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Ethical Challenges in Demand Prediction: A Case Study in the Wholesale Grocery Sector

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Abstract. Artificial Intelligence (AI) has emerged as a transformative tool in inventory management and demand prediction within the wholesale grocery sector. By leveraging machine learning algorithms, businesses can analyze historical sales data, market trends, and seasonal variations to optimize inventory levels, reducing overstock and stockouts. AI-driven demand prediction models provide accurate forecasts, enabling wholesalers to anticipate customer needs and streamline supply chain operations. This article examines the ethical challenges associated with developing and implementing AI-driven demand prediction models in the wholesale grocery sector. As businesses seek to optimize their operations through artificial intelligence, significant ethical concerns arise that must be addressed to ensure responsible and fair implementation. This case study highlights the main ethical challenges identified in a grocery wholesaler, focusing on issues such as transparency, accountability, fairness, and human control. Through the analysis of a specific demand prediction model, we discuss how these ethical concerns not only influence user acceptance of the model but also impact operational efficiency and customer satisfaction. The article aims to contribute to the ongoing dialogue on ethics in data science, providing insights and recommendations for companies looking to adopt predictive technologies ethically.

Keywords. Demand prediction, ethical challenges, artificial intelligence in retail, AI ethics, ethical AI framework.

1 Introduction

The integration of artificial intelligence (AI) models in inventory management and demand prediction in the wholesale grocery sector offers significant promises in terms of operational efficiency and customer satisfaction. ”According to a 2018 analysis by consulting firm McKinsey[7], the potential value created by applying artificial intelligence and data analytics in the retail industry was estimated to be $1.26 trillion annually.

However, the development and deployment of these technologies are not without ethical challenges that can affect all stakeholders involved, from employees to customers and suppliers. This article focuses on a case study in a wholesale grocery company to explore the specific ethical issues that arise when applying predictive models in this context.

In the company in question, challenges related to inventory management, manual and subjective decision-making processes, and the need to leverage data available through its ERP system are central issues that have led to economic losses, customer dissatisfaction, and obstacles to commercial growth. The project addresses these issues by developing a demand prediction model that optimizes the synchronization between supply and demand, thus improving profitability and operational efficiency.

As companies seek to harness the potential of AI to enhance the accuracy of sales predictions and inventory management, crucial ethical concerns arise related to data privacy, algorithmic process transparency, fairness in automated decision-making, and human control over autonomous systems. These aspects not only influence the perception and effectiveness of AI but also raise fundamental questions about responsibility and technological governance.

In this study, we identify and discuss the main ethical challenges detected in the implementation of a demand prediction model in the company studied. The implications of these challenges for the model's acceptance by internal users, as well as its impact on the company's value chain, are analyzed. Through this analysis, we seek to contribute to the development of an ethical framework that can guide companies in the responsible adoption of advanced technologies in demand prediction.

2 Ethical Challenges in Demand Prediction: A Case Study in the Wholesale Grocery Sector

The adoption of artificial intelligence (AI) models for demand prediction in the wholesale grocery sector not only promises to increase operational efficiency but also poses significant ethical challenges. These models, although superior in certain specific tasks, often operate as “black boxes”, which can compromise their acceptance and trust among users and other stakeholders.

Additionally, as Doshi-Velez and Kim note, these systems require optimization not only in expected task performance but also in additional criteria such as safety and non-discrimination [5]. The analysis of ethical principles for AI, as discussed by Floridi and Cowls [6], reveals a convergence around five fundamental principles: beneficence, autonomy, justice, non-maleficence, and explicability.

These principles aim to ensure that AI technology, as it advances, promotes human well-being and avoids causing harm, while also respecting human dignity and justice [6]. However, the applicability of these principles in practical scenarios and their interpretation can vary significantly, often leading to ambiguities and challenges in implementation.

Our project focuses on addressing these ethical challenges by developing a demand prediction model that is not only operationally efficient but also transparent, fair, and explicable. Through detailed analysis of inventory and sales data and the use of advanced machine learning techniques, our model seeks to optimize inventory management while minimizing biases and promoting a greater understanding of its decision-making processes. This approach not only improves user acceptance of the model but also ensures compliance with emerging ethical standards in AI.

This integrated approach to developing predictive technologies in the wholesale grocery sector not only addresses an operational need but also tackles the ethical imperatives that are crucial for the sustainable adoption of AI. By combining operational optimization with a strong ethical orientation, our project hopes to set a standard for the development and future implementation of AI systems in similar industries.

3 Review of Ethical Requirements

There are at least eight fundamental issues that were analyzed to ensure an ethical and responsible development of our demand prediction model. These issues are as follows:

- Privacy.
- Accountability.
- Safety and protection.
- Transparency and explainability.
- Fairness and non-discrimination.
- Human control of AI.
- Professional responsibility.
- Promotion of human values.

After our study, we concluded that the demand prediction model does not pose a risk to these eight issues. For example, we are aware that it is essential to ensure the privacy and security of the data of customers, suppliers, and employees of the grocery wholesaler where we will implement the demand prediction model.

However, it is not anticipated to collect or use this type of data. If that decision changes in the future, robust security measures must be implemented to protect confidential information and comply with data privacy regulations. Next, we will only address the ethical concerns that we might risk if we decide to implement our demand prediction model and also mention how to manage them.

3.1 Transparency in Data Use

To be transparent, we must inform users about how the demand prediction model works, including whether it is possible to adjust data collection and to what extent decisions are autonomous or involve human intervention. We must also be aware that employees in this grocery sales business do not have knowledge of machine learning or experience in handling demand prediction tools. In many cases, the educational level of the workers is very low, so it is important to consider offering courses to help them better understand the project, contributing to the interpretability of the results.

3.2 Accountability and Human Control

While the demand prediction model will be an effective tool for preventing inventory shortages in the wholesale grocery company, the responsibility for making decisions rests with humans, so the introduction of this system would not put people's jobs at risk. The company must consider how to address communication and carry out these talks with its staff to avoid concerns among the personnel who work there.

3.2.1 Professional Responsibility

To ensure that the development and implementation of the demand prediction model are carried out with accuracy, scientific integrity, and responsible design, it must be ensured that the data used are accurate, that the model design is ethical, and that the long-term effects of its implementation are considered. See the next point.

3.2.2 Consideration of Long-term Effects

It is essential to anticipate the possible future impacts of implementing the demand prediction model, both in terms of operational efficiency and customer satisfaction. Therefore, a monthly audit should be implemented to verify the accuracy of the predictions compared to actual demand.

3.2.3 Multisectoral Collaboration

We must promote collaboration among different areas of the company (purchasing, sales, warehouse managers, etc.) to ensure effective implementation of the demand prediction model. Involving various stakeholders in the process can help identify potential biases and ensure that informed and ethical decisions are made.

3.3 Justice

The use of a demand prediction system in a wholesale grocery company may have implications in terms of justice and non-discrimination, especially in relation to market competition. Below are some ways in which this price prediction system can affect justice and competition.

Since the demand prediction models will not use personal data from customers, employees, or suppliers, we can guarantee that they will not be biased toward certain groups of people. However, bias could occur regarding products, favoring certain products and therefore suppliers to the detriment of others.

Another situation that could jeopardize justice would be in terms of competition. If the wholesale grocery company benefits from a highly accurate and effective price prediction system, it could obtain an unfair competitive advantage over its competitors who do not have access to such predictive models.

3.4 Professional Responsibility

By involving various stakeholders in the process, possible failures in the prediction model can be identified, but the potential future impacts of implementing the demand prediction model must be anticipated, both in terms of operational efficiency and customer satisfaction.

Employees of the grocery wholesaler may feel relaxed regarding their responsibilities, so it must be clear that the responsibility for purchasing products and making logistics decisions remains human. Additionally, mechanisms for auditing the obtained results must be incorporated so that adjustments can be made if necessary, such as retraining with new data.

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Table 1. RPN values

RPN value	Failure risk level
500 - 1000	High risk of failure
125 - 499	Medium risk of failure
1 - 124	Low risk of failure
0	No risk of failure

3.5 Laws That Apply in the Domain and Related to Ethical Dilemmas

In the development of our demand prediction model for the wholesale grocery sector, it is imperative to ensure that all stages of implementation not only achieve technical efficiency but also adhere to the highest ethical standards.

This adherence is not merely a matter of corporate responsibility but a fundamental requirement to navigate the complex regulatory and ethical landscape in which such technologies operate.

As we integrate advanced data analytics and machine learning techniques into our operations, we must rigorously consider how our model aligns with existing laws, company policies, and universally recognized ethical principles.

The following section outlines the key legal frameworks, ethical principles, and company policies that our project must conform to, ensuring that our practices not only meet but exceed the expectations for ethical compliance in AI deployment.

This adherence safeguards our stakeholders' interests and upholds our commitment to ethical business practices, setting a precedent for responsible innovation in our industry. In Mexico, there are no specific laws regulating the use of artificial intelligence in a company of this type.

Below is a list of various laws in Mexico applicable to different areas such as technology, privacy, or health, but none of these regulate the use of our demand prediction model that we are going to implement, so our model does not infringe any of these laws.

3.5.1 The Federal Law for the Protection of Personal Data Held by Private Parties

Regulates the processing of personal data held by private parties. It seeks to guarantee privacy and the right to informational self-determination of individuals [2].

3.5.2 The Federal Copyright Law and the Industrial Property Law

Protect intellectual works and inventions, respectively. These laws cover the moral and property rights of authors and creators over their works and inventions [1].

3.5.3 The Federal Telecommunications and Broadcasting Law

Along with other regulations, govern aspects related to ICTs, including cybersecurity, access to information, and data protection [3].

3.5.4 Criminal and Civil Law

Provisions in criminal and civil law [4] can be applied in situations where ethical dilemmas related to fraud, computer crimes, liability for products or services, among others, arise.

3.6 Company Policies Related to the Domain and the Development of Intelligent Systems

Although the company does not have a specific policy for the development of intelligent systems, it has established a framework that ensures compliance with Mexican laws. Our prediction system does not jeopardize this framework or the company's internal policies regarding the use of systems or software tools.

This project will serve as a basis for the company to set internal policies for the use of this and other possible machine learning models that could infringe on privacy in other use cases where it is necessary to analyze personal data.

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3.7 Ethical Principles and Criteria

Although the company does not have formal policies or specific manuals focused on ethical criteria for the development of intelligent systems, it is governed by a set of fundamental values reflected in its internal regulations and its commitment to the Federal Law for the Protection of Personal Data Held by Private Parties (LFPDPPP) [2].

The company's regulations, being a family business, underline the importance of acting with honesty and ethics, not only for the benefit of the company and its employees but also for the customers. This approach establishes a solid foundation for the integration of principles and ethical criteria in all its operations, such as.

3.7.1 Integrity

Maintaining high standards in all operations, ensuring transparency and truthfulness in communication and in the management of relationships with colleagues, customers, and suppliers.

3.7.2 Respect

Valuing the dignity, rights, and contributions of all individuals, including employees, customers, and partners. This involves promoting an inclusive and discrimination-free work environment.

3.7.3 Responsibility

Taking responsibility for actions and decisions.

3.7.4 Privacy Protection

Committing to the protection of personal information of employees, customers, and other stakeholders, strictly complying with applicable legislation and best practices in privacy and data protection.

3.7.5 Quality and Excellence

Committing to continuous improvement and the pursuit of excellence in products, services, and processes, ensuring safety and reliability.

We can see that our demand prediction model does not contradict these internal policies, but as I have mentioned in other sections, it is important to make it clear that decisions will continue to be made by humans to not detract from their responsibilities or human control.

3.8 Other Criteria

Given the context of Mexico and the absence of specific policies in the company on the development of intelligent systems and ethics, it is crucial to establish a framework of ethical criteria that guides the development, implementation, and use of these technologies.

These criteria should not only align with existing laws but also reflect international best practices and universal ethical principles mentioned in section 3. The following recommendations will help the company ensure compliance with current Mexican legislation and lay the foundation for the responsible and ethical development of intelligent systems in the future.

3.8.1 Develop a Privacy and Data Protection Policy

Although there is currently no specific policy for the development of intelligent systems, and although our model does not use personal data, the company should develop a privacy and data protection policy aligned with the LFPDPPP that guides data processing in all its systems, including new models that might be implemented in the future.

3.8.2 Training and Awareness

Train the staff involved in the development and management of the demand prediction system.

Table 2. Calculation of the RPN value for each potential failure

Failure mode	Failure effect	Severity	Causes	Ocurrency	Control process	Detection	RPN
Error when collecting data	Models cannot be trained	10	CRM doesn't work	2	CRM database backup	5	100
Model does not fit	Wrong predictions	10	Poor data quality	10	Cleaning and preprocessing	1	100
Buyer does not use the tool	Inventory breakdown	10	Low trust in the system	10	Training and support	2	200
Model does not capture seasonality	Bad predictions in seasonal products	10	Original data doesn't contain seasonality variables	5	Add new variables	1	50

3.8.3 Appoint a Data Protection Officer

In order to ensure compliance with data protection laws, safeguard sensitive information, and build trust with customers and stakeholders.

3.8.4 Implement Cybersecurity Mechanisms

That allow the grocery wholesaler to protect its information from potential cyberattacks. Additionally, create data backup mechanisms, as they have repeatedly lost historical information.

4 Ethical Design Proposal

In this section, we delineate the structured approach that our project will adopt to ensure the ethical integrity and effectiveness of our demand prediction model within the wholesale grocery sector.

The overarching goals of our ethical design proposal are to preempt potential damages and promote the common good by ensuring our AI systems are designed and implemented in a manner that upholds ethical principles and protects stakeholder interests.

We aim to establish a model that not only meets the operational needs of the wholesale grocery sector but also sets a benchmark for ethical AI practices.

4.1 Stakeholder and Role Mapping

Initially, we will conduct a comprehensive mapping of all stakeholders involved in or affected by the deployment of the demand prediction model. This process helps in recognizing the needs, expectations, and concerns of each group, ranging from company employees and suppliers to end consumers. Understanding these dynamics is crucial for tailoring our ethical design strategy to address and respect the interests of all parties.

4.1.1 Warehouse Managers and Purchasing Staff

These individuals are concerned about how automation and improved efficiency might impact their roles and job security. Successful project implementation could mean a reduction in manual workload and the opportunity to focus on more strategic tasks.

4.1.2 Company Customers

They would expect better product availability and overall satisfaction due to more efficient inventory management. However, there is a risk of negative impact if demand prediction results in stocking less than the required demand or leads to over-optimization that results in a reduced variety of products available.

4.1.3 Suppliers

They view the implementation positively as it could benefit them with more predictable demand planning and more consistent orders. However, they fear that the volume of purchases might decrease due to automation or that they might lose market share to competitors.

4.2 Ethical Impact Analysis

We will perform an in-depth analysis of the potential ethical impacts associated with the model. This analysis will assess both the direct and indirect effects of the model's deployment on various stakeholders. Key considerations include data privacy, bias and fairness.

4.2.1 Model Accuracy Failures

If the model does not accurately predict demand, it could lead to excess inventory or stockouts. Therefore, it will be necessary to conduct regular audits of the model's performance and adjust it as needed.

4.2.2 Bias

A biased model could favor certain products or suppliers, and it might also incorrectly predict the demand for a product by not taking into account its direct competition. For this reason, we need to contrast the results of the prediction model with the actual sales of the products and based on the error, analyze the results.

4.2.3 Data Privacy Violation

Although personal data will not initially be used, any change in this policy must be handled carefully. Implement robust data security measures and comply with all local privacy laws.

4.3 Failure Mode and Effects Analysis

To support our ethical impact assessment, we will utilize FMEA—an approach traditionally used in engineering to identify and evaluate potential failures.

FMEA stands for Failure Mode and Effects Analysis, it's a set of guidelines, a method, and a way to identify potential problems or errors and their possible effects on a process, product, or system in order to prioritize them and focus resources on prevention, monitoring, and response plans.

This analysis enables us to implement preventive measures to reduce risks and enhance system reliability and ethical compliance. Some definitions:

– **Severity (S):** The importance of the effect in terms of its functional consequences (product) or degree of defectiveness (process).

– **Occurrence (O):** Probability of a failure occurring in the product or process after a failure cause has occurred.

– **Detection (D):** Probability of not detecting the failure before it occurs.

To calculate the Risk Priority Number (RPN) for each effect, we use the following formula:

$$\mathrm{RPN} = \text{Severity} \cdot \text{Occurrence} \cdot \text{Detection}. \quad (1)$$

The resulting value is a number that establishes a ranking of problems through the multiplication of the degrees of occurrence, severity, and detection. This provides the priority with which each identified failure mode should be addressed according to the following table 1.

To rate severity, occurrence, and detection, we use the same American Society for Quality metrics with a scale ranging from the lowest value indicated by the number 1 to the highest value indicated by the number 10. In the following table 2 we will see the calculation of RPN for each potential failure mode.

