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Dynamic Modeling of Controllable Returns in E-commerce: The Impact of Seller Restrictions on Platforms

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ABSTRACT

Effective operations management is pivotal in driving revenue and profitability for organizations in today's business world, particularly in e-commerce and online markets. Among the critical areas of operations management, product returns have garnered increasing attention. Although product returns could benefit businesses by increasing customer loyalty, trust, and satisfaction, reducing advertising costs, and attracting new customers for sellers, they can also harm sellers by increasing transportation costs, reducing profits, and affecting product quality. As a result, e-commerce platforms need to determine an optimal level of strictness in product returns policy. This study examines the dynamic model of seller-controllable returns in e-commerce platforms and investigates how imposing restrictions on sellers with high return rates influences overall return volume. The findings demonstrate that as seller restrictions tighten, the return rate decreases, suggesting that e-commerce platforms should consider implementing policies restricting sellers with high return rates to reduce their product returns.

Keywords

Product returns, Return policies, E-Commerce Platforms, System dynamics.

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1. Introduction

The online shopping industry has become a vital part of the business world today, as more and more people prefer to buy things online (Gupta et al., 2023). To compete in this market, online sellers must offer good customer service and improve customer satisfaction. One way to do this is to allow customers to return the products they buy if unsatisfied (Abdulla et al., 2022). However, this poses a major challenge for online platforms, as product returns have advantages and disadvantages. On the one hand, product returns may increase customer trust and loyalty, lower advertising costs, and attract new customers for sellers. On the other hand, product returns can also increase transportation costs, lower profits, and damage the quality of products. Therefore, online platforms must find the best balance between being strict or permissive in their product returns management (Stock et al., 2006).

Customers could have different reasons for returning products, affecting customer satisfaction, seller profit, and platform performance. Stock et al. (2006) classified product returns into two main types: (1) Uncontrollable returns when the customer changes his or her mind and returns the product in the same condition as he or she received it. This type of return is not the seller's fault and does not lower the seller's performance rating. In this case, the product can be sold again. However, the business unit has little control over this type of return in the short term. (2) Controllable returns: when the customer returns the product because of something the seller did wrong, such as sending the wrong product, delivering a defective or broken product, or delivering late. This type of return is the seller's responsibility and lowers the seller's performance rating. In this case, the product cannot be sold again or can only be sold at a lower price. On the other hand, the business unit can reduce this type of return by implementing policies.

This research aims to develop a dynamic model for e-commerce platforms and examines how they can reduce controllable returns, which are not related to customer preferences. The authors investigate how restriction policies, which restrict sellers with high return rates from the platform, influence the total number of controllable returns and customer satisfaction. To do this, the authors build the theoretical framework, specify the system's assumptions, parameters, and dynamic equations, and run the model using the Vensim PLE simulator. Finally, the authors compare the model results with real data from a leading e-commerce platform in Iran, perform sensitivity analysis, assess different scenarios, and report and present the results and recommendations.

The scientific contribution of this research is significant in e-commerce and operations management. The study systematically explores the interplay between product returns and seller restrictions as a return policy by developing a dynamic model for online platforms. It identifies and quantifies the impacts of various return types on platform performance, offering insights into the effectiveness of policies targeting sellers with high return rates. This study advances academic knowledge by comparing model outcomes with real-world data from a leading Iranian e-commerce platform. It provides practical guidance for improving operational practices, equipping stakeholders to navigate the complexities of the online retail landscape effectively.

1. Literature Review

Digitalization and advancement in related technologies are driving significant innovation in the retail industry (Mostaghel et al., 2022). The Internet has become a pervasive way for businesses to sell and distribute commodities to consumers; this has attracted the attention of researchers in the operations, logistics, and supply chain management fields (Griffis et al., 2012). With the surge of e-commerce, traditional retail sales and online sales now fiercely compete; notably, online prices are 9-16% lower than those found in brick-and-mortar stores, as evidenced by prior research (Ramcharran, 2013; Prashar et al., 2015). The ratio of online retail sales to total retail sales in the US rose from about 3% in 2002 to more than 6% in 2008: online retail stores have shown substantial growth despite the recession. While most physical retailers had trouble making enough sales, online retailers achieved 11% annual sales growth in 2009 (Griffis et al., 2012). This trend has continued in recent years. During the Covid-19 crisis, the pace of change in e-commerce growth has markedly accelerated. The pandemic prompted consumers to transition from in-store shopping to online platforms, compelling retailers to adjust and establish a competitive online presence (Ghandour et al., 2023). Global shopping volumes surged from February 2020 to April 2021, leading to a 35% increase in the online retail market capitalization (Bradley et al., 2021). In 2022, the US National Retail Federation stated that online sales, a crucial but challenging source of growth for retailers, make up about 25% of US retail sales (Karlsson et al., 2023). There are two main reasons for this: First, the number of internet users has grown significantly in the past decade; second, the proportion of internet users who buy things online has increased (Griffis et al., 2012). Consequently, the authors witness a surge in innovative retail business models to meet heightened customer expectations (Mostaghel et al., 2022).

One of the major challenges that the online retail industry faces is return management (Griffis et al., 2012), which refers to handling customer reviews, complaints, and product returns. When consumers consider buying a product online, they often assess the risk associated with their decision. This risk can be financial (e.g., wasting money on an unsatisfactory product) or psychological (e.g., regret after a purchase). Online consumers often lack the opportunity to physically examine the products before purchasing them (Dholakia et al., 2005), which makes product evaluation more difficult and increases the likelihood of returns (Peck & Childers, 2003). As online sales continue to rise, especially in the post-Covid era, product return rates exhibit a similar trend (Karlsson et al., 2023). Based on a report published by the National Retail Federation of the US and Retail Appraisal in 2021, in 2020, US consumers returned $428 billion worth of products, which accounted for about 10.6 percent of the total US retailer sales that year, and this was a 64.6 percent increase compared to the previous five years (Li et al., 2022). According to Ambilkar et al. (2022), online returns are expected to reach $7 billion in 2023.

Product returns, in particular, pose a significant problem for online retailers, resulting in a loss of 3.8% of profit per year (Petersen and Kumar, 2010). In 2020, product returns resulted in an estimated 16 million tons of CO_2 and 5.8 billion pounds of waste, and the cost for an online retailer to process a $50 product return was estimated at $33 (Ambilkar et al., 2022). Therefore, it can be seen that consumer product returns significantly impact the industry and society (Karlsson et al., 2023).

Therefore, given the vital importance of handling product returns, especially considering pricing, demand, and product quality uncertainties, effective return management is crucial for businesses (Ambilkar et al., 2022). Managing product returns, developing strategies, and designing product return policies are some of the most important issues the online retail industry should consider. According to a survey, 87% of supply chain managers considered return management important or very important for their organization's operational and financial performance (Griffis et al., 2012).

In 2002, Rogers et al. emphasized that a firm's returns management capabilities can strategically enhance the overall performance of the company. Many recent studies have delved into returns management from a strategic standpoint, examining its impact on overall company performance (Karlsson et al., 2023). Rokonuzzaman et al. (2021) have also shown that retailers have the opportunity to strategically shape their return policies to boost customer confidence and foster loyalty to their stores. Recent empirical research examining the impact of various factors on consumers' digital shopping experience also reveals that implementing a robust return policy significantly enhances online shopping, leading to increased customer loyalty and repeat purchases (Patro, 2023).

Russo et al. (2018) identified specific return practices that contribute to customer satisfaction and align with broader business objectives. Interestingly, they found instances where customer satisfaction remained high despite equally high return rates. Therefore, it can be seen that return policy affects customer buying intention and return behavior (Abdulla et al., 2022) and, as a result, sales and profitability (Karlsson et al., 2023). The Cue Diagnosticity Framework also suggests that consumers use various cues to evaluate a retailer, one of which is their return policies (Rokonuzzaman et al., 2021). Return policies can influence customers' willingness to buy because they may opt for other sellers with more permissive return policies.

In another study, Son et al. (2019) have shown that return amounts do not harm order amounts, and a high amount of returns does not necessarily mean lower profits. They demonstrate that within the low- and medium-price segments, returns positively affect order values, underscoring the significance of adaptable return policies. However, for high-priced items, returns do not notably affect order amounts, implying that dissatisfied consumers in this category might not make repeat purchases from the same brand.

The literature reviewed in this paper highlights the importance of effective return management within the supply chain for achieving organizational success. Ambilkar et al. (2022) argue that information transparency is a key to improving product return management. By providing clear and detailed product information, companies can enhance the efficiency of their return processes (Ambilkar et al., 2022). Moreover, a generous return policy can reduce the perceived risk of online purchases and increase the customer's positive attitude toward the store (Rokonuzzaman et al., 2021). Table 1 provides a summary of the reviewed articles.

Table 1. Key Points in reviewd papers

Key Point	Details	References
Strategic Impact on Performance	Effective returns management enhances overall company performance by improving customer satisfaction and loyalty.	Rogers et al. (2002), Karlsson et al. (2023)
Customer Confidence and Loyalty	Retailers can shape return policies to boost customer confidence and foster loyalty.	Rokonuzzaman et al. (2021)
Digital Shopping Experience	Robust return policies enhance online shopping, increasing customer loyalty and repeat purchases.	Patro (2023)
Customer Satisfaction Despite High Return Rates	Specific return practices can maintain high customer satisfaction even with high return rates.	Russo et al. (2018)
Influence on Buying Intentions	Return policies affect customer buying intentions and return behavior, impacting sales and profitability.	Abdulla et al., (2022), Karlsson et al. (2023) Yan et al., 2019
Adaptable Return Policies	Adaptable return policies positively affect order values in low- and medium-price segments.	Son et al. (2019)
Information Transparency	Information transparency is key to improving product return management.	Ambilkar et al. (2022)
Perceived Risk Reduction	Generous return policies reduce the perceived risk of online purchases and increase positive customer attitudes.	Rokonuzzaman et al. (2021)

This paper concludes that product return policies have significant implications for not only the customer-organization relationship and the organizational performance but also the wider industry and society. Given this importance, there is a need for further research on the different types of product return policies and their impact on various outcomes. This paper identifies a gap in the literature and suggests some directions for future research on the return impact.

2. Methodology

This research adopts the System Dynamics (SD) modeling approach, a mixed-methods approach of quantitative and qualitative methods. It provides a powerful method for analyzing and assessing the dynamic properties of large-scale complex systems (Alamerew & Brissaud, 2020). SD modeling can capture the feedback loops, delays, and nonlinearities that characterize complex systems, such as social, economic, or environmental systems (Khadivar et al.,2024). This approach models and simulates the system using a cause and effect diagram, stock and flow diagram, and system dynamic equations. This study identified the key variables that affect the controllable returns of e-commerce platforms. Then, it specified the parameters and equations representing the relationships and interactions among these variables.

The authors used Vensim PLE software to develop and execute our model and validated it by comparing its outputs with historical data. Vensim is a robust simulation software designed to enhance the performance of real-world systems (Ventana Systems Inc., 2023). It offers many possibilities for sensitivity analysis, scenario evaluation, and diagram creation in system dynamics modeling. This article used the graphical interface to draw the causal loop, stock and flow diagrams, and the equation editor to enter the equations and parameters. This study simulated for 100 days, with a time step of one day. This study conducted a sensitivity analysis to investigate the impact of different parameter values on the model behavior. The diagram creation function is also used to generate graphs and tables that illustrate the model results and insights. To provide a clear overview of the research methodology, Figure 1 presents a flowchart outlining our study's key steps.

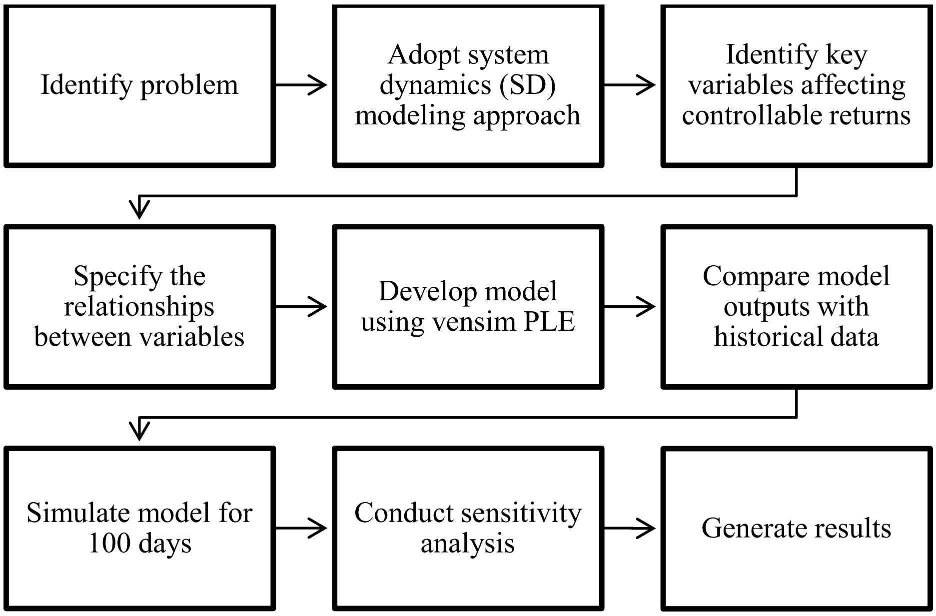

Figure 1. Research methodology steps

2.1. Definition of model variables

Given the multitude of factors at play in the sales system of an online retailer, it is difficult to account for all of them. The boundary of the system under investigation is determined by the study's research question (Yan et al., 2019). The present study has confined the analysis to examining a single return policy, specifically, the policy that imposes restrictions on sellers who exhibit high rates of controllable returns. The impacts of other return policies are not explored within the scope of this research. The variables within the boundary of the system under investigation are delineated in Table 2.

Table 2. Key variables related to the return policy for sellers with high rates of controllable returns

Row	Variable	Description	Unit
1	Controllable return	A type of product return results from the seller's mistakes, such as sending the wrong product, delivering a defective or broken product, or delivering late. Controllable returns are the seller's responsibility and affect the performance score. The product cannot be sold again or can only be sold at a lower price, as well.	Number
2	Product return rate	The ratio of products returned from a day's sale on the platform.	Dimentionless
3	Strict policies in product return processes	The rules and conditions that the platform sets for product return these policies may include seller restrictions, limiting allowable time to return products, asking for reasons and information, deducting shipping fees or penalties, or defining non-returnable items.	Dimentionless
4	The number of restricted sellers	The number of sellers whose access to the e-commerce platform has been temporarily or permanently blocked or limited due to the high return rate of their products by customers.	People

Row	Variable	Description	Unit
5	Average sales by restricted sellers	The average amount of sales of sellers whose access to the e-commerce platform has been temporarily or permanently blocked or limited due to the high return rate of their products by customers.	Number
6	Restricted sales	The total amount of sales of all sellers whose access to the e-commerce platform has been temporarily or permanently blocked or limited due to the high return rate of their products by customers.	Number
7	The number of new sellers on the platform	The number of sellers who have joined the platform and started selling since the start of the day.	People
8	Seller population on the platform	The total number of seller accounts on the platform minus the restricted sellers.	People
9	Total sales	The number of products sold by the sellers or bought by the customers in a period. The number of sales depends on customer demand, seller supply, price, market, and competition.	Number

2.2. Causal loop diagram

Figure 2 shows a causal loop diagram of the model, which consists of three main loops. The first loop (Reinforcing Sales Improvement Loop) is a reinforcing loop that illustrates how restricting sellers with high return rates increases the total sales by improving the average quality of products on the platform. Reinforcing Sales Improvement Loop implies that strict policies and more access denials motivate sellers to sell better-quality products, as the return rate entails a higher risk of reduced profit due to access denial, and the return rate is higher for low-quality products. Therefore, as the average quality of products on the platform increases, buyers become more satisfied and buy more products, which leads to higher sales. Assuming that the return rate is constant, higher sales also result in a higher controllable return rate, increasing the platform policymakers' desire to restrict sellers from reducing the return rate.

