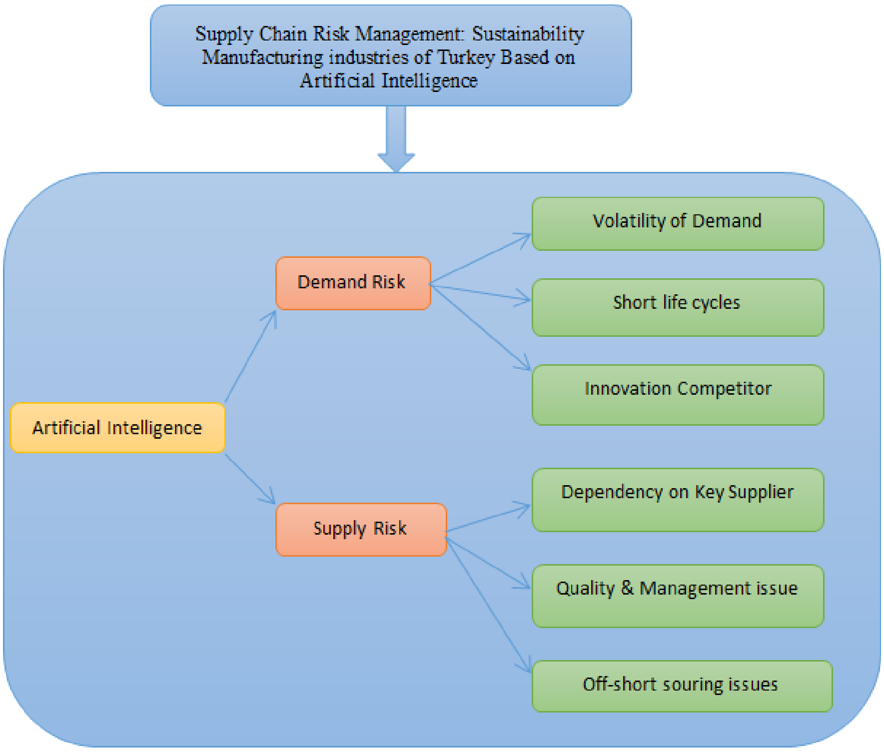

Figure 1 Hypothesis Framework.

H1: AI has a positive impact on reducing demand risk.
H2: AI has a positive impact on reducing supply risk.

4: Proposed Method

4.1: Research Design

In the field of academic research, the design acts as the plan or model that determines how inquiries are organized and carried out. The selected methodology for this paper is quantitative, as it allows for the objective measurement of variables and the drawing of statistical conclusions from them [23] The research aims to analyse the patterns and interactions between the adoption of AI and its impact on the sustainability performance of supply chains in the industrial industries of Turkey, using a quantitative design. The decision to choose a quantitative research approach is mostly based on the study's objectives. Considering the extent of the paper, it was necessary to evaluate a significant number of manufacturing companies in order to obtain a thorough comprehension of the issue. Quantitative approaches, namely surveys, are highly skilled at gathering data from large populations, making them well-suited for this purpose [24] The online questionnaire served as the main method for collecting data, enabling the effective distribution and gathering of responses from a diverse range of manufacturing businesses. This approach provided a comprehensive perspective on the industry's attitude regarding the use of AI in managing supply chain risks. Moreover, the primary research framework guiding this investigation is positivism, a paradigm that is highly suitable for quantitative research. Positivism is based on the idea that knowledge can be obtained by examining and measuring observable facts. It suggests that phenomena may be separated and analysed in a controlled way [25]. Using this perspective, the study aims to assess the extent and characteristics of the influence of AI on the sustainability of the supply chain, ensuring that any findings made are supported by measurable data. The research design for this study has been carefully devised to guarantee that the collected data yields a distinct and unbiased comprehension of AI's involvement in supply chain risk management within Turkey's industrial industries. The utilization of an online questionnaire, under the positivist paradigm, provides a strong framework to analyse the complex dynamics of this current subject matter

4.2: Population and Sample

Understanding the population and sample of a study is essential to appreciate the breadth and depth of the research's findings. It provides context, scale, and relevance to the data collected, which in turn, gives weight to the subsequent analysis.

4.2.1 Population under Study

The main population for this paper consists of all manufacturing industries currently operating within Turkey. Turkey's industrial environment is characterized by a wide range of sectors, including automotive, electronics, and textiles, as well as more specialized areas like defence and aerospace manufacture. The inclusion of Turkey's manufacturing sector provides a thorough perspective of the current industrial environment, as it plays a considerable role in the country's GDP and employs a large share of its workforce [26].

4.3 Criteria for Inclusion

To narrow down the population and ensure the relevancy of respondents to the paper's focus on AI and supply chain sustainability, several inclusion criteria were defined. Companies eligible for the study must:

- Be actively involved in manufacturing activities within Turkey.
- Have some level of engagement with supply chain management, be it rudimentary or advanced.
- Be open to or have some form of AI implementation in their operations or supply chain processes.
- Companies that did not meet these criteria were excluded to maintain the study's focus and relevance.

4.3.1Determination of Sample Size:

Given the vast number of manufacturing entities in Turkey, sampling was crucial to make the study feasible. Utilizing Krejcie and Morgan's (1970) formula for determining sample size for research activities, and based on the estimated number of manufacturing firms in Turkey, a sample size of 350 was deemed representative. This sample size is statistically sound, allowing for meaningful conclusions while also being manageable in terms of data collection and analysis.A precise delineation of the population and sample ensures that the research findings are representative, relevant, and grounded in the Turkish manufacturing context. It sets the stage for the subsequent data collection and paints a picture of the industrial milieu in which AI's role in supply chain sustainability is being explored. For this research, with the aim to garner a comprehensive understanding of the role of AI in supply chain sustainability within Turkish manufacturing industries, a total of 500 online questionnaires were distributed. This distribution took into account various sectors, company sizes, and geographic locations within Turkey to ensure a diverse set of responses. Out of these 500 questionnaires, a total of 375 were successfully returned, yielding a commendable response rate of 75%. However, upon close inspection of the returned questionnaires, 25 of them were either incomplete or had inconsistent responses, thus rendering them unsuitable for the research analysis. Consequently, the final sample size used for the study was 350. This robust sample, derived from the defined population, ensures a statistically valid representation and serves as a solid foundation for subsequent analyses. The high response rate and the rigorous selection process for the final sample reiterate the study's commitment to capturing an accurate snapshot of the prevailing trends and sentiments within the Turkish manufacturing landscape.

5: Instrumentation

The selection of a suitable instrument is crucial for ensuring the dependability and accuracy of a research study, particularly in the context of quantitative research. To examine the impact of AI on supply chain risk management in the manufacturing sector in Turkey, a carefully designed online questionnaire was employed to collect the necessary data. The creation of this questionnaire was based on a thorough examination of relevant literature on supply chain management, the use of artificial intelligence in various industries, and sustainable practices [21]. This literature research facilitated the identification of crucial factors and structures that the study attempted to assess, guaranteeing consistency with established frameworks while also considering special intricacies pertinent to the Turkish manufacturing sector. The online questionnaire was organized in a coherent and systematic manner, with separate sections for each topic. The primary objective of the initial section was to collect demographic information regarding the respondent and the manufacturing entity. This included, but was not limited to, details such as firm size, sector, and years of operation. This was crucial in placing the responses in their proper context and offering valuable insights into any possible industry-specific patterns. Prior to the comprehensive dissemination to a sample size of 500, the online questionnaire completed a preliminary testing phase. The feedback received during this phase played a crucial role in improving the clarity and relevancy of the questions, as well as reducing potential biases. Utilizing an online platform enabled more convenient dissemination, higher rates of response, and quick aggregation of data and initial analysis.

6: Data Collection Method

Online data gathering has become indispensable in the present research landscape, providing extensive coverage, cost-effective benefits, and accelerated response times. This is particularly relevant for research endeavors such as this, which explore the impact of artificial intelligence on the sustainability of supply chains in Turkey's manufacturing sector [27]. The selected tool for this investigation was an online questionnaire. The survey was sent using SurveyMonkey, a platform known for its reliability, user-friendly interface, and adaptability [28]. To align with the global nature of Turkey's manufacturing industry, the questionnaire was predominantly formulated in English. Out of the 500 online questionnaires sent out, 350 were successfully collected, resulting in a response rate of 70%. This statistic greatly exceeds the average response rate of 30% commonly observed in online surveys [29]. The high return rate can be attributed to the study's thematic relevancy, smart dissemination technique, and intuitive questionnaire design. The online data collection technique has successfully enabled the comprehensive, reliable, and efficient gathering of insights from key stakeholders in Turkey's manufacturing industry.

7: Data Analysis

Due to the study's quantitative nature, the analysis primarily consisted of statistical methods. In order to achieve this objective, the researchers utilized the Statistical Package for the Social Sciences (SPSS) program, which is well-known for its extensive range of tools that address various quantitative research requirements [30]. The unprocessed data from the online questionnaire was entered into the software, where it underwent first inspections for any inconsistencies, extreme values, or missing entries. Following the screening process, the data was determined to be suitable for analysis. Various statistical tests were employed, taking into account the nature of the data and the research goals. Descriptive statistics, including measures such as mean, median, mode, and standard deviation, offer a comprehensive summary of the central patterns and the variability of the responses. Statistical inference techniques, such as t-tests and analysis of variance (ANOVA), were utilized to determine disparities between groups, particularly in relation to different sectors within the manufacturing business. Researchers used correlational analyses to find the strength and direction of correlations between variables. This is important for understanding how the use of AI affects different parts of supply chain sustainability. The utilization of SPSS's robust statistical tools in this study has played a crucial role in analyzing the quantitative data and deriving meaningful and important conclusions on the impact of AI on improving supply chain sustainability in Turkey's manufacturing sectors.

8: Experiment Results and Discussion

8.1: Data Reliability

Data reliability is of utmost importance in any academic research. Data dependability pertains to the uniformity and steadfastness of the data gathered during the investigation. A strong level of dependability suggests that the research findings can be reproduced and are not a result of random occurrences, hence enhancing the study's credibility and validity.

Table 1 Data reliability.

Variables	Cronbach's Alpha	No. of Items.
AI (Artificial Intelligence)	.919	4
Demand Risks	.719	4
Supply Risks	.918	4
Paragraph	.979	20

The reliability statistics for the variables under study are presented in Table 1. Cronbach's alpha values are employed to evaluate the internal consistency of the items that represent each variable. Generally, a Cronbach's alpha score greater than 0.7 is deemed acceptable for research purposes. All variables demonstrate good reliability, with 'AI (Artificial Intelligence)' getting an alpha coefficient of 0.919 and 'Paragraph' attaining the highest reliability at 0.979. Except for 'Paragraph', each variable comprises 2 elements, but 'Paragraph' includes 12 items. The table highlights the strength and reliability of the research tool, guaranteeing the uniformity and reliability of the data gathered for this study.

8.2: Respondents' Profile

This section presents a concise summary of the demographic and organizational attributes of the individuals included in the paper. The data includes information on the respondents' age group, educational background, years of operation, and industry classification. This information provides contextual details to comprehend the varied backgrounds of the respondents.

Table 2 Industry type/segment.

		Frequency	Percentage	Valid Percent	Cumulative Percent
Valid	Automotive	51	14.6	14.6	14.6
	Textiles	35	10.0	10.0	24.6
	Electronics	77	22.0	22.0	46.6
	Food and Beverages	36	10.3	10.3	56.9
	Chemicals & Petrochemicals	39	11.1	11.1	68.0
	Metal & Machinery	39	11.1	11.1	79.1
	Pharmaceuticals & Biotechnology	38	10.9	10.9	90.0
	Agricultural Machinery & Equipment	35	10.0	10.0	100.0
	Total	350	100.0	100.0	

Table 2 illustrates the categorization of participants according to their industry type or segment. Among the 350 participants, the electronics industry is the most well-represented, with 77 respondents, making up 22% of the total. The automotive sector closely follows, with 51 respondents, accounting for 14.6%. The sectors of textiles, food and beverages, chemicals and petrochemicals, metal and machinery, pharmaceuticals and biotechnology, and agricultural machinery and equipment are evenly distributed, with each sector representing between 10% and 11.1% of the total respondents. The cumulative percent column displays the entire percentage distribution, which reaches 100%, indicating that all industry segments have been comprehensively included in this analysis. This table provides a thorough understanding of the various industry backgrounds of the participants in the study.

Table 3 Company size (in term of employee's number).

		Frequency	Percentage	Valid Percent	Cumulative Percent
Valid	Less than 50	83	23.7	23.7	23.7
	50 to less than 100	69	19.7	19.7	43.4
	100 to less than 150	114	32.6	32.6	76.0
	150 and above	84	24.0	24.0	100.0
	Total	350	100.0	100.0	

Table 3 provides a systematic analysis of the participants' enterprises, categorized according to the number of employees they have. Out of the 350 enterprises that took part, 23.7% (83 companies) have less than 50 employees. Respondents included 69 organizations, representing 19.7% of the total, with employee counts ranging from 50 to less than 100. The most significant category consists of enterprises with a workforce ranging from 100 to less than 150 employees, representing 32.6% or 114 companies. In conclusion, there are 84 enterprises, which account for 24% of the total, that have 150 employees or more. The cumulative percent column provides a continuous total, guaranteeing a thorough depiction of all size groups. The table offers useful insights on the diverse magnitudes of the participant companies in the study.

Table 4 Years in operation.

		Frequency	Percentage	Valid Percent	Cumulative Percent
Valid	Less than 5 years	69	19.7	19.7	19.7
	5 to less than 10 years	118	33.7	33.7	53.4
	10 to less than 15	92	26.3	26.3	79.7
	15 and above	71	20.3	20.3	100.0
	Total	350	100.0	100.0	

Table 4 presents a comprehensive representation of the participating companies, categorized according to their operating lifetime. Out of the 350 companies that were examined, 69 companies, which account for 19.7% of the total, have been in operation for less than 5 years. Subsequently, there is a substantial portion of organizations, specifically 118 in total (33.7%), that have been in operation for a period ranging from 5 to less than 10 years. The following category features enterprises that have been operational for a duration of 10 to less than 15 years, accounting for 26.3%, or a total of 92 companies. Furthermore, a total of 71 enterprises, which represents 20.3% of the total, have been in existence for 15 years or more. The cumulative percentage column displays a gradually increasing total, affirming the inclusive portrayal of enterprises throughout various operational time frames. This table clarifies the diverse levels of experience among the organizations participating in the survey.

Table 5 Educational background.

		Frequency	Percentage	Valid Percent	Cumulative Percent
Valid	Diploma	52	14.9	14.9	14.9
	Bachelors	128	36.6	36.6	51.4
	Master's	93	26.6	26.6	78.0
	Ph.D.	77	22.0	22.0	100.0
	Total	350	100.0	100.0	

Table 5 provides a clear explanation of the educational qualifications of the participants in the study. Among the 350 participants, there are 52 individuals who possess a diploma, accounting for 14.9% of the total. The majority of respondents, comprising 36.6% of the sample, or 128 people, hold a bachelor's degree. Next in line are respondents holding a Master's degree, accounting for 26.6%, or 93 persons. Significantly, 22%, or 77 participants in the study, possess a Ph.D. degree. The cumulative % column ensures a thorough encapsulation of all educational levels by providing a continual accumulation. This table provides essential information on the varied educational degrees of the participants, showcasing a wide range of academic backgrounds.

Table 6 Age group.

		Frequency	Percentage %	Valid Percent	Cumulative Percent
Valid	18-24	104	29.7	29.7	29.7
	25-34	83	23.7	23.7	53.4
	35-44	106	30.3	30.3	83.7
	45 and above	57	16.3	16.3	100.0
	Total	350	100.0	100.0	

Table 6 provides a detailed analysis of the survey participants categorized by their age groups. Out of the total of 350 participants, a significant number of 104 persons, which is equivalent to 29.7%, belong to the age group of 18–24. There are 83 respondents in the age group of 25–34 years, which makes up 23.7% of the total. Notably, the age group of 35–44 has a significantly larger portion of the sample, consisting of 106 individuals, which accounts for 30.3% of the total. The age category of 45 and above comprises the smallest group, with 57 participants, or 16.3% of the total. The cumulative % column successively aggregates the data, ensuring that all age categories are effectively captured. This table provides insight into the age demographics of the participants in the study, showcasing a diverse range of ages.

Table 7 Gender.

		Frequency	Percentage	Valid Percent	Cumulative Percent
Valid	Male	160	45.7	45.7	45.7
	Female	190	54.3	54.3	100.0
	Total	350	100.0	100.0	

Table 7 provides a concise depiction of the distribution of genders among the respondents. Among the 350 participants, 160 of them are male, accounting for 45.7% of the sample. In contrast, the female population accounts for a significantly greater proportion, with 190 participants representing 54.3% of the total. The cumulative percentage column verifies the inclusive distribution, with the male percentage reaching its highest point at 45.7% and the female percentage completing the total at 100%. This table highlights an almost equal gender distribution in the study, with a slight majority of female participants. This distribution ensures a comprehensive viewpoint, guaranteeing that the obtained insights accurately represent both gender demographics.

8.3: Descriptive Analysis

This section is dedicated to presenting the statistical results of the research. It will encompass the findings from the Normality test, provide insights into the Mean and standard deviation values, and elucidate the Correlations identified among the variables. These analyses are crucial for understanding the data's underlying patterns and relationships.

Table 8 Normality test.

	Shapiro-Wilk		
	Statistic	df	Sig.
AI (Artificial Intelligence)	.895	350	.069
Demand Risks	.945	350	.164
Supply Risks	.895	350	.072

Table 8 presents the outcomes of the Shapiro-Wilk test, a commonly employed technique for evaluating the normality of data distributions. The variable 'AI (Artificial Intelligence)' has a Shapiro-Wilk statistic of.895 and a significance value of.069, suggesting a distribution that is close to normal. Comparable near-normal patterns are evident for 'Supply Risks and Performance' with a correlation coefficient of.895. The variable 'Demand Risks and Performance' has a statistic of.945, indicating a stronger adherence to a normal distribution. It is worth mentioning that all the significance values are higher than the usual threshold of 0.05, indicating that the distributions do not vary significantly from normality. This enhances the credibility of future statistical analyses conducted with this data.

Table 9 Mean and std. deviation.

	Mean	N	Std. Deviation
AI (Artificial Intelligence)	3.3600	350	1.35115
Demand Risks	3.5171	350	1.00396
Supply Risks	3.4207	350	1.24460

Table 9 provides a clear and detailed overview of the average values and spread of each variable in the study. The term 'AI (Artificial Intelligence)' has a mean value of 3.3600, representing the average response on the scale. It also has a standard deviation of 1.35115, which indicates the extent of variability in the replies around this average number. The 'Demand Risks and Performance' data set has a somewhat higher average of 3.5171 and a lower standard deviation of 1.00396, indicating a more focused range of responses. The mean values of the variables 'Supply Risks and Performance'. Their respective standard deviations indicate diverse levels of dispersion around these means. As a whole, this table offers a brief summary of the average responses and their distribution for each variable.

Table 10 Correlations.

		AI (Artificial Intelligence)	Demand Risks	Supply Risks
AI (Artificial Intelligence)	Pearson Correlation	1	.886**	.876**
	Sig. (2-tailed)		.000	.000
	N	350	350	350
Demand Risks	Pearson Correlation	.886**	1	.822**
	Sig. (2-tailed)	.000		.000
	N	350	350	350
Supply Risks	Pearson Correlation	.876**	.822**	1
	Sig. (2-tailed)	.000	.000	
	N	350	350	350
**. Correlation is significant at the 0.01 level (2-tailed).				

Table 10 displays the Pearson correlation coefficients between the study variables, providing information on their interrelationships. The diagonal of the matrix indicates a perfect correlation of 1 for each variable with itself, as anticipated. All correlations are statistically significant at the 0.01 level, as shown by the double asterisks (**). The AI variable demonstrates significant positive correlations with all other components. Additional variables, such as 'Supply Risks and Demand Risk, also exhibit a strong correlation of.900. The p-values (Sig. 2-tailed) for all correlations are.000, indicating the strong and significant nature of these associations. This table demonstrates significant positive interdependencies across the variables, emphasizing their interrelated nature within the study's environment.

Table 11 Inter-item correlation matrix.

	AI (Artificial Intelligence)	Demand Risks	Supply Risks
AI (Artificial Intelligence)	1.000	.886	.876
Demand Risks	.886	1.000	.822
Supply Risks	.876	.822	1.000

The inter-item correlation matrix for the study's variables is presented in Table 11, offering information about the extent of linear associations among them. The diagonal, with values of 1.000, signifies the ideal correlation of each variable with itself. The variable 'AI (Artificial Intelligence)' shows significant positive correlations with all other measures. This matrix highlights that although each variable retains its individual characteristics, there are substantial linear connections between them. Different links emphasize the possible impact and interaction of different factors in the setting being researched.

Table 12 Inter-item covariance matrix.

	AI (Artificial Intelligence)	Demand Risks	Supply Risks
AI (Artificial Intelligence)	1.826	1.202	1.473
Demand Risks	1.202	1.008	1.027
Supply Risks	1.473	1.027	1.549

Table 12 presents the inter-item covariance matrix for the variables in the study, providing insight into the co-variation between the variables. Covariance denotes the orientation of the linear correlation between two variables. The covariances of AI (artificial intelligence) range from 1.202 (with 'Demand Risks and Performance') to 1.826 (with itself). With a value of 1.854. This means that the two variables are significantly related. 'Supply Risks and Performance' exhibits a covariance of 1.549 with itself. This matrix enhances comprehension of the relationship between variables, highlighting the crucial component of understanding interdependencies in the study.

Table 13 Summary item statistics.

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	No. of Items
Item Means	3.378	3.166	3.517	.351	1.111	.017	5
Item Variances	1.651	1.008	1.973	.965	1.957	.155	5
Inter-Item Covariances	1.447	1.027	1.854	.827	1.805	.093	5
Inter-Item Correlations	.883	.782	.957	.175	1.224	.004	5

Table 13 presents a succinct overview of the item statistics for the variables examined in the study. The item's mean value is 3.378, with a minimum of 3.166 and a high of 3.517, resulting in a range of.351. The item means exhibit a maximum-to-minimum ratio of 1.111, while the variation across the 5 items is.017. Regarding item variances, the average value is 1.651, and the range is.965, suggesting a significant dispersion of data. The average inter-item covariances are 1.447, with a variance of.093. The average inter-item correlations are.883, indicating a strong linear relationship between the items. This table presents a detailed overview, emphasizing important statistical measures for items, which is crucial for comprehending the distribution, variability, and correlations among the variables studied.

Table 14 ANOVA.

<table>
<tr><th colspan="2"></th><th>Sum of Squares</th><th>df</th><th>Mean Square</th><th>F</th><th>Sig</th></tr>
<tr><td colspan="2">Between People</td><td>2595.598</td><td>349</td><td>7.437</td><td></td><td></td></tr>
<tr><td rowspan="3">Within People</td><td>Between Items</td><td>24.196</td><td>4</td><td>6.049</td><td>29.561</td><td>.000</td></tr>
<tr><td>Residual</td><td>285.654</td><td>1396</td><td>.205</td><td></td><td></td></tr>
<tr><td>Total</td><td>309.850</td><td>1400</td><td>.221</td><td></td><td></td></tr>
<tr><td colspan="2">Total</td><td>2905.448</td><td>1749</td><td>1.661</td><td></td><td></td></tr>
<tr><td colspan="7">Grand Mean = 3.3784</td></tr>
</table>

Table 14 displays the outcomes of an analysis of variance (ANOVA) performed to evaluate disparities among individuals in relation to the items being examined. The variation "Between People" has a sum of squares of 2595.598 with 349 degrees of freedom, resulting in a mean square of 7.437. In the "Within People" category, the variance known as "Between Items" has a total of squares equal to 24.196. The mean square is calculated as 6.049, resulting in an F-statistic of 29.561. This F-statistic is significant at the 000 level. This suggests that there are statistically significant disparities among the items. The intra-individual residual variance is 285.654. The overall dataset has a grand mean of 3.3784. This table offers a thorough comprehension of the variability seen among persons and things, emphasizing noteworthy distinctions at the item level.