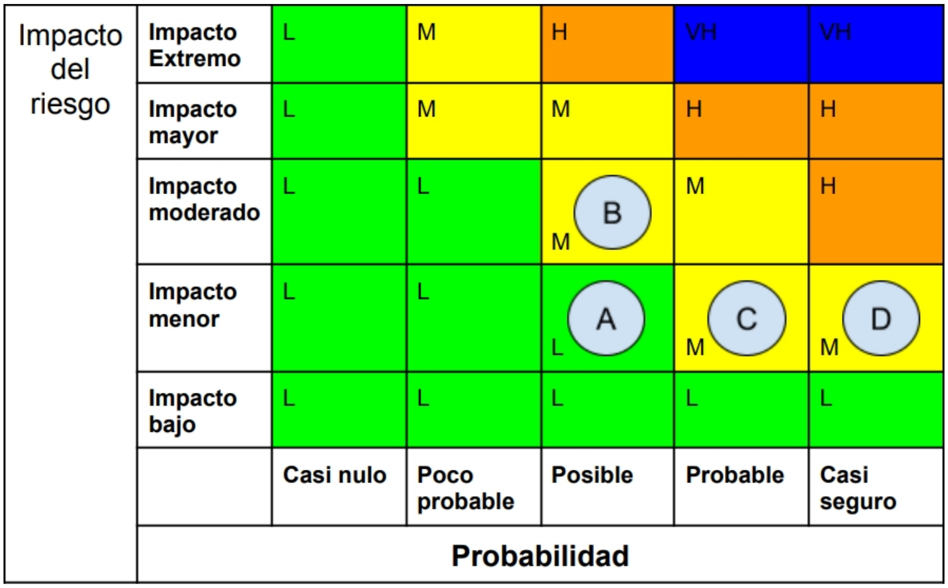

Fig. 1. Risk impact

4.4 Ethical Design throughout the Lifecycle

We commit to integrating ethical considerations into every phase of the AI system's lifecycle—from initial design through development, deployment, and eventual decommissioning. This ongoing commitment ensures that our practices remain aligned with ethical standards over time, adapting to new challenges and innovations in the field.

4.4.1 Design Phase

Choose interpretable models whenever possible and preprocess data without using data that contains sensitive information from clients or suppliers.

4.4.2 Development and Testing

Ensure that the model is thoroughly tested to detect and correct biases, errors, and vulnerabilities.

4.4.3 Implementation

Continuously monitor the system's impact on all stakeholders, adjusting policies and the model as necessary to ensure a fair balance.

4.4.4 Review and Maintenance

Conduct regular audits to assess the model's performance, the fairness of the impacts, and stakeholder satisfaction, and make adjustments based on these findings. This proactive approach to risk and benefit management will help maximize the benefits of the project for the company and its stakeholders, while minimizing potential harms and promoting the common good.

4.5 Data Collection

The wholesale grocery company faces significant challenges with its Enterprise Resource Planning (ERP) system, developed by a small software house.

The lack of an in-house systems department means they are entirely dependent on their software provider for data management and extraction, limiting their ability to handle information directly and complicating data-driven decision-making. Moreover, the coexistence of two versions of the ERP software further complicates the situation.

An older version still used at one checkout does not synchronize with the latest version,

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which manages the rest of the operations, causing inconsistencies in the data collected. Transactions made at the checkout running the older software are not reflected in the main system, preventing it from serving as a true "source of truth."

Further complicating matters, the company lacks qualified personnel to understand the database structure of the ERP, forcing the owners to specifically request their software provider to export the sales information for each product.

Given that the company manages over two thousand products, and the need to manually integrate and adjust data from both versions of the software, they use three Excel files per product, a method that is impractical and time-consuming.

In response to these challenges, it was agreed with the store owner to focus efforts on the products with the largest inventory to optimize inventory management and cash flow using demand prediction tools. This strategy aims not only to improve operational efficiency but also to determine the time needed to recover the investment in inventory.

The company's purchasing policy is adjusted to maintain sufficient stock for one month, taking advantage of the 30-day credit terms offered by suppliers. Decisions to purchase stock for longer periods are occasionally made to take advantage of discounts or anticipate price increases, based on past experiences and analysis of sales.

Finally, the dataset used is described: from the Excel files received, we generate a CSV file that includes detailed information such as date, product identifier, net sales, returns, entries and exits from the warehouse, and inventory levels. Additionally, to capture seasonality and improve prediction accuracy, the date was decomposed to obtain additional variables and indicators for holidays were created. Sales information has been available only since March 2020. Prior to hiring the current software provider, the company conducted testing that led to the simultaneous use of two different ERP systems.

This created a fragmented environment with no single reliable source of sales data, making our first challenge the consolidation of data from these two sources. Fortunately, the wholesale company performs periodic inventories to track its actual stock. Using this inventory data and the sales files from both software versions, we were able to construct a reliable dataset for this work.

The files generated by each ERP system are notably different. One system records daily transactions, resulting in multiple entries for the same date, while the other system consolidates information at the order level. Despite their structural differences, the files share common variables that enabled us to merge them effectively.