The second loop (Quality-Return Balancing Loop) is a balancing loop that depicts how restricting sellers reduces the return rate by enhancing the average quality of products on the platform. Quality-Return Balancing Loop indicates that higher-quality products increase customer satisfaction and decrease their willingness to return products, which lowers the return rate of customers. As a result, the overall return rate of the platform decreases, and the platform policymakers' tendency to increase seller restrictions diminishes.

The third loop (Price-Return Balancing Loop) is another balancing loop that demonstrates how restricting sellers reduces the return rate by raising the average price of products on the platform. Price-Return Balancing Loop suggests that sellers prefer to sell higher-quality products by applying strict policies and increasing access denials, which means higher prices for average platform products. Studies show that cheaper products have a higher return rate, which implies that as the average price of products increases, the return rate and the overall return rate of the platform decrease, which reduces the platform policymakers' desire to increase seller restrictions.

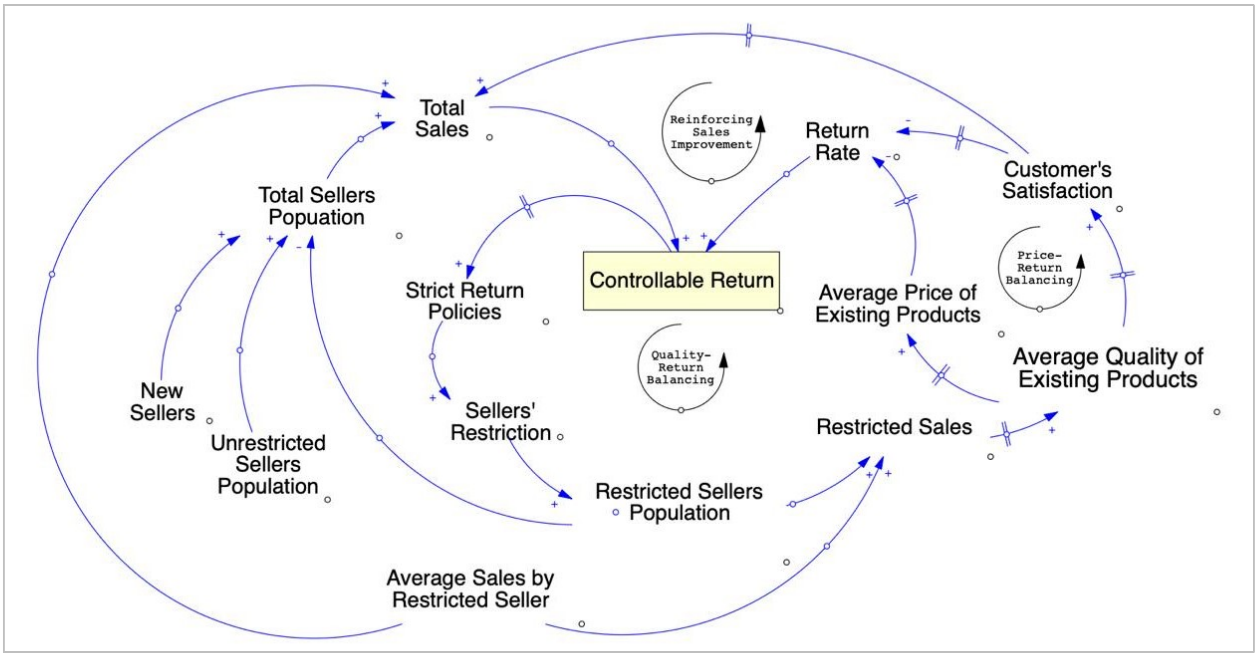

Figure 2. Causal loop diagram of controllable return

The data is analyzed by an e-commerce company, focusing on the controllable return rate of products and restricting sellers. Our regression analysis aimed to uncover any significant associations between these variables and product sales. Figure 3 illustrates that the controllable return rate of products exhibits a significant negative correlation with seller restriction. However, neither of these variables shows a statistically significant relationship with the total number of product sales.

Based on Figure 3, it can be concluded that restricting sellers with high return rates improves product returns but does not substantially impact total sales. This phenomenon can be attributed to the vast product diversity and intense competition on e-commerce platforms. Sellers' entry and exit also become relatively insignificant in the context of the platform's extensive product offerings.

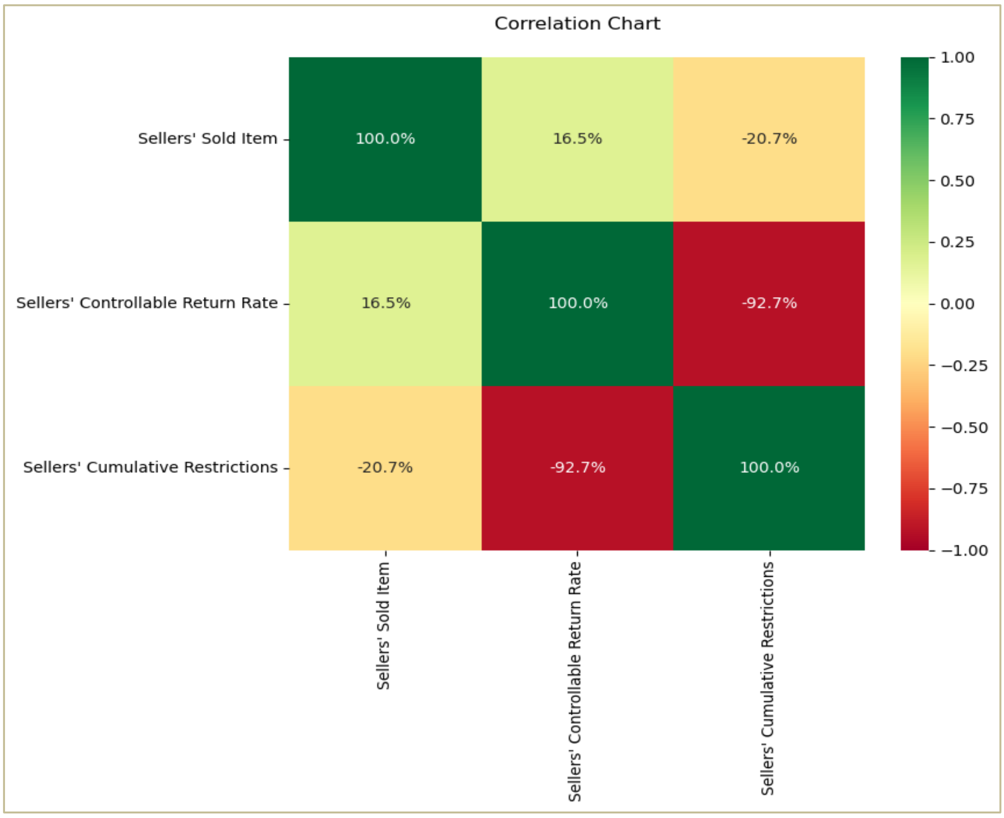

Figure 3. Correlation diagram of three variables: "sold items", "controllable return rate", and "cumulative number of restricted sellers"

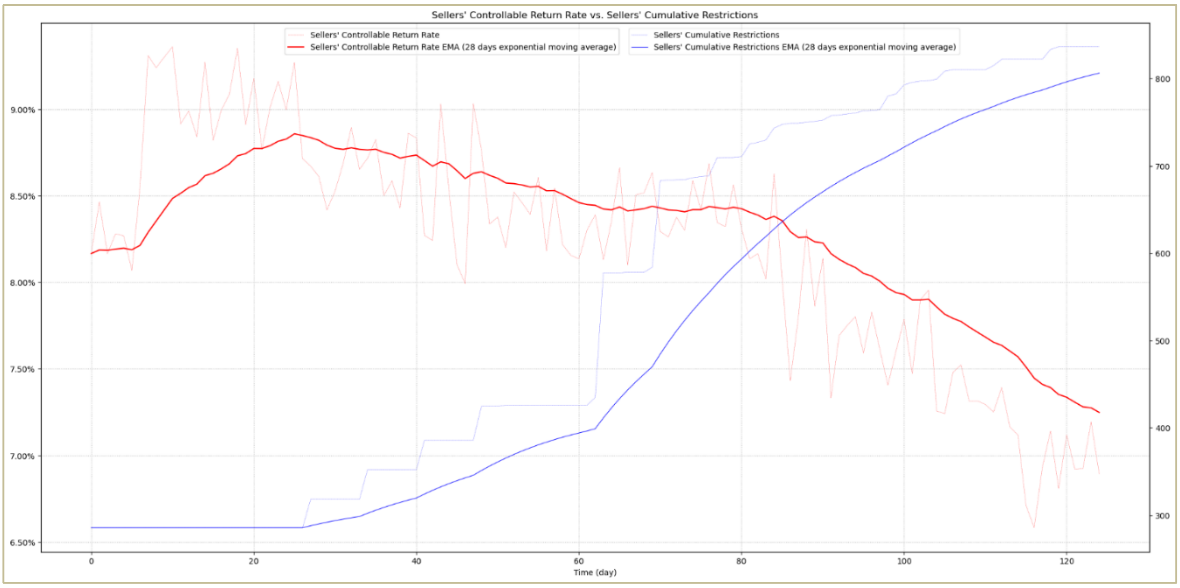

Figure 4. Sellers'controllable return rate changes vs. sellers'cumulative restriction

Furthermore, Figure 4 depicts the trends in the controllable return rate and the cumulative number of restricted sellers over a specific period.

2.3. *Model description*

The research examines how the policy of increasing access restrictions for sellers with high returns and limiting their sales on the platform affects the amount of controllable returns in e-commerce. As illustrated in Figure 5, the model designed in Vensim PLE software uses equations to describe the relationships between system variables. The key relationship that drives the system behavior is the relationship between the return rate variable and the sales of limited sellers, which was derived from the results of the regression analysis (as shown in Figure 4) in Equation 1:

$$\text{Return Rate} = -5.15*10 \wedge (-9) * \text{Sales of Restricted Sellers} + C \qquad (1)$$

where C represents the rate of controllable returns at the beginning of the study. The following equations are presented below:

$$\text{Return} = \int(\text{Increase/Decrease in Return}) \qquad (2)$$

$$\text{Increase/Decrease in Return} = \text{Return Rate} * \text{Total Sales} \qquad (3)$$

The sales of the entire platform during different periods are regarded as fixed and equal to 200,000 products to simplify the model and aid in its development.

$$\text{Sales of Restricted Sellers} = \int (\text{Increase/Decrease in Sales of Restricted Sellers}) \qquad (4)$$

$$\text{Increase/Decrease in Sales of Restricted Sellers} = \text{Average Sales of Restricted Sellers} * \text{Restricted Sellers Population} \qquad (5)$$

In order to build the model, it can be assumed that each seller sells 100 products on average per day and that these products will be removed from the market once the seller's restrictions are implemented. The number of sellers subject to restriction varies depending on the return policies of the platform, which may be categorized as either strict, moderate, or permissive.

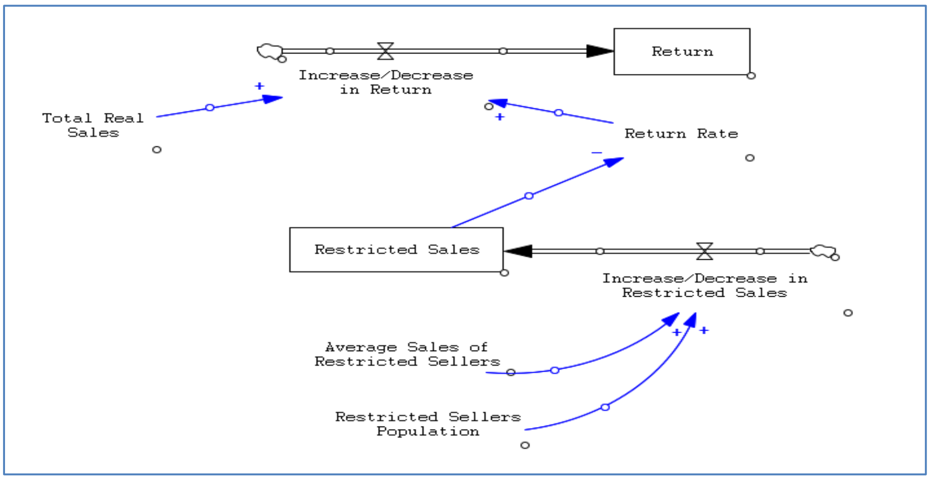

Figure 5. Stock-and-flow diagram, describing the effects of restricting sellers on the returns amount

3. Results

3.1. Model validation

This section aims to validate the model and simulation developed for the study. A multidimensional process is necessary to ensure the model's accurate functioning. This process involves creating problem representations, deciphering logical structures, and exploring mathematical cause-and-effect relationships (Liu et al., 2023; Saghaei et al., 2022). Validation is the systematic process of assessing the reliability and utility of a model. In the context of system dynamics models, validation becomes intricate due to the diverse stakeholders, each with distinct objectives and evaluation criteria (Forrester and Senge, 1980). For a scientific audience, a model's utility lies in its ability to provide insights into the underlying structure of real-world systems, make accurate predictions, and inspire relevant inquiries for future research (Forrester and Senge, 1980).

3.1.1. Test of model boundaries adequacy

The boundary adequacy test assesses the appropriateness of model aggregation and whether the model includes all relevant components (Forrester and Senge, 1980). In other words, this test checks whether the exogenous and endogenous variables are within the defined ranges for the model. The exogenous variables are the inputs determined outside the model, such as seller satisfaction and profit. The endogenous variables, such as quality and price, are the outputs determined by the model. The defined ranges are the minimum and maximum values the variables can take based on the real system and the model assumptions. The results confirm that all variables are within the acceptable range, meaning the model boundaries are adequate and realistic.

3.1.2. Test of model structural verification

Structural verification ensures that the model adequately incorporates the relationships relevant to the research goals (Kaveh Pishghadam and Esmaeeli, 2021). The test results demonstrate that the model is constructed with a systematic methodology and responds appropriately to the changes in the inputs and parameters. The model structure is valid and reliable.

3.1.3. Test of model behaviour under extreme conditions

This examination explores the model's behavior when its inputs are at the boundary conditions: when they attain their minimum or maximum levels (Kaveh Pishghadam and Esmaeeli, 2021). When extreme conditions are considered, the model typically exhibits improvement within the normal operational range (Forrester and Senge, 1980). Zero demand, zero in-process inventories, infinite supply, or negative prices are some examples of extreme conditions. The test aims to assess the robustness and stability of the model under these conditions. The results show that none of the state variables become negative, and the flow of information and materials follows the right directions based on the model assumptions. The model behavior is reasonable and consistent under extreme conditions.

3.1.4. Test of model dimensional consistency

This test involves applying dimensional analysis to the rate equations of a model and verifies the accuracy and consistency of different units of variables (Forrester and Senge, 1980). The results indicate that all variables are assigned to suitable units, and no conflict or inconsistency exists among them. The model dimensional consistency is maintained and verified, as illustrated in Figure 6.

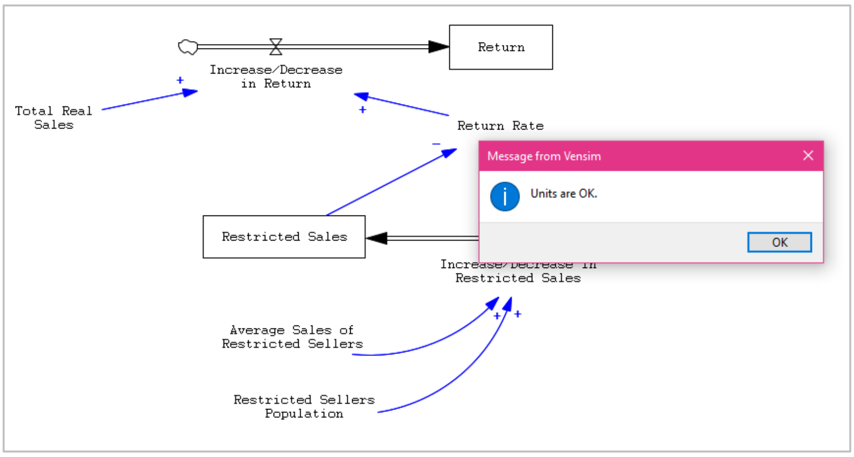

Figure 6. The result of the test of model dimensional consistency

3.2. Sensitive analysis

This section reports the sensitivity analysis results of how the system behaves under different policies. Three scenarios were examined, and Figures 7 to 12 display the analysis outcomes.A) Permissive policy that restricts only one seller on average per day: The sensitivity analysis of this policy indicates that the controllable return amount attains about 311,000 products after 100 days, as Figure 7 illustrates. This is because the return rate (Figure 8) declines marginally from 1.558% on the first day to 1.552% on the hundredth day, which is an insignificant change. Therefore, the total return change rate (Figure 9) stays nearly constant and unchanged at around 3100. Assuming this policy restricts only one seller per day, the restricted seller population remains at one during the period (Figure 10). Based on the assumption that the average number of products these sellers sell is steady at 100 products per day, the restricted sales change rate remains constant at 100 throughout the hundred days (Figure 11). Figure 12 demonstrates that the cumulative number of restricted products reaches 10,000 after the hundredth day, based on the policy of restricting one seller per day.

B) Moderate scenario that restricts 25 sellers on average per day: The sensitivity analysis of this scenario shows that the controllable return amount decreases to approximately 299,000 products after 100 days, as Figure 7 depicts. This is because the return rate (Figure 8) declines slightly from 1.558% on the first day to 1.429% on the hundredth day, about 65 times more than the change in the first scenario. As a result, the restricted sales change rate, as illustrated in Figure 9, also declines from 3,100 products per day on the first day to 2,860 products per day on the hundredth day. Assuming that this scenario restricts 25 sellers per day, the restricted seller population remains at 25 during the period (Figure 10), and based on the assumption that the average number of products sold by these sellers is constant at 100 products per day, the restricted sales change rate also stays constant at 2,500 products per day throughout the hundred days (Figure 11). The cumulative number of restricted products reaches 250,000 after the hundredth day, as Figure 12 indicates, based on the scenario of restricting 25 sellers per day.

C) Strict scenario that restricts 50 sellers on average per day: The sensitivity analysis of this scenario shows that the controllable return amount decreases to approximately 286,000 products after 100 days, as Figure 7 depicts. It is lower than the controllable return amount of both the first and second scenarios. This is because the return rate (Figure 8) decreases significantly from 1.558% on the first day to 1.3% on the hundredth day, about 130 times more than the change in the first scenario. As a result, the total return change rate (products per day) (Figure 9) also decreases from 3,100 on the first day to 2,600 on the hundredth day. Assuming this scenario restricts 50 sellers per day, the restricted seller population remains at 50 (Figure 10). Based on the assumption that the average number of products these sellers sell is constant at 100 products per day, the restricted sales change rate also stays constant at 5,000 products per day throughout the hundred days (Figure 11). Figure 12 indicates that the cumulative number of restricted products reaches 500,000 after the hundredth day, based on the scenario of restricting 50 sellers daily.

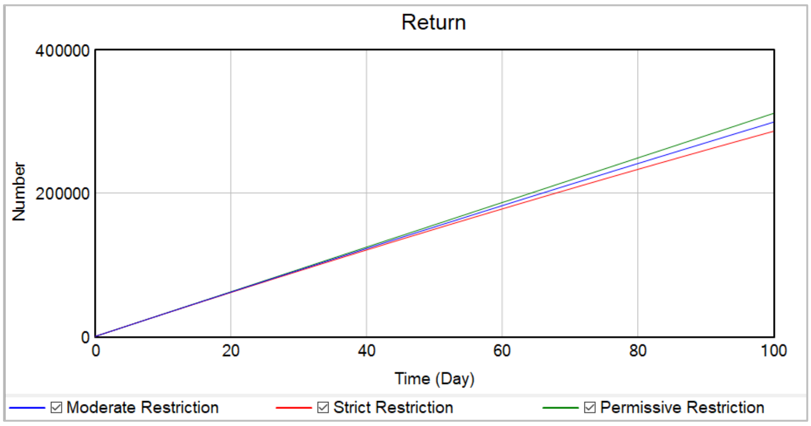

Figure 7. The number of controllable returns, under three scenarios of seller restriction policies