Table 15 Hotelling's T-Squared Test.

Hotelling's T-Squared	F	df1	df2	Sig
185.112	45.880	4	346	.000

Table 15 displays the outcomes of Hotelling's T-Squared Test, which is a statistical technique used to identify significant variations in means between two groups on several dependent variables. The test statistic value for Hotelling's T-squared is 185.112, resulting in an F-statistic of 45.880. The degrees of freedom (df1) are 4 and (df2) are 346, indicating a significance level (Sig) of.000. The exceptionally small p-value indicates that the observed disparities have statistical significance. This table demonstrates significant multivariate differences between the groups being studied, hence strengthening the importance and credibility of the observed contrasts within the research setting.

8.4: Hypotheses Analysis Results

This section elucidates the findings from the data analysis pertaining to the proposed hypotheses. Through rigorous statistical methods, the subsequent pages will unveil insights into the relationships and patterns under investigation, offering a comprehensive understanding of the dynamics between the variables in question.

H1: AI has a positive impact on reducing demand risk.

Table 16 Correlations-H1**.**

		AI (Artificial Intelligence)	Demand Risks
AI (Artificial Intelligence)	Correlation Coefficient	1.000	.891**
	Sig. (2-tailed)	.	.000
	N	350	350
Demand Risks	Correlation Coefficient	.891**	1.000
	Sig. (2-tailed)	.000	.
	N	350	350
**. Correlation is significant at the 0.01 level (2-tailed).			

Table 17 Model summary-H1.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.886a	.786	.785	.46538
a. Predictors: (Constant), AI (Artificial Intelligence)				

Table 18 ANOVA-H1.

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	276.404	1	276.404	1276.256	.000b
	Residual	75.368	348	.217		
	Total	351.772	349			
a. Dependent Variable: Demand Risks						
b. Predictors: (Constant), AI (Artificial Intelligence)						

Table 19 Coefficients –H1.

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.304	.067		19.535	.000
	AI (Artificial Intelligence)	.659	.018	.886	35.725	.000
a. Dependent Variable: Demand Risks						

The analysis aims to examine hypothesis H1, which suggests that artificial intelligence (AI) has a beneficial impact on mitigating demand concerns. The results obtained from the several tables provide deep insights into this relationship. Starting with the Correlations-H1 table, there is a significant positive association between AI and demand risks, as indicated by a Pearson correlation coefficient of.891. The high coefficient indicates a robust linear correlation between the deployment of AI and its effect on reducing demand risks. The statistical significance of this correlation is emphasized by a p-value (Sig.) of.000, which is far lower than the customary threshold of 0.01, providing further confirmation of the strength and reliability of this association. Examining the model summary (H1), the R value of.886 indicates a strong correlation between the observed and anticipated outcomes of the model. The R square value of.786 indicates that AI can explain approximately 78.6% of the variance in demand risks, highlighting the significant impact of AI. The adjusted R square only decreased by 0.785, which demonstrates the model's strong ability to predict the result considering the number of predictors. The estimate has a standard error of.46538, indicating the differences between the observed values and the projected values of the model. The ANOVA-H1 table provides additional confirmation of the model's predictive ability. The F-value, which is an impressive 1276.256, when compared to a p-value (Sig.) of.000, clearly demonstrates the statistical significance of the regression model. The discrepancy between the regression sum of squares (276.404) and the residual sum of squares (75.368) highlights the effectiveness of the model in accounting for the variability. Finally, the Coefficients-H1 table provides valuable information about the nature and intensity of the correlation between AI and demand risks. The unstandardized coefficient (B) of.659 indicates that there is a direct relationship between an increase in AI and a commensurate rise of.659 units in the decrease of demand risks. The standardized coefficient (Beta) of.886 enhances the effectiveness of AI as a strong predictor. The t-value of 35.725, along with a p-value (Sig.) of 0.000, confirms the statistical relevance of AI in anticipating demand hazards. Overall, the data analysis strongly confirms hypothesis H1. The findings, which encompass correlation and regression analyses, convincingly assert that AI is essential in reducing demand risks. This highlights the capacity of AI not only as an impressive technological advancement but also as a strategic instrument that can be utilized to tackle and diminish uncertainties in demand. This is a vital factor for firms that aspire to achieve sustainable growth and resilience.

H2: AI has a positive impact on reducing supply risk.

Table 20 Correlations-H2.

