Computer and Decision Making

An International Journal

Journal homepage: www.comdem.org
eISSN: 3008-1416

Impact of Transportation Time on Inventory Management Costs: Analyzing the Relationship in Food Waste Management

Elnaz Hesami Naghshbandi*

[1] Department of Industrial Engineering, Islamic Azad University, Arak, Iran

ARTICLE INFO

Article history:
Received 18 October 2024
Received in revised form 30 November 2024
Accepted 20 December 2024
Available online 10 January 2025

Keywords:

Food waste management; Logistics decision; Inventory optimization; Sustainability

ABSTRACT

In today's world, environmental sustainability and resource conservation have become major concerns globally. In general, logistics, and more specifically, transportation time, play a crucial role in decision-making aimed at reducing spoilage and related expenses. This study investigates how variations in transportation time impact inventory management costs in food waste recycling across three sectors: composting, mushroom cultivation, and insect farming. A synthetic dataset was created, simulating realistic scenarios in food waste management, including variables such as transportation time, type of waste, energy usage, seasonal variations, and inventory management costs. Computational models and statistical analyses, including moderation and mediation analyses, were conducted using R programming language to evaluate three hypotheses. The results indicate a marginal moderating impact of waste type, where perishable waste marginally increased the cost impact of transportation time without reaching conventional significance. Energy usage mediated the relationship, where increased transportation time correlated with increased energy use and costs. Seasonal variations moderated the relationship, especially in winter and summer, indicating enhanced sensitivity to transport time.

1. Introduction

Food waste management is an important issue with consequences for sustainability, society and the environment. Key factors such as transportation time and inventory management costs play a crucial role in addressing these challenges. Transportation time refers to the duration required to move food waste from collection points to processing facilities. Delays in transportation, particularly for perishable waste, can exacerbate spoilage and increase overall costs. Inventory management costs include expenses associated with storing, handling, and managing food waste inventory. These costs directly impact the economic feasibility and efficiency of food waste recycling operations. The effect of transportation time on inventory management costs in food waste management is a multidimensional problem that requires attention. Food waste not only causes economic losses but also environmental degradation because of food production, storage, transportation, and waste management methods [15]. In the retail industry, unnecessary transportation of products and materials could result in extra

* Corresponding author.
E-mail address: Elnaz.hesaminaghshbandi@gmail.com
https://doi.org/10.59543/comdem.v2i.11119

time, distance, and energy consumption [8]. Inventory management models could substantially affect waste in the distribution component of the supply chain, therefore making optimal inventory procurement procedures needed [23]. Moreover, the development of food waste as an environmentally friendly issue has diverted initiatives toward finding solutions in the retail industry, creating policy and incentive programs for the reduction of food waste [*17*]. Transportation as part of the food supply chain has a considerable influence on food waste management [6].

The financial effect of food waste is displayed in the expense of waste management and the monetary losses resulting from the disposal of edible food [*23*]. Solutions to food waste management issues, such as eco-friendly dehydrator machines and circular consumption practices, are being explored [22-26]. Knowing the different factors influencing food waste along the supply chain and also applying effective logistics and inventory management methods can bring down food waste, promote sustainability, and lower the environmental impact of consumption. The huge volume of waste created by the food industry indicates a loss of resources and creates huge management challenges on both environmental and economic levels [*16*]. Understanding household food waste behaviors and usage patterns is crucial to inform targeted interventions to decrease waste generation at the source [26]. Since food waste is increasingly recognized as having damaging effects on society and the environment, efforts are being made to come up with new solutions in addition to best sustainable practices. Exploring food waste management complexity, including transportation time and logistical operations, can motivate stakeholders toward a more sustainable and efficient food supply chain that reduces waste generation, conserves resources, and promotes circular consumption.

Modifications in transportation time between waste producers and recycling facilities are crucial to inventory management costs, particularly for perishable items, including food waste, which should be transported within less than 24 hours. Hence, it is important to categorize different waste types [14]. The requirement of efficient transportation logistics to minimize inventory holding costs and prevent food waste leads to substantial economic losses [18]. Food spoilage impacts producers and consumers economically along with the supply chain efficiency [18]. Enhancing waste collection routes might lead to decreased gas use and car emissions, proving the benefits of efficient transportation of waste management [4]. Artificial intelligence applications in waste logistics have attained satisfactory results in minimizing transportation distance, time, and costs. Therefore, advanced technologies can help to effectively transport goods [27]. In urban environments, effective waste transportation requires careful planning to attain optimum transport time and minimal environmental impacts [21]. Additionally, the real-time GIS management systems for waste transportation could further optimize cost optimization and operational efficiency [5]. By combining smart technologies and optimizing transportation routes, the overall environmental and financial effects of waste management could be improved [11]. In a supply chain, effective logistics backed up by cutting edge technologies and optimal routes are required to minimize expenses, reduce environmental impacts, and stop food spoilage.

The role of transportation in waste management is to keep waste supplies moving and make sure they reach their ultimate destinations in time. Jat and Muyldermans [9] compare the costs and efficiency of service parts logistics concerning different service time commitments. They demonstrate that service times differentially influenced by hierarchical versus non-hierarchical setups may substantially affect the operation efficiency in addition to the cost effectiveness of the distribution network. Ghaderi *et al.* [12] provide empirical evidence that cooperative transport strategies can lead to significant reductions in lead time and variability, thereby enhancing the overall efficiency of the supply chain. Kmiecik [24] highlights how third-party logistics use advanced forecasting tools to enhance transportation planning and inventory management, suggesting a model that could be mirrored in food waste management to improve sustainability and efficiency. The quantity and quality of collected waste impact transportation procedures and show the importance of logistics in waste management operations. Challenges in transportation logistics consist of route optimization, vehicle load management, and cost minimization. Uncertainty within supply chain activities can be a problem in transportation logistics which influences path preparation and resource allocation [3]. Creating efficient transport operations requires addressing uncertainties and also optimizing logistics processes for waste material flow [3]. Advances in software for route planning and vehicle tracking also have made waste transportation operations more efficient and accurate [7].

A novel group decision-making framework has been developed for evaluating sustainable urban transportation management alternatives, applying fuzzy ZE-numbers to enhance decision reliability in complex urban contexts such as Mexico City during major events [28]. Another group decision support model using the Logarithm Methodology of Additive Weights (LMAW) and MARCOS method based on fuzzy ZE-numbers has been introduced to handle the complexity of choosing optimal land-use transport projects, integrating economic, environmental, technical, and political criteria to ensure decisions are socially and economically inclusive [29]. To address limitations in traditional risk assessment, a novel approach using Z-SWARA and Z-MOORA methods based on Z-number theory has been introduced to improve the reliability and prioritization of failures by considering uncertainty in the evaluation of Risk Priority Numbers (RPN) [20]. Industry 4.0 technologies have promoted environmental awareness and sustainability through waste collection routing and improved operational processes [7]. Resolving challenges of transportation logistics, applying technological innovations, and optimizing transportation can enable waste management facilities to increase their operational efficiency and environmental sustainability in waste transportation practices.

Inventory management is the keeping of a desired stock of defined items or products while balancing customer service and investment [23]. The integration of inventory management concepts in supply chain operations might enhance performance and cost effectiveness [2]. Inventory management cost factors like storage, handling, and spoilage affect the total operational cost of recycling facilities. Proper inventory control strategies such as economic order quantity (EOQ) methods might balance customer service and investment in order to attain optimal inventory levels [10]. Swanson *et al.* [13] suggest that ordering inventory less frequently can reduce transportation costs due to economies of scale, but it may lead to higher inventory carrying costs. In a study conducted by Luo *et al.* [25] it is found that enhanced supply chain operations management not only improves inventory efficiency but also contributes significantly to waste reduction. Optimizing inventory management through better coordination, information sharing, and technology can be an effective strategy to substantially reduce food waste in retail supply chains [19]. Good inventory management can enhance market liquidity, working capital and accounting methods and thus impact return on assets. Efficiency in inventory management methods is shown to positively impact firm performance, as timely and informative customer demand data reduce inventories and enhance operational outcomes.

Management of Food waste by conversion into compost, use by insects, and cultivation of mushrooms offers novel and sustainable solutions for waste reduction and resource recovery. Composting food waste diverts waste from landfills and also creates soil amendments with nutrients. Insects can process organic waste materials effectively to get protein and fat-rich biomass. Insect-based bioconversion offers an alternative to managing food waste and creates resources for animal feed and bioenergy generation. Mushrooms could be utilized to digest organic material into protein and also provide a green alternative use of food waste. Recent studies emphasized the synergistic effects of combining these approaches to achieve maximum waste diversion, environmental sustainability, and resource recovery. Integrating composting, insect bioconversion, and mushroom cultivation creates a closed-loop system that turns food waste into useful resources. Finally, food waste management based on composting, insect farming, and mushroom cultivation provides promising approaches for sustainable waste reduction. By using these methods, food waste might be processed into valuable products and also plays an important role in a circular and green friendly waste management program.

2. Hypotheses Development:

Various food wastes present different waste management challenges. Perishable foods like fresh fruits and veggies spoil quickly and, therefore, require immediate processing and short transportation times to stay away from spoilage and loss of value. In comparison, non-perishable items are less prone to time delays and might thus need much more flexible and less costly logistics solutions. This differentiation in handling and processing requirements indicates the impact of transportation time on inventory management costs might depend on food waste perishability.

Hypothesis 1: The connection between transport time and inventory control expenses is moderated by the kind of food waste (perishable vs. non-perishable).

Extended transportation times are inevitably associated with higher energy consumption. This relationship is applicable to waste management, in which the transportation duration can influence the energy expenditure for shifting waste materials from collection points to recycling centers. Understanding the transportation time would influence energy consumption and consequently, inventory management costs.

Hypothesis 2: Increased transportation time results in increased energy usage and higher inventory management costs.

Seasonal changes can impact transportation logistics, from transportation route accessibility to delivery speed. As an example, poor weather in winter might delay transportation and increase costs, as well peak seasons such as holidays might increase the need for quicker waste processing. These seasonal fluctuations should moderate the transportation time costs. Therefore, it is necessary to examine exactly how these periodic variations affect overall waste management efficiency.

Hypothesis 3: Seasonal variations impact the transport time and inventory management cost relationship.

3. Methodology

A synthetic dataset was developed to evaluate three hypotheses regarding the impact of transportation time on inventory management costs while controlling moderating and mediating variables such as type of food waste, energy consumption, and seasonal variation. The dataset comprised transportation time, type of waste (perishable vs. non-perishable), seasonal categories, energy consumption, and inventory costs. For the first hypothesis, I assumed that type of food waste moderates the transportation time and inventory management cost relationship. This hypothesis was evaluated by building a linear regression model with an interaction term of transportation time and waste type. The impact of transportation time and waste type on inventory costs was evaluated using regression analysis and an interaction plot using ggplot2. In the second hypothesis, energy usage mediates the association between increased transportation time and inventory management costs. A causal mediation assessment was conducted using the R mediation package. Mediation analysis was employed to investigate the underlying mechanism through which transportation time influences inventory management costs. Specifically, this method was chosen to test the hypothesis that energy usage acts as a mediator in this relationship. By using mediation analysis, we can decompose the total effect of transportation time on inventory costs into direct and indirect effects, providing a more nuanced understanding of how transportation logistics contribute to cost variations. This approach is particularly relevant for this study because it highlights the role of energy consumption as an intermediary factor, which is crucial for developing strategies to optimize both cost efficiency and environmental sustainability in food waste management. Two regression models were created: the mediator model predicted energy usage from transportation time, and the outcome model predicted inventory costs from transportation time and energy consumption. Then, the Average Causal Mediation Effect (ACME), Average Direct Effect (ADE), and total effect were estimated from the mediate function. The third hypothesis proposed that seasonal variations moderate the transport time and inventory management costs relationship. Similar to hypothesis one, an interaction analysis was carried out incorporating seasonal variations as a factor with interaction terms. A linear regression framework with interaction terms estimated for every season has been calculated. An interaction plot with ggplot2 was produced to demonstrate seasonal variations in the slopes of the relation between transportation time and inventory costs. All computational analyses have been performed in R, a statistical programming language that contains lM (linear models), mediation (causal mediation evaluation), and ggplot2 (data visualization). For each hypothesis testing, model diagnostics have been carried out to fulfill linear regression assumptions. Diagnostic plots for heteroscedasticity or non-normality for the residuals were checked out. The significance of the regression coefficients was examined with t-tests, and the total model fit was analyzed using F-tests and R-squared values.

4. Result

R output provides the results of a linear regression analysis to test the first hypothesis whether the effect of transportation time on inventory costs is moderated by the type of food waste. The intercept coefficient was estimated at 0.19111, with a standard error of 0.23737. This coefficient was not significant ($t = 0.805$, $p = 0.421$), suggesting that when all other variables are null, the expected value of the response variable isn't substantially different from zero. Transportation Time coefficient was significant (t = 39.232, p < 2e -16), estimated at 1.69408 with a standard error of 0.04318. This suggests that the bigger Transportation Time equals the bigger response variable when other factors are constant. The coefficient for the type of waste being Perishable was estimated to be 49.70227 with a standard error of 0.27969, also extremely significant (t = 177.707, p < 2e -16). This indicates a significant effect of perishable waste on the response variable. The interaction term between Transportation Time and the type of waste being Perishable has been estimated at 0.09597 and had a standard error of 0.05525. The t-value and the p-value were 1.737 and 0.0827, respectively, suggesting the interaction effect isn't statistically significant at 5%.

Table1

Regression Results showing the Impact of Transportation Time and Type of Waste on Inventory Costs

Variable	Estimate	St. Error	t-value	p-value
Intercept	0.1911	0.2373	0.805	0.4210
Transportation Time	1.6948	0.0431	39.23	< 2e-16
Type of Waste (Perishable)	49.7022	0.2796	177.70	< 2e-16
Transportation Time*Type of Waste	0.0959	0.0552	1.737	0.0827

The marginal significance of the interaction term supports the theory that food waste type moderates the association between transportation time and inventory management expenses. Nevertheless, this particular evidence is not enough to accept the idea at the conventional 0.05 significance level. Given the marginal p-value, this likely moderation effect might need further investigation, possibly with a bigger sample size, to evaluate if the effect gets stronger with more data. In fact, while the type of waste influences costs and transport time raises expenses, the combination of the two does not increase costs considerably at a level that is usually considered statistically significant. The Average Causal Mediation Effects (ACME) is 2.94 with a 95% quasi-Bayesian Confidence Interval (CI) between 1.27 and 4.53. The effect was statistically significant (p < 2e -16) and also constituted a powerful mediation outcome in the causal pathway. The Average Direct Effects (ADE) have been calculated at -5.11, with a 95% CI between -3.20 and -6.78. The direct effect of the independent variable on the dependent variable was statistically significant (p < 2e -16), indicating a direct causal connection. The Total Effect of the independent variable on the dependent variable has been estimated to be -2.17, with 95% CI from -2.96 to -1.40. This effect was statistically significant (p < 2e -16), indicating the overall causal effect is considerable and not exclusively because of the mediation process. The proportion, which is the Proportion of the total effect that is Mediated, was estimated at -1.37 with 95% CI ranging from - 2.64 to -0.54. This proportion was significant (p < 2e -16), indicating that a considerable portion of the total effect is through the mediator. Moreover, the negative values for the ADE and the complete outcome might usually symbolize a direction contrary to that of the mediator's effect. The negative proportion mediated may indicate the mediation effect is the opposite of the total effect, or there may be suppression effects. The findings underscore the importance of transportation time and perishability in determining inventory management costs. Recent advancements in cold supply chain logistics have shown significant potential in reducing food waste, particularly in managing perishables like meat. Prawiranto et al. (2024) review two decades of innovations in this field, highlighting the role of temperature-controlled transportation and storage systems in minimizing spoilage. These advancements align with the findings of this study, particularly regarding the moderating effects of food perishability and seasonal variations on transportation time and inventory costs. By applying similar cold chain strategies across other sectors of food waste management, such as composting or insect farming, substantial improvements in logistics efficiency and waste reduction can be achieved.

Table2

Mediation Analysis of Energy Usage in Transportation Time and Inventory Costs

ACME (Average Causal Mediation Effect)	2.94	1.27	4.53	< 2e-16
ADE (Average Direct Effect)	-5.11	-6.78	-3.20	< 2e-16
Total Effect	-2.17	-2.96	-1.40	< 2e-16
Proportion Mediated	-1.37	-2.64	-0.54	< 2e-16

The estimated intercept is 54.5212, and the standard error is 3.6223. This intercept is statistically significant (t = 15.052, p < 2e -16), indicating the anticipated value of inventory costs when Transportation Time and all seasons are at their reference levels. The coefficient of Transportation Time is -3.0348 with a standard error of 0.7677. The effect of Transportation Time on Inventory Costs isn't statistically significant (t = -3.953, p = 0.00008), implying other variables controlling Inventory Costs. The Spring coefficient is 5.4882 with an average error of 5.1702. This effect isn't statistically significant (t = 1k.061, p = 0.28872) and also suggests the Spring season doesn't affect Inventory Costs in comparison with the baseline season. The coefficient for the Summer is -11.5618 with a standard error of 5.2746 (t = -2.192, p = 0.02861). This means Inventory Costs are lower in the Summer than for the baseline season. The coefficient for the Winter season is -5.2461, the standard error is 5.0350, and it isn't statistically significant (t = -1.042, p = 0.29769), suggesting that Winter varies not in Inventory Costs from the baseline season. The interaction term of Transportation Time together with the Spring season is -1.2885 with a standard error of 1.0916 and isn't statistically significant (t = -1.180, p = 0.23815), suggesting the relationship between Transportation Time and Inventory Costs doesn't change much throughout Spring. The interaction term of Summer is 2.9468 with a standard error of 1.1280, which is significant (t = 2.612, p = 0.00913). This suggests a more substantial relationship between Transportation Time and Inventory Costs during the Summer. For Winter the interaction term is 2.1839 with a standard error of 1.0768 that is statistically significant (t = 2.028, p = 0.04282). This suggests that Transportation Time influences Inventory Costs differently in Winter.

Table3

Regression Analysis of the Impact of Transportation Time and Seasonal Variations on Inventory Costs

Variable	Estimate	St. Error	t-value	p-value
Intercept	54.21	3.62	15.05	< $2e^{-16}$
Transportation Time	-3.03	0.76	-3.59	8.2*e-5

Season (Spring)	5.48	5.17	1.06	0.28872
Season (Summer)	-11.56	5.27	-2.19	0.02861
Season (Winter)	-5.24	5.03	-1.04	0.29769
Transportation Time x Season (Spring)	-1.28	1.09	-1.18	0.23815
Transportation Time x Season (Summer)	2.94	1.12	2.61	0.0093
Transportation Time x Season (Winter)	2.18	1.07	2.02	0.0428

The analysis found marginal consequences for transportation time with type of food waste on inventory management costs. Although transportation time is positively associated with increased costs and perishable waste costs greater than non-perishable waste, the anticipated interaction effect that predicted a better relationship for perishables wasn't supported. This implies that while food waste type is an important cost variable, its moderator role in relation to transport time needs further study.

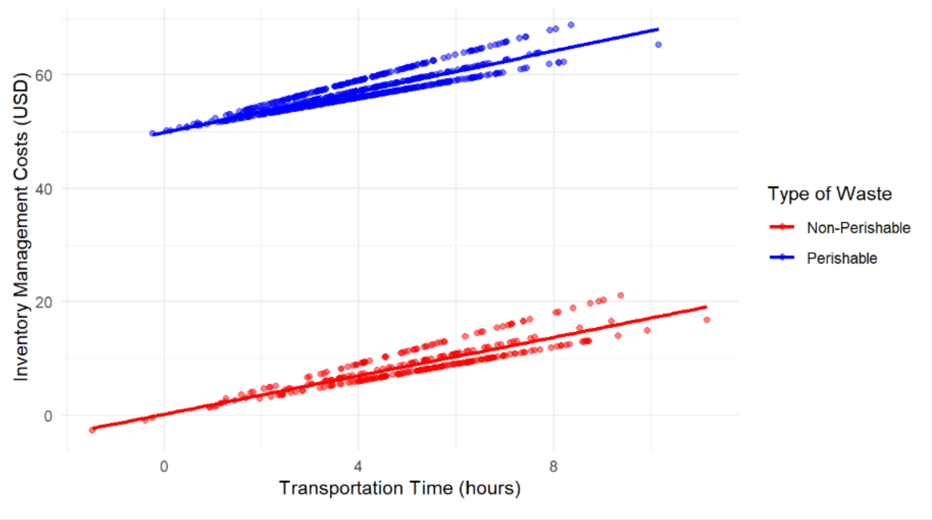

Fig. 1. Relation between Transportation Time and Inventory Costs for food waste

The mediation analysis discovered that Energy Usage mediated the transportation time and inventory management cost relationship. The Average Causal Mediation Effect (ACME) was significant indicating that extra transportation time results in increased energy usage and greater inventory management costs. The direct effect (ADE) was negative, suggesting a complex relationship where transportation time is related to cost reduction when controlling energy usage. This indicates other mechanisms that may lower costs independent of energy use.

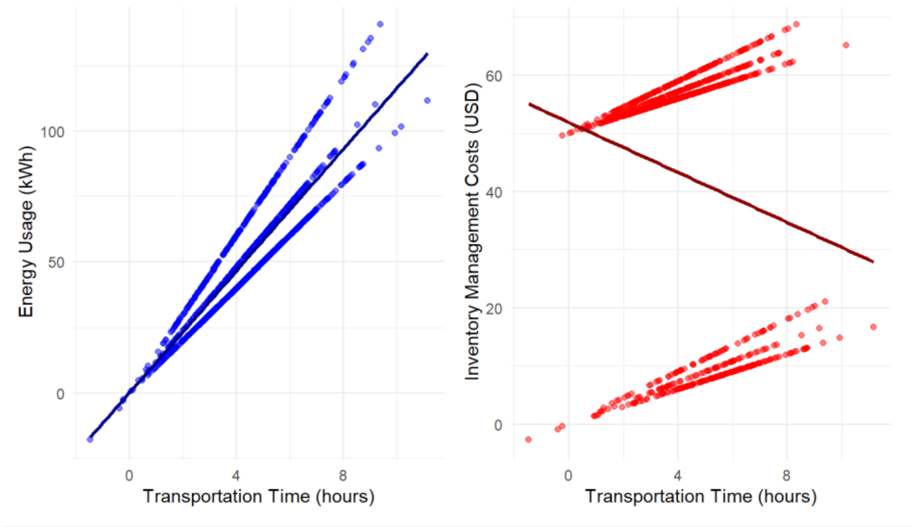

Fig. 2. Effect of transportation time on energy usage and inventory management costs

Seasonal variations moderated the transport time, and inventory management cost relationship. Summer and winter interaction terms were statistically significant, suggesting that transportation time has a greater negative impact on inventory management costs during these seasons than autumn. This seasonal impact wasn't observed for spring, suggesting the impact of transportation time on costs is not the same across seasons.

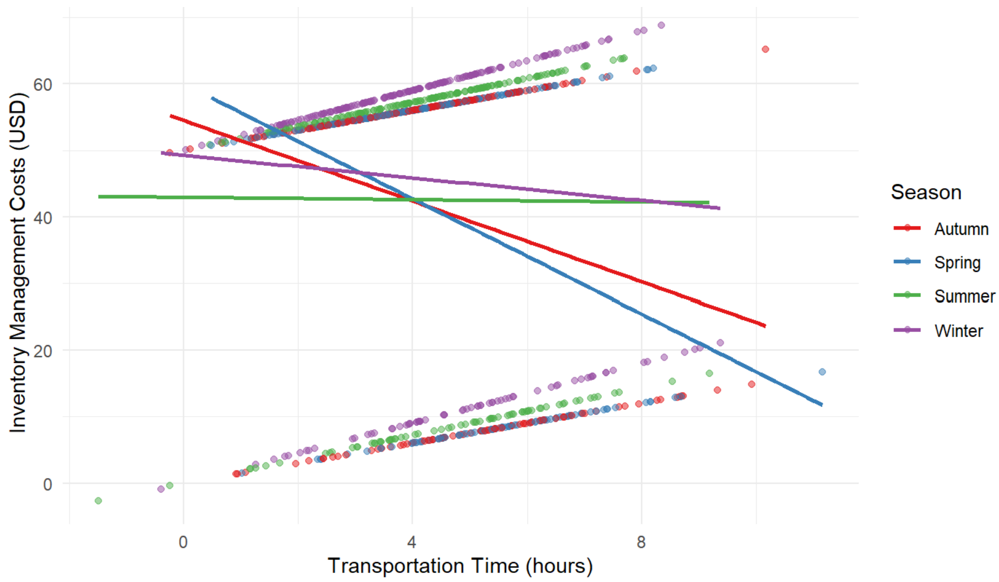

Fig. 3. Moderating effect of season on transportation time and inventory costs

5. Conclusion

The findings offer insights into decision-making processes in logistics, particularly how computational approaches can optimize transportation and inventory management in the context of food waste management. The moderating role of waste type was suggestive but not conventional. This may be due to the nature of the synthetic data, or the relationship may have been less strong than hypothesized. The mediation effect of energy usage indicates that logistical efficiency is needed for controlling costs particularly with increasing transportation times. A more detailed investigation is required to understand the surprising negative correlation between transportation time and costs. This could suggest that longer transportation times allow for better-planned routes, economies of scale in bulk transportation, or other cost-saving operational efficiencies. Seasonal variations as a moderating factor are important to adaptive logistics strategies. In summer and winter, higher costs may result from temperature control methods, weather delays, and changes in demand patterns. This variability makes seasonally-adjusted planning essential for optimum inventory management costs in the food waste supply chain. These findings shed light on the complicated inventory management in food waste logistics. They emphasize the need to consider various kinds of waste, seasonal changes, and energy consumption in transportation and inventory management.

The analyses assume linear relationships and interactions among variables. In practice, these relationships might be nonlinear and mediated by threshold effects or any other nonlinear dynamics that the linear modeling approach cannot model. The moderate R-squared values, particularly for the model evaluating the seasonal variations, suggest the models explain just a tiny section of the variation of inventory control expenses. This suggests other unaccounted variables influencing the outcomes. Moreover, the statistical power to identify considerable effects, particularly in moderation by kind of food waste, could be impacted by the dataset size or the variable distribution. Expanding the model to additional variables and possibly nonlinear relationships may also offer additional insights. Furthermore, studying locations could help in understanding how local conditions impact the generalizability of results.

This paper highlights the significant relationship between transportation time and inventory management costs in food waste management. The nuanced relationship with varying waste types, energy usage, and seasonal variations highlights the need for strategic logistics planning. Though perishable waste types and longer transport times typically increase costs, energy efficiency and seasonal adjustments play a crucial mitigation role. It has illustrated how advanced logistical methods could reduce environmental impact while enhancing operational efficiency in different food waste recycling sectors. Future research must further examine these relationships with advanced modeling strategies to capture the dynamic and multifaceted nature of food waste logistics. This could allow more specific and powerful interventions balancing cost management and eco-friendly waste methods, leading to a more resilient and environmentally friendly supply chain.

6. Discussion and Limitations

This study provides valuable insights into the relationship between transportation time and inventory management costs in food waste management. However, several limitations must be acknowledged to contextualize the findings and highlight areas for future research. The analysis relied on synthetic data, which, while enabling controlled experimentation and the simulation of various scenarios, has inherent constraints. Synthetic datasets may not fully capture the complexity and variability of real-world food waste management systems. Factors such as unexpected disruptions, nuanced behavioral patterns, and organizational dynamics are difficult to replicate in artificial settings. Additionally, synthetic data may oversimplify certain relationships or fail to account for unobserved variables that could influence outcomes in real-world contexts. For example, real-world transportation logistics often involve intricate interactions among stakeholders, regulatory frameworks, and environmental factors, which may not be accurately reflected in synthetic datasets. To address these limitations, future research should validate the results using real-world data to ensure robustness and practical applicability. Incorporating observational data from actual operations would help to mitigate potential biases and provide deeper insights into the practical implications of the relationships examined in this study.

The sample size used in this study may have influenced the statistical power of the analyses and the significance of the findings. A smaller sample size can restrict the ability to detect subtle effects, particularly interactions and moderating effects. This limitation could explain why some hypothesized relationships, such as the interaction between transportation time and waste type, did not reach conventional significance levels. For instance, the interaction term between transportation time and waste type yielded a p-value of 0.0827, suggesting that with a larger sample size, this relationship might have achieved statistical significance. A larger dataset would enhance the precision of effect estimates and potentially uncover significant interactions or effects that were only marginally significant in this study. Expanding the sample size would also improve the generalizability of the results to a broader range of contexts within food waste management.

Potential outliers were carefully considered to ensure the validity and reliability of the results. Synthetic data inherently reduces the risk of extreme or unexpected values, as it is generated within controlled boundaries. However, to simulate realistic scenarios, variability was introduced in the dataset, which could produce values resembling outliers in real-world data. During the data analysis, diagnostic checks such as residual diagnostics from regression analyses were performed to identify any extreme values or influential points. No extreme outliers were observed that warranted removal or adjustment in this study. It is important to note that real-world datasets may contain significant outliers due to unforeseen events or errors in data collection. Future research should incorporate robust outlier detection and handling mechanisms when using real-world data. Methods such as Cook’s Distance for identifying influential data points or robust regression techniques that minimize the impact of outliers could be particularly useful.

Addressing these limitations is essential for strengthening the practical applicability of findings. Using real-world data and increasing the sample size would not only validate the relationships explored here but also provide a more comprehensive understanding of the interplay between transportation logistics and inventory management costs. Additionally, incorporating advanced methods for outlier detection and handling would ensure that findings are robust and reflective of the complexities inherent in real-world scenarios. Such advancements could help stakeholders develop more effective and sustainable strategies for managing food waste in diverse operational environments.

Acknowledgement

This research was not funded by any grant.

References

[1] Koumanakos, D. P. (2008). The effect of inventory management on firm performance. International journal of productivity and performance management, 57(5), 355-369. http://dx.doi.org/10.1108/17410400810881827

[2] Sanchez Rodrigues, V., Stantchev, D., Potter, A., Naim, M., & Whiteing, A. (2008). Establishing a transport operation focused uncertainty model for the supply chain. International Journal of Physical Distribution & Logistics Management, 38(5), 388-411. http://dx.doi.org/10.1108/09600030810882807

[3] Tavares, G., Zsigraiova, Z., Semiao, V., & Carvalho, M. D. G. (2009). Optimisation of MSW collection routes for minimum fuel consumption using 3D GIS modelling. Waste management, 29(3), 1176-1185. https://doi.org/10.1016/j.wasman.2008.07.013

[4] Zhu, Y., Lin, C. J., Zhong, Y., Zhou, Q., Lin, C. J., & Chen, C. (2010). Cost optimization of a real-time GIS-based management system for hazardous waste transportation. Waste management & research, 28(8), 723-730. https://doi.org/10.1177/0734242x09345277

[5] Pullman, M. E., Fenske, R., & Wakeland, W. (2010). Food delivery footprint: Addressing transportation, packaging, and waste in the food supply chain. https://doi.org/10.15760/TREC.129

[6] Tieman, M., Van der Vorst, J. G., & Ghazali, M. C. (2012). Principles in halal supply chain management. Journal of Islamic Marketing, 3(3), 217-243. http://dx.doi.org/10.1108/17590831211259727

[7] Chabada, L., Dreyer, H. C., Romsdal, A., & Powell, D. J. (2013). Sustainable food supply chains: Towards a framework for waste identification. In Advances in Production Management Systems. Competitive Manufacturing for Innovative Products and Services: IFIP WG 5.7 International Conference, APMS 2012, Rhodes, Greece, September 24-26, 2012, Revised Selected Papers, Part I (pp. 208-215). Springer Berlin Heidelberg. https://dx.doi.org/10.1007/978-3-642-40352-1_27

[8] Jat, M. N., & Muyldermans, L. (2013). Time-differentiated service parts distribution: Costs under hierarchical and non-hierarchical setups. In 2013 IEEE Symposium on Computational Intelligence in Production and Logistics Systems (CIPLS) (pp. 17-24). IEEE. https://doi.org/10.1109/CIPLS.2013.6595195

[9] Vidovic, M., Ratkovic, B., Bjelic, N., & Popovic, D. (2014). Optimization of recyclables collection processes. Operations and Supply Chain Management: An International Journal, 4(2), 90-98. http://doi.org/10.31387/oscm0100062

[10] Ahamed, A., Yin, K., Ng, B. J. H., Ren, F., Chang, V. C., & Wang, J. Y. (2016). Life cycle assessment of the present and proposed food waste management technologies from environmental and economic impact perspectives. Journal of Cleaner Production, 131, 607-614. https://doi.org/10.1016/j.jclepro.2016.04.127

[11] Ghaderi, H., Dullaert, W., & Amstel, W. P. V. (2016). Reducing lead-times and lead-time variance in cooperative distribution networks. International Journal of Shipping and Transport Logistics, 8(1), 51-65. http://dx.doi.org/10.1504/IJSTL.2016.073316

[12] Swanson, D., Williams, B. D., Gu, J., & Waller, M. A. (2016). Full steam ahead: Firms in the US economy adjust inventory for changes in transportation costs but not the reverse. Transportation Journal, 55(3), 282-295. http://dx.doi.org/10.5325/transportationj.55.3.0282

