Optimizing Customer Orders with a Dynamic Balanced Scorecard Model

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Abstract
In today's competitive business environment, achieving excellence in managing customer orders is essential for organizational success. This necessitates creating value through optimal investments, which enhances the ability to attract and retain customers. The Balanced Scorecard (BSC) framework offers a standardized framework for aligning goals and initiatives across organizational perspectives. However, optimizing customer orders presents complex challenges, requiring organizations to determine effective investment strategies and implement policies that deliver superior outcomes. The purpose of this study is to leverage the System Dynamics (SD) methodology to explore the influence of organizational capacity on customer orders, considering feedback loops, time delays, and nonlinear relationships. It seeks to optimize customer orders within the BSC framework by analyzing the interconnected impacts of organizational capacity, internal processes, customer satisfaction, and financial performance. The study begins by formulating dynamic hypotheses to identify the key factors influencing customer orders. A simulation model is subsequently developed and validated. Finally, a set of policies is identified and evaluated for their impact on the model. The results reveal the optimal investment values for customer orders. This paper presents a case study from a profit-driven business and industry organization, using SD modeling and simulation to achieve order optimization.

Keywords and Phrases: Customer Orders; Optimization; Balanced Scorecard; System Dynamics.

1. Introduction

In a competitive world, organizations must continuously adapt to dynamic and unpredictable changes to survive and thrive in the marketplace (Saryazdi et al., 2012). To achieve this, they strive to improve their market position (Hosseini-Nasab et al., 2013). Performance models have emerged as effective tools for evaluating an organization's market standing (Saryazdi & Owlia, 2014). These models have also paved the way for achieving world-class functionality and enhancing work processes (Dehghani et al., 2009). One of these models is the BSC, which was developed by Kaplan and Norton in the early 1990s and includes four key perspectives: financial, customer, internal business processes, and organizational capacity (learning and growth) (Chavan, 2009). It is designed to evaluate organizational strategy and performance through four perspectives, as illustrated in Figure 1. The financial perspective focuses on how owners and investors assess the organization's financial health and return on investment. The customer perspective evaluates how customers and stakeholders perceive products and services, particularly in terms of their ability to meet needs at an appropriate price. The internal process perspective examines how management and staff efficiently transform resources into outputs that satisfy customers. Lastly, the organizational capacity perspective addresses foundational elements—technology and infrastructure, culture, and employee capabilities—that support the planning, design, and delivery of products and services (Rohm & Montgomery, 2011).

Figure 1: The Four BSC Perspectives (Rohm & Montgomery, 2011)

Kaplan and Norton established a framework to translate strategic objectives into tangible goals, emphasizing alignment, operational integration, and ongoing strategy engagement (Abdalkrim, 2014). Many companies have adopted the BSC, which addresses key managerial needs and integrates diverse aspects of a company's competitive strategy, such as customer orientation, into a unified report (Kaplan & Norton, 2005). Analyzing the progress and future directions of the BSC since its introduction in 1992 reveals key themes that highlight contributions from global authors across multidisciplinary journals. Important themes include customer orientation, financial management, and the integration of systems thinking (Kumar et al., 2024).

SD is a method used to analyze how complex systems behave and change over time (Azabadi et al., 2012). It addresses internal feedback loops and time delays, as well as their effects on decision-making (Saryazdi et al., 2011). Real improvements in business thinking and practice emerge when managers are responsible for modeling systems within functional areas (Saryazdi et al., 2018). By comparing static and dynamic business management models, the advantages of dynamic systems are highlighted in terms of complexity, flexibility, and problem-solving in strategic performance management (Gozali et al., 2022). SD is a methodology used to analyze social or organizational systems by modeling and tracking their changes over time (Saryazdi & Mehrjerdi, 2014). Discussing the integration of SD tools with the BSC enhances their effectiveness in managing complex business systems. Through workshops that include lectures, exercises, and a simulation game, the authors aim to teach managers how to dynamically model their business systems, incorporating feedback loops and delays to improve decision-making and strategic performance measurement (Rydzak et al., 2004).

Introducing a "Customer Satisfaction" perspective into the BSC framework allows organizations focused on product development to improve both the quality and quantity of their outputs. By aligning goals with customer expectations, this approach enhances the flow of inputs and the quality of the products produced, leading to more effective management of the development and production processes (Tsygankov et al., 2023). Integrating SD creates real-time feedback loops that improve organizational responsiveness to customer orders. By continuously monitoring customer behavior and market conditions, businesses can quickly identify shifts in preferences and adjust strategies accordingly. This responsiveness boosts customer satisfaction and optimizes resource allocation and production processes. Overall, SD promotes proactive decision-making, enabling organizations to anticipate challenges and seize opportunities, fostering agility and competitiveness (Nielsen et al., 2015). Additionally, using SD allows for the development of a model that links customer satisfaction to profitability through dynamic diagrams. By simulating various scenarios, it is possible to explore the interactions among customer satisfaction, retention, and revenue. The findings suggest that even a small increase in retention can significantly boost revenue (Ezzabadi et al., 2013). The integration of the BSC with SD provides a more dynamic and comprehensive understanding of performance metrics, facilitating better strategic planning and operational execution. This combination serves as a significant approach to enhancing customer order management in organizations. By leveraging the strengths of both methodologies, organizations can effectively monitor customer satisfaction and adapt to changing market conditions.

This study focuses on investing in organizational capacities to optimize customer orders. It addresses three critical questions:

• What proportion of financial outcomes should be allocated to different views of organizational capacity to improve customer orders?

• What is the optimal investment in views of organizational capacity to achieve the greatest effectiveness?

• What is the optimal price to optimize customer orders?

This research introduces a framework for identifying and evaluating policies to determine the optimal investment values for optