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RESEARCH ARTICLE / ARAŞTIRMA MAKALESİ

A study on the impact of artificial intelligence on demand forecasting in food industries

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Abstract

This study examines how artificial intelligence (AI) is transforming the food supply chain by improving forecasting, demand planning, and operational efficiency. AI technologies like predictive analytics and machine learning enhance accuracy and responsiveness but face challenges such as data quality, system integration, and high costs. By surveying 370 food industry professionals, the research explores the benefits and barriers of AI adoption, providing actionable insights to optimize supply chain processes. The findings aim to support businesses and policymakers in leveraging AI strategically for competitive advantage and supply chain resilience.

Keywords: Artificial Intelligence, Supply Chain, Food Industry, Forecasting, Demand Planning.

JEL codes: M10, M150, M110, M210

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1. INTRODUCTION

Supply Chain Management (SCM) is a heterogeneous process used in the food industry to navigate the complex operations of getting food to the final consumer In many other industries food supply makes it especially challenging, because food perishes and food safety is of utmost importance (Johnston, 2019) There is a need to adhere to strict quality control procedures throughout the supply chain (Smith et al., 2020) . SCM in the food industry from farm to pan must be well planned to ensure quality while maintaining quality and safety standards (Gupta & Sharma, 2018). In addition, the food supply chain must be flexible and sensitive to changes in the market due to factors such as seasons and changes in demand. Using a cold chain is also key, and many foods need a temperature-controlled environment to stay fresh. Traceability and transparency are becoming increasingly important, with consumers demanding knowledge of the origin and transport of their food. Furthermore, sustainable development and ethical outcomes emerge as important considerations, driving improvements in waste reduction, environmental design, and enforcement of appropriate business practices Technology adoption accelerates SCM transformation in the food industry, better forecasting, inventory management, supply chain partners and enables interoperability between them In this case a in this dynamic context, it is imperative that the SCM is effective to meet customer expectations for food safety, and sustainable sourcing , and, in order to increase efficiency and control risks attached.

According to Mentzer et al. (2001), "A supply chain is the network of organizations that are involved, through upstream and downstream linkages, in the different processes and activities that produce value in the form of products and services delivered to the ultimate consumer". To work well in the complex environments in which supply chains operate—and to create more sharp and flexible supply chains these processes, and activities require monitoring, forecasting, prediction, and optimization.

In recent years, applications based on artificial intelligence (AI) have emerged in several different fields including supply chains (Borges et al., 2020).

2. LITERATURE REVIEW

2.1. Historical Evolution of Supply Chain Management

Supply Chain Management (SCM) has progressed significantly over the years and created key milestones. Initially, SCM was primarily focused on optimizing individual functions within organizations, such as inventory management and procurement. However, the concept of SCM as we know it today began to take shape in the late 20th century with the emergence of incorporated supply chain systems (Mentzer et al., 2001).

One of the earliest milestones in SCM was the introduction of Material Requirements Planning (MRP) systems in the 1960s, which enabled manufacturers to better plan and manage their production processes (Forrester, 1958). This was followed by the development of Enterprise Resource Planning (ERP) systems in the 1990s, which integrated various business functions including production, finance, and logistics into a single cohesive system (Davenport, 1998).

The 21st century saw the rise of globalization and the increasing complexity of supply chains, leading to the need for more sophisticated SCM practices. Technological advancements such as the internet, RFID (Radio Frequency Identification), and cloud computing revolutionized supply chain processes, enabling real-time visibility and collaboration across global networks (Gunasekaran et al., 2008).

The concept of supply chain integration also got notable achievements during these times, focusing on collaboration and effective communication among the supply chain partners leading to more efficient processes (Lambert et al., 1998). This shift towards integration was further accelerated by the advent of supply chain digitization and the rise of e-commerce platforms, which transformed traditional supply chain models and enabled new forms of customer-centricity and agility (Lee, 2000).

Today, SCM continues to evolve rapidly with the development of emerging technologies. These technologies offer new opportunities for automation, optimization, and risk management within supply chains, further reshaping the landscape of SCM in the digital age (Kamble et al., 2014).

The integration of the supply chain has been of substantial importance in today's world for every organization. The systematic communication and collaboration among the employees and stakeholders has reduced the downtime remarkably. Moreover, a well-organized supply chain network can achieve notable progress in the financial health of the organization. A structured supply chain has become one of the most important pillars of any business and can also be the source of competitive advantage for the organizations. Especially, in terms of planning, studies have shown that a well-planned organization has less amount of waste of resources as compared to an unplanned organization. A satisfactory utilization of resources can be achieved through systematic planning and a collaborative supply chain plays an important role in it.

2.2. Traditional Approaches vs AI

Traditional SCM methodologies often rely on deterministic models and heuristic algorithms to optimize supply chain processes. These approaches are effective to a certain extent but are limited in their ability to handle the complexity and uncertainty inherent in modern supply chains. For example, traditional forecasting methods such as time series analysis and exponential smoothing may struggle to accurately predict demand patterns in volatile markets or for products with erratic sales patterns (Chopra & Meindl, 2016)

Conversely, AI-driven approaches leverage advanced machine learning algorithms, such as neural networks, decision trees, and reinforcement learning, to analyse large volumes of data and extract valuable insights. By harnessing the power of AI, supply chain managers can gain deeper visibility into demand patterns, identify hidden correlations, and make more informed decisions in real-time (Chen et al., 2020). For instance, AI-driven demand forecasting models can incorporate multiple variables, including economic indicators, social media sentiment, and weather forecasts, to generate more accurate predictions compared to traditional methods.

One of the key limitations of traditional SCM methodologies is their reliance on static, rule-based models that may fail to adapt to changing market conditions or unforeseen disruptions. In contrast, AI-driven approaches offer greater flexibility and adaptability by continuously learning from new data and adjusting their models accordingly (Verhoef & Kotler, 2020). This dynamic nature of AI allows supply chain managers to respond quickly to changing demand patterns, optimize inventory levels, and mitigate risks in real-time.

Furthermore, integrating AI models into SCM processes can unlock several potential benefits, including improved forecast accuracy, reduced inventory holding costs, enhanced customer satisfaction, and increased operational efficiency (Chen et al., 2020). AI-driven optimization algorithms can identify optimal routes for transportation, minimize lead times, and optimize production schedules, leading to cost savings and productivity gains across the supply chain.

2.3. Artificial Intelligence and Supply Chain Management

In recent years, data has shown that many businesses were forced to close due to not being able to keep up with the technological advancements and rapid changes in today's world. Conventional methods of the supply chain have been obsolete and organizations following those and not developing technological infrastructures might be able to lose their market share and eventually face permanent shutdowns. For instance, Nokia went out of business because they did not give importance to consumer behavior and were unable to follow up with the technology but organizations like Amazon was able to make most of the business through their efficient supply chain and better technology advancement which eventually lead them to streamline their revenue and increasing financial health of the organization.

In today's world, artificial intelligence plays a vital role in managing the supply chain. Technology in every era has been crucial for organizations if the organization maintains the progress in technology as time passes the world advances and more researches take place, the researchers come up with more advanced ways to manage the businesses. Baryannis, Validi, et al. (2019) have disclosed that AI-based Supply chain management can help the organization improve their decision skills moreover it can also make decisions based on the previous history of any operation because an AI-based supply chain has the attribute of learning through self-study.

Artificial Intelligence (AI) finds extensive application across multiple facets of Supply Chain Management (SCM), revolutionizing traditional practices and enhancing operational efficiency. In demand forecasting, AI-driven models analyse vast datasets and external factors to generate accurate predictions. For instance, Duan, Gu, and Whinston (2020) demonstrate the efficacy of machine learning approaches in retail sales forecasting, exemplifying how Walmart employs AI to optimize inventory planning and mitigate stockouts. Inventory management benefits from AI's ability to analyze demand patterns and optimize stock levels dynamically. Amazon's Autonomous Mobile Robots (AMRs), guided by AI algorithms, navigate warehouses efficiently, leading to enhanced productivity and reduced operational costs (Amazon, 2022). Logistics optimization, a crucial SCM component, leverages AI to optimize transportation routes and scheduling. UPS utilizes AI-based route optimization algorithms to streamline package delivery, minimizing fuel consumption and reducing environmental impact (UPS, 2012). Supplier selection, another critical aspect, benefits from AI's analytical prowess. IBM's Watson Supply Chain Insights employs AI to evaluate supplier performance and mitigate risks by recommending alternative suppliers, ensuring continuity in supply chain operations (IBM, 2018). Finally, AI plays a pivotal role in risk management, proactively identifying and mitigating potential disruptions. Maersk employs AI-powered risk management tools to analyze global shipping data and geopolitical risks, enhancing supply chain resilience (Maersk, 2023). These real-world examples underscore the transformative impact of AI technologies in SCM, driving efficiency, resilience, and competitiveness.

2.4. Artificial Intelligence in Forecasting and Demand Planning

Forecasting and demand planning are critical components of supply chain management, particularly in the food industry where demand can be highly variable due to factors such as seasonality, market trends, and consumer preferences. Accurate forecasting ensures that companies can meet customer demands without overproducing, which is crucial for minimizing waste and optimizing inventory levels (Chopra & Meindl, 2016).

Artificial Intelligence has revolutionized forecasting and demand planning by enabling more accurate and efficient predictions. Machine learning algorithms. Techniques such as neural networks, regression models, and time series analysis are commonly employed (Agrawal, Gans, & Goldfarb, 2018).

3. THE STUDY

3.1. Aim of the Study

The intent of the paper is to evaluate the influence of AI utilization on the accuracy of forecasting and demand planning, as well as to investigate how the implementation of AI-driven predictive analytics tools affects supply chain responsiveness in addressing fluctuating consumer demand within the food industry.

3.2. Research Questions

This study will yield respionse to:

RQ1 How does the utilization of artificial intelligence (AI) technologies impact the accuracy of forecasting and demand planning in the food supply chain?

RQ2 How does the implementation of AI-driven predictive analytics tools influence supply chain responsiveness in meeting fluctuating consumer demand in the food industry?

3.3 Hypothesis

The hypothesis this study is going to be examining is as follows:

H1 There is a significant relationship between the utilization of AI technologies and the accuracy of forecasting and demand planning in the food supply chain.

H0 There is no significant relationship between the utilization of AI technologies and the accuracy of forecasting and demand planning in the food supply chain.

3.4. Population and Sample

The population for this study consists of individuals who meet the following criteria: they should be employed in the food industry and engaged in roles related to forecasting, planning, or management. They should be using Artificial intelligence in their company. The exclusion criteria was, that participants who were not using AI in the company were excluded. Participants that were not involved in demand planning or forecasting were excluded from the study. Data was collected from 370 participants out of which 350 participants meet the inclusion criteria therefore, 20 participants were excluded from the study. The population is estimated to include up to 350 individuals.

The sample was drawn from this population using a random sampling method, as the results from this selected sample were generalized to a larger population. The sample was representative in terms of years of experience, job position, and size of the industry they worked in. The sample included both men and women with varying levels of experience in the food industry.

The sample selection criteria were designed to ensure the relevance to the study's objectives. Companies were categorized based on their number of employees into three groups: small enterprises (fewer than 50 employees), medium-sized companies (50–500 employees), and large corporations (more than 1,000 employees). within the food industry to capture the diverse range of AI adoption levels. Participants were selected based on their direct involvement in supply chain management, including roles such as managers, planners, executives, and directors. This ensured that insights from a diverse perspective of professionals engaged in AI usage in the food industry were gathered. By incorporating a diverse sample this study aims to provide a comprehensive understanding of the role of AI in planning in the food industry.

Table 1. Respondent Demographics

Respondent Demographics	Frequency	Percentage
	n	%
Role/Job Title		
Manager	75	21.40%
Analyst	52	14.90%
Planner	74	21.10%
Executive	103	29.40%
Director	46	13.10%
Years of Experience		
Less than 1 year	8	2.30%
1-3 years	25	7.10%
4-7 years	184	52.60%
8 years or more	133	38.00%
Company size		
<50 employees	26	7.40%
50-500 employees	131	37.40%
>500 employees	193	55.10%

3.5. Instrument and Method For Data Collection

Data for this study was collected using surveys in the form of questionnaires created with Google Forms. The survey questions were structured as close-ended questions, providing respondents with a five-point Likert scale, ordinal scale, and nominal scale to select their responses. The questions were formulated in a straightforward manner as it is a quantitative study, and the questionnaire was organized into 7 sections to comprehensively address the hypotheses being tested, as well as to ensure that the research questions were sufficiently covered. These questionnaires were distributed to professionals of the food industry via the Internet, which proved to be a highly cost-effective method for collecting data from a sample size of 370 participants for statistical analysis. This method was convenient for both the participants and myself, as the forms could be accessed and completed at any time, and results could be viewed promptly.