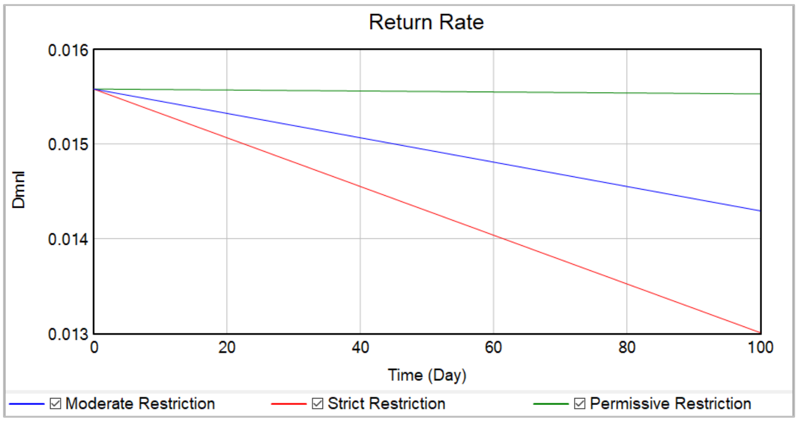

Figure 8. The controllable return rate, under three scenarios of seller restriction policies

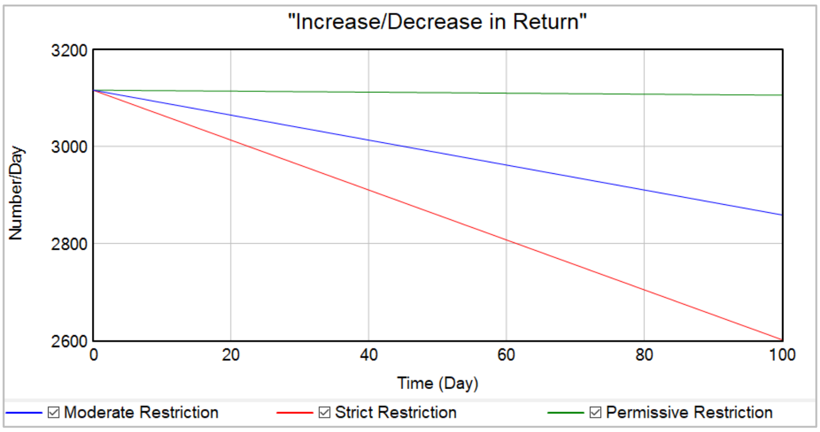

Figure 9. Changes in controllable return rate, under three scenarios of seller restriction policies

Figure 10. Restricted seller population, under three scenarios of seller restriction policies

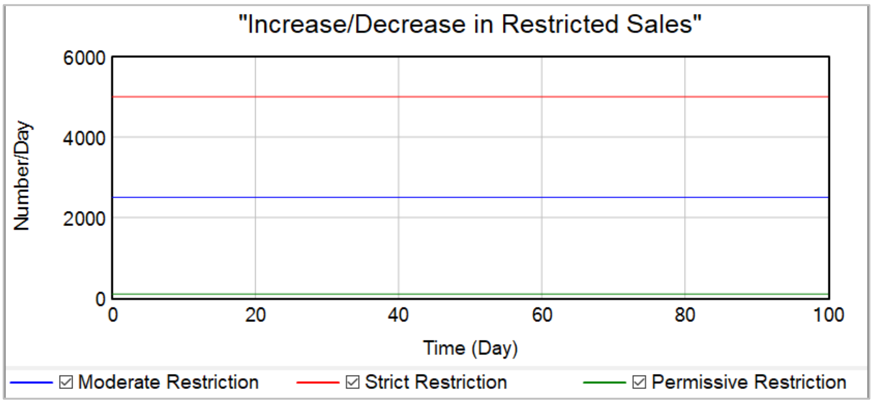

Figure 11. Changes in restricted sales, under three scenarios of seller restriction policies

Figure 12. Cumulative number of restricted sales, under three scenarios of seller restriction policies

4. Conclusion and suggestions

E-commerce platforms grapple with managing product returns, which impact customer satisfaction, operational efficiency, and financial outcomes. The controllable return dynamics model offers a framework to address these complexities. This research delves into the controllable return dynamics model within the e-commerce landscape. Our findings demonstrate that implementing a policy of increased restriction for sellers with high sales returns significantly reduces the overall number of returns. Notably, stricter restriction policies lead to a more rapid decline in controllable returns. Consequently, the authors recommend adopting this policy as a proactive measure to improve overall platform performance.

Future research can extend the model to explore the impact of increased seller restriction on customer satisfaction, seller experience, cost savings, and revenue gains. Additionally, this modeling can be developed by considering supplementary variables related to product return policies, such as varying customer return costs, adjusting the time window for accepting returned goods, and identifying and labeling customers with high return rates. This approach can provide insights into sales variables, return rate, customer satisfaction, seller satisfaction, and e-commerce profit. In conclusion, the controllable return dynamics model provides insights for e-commerce platforms. By strategically managing restrictions, platforms can optimize returns while maintaining positive user experiences and financial health.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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