The net sale is our variable to predict. It is important to mention that all variables that store information regarding the quantity of boxes are of the float type because some products are sold in quantities less than a box, such as half a box. Other products, like powdered drink sachets or products sold by display units, are equivalent to a fraction of a box.

4.6 Model Documentation

For demand prediction in our wholesale grocery business, we have selected three main models due to their effectiveness and adaptability to different types of data and complexities. Below, each model is described along with its specific application in our context.

4.6.1 Linear Regression

Features

– Supervised learning model used to predict numerical values.

– Assumes a linear relationship between input features and the target variable.

– Computationally efficient and easy to train.

Application for Demand Prediction. Linear regression is used to model the linear relationship between factors such as time, promotions, and prices, and the demand for a specific SKU. While effective for direct relationships, its utility may be limited under conditions of non-linearity or complex interactions between variables. An exploratory data analysis is essential to ensure that the relationship between variables fits the assumptions of the model.

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4.6.2 Random Forest

Features

– Extends decision trees by training multiple trees in parallel and combining their predictions.

– Each tree is trained with a random sample and selection of features, which helps reduce overfitting and improves generalization.

– Suitable for handling large datasets with many features.

Application for Demand Prediction. Random Forest is used to combine multiple decision trees trained on different data subsets, improving accuracy by reducing the risk of overfitting and capturing a wider variety of patterns. This model is particularly useful in environments with large and complex data where interactions between variables are difficult to model with simpler methods.

4.6.3 XGBoost

Features

– Efficient and scalable implementation of the gradient boosting algorithm.

– Sequence of weak decision trees that iteratively improve prediction.

Application for Demand Prediction. XGBoost is ideal for situations where high precision is required. This model learns from residual errors iteratively by adjusting new trees to continuously improve accuracy. Capable of capturing complex relationships between features, it is especially valuable when handling large volumes of data and precision in prediction is critical.

4.6.4 Conclusions

These models have been selected not only for their technical performance but also for their ability to adapt to the specifics of our data context and business needs. We will continue to evaluate and adjust these models as necessary to ensure that demand prediction is as accurate and useful as possible for strategic decision-making in the company.

5 Technical, Operational and Organizational Requirements for Ethical Design

The ethical risks identified relate to concerns about fairness, professional responsibility, and human control. By mapping these on the figure 1 , we can observe that there are no significant ethical risks.

a) **Risk in Fairness (Products).** The model favors certain products over others, causing a feeling of injustice among suppliers.

b) **Risk in Fairness (Competition).** The trading company will have a competitive advantage over other companies in the industry that do not have access to demand prediction models.

c) **Human Control.** The model will not displace staff. Purchasing managers will use the model as a tool, but the final decision will be made by them.

d) **Professional Responsibility.** Staff might relax their sense of responsibility by relying entirely on the demand prediction model. It is important to conduct audits to ensure the model's accuracy and retrain it when necessary.

To mitigate the impacts of the identified ethical risks, the following recommendations are proposed:

a) **Risk in Fairness (Products).** Balance in the products for which demand will be predicted, implementing an equitable rotation system based on the results of the demand prediction model. This will help avoid the perception of favoritism toward certain products and promote equity among suppliers.

b) Transparency in Selection Criteria: Provide clarity on the criteria used to select the products to promote. This can include objective metrics such as profitability, inventory turnover, and historical demand, which will help justify the decisions made by the model.

c) **Risk in Fairness (Competition).** Collaboration and Equitable Access: Encourage collaboration among companies in the same industry to share knowledge and resources, including demand prediction models. This can help level the playing field and reduce the unfair competitive advantage that a single company might have.

d) **Human Control.** Training and Education: Provide ongoing training and education to staff on the use and interpretation of the results of the demand prediction model. This will help ensure they understand their role in the process and use the model as a complementary tool rather than replacing their human judgment.

e) **Encourage Collaboration.** Promote a collaborative work environment where staff feel comfortable using the demand prediction model as a tool to inform their decisions, but are also encouraged to share their experience and insights to complement the model's results.

f) **Professional Responsibility.** Regular Audits: Conduct regular audits to assess the accuracy and performance of the demand prediction model. This can help identify potential biases or errors in the model and ensure its reliability in decision-making.

Implementing these strategies can help mitigate the impacts of the identified ethical risks and promote an ethical and responsible implementation of demand prediction models in the wholesale grocery trading company.

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