This approach also allowed for easy standardization of data collection procedures, minimizing the potential for bias in respondents' answers.

3.6. Method of Data Analysis

Once the quantitative data was collected it was monitored and checked. Sections that represented similarity were recognized and coded. This helped in the categorization of data in a significant method and in reaching meaningful outcomes. To analyse the data, IBM SPSS (Statistical Package for Social Sciences) was used to run descriptive and correlation tests. The study employs multiple regression analysis to examine the impact of AI utilization on demand forecasting accuracy while controlling for company size, job role, and years of experience. Cronbach's alpha was used to assess the reliability of the survey instrument, ensuring internal consistency. Descriptive analysis provided summaries of key dataset characteristics, such as means and frequency distributions. These tests were chosen to validate relationships, ensure data reliability, and enhance the clarity of findings.

3.7 Limitations Of The Research

The study acknowledges potential bias, including selection bias and response bias. In order to avoid these biases, a diverse sample was selected based on company size (less than 50, 50-500, and more than 1000), years of experience, and job position. Anonymity was maintained to encourage honest responses, reducing social desirability bias. sınce the scale was in a quantitative form, self-reporting bias could not be mitigated completely. Additionally, Cronbach's alpha was used to assess internal consistency, ensuring reliability in responses.

Table 2. Perceived Impact of AI on Forecasting and Demand Planning

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.791	.791	2

Multiple regression analysis helped control for confounding variables, minimizing bias in interpreting AI's impact on demand forecasting accuracy.

In the duration of this research, several limitations were also encountered during the data collection process. There was a limitation in obtaining primary data sources. For instance, there is not a strong research culture prevalent in the Food industries, resulting in some reluctance among individuals to participate in

surveys. As a result, significant time and effort were dedicated to encouraging participation and ensuring the questionnaires were completed.

4. FINDINGS

4.1. Impact of Artificial Intelligence (AI) on Forecasting Accuracy and Demand Planning in the Food Supply Chain

In the analysis for Research Question 1, the interaction between the types of AI technologies employed in forecasting and demand planning and the perceived accuracy of these activities is examined. The study categorizes AI technologies into six types and perceived forecasting accuracy is categorized into five levels.

The regression analysis results presented in Table 3, revealed that the nature of AI technologies employed is statistically significant to the perceived accuracy of the forecasts. The results show that using an unstandardized coefficient for the type of AI technologies applied the value of B = 0.044, and the standard error is equal to 0.014, meaning the perceived forecasting accuracy increases by 0.044 units with each unit increase in the use of AI technologies. Coefficients of standardized values (Beta) =0.164 clearly connote that AI technologies deployed impact the perceived accuracy of forecasting in a positive manner, but its impact is moderate in nature. The t-statistic is 3.109, and the test statistic is statistically significant when it is less than .05, and, in this case, it is. This means that the incorporation of AI technologies leads to enhanced forecast accuracy levels. Also, considering the coefficient of the type of AI technologies used, the 95% Confidence Interval is 0.016 to 0.072; therefore, it does not include zero, making it statistically significant.

Therefore, the findings of the research are that AI-related technologies, especially if used in the integrated form, provide a positive and statistically significant impact on the perceived accuracy of the forecasts in the food supply chain. The findings of the regression analysis are consistent with the hypothesis that as the use of AI technologies increases, so will the effectiveness of forecasting and demand planning. The insights derived from this research should underscore the necessity of further AI implementation into forecasts to improve its accuracy. More subsequent research can be done to understand which kind of AI technologies is most effective in these enhancements and how AI can be adopted in an organization and enhanced for greater accurate prediction.

4.2. Employees' attitudes toward AI adoption

The bar chart illustrates the general perception of AI's role, with the majority (59%) agreeing that AI plays a significant role. A smaller portion (33.43%) remains neutral, while 5.71% strongly agree. Only a minimal percentage disagree (2.57%) or strongly disagree (0.29%), indicating an overall positive perception of AI's role.