			AI (Artificial Intelligence)	Supply Risks and Performance
	AI (Artificial Intelligence)	Correlation Coefficient	1.000	.869**
		Sig. (2-tailed)	.	.000
		N	350	350
	Supply Risks and Performance	Correlation Coefficient	.869**	1.000
		Sig. (2-tailed)	.000	.
		N	350	350
**. Correlation is significant at the 0.01 level (2-tailed).				

Table 21 Model summary-H2.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.876a	.767	.766	.60189
a. Predictors: (Constant), AI (Artificial Intelligence)				

Table 22 ANOVA –H2.

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	414.542	1	414.542	1144.290	.000b
	Residual	126.070	348	.362		
	Total	540.612	349			
a. Dependent Variable: Supply Risks						
b. Predictors: (Constant), AI (Artificial Intelligence)						

The analysis aims to examine hypothesis H2, which suggests that artificial intelligence (AI) has a beneficial effect on mitigating supply risk. Upon examining the correlations-H2 table, it becomes apparent that there is a significant positive linear correlation between AI and both supply risks and performance. The Pearson correlation value of.869 indicates a strong and reliable link between the two variables. The p-value of.000 supports the statistical significance of this correlation at the 0.01 level. The R-value of.876 in the model summary-H2 section suggests a strong connection between the observed and predicted values. The strong link indicates that AI is a substantial predictor of both supply risks and performance. In addition, the R square value of.767 indicates that approximately 76.7% of the variability in supply risks can be accounted for by AI. The adjusted R square has decreased slightly to 0.766, indicating that a significant percentage of the explained variation is still accounted for, considering the number of variables. The standard error of the estimate, which is.60189, indicates the degree of dispersion of scores around the projected values. Turning our attention to the ANOVA-H2 table, we obtain further statistical insights. The regression model demonstrates a high F-value of 1144.290 and a significance level of.000, indicating its strong predictive ability compared to the mean. It's crucial to note the contrast between the regression sum of squares (414.542), which represents the variation that the model describes, and the residual sum of squares (126.070), which denotes the remaining unexplained variation. The obvious delineation emphasizes the effectiveness of AI as a prediction tool in this particular setting. To summarize, the data analysis strongly supports hypothesis H2. The correlation, model summary, and ANOVA combined emphasize the substantial impact of AI in forecasting and perhaps mitigating supply issues. The results show that using AI-driven strategies and solutions can significantly help businesses and organizations trying to reduce supply risks. The evidence provided, derived from rigorous statistical testing, confirms the revolutionary capacity of AI to reconfigure supply chain dynamics and improve performance outcomes.

9: Conclusion

This paper delves into the culmination of our study titled "Risk Management: the role of AI on supply chain sustainability performance among manufacturing industries of Turkey." Herein, we present the conclusions drawn, implications for the industry, limitations encountered, and potential directions for future research. The inquiry into the influence of artificial intelligence (AI) on mitigating demand uncertainties has produced interesting observations. Clearly, AI has a crucial function in reducing these risks, emphasizing its transformational capacity in the field of demand management. Businesses frequently struggle with uncertainties in demand, which can hinder their strategic planning, inventory management, and overall profitability. The results of this investigation highlight the significant benefits that AI provides in tackling these difficulties, acting as a powerful instrument that can forecast, examine, and subsequently reduce risks associated with demand. Hence, it is evident that incorporating AI into corporate operations is not just a technology enhancement but a crucial strategic necessity to promote resilience and sustainability. The inquiry into the influence of artificial intelligence (AI) on mitigating demand uncertainties has produced fascinating revelations. Clearly, AI has a crucial function in reducing these risks, emphasizing its revolutionary capacity in the field of demand management. Businesses frequently struggle with uncertainties in demand, which can hinder their strategic planning, inventory management, and overall profitability. The results of this investigation emphasize the significant benefits that AI provides in tackling these difficulties, acting as a powerful instrument that can forecast, examine, and subsequently reduce risks associated with demand. Hence, it is evident that incorporating AI into corporate operations is not just a technology enhancement but a crucial strategic necessity to promote resilience and sustainability. The inquiry into the influence of artificial intelligence (AI) on mitigating demand uncertainties has produced convincing revelations. Clearly, AI has a crucial function in reducing these risks, emphasizing its revolutionary capacity in the field of demand management. Businesses frequently struggle with uncertainties in demand, which can hinder their strategic planning, inventory management, and overall profitability. The results of this investigation highlight the significant benefits that AI provides in tackling these difficulties, acting as a powerful instrument that can forecast, examine, and subsequently reduce risks associated with demand. Hence, it is evident that incorporating AI into corporate operations is not just a technological enhancement but a crucial strategic necessity to promote resilience and sustainability. The inquiry into the influence of artificial intelligence (AI) on mitigating demand uncertainties has produced convincing revelations. Clearly, AI has a crucial role in reducing these risks, emphasizing its ability to bring about significant changes in the field of demand management. Businesses frequently struggle with uncertainties in demand, which can hinder their strategic planning, inventory management, and overall profitability. The results of this investigation highlight the significant benefits of AI in tackling these difficulties, as it acts as a powerful instrument that can forecast, examine, and subsequently reduce risks associated with demand. Therefore, it is evident that incorporating AI into corporate operations is not just a technological enhancement but a crucial strategic necessity to promote resilience and sustainability.