[13] Garcia-Garcia, G., Woolley, E., Rahimifard, S., Colwill, J., White, R., & Needham, L. (2017). A methodology for sustainable management of food waste. Waste and biomass valorization, 8(6), 2209-2227. https://doi.org/10.1007/s12649-016-9720-0

[14] Schanes, K., Dobernig, K., & Gözet, B. (2018). Food waste matters-A systematic review of household food waste practices and their policy implications. Journal of cleaner production, 182, 978-991. https://doi.org/10.1016/j.jclepro.2018.02.030

[15] El Bilali, H., & Ben Hassen, T. (2020). Food waste in the countries of the gulf cooperation council: a systematic review. Foods, 9(4), 463.
https://doi.org/10.3390/foods9040463
[16] Rosenlund, J., Nyblom, Å., Ekholm, H. M., & Sörme, L. (2020). The emergence of food waste as an issue in Swedish retail. British Food Journal, 122(11), 3283-3296.
https://doi.org/10.1108/BFJ-03-2020-0181
[17] Odeyemi, O. A., Alegbeleye, O. O., Strateva, M., & Stratev, D. (2020). Understanding spoilage microbial community and spoilage mechanisms in foods of animal origin. Comprehensive reviews in food science and food safety, 19(2), 311-331.
https://doi.org/10.1111/1541-4337.12526
[18] Nikolicic, S., Kilibarda, M., Maslaric, M., Mircetic, D., & Bojic, S. (2021). Reducing food waste in the retail supply chains by improving efficiency of logistics operations. Sustainability, 13(12), 6511.
https://doi.org/10.3390/su13126511
[19] Ghoushchi, S. J., Gharibi, K., Osgooei, E., Ab Rahman, M. N., & Khazaeili, M. (2021). Risk prioritization in failure mode and effects analysis with extended SWARA and MOORA methods based on Z-numbers theory. Informatica, 32(1), 41-67.
10.15388/20-INFOR439
[20] Ashik-Ur-Rahman, M., Waheduzzaman, M., & Waresul Hassan Nipun, M. (2022). Optimized municipal solid waste transportation with landfill requirement in a coastal city of Bangladesh. Environmental Quality Management, 31(4), 197-210.
https://doi.org/10.1002/tqem.21804
[21] Ibrahim, H., & Abdelmawla, N. (2022). Eco-Friendly Dehydrator Machine for Food Recycling: A Waste Management System. Nile Journal of Communication and Computer Science, 4(1), 12-30.
https://doi.org/10.21608/njccs.2022.279497
[22] Gunawan, I. N. D., & Setiawan, P. Y. (2022). Inventory Management with EOQ Method at “Nitra Jaya” Fashion-Making Company in Badung. European Journal of Business and Management Research, 7(3), 347-351.
http://dx.doi.org/10.24018/ejbmr.2022.7.3.1444
[23] Kmiecik, M. (2022). Logistics coordination based on inventory management and transportation planning by third-party logistics (3PL). Sustainability, 14(13), 8134.
https://doi.org/10.3390/su14138134
[24] Luo, N., Olsen, T., Liu, Y., & Zhang, A. (2022). Reducing food loss and waste in supply chain operations. Transportation Research Part E: Logistics and Transportation Review, 162, 102730.
https://doi.org/10.1016/j.tre.2022.102730
[25] Kumari, S., Bharti, N., & Rahaman, S. (2022). Antecedents towards social circular consumption of food wastes in emerging economies: Transition towards food circular economy. Business Strategy & Development, 5(4), 322-334.
https://doi.org/10.1002/bsd2.201
[26] Fang, B., Yu, J., Chen, Z., Osman, A. I., Farghali, M., Ihara, I., ... & Yap, P. S. (2023). Artificial intelligence for waste management in smart cities: a review. Environmental Chemistry Letters, 21(4), 1959-1989.
https://doi.org/10.1007/s10311-023-01604-3
[27] Haseli, G., Bonab, S. R., Hajiaghaei-Keshteli, M., Ghoushchi, S. J., & Deveci, M. (2024). Fuzzy ZE-numbers framework in group decision-making using the BCM and CoCoSo to address sustainable urban transportation. Information Sciences, 653, 119809.
https://doi.org/10.1016/j.ins.2023.119809
[28] Haseli, G., Deveci, M., Isik, M., Gokasar, I., Pamucar, D., & Hajiaghaei-Keshteli, M. (2024). Providing climate change resilient land-use transport projects with green finance using Z extended numbers based decision-making model. Expert Systems with Applications, 243, 122858.
https://doi.org/10.1016/j.eswa.2023.122858
[29] Prawiranto, K., et al. (2024). Two Decades of Advancements in Cold Supply Chain Logistics for Reducing Food Waste: A Review with Focus on the Meat Industry. Sustainability, 16(16), 6986.
https://doi.org/10.3390/su16166986