4.3. Impact of AI-Controlled Predictive Analytics Tools on Supply Chain Reactivity in the Food Industry

Research Question 2 focuses on the examination of how the introduction of AI-controlled predictive analysis tools affects supply chain reactivity in satisfying the variable demand in

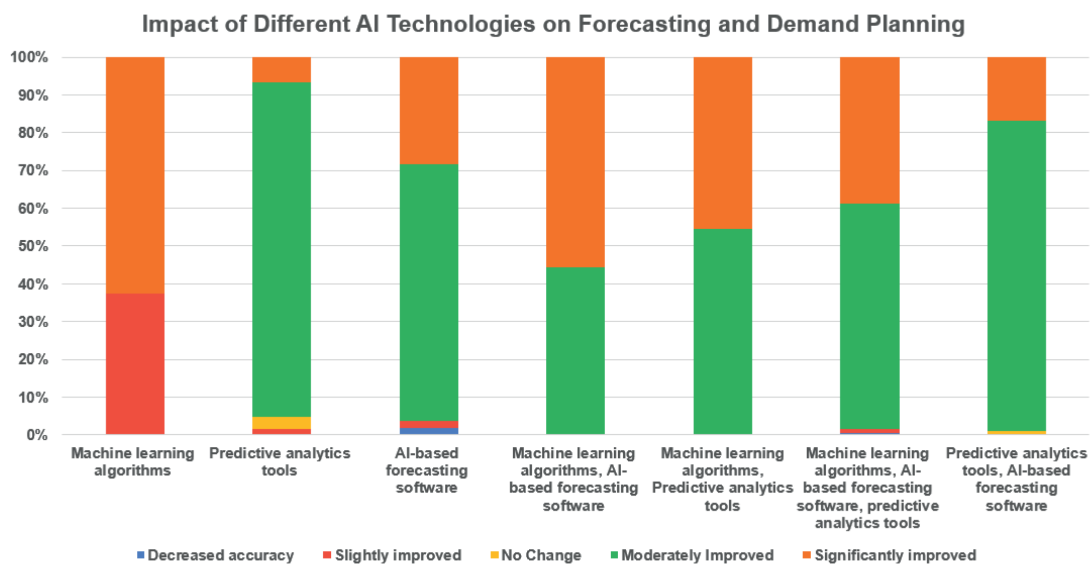

Figure 1. Impact of Different AI Technologies On Forecasting and Demand Planning

Table 3. Result of Regression Analysis RQ1

		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
Model	Type of AI technologies used	0.044	0.014	0.164	3.109	0.002	0.016	0.072

the food industry. Specifically, the regression analysis investigates the impact of the type of AI technologies used on the level of supply chain responsiveness as the dependent variable. The variable incorporated in the analysis is the use of AI technologies that broadly capture various forms of AI applications and their role in increasing firms' sensitivity to dynamics in consumer demand.

The regression results reveal a statistically significant and positive relationship between the type of AI technologies and the responsiveness of the supply chain. The unstandardized coefficient for the type of AI technologies used is B =0.031, SE = 0.014, which shows that if the use of AI technology is one unit, the corresponding increase in supply chain responsiveness is 0.031 units. The standardized coefficient (Beta) of 0.114 indicates that the proposed relationship is of a moderately positive nature for the implementation of AI technologies to improve the flexibility of the supply chain to meet the demands.

The t-statistic for this relationship is 2.147, and for its significance, the 'p-value' is estimated at 0.032, concluding the hypothesis test at a 0.05 level of significance. This proves that the adoption of AI technologies, especially predictive analytics tools, has a positive effect on supply chain responsiveness in the food industry. The p-value was found to be 0.000 less than 0.05, and the 95% Confidence Interval for the coefficient of AI technologies is 0.003 to 0.059, which excludes zero and ensures the reliability of the result. Therefore, the study presents a conclusive view that indicates that upon integration of AI predictive analytics tools, the degree of supply chain responsiveness is improved, particularly in addressing the dynamics of demand in the food industry. As signified in this study, and propping up the positivist research stance and the research hypotheses, the correlation value obtained trails in the positive direction and statistically significant value supporting, hence the prognosis of enhancing AI technologies to unlock supply chain systems that are more responsive and flexible. Future studies could