The research on the impact of artificial intelligence (AI) on demand risks has yielded substantial results. Artificial intelligence (AI) plays a vital role in mitigating these risks, demonstrating its groundbreaking ability to manage demand. Numerous enterprises encounter volatile demand patterns, which impact their strategy choices, inventory management, and financial gain. This analysis highlights the significant advantage of AI in addressing these problems. AI is a potent tool that can not only forecast and analyze but also mitigate risks linked to demand. Hence, the incorporation of AI into corporate operations represents more than just technological progress. This is an important strategic decision to improve the ability to recover quickly and ensure continued success in the future. The integration of AI assists organizations in effectively managing uncertain demand, optimizing inventories, and improving overall business sustainability. The crucially of AI in contemporary corporate strategy goes beyond its technological aspects.

10: Implications

The discoveries have far-reaching and significant ramifications. For organizations, using AI can revolutionize demand forecasting by enabling more precise and efficient projections. Consequently, this can result in improved inventory control, streamlined supply chains, and decreased operational expenses. Furthermore, by mitigating demand uncertainties, organizations can strengthen their competitive edge, guaranteeing timely and effective fulfillment of consumer requirements. AI-driven analytics can provide valuable insights that can be used to make important business choices, such as those related to product development and market entry tactics. Furthermore, firms that utilize AI to reduce demand risks demonstrate a forward-thinking strategy, thereby enhancing trust and confidence in the brand among stakeholders, including investors and consumers. Within the larger economic context, the extensive implementation of AI for demand risk management has the potential to result in more stable markets, less inefficiency, and improved consumer contentment. As industries progress in the digital era, the focus on AI as a means to decrease demand risks will certainly increase, leading to more robust, effective, and environmentally friendly corporate ecosystems.

The discoveries have far-reaching and significant ramifications. Integrating AI into enterprises can have a transformative impact on demand forecasting, enabling more precise and efficient projections. Consequently, this can result in improved inventory control, streamlined supply networks, and decreased operational expenses. Furthermore, by mitigating demand uncertainties, organizations can strengthen their competitive edge, guaranteeing they fulfill consumer requirements swiftly and effectively. AI-driven analytics can provide valuable insights that help guide important company choices, ranging from product development to market entry tactics, from a strategic perspective. Additionally, for stakeholders, from investors to consumers, businesses leveraging AI to mitigate demand risks signal a forward-thinking approach, reinforcing trust and confidence in the brand. Widespread implementation of AI for demand risk management in the overall economic context can result in more stable markets, decreased inefficiency, and improved consumer contentment. In the digital era, as companies progress, there will be an increasing focus on utilizing AI as a means to decrease the risks associated with demand. This will lead to the development of more robust, streamlined, and environmentally friendly corporate ecosystems.

The discoveries have far-reaching and significant ramifications. Integrating AI into enterprises can significantly impact demand forecasting, enabling more precise and efficient projections. Consequently, this can result in improved inventory control, streamlined supply networks, and decreased operational expenses. Moreover, by reducing demand risks, companies can enhance their competitive advantage, ensuring they meet customer needs promptly and efficiently. From a strategic viewpoint, the insights drawn from AI-driven analytics can inform critical business decisions, from product development to market entry strategies. Additionally, for stakeholders, from investors to consumers, businesses leveraging AI to mitigate demand risks signal a forward-thinking approach, reinforcing trust and confidence in the brand. Widespread implementation of AI for demand risk management in the overall economic context can result in more stable markets, decreased inefficiency, and improved consumer contentment. As industries continue to evolve in the digital age, the emphasis on AI as a tool to reduce demand risks will undoubtedly intensify, paving the way for more resilient, efficient, and sustainable business ecosystems.

The implications of these findings are multifaceted and profound. Integrating AI into enterprises can significantly impact demand forecasting, enabling more precise and efficient projections. Consequently, this can result in improved inventory control, streamlined supply networks, and decreased operational expenses. Furthermore, by mitigating demand uncertainties, organizations can strengthen their competitive edge, guaranteeing timely and effective fulfillment of consumer requirements. AI-driven analytics can provide valuable insights that help guide important company choices, ranging from product development to market entry tactics, from a strategic perspective. Additionally, for stakeholders, from investors to consumers, businesses leveraging AI to mitigate demand risks signal a forward-thinking approach, reinforcing trust and confidence in the brand. Widespread implementation of AI for demand risk management in the overall economic context can result in more stable markets, decreased inefficiency, and improved consumer contentment. As industries continue to evolve in the digital age, the emphasis on AI as a tool to reduce demand risks will undoubtedly intensify, paving the way for more resilient, efficient, and sustainable business ecosystems.

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