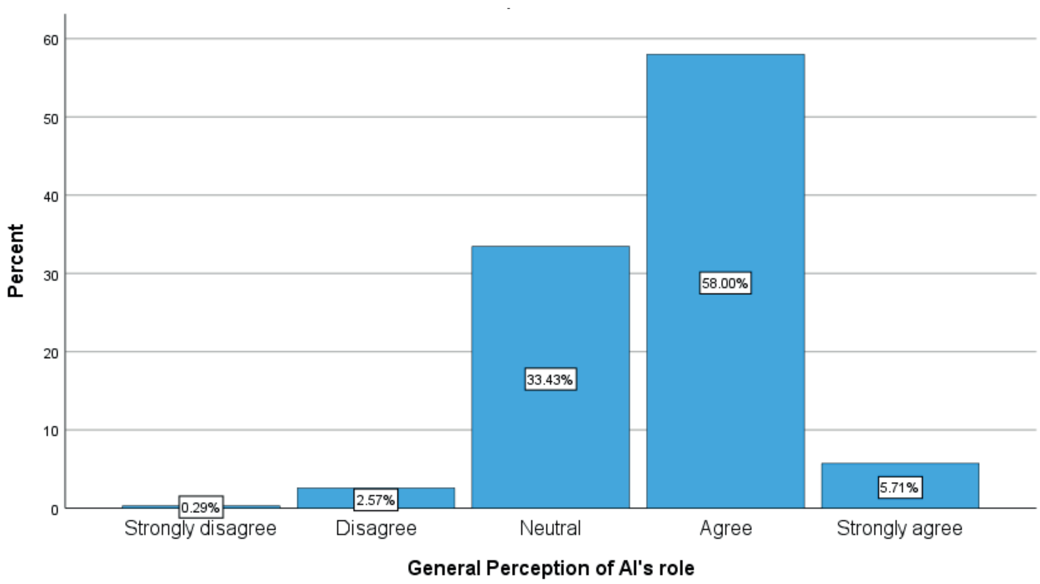

Figure 2. General Perception Of AI's Role in the Supply Chain

. **Table 4.** Result of Regression Analysis RQ2

		Unstandardized Coefficients		**Standardized Coefficients**	**t**	**Sig.**	**95.0% Confidence Interval for B**	
		B	**Std. Error**	**Beta**			**Lower Bound**	**Upper Bound**
Model	Type of AI technologies used	0.031	0.014	0.114	2.147	0.032	0.003	0.059

shed more light on the individual techniques responsible for the increase in responsiveness and the possible challenges that can hinder the adaptation of such tools in various areas of the food chain.

4.5. Empirical Findings and Observations

The quantitative research consists of six regression models, including and excluding demographics that have been analyzed, which compare and highlight the significance of the interaction between the use of AI in the forecast and the demand planning performance and control variables. In Model 1, the independent variable (AI utilization) is used, we find that the effect of AI on the dependent variable is positive and significant with a coefficient of 0.075, a t-statistic of 2.521, and a significance level of 0.004, which permits us to reject the null hypothesis that there is no impact. However, when more variables enter into the following models, the relationship becomes weak and insignificant. In model 2, which introduces AI implementation challenges as a control variable, AI's effect weakens (B = 0.049, p = 0.061) and becomes insignificant. At the same time, implementation challenges emerge as a significant predictor of forecasting accuracy (B = 0.205, p < 0.001).

In Model 3, these findings reveal that the likelihood of AI utilization is statistically marginally close to significance (B = 0.051, p = 0.051) but a nonsignificant predictor. Overall, there are still significant barriers to the implementation of AI (F = 37.240, B = 0.201, p < 0.001), though job role (F = 3.672, B = 0.032, p = 0.131) does not explain accuracy. The same remains true in Model 4, showing that the aspects of AI utilization are not significant predictors (B = 0.038, p = 0.162), while challenges in implementing AI (B = 0.201, p < 0.001) remain impactful. However, years of experience (B = 0.072, p = 0.100) has emerged insignificant in this study at a marginal level whereas job role continues to exercise no considerable effect.

In Model 5, the coefficients for artificial intelligence utilization (B = 0.040, p = 0.142) and other independent variables including job role (B = 0.030, p = 0.160), and company size (B = -0.035, p = 0.490) are non-significant. The current relevance is maintained by challenges in AI implementation (B = 0.199, p < 0.001) and years of experience (B = 0.084, p = 0.074). Finally, in Model 6, AI utilization (B = 0.025, p = 0.353) is no longer significant as other factors such as income (B = -0.071, p = 0.012) and age (B = 0.078, p < 0.001). However, years of experience appears as a significant factor (B = 0.099, p = 0.028), and perceived future potential as the most powerful factor (B = 0.321, p < 0.001) for forecasting accuracy.

In conclusion, after excluding other variables,

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95.0% Confidence Interval for B Lower Bound	95.0% Confidence Interval for B Upper Bound
1	(Constant)	3.785	.084		45.306	.000	3.621	3.949
	Alutilization	.075	.026	.153	2.892	.004	.024	.126
2	(Constant)	3.128	.180		17.424	.000	2.775	3.481
	Alutilization	.049	.026	.100	1.877	.061	-.002	.100
	ChallengesINAI	.205	.050	.219	4.110	.000	.107	.303
3	(Constant)	2.898	.229		12.659	.000	2.448	3.349
	Alutilization	.040	.027	.083	1.472	.142	-.014	.094
	ChallengesINAI	.199	.050	.213	3.986	.000	.101	.297
	Role/Job Title	.030	.021	.073	1.409	.160	-.012	.072
	Years of Experience	.084	.047	.105	1.789	.074	-.008	.177
	Company size	-.035	.050	-.040	-.690	.490	-.134	.064
4	(Constant)	2.443	.232		10.534	.000	1.987	2.899
	Alutilization	.025	.026	.050	.930	.353	-.027	.076
	ChallengesINAI	.001	.058	.001	.022	.982	-.113	.116
	Role/Job Title	.019	.020	.047	.947	.344	-.021	.059
	Years of Experience	.099	.045	.124	2.205	.028	.011	.187
	Company size	-.019	.048	-.021	-.389	.697	-.113	.076
	Percieved future potiential	.321	.055	.366	5.874	.000	.213	.428

a. Dependent Variable: Alimpact

Figure 3. Output of Multiple Regression Analysis

AI usage seems not to have a very strong impact, and therefore, the null hypothesis cannot be dismissed in the subsequent models. Optimistic views, and the perceived potential of implementing AI solutions in the future were also found to have a significant positive influence on the degree of forecast accuracy, thus the need to overcome various barriers to AI implementation and being optimistic about the future of AI. Years of experience is also important, although its importance appears in later models, which shows that experience leads to better forecasts. To successfully adopt AI, organizations must focus on overcoming barriers and fostering optimism about the future capabilities of AI.

5. CONCLUSION AND DISCUSSION

This study highlights that the direct impact of AI on forecasting and demand planning accuracy in the food supply chain is less pronounced than initially expected. However, the perceived future potential of AI, combined with a positive outlook on its adoption, significantly influences forecasting outcomes. The study underscores the importance of addressing key implementation barriers, such as high costs, integration challenges, and a lack of skilled personnel, to unlock AI's full potential. Additionally, years of professional experience enhance forecasting accuracy, especially as AI adoption progresses, demonstrating the continuing relevance of human expertise alongside technological advancements.

The findings indicate that for industrial practitioners and policymakers, it is essential to focus on addressing these obstacles and promoting a strategic and positive mindset toward AI integration. Sustainable enhancements in demand forecasting and planning rely on advancements in technology as well as the preparedness of the workforce.

The findings of this study align with those of Marwaha, Dey, and Brar (2024), who explored AI integration in urban and regional planning in India. Both studies identify significant challenges in AI implementation, including data limitations, infrastructure constraints, and the necessity for specialized expertise. While acknowledging AI's potential to enhance decision-making, both studies emphasize that its success is contingent upon overcoming these systemic obstacles and effectively integrating AI into existing processes.

Future research should examine the particular AI technologies that yield the greatest enhancements in forecasting precision, including predictive analytics and machine learning models. It is essential for studies to address strategies aimed at overcoming obstacles such as data quality issues, elevated costs, and integration difficulties while also considering affordable AI solutions and improvements in data management systems. Furthermore, exploring training and upskilling initiatives for the workforce is vital to ensure that employees can competently collaborate with AI technologies, thereby closing the divide between potential benefits and actual results.

Further research could also examine the psychological and organizational factors influencing AI adoption, particularly the role of optimism and growth strategies in enhancing forecasting outcomes. Studies on the synergy between human expertise and AI-driven systems would also provide valuable insights into optimizing supply chain processes. Exploring incremental adoption strategies and their impact on AI integration could reduce resistance and provide sustainability in the long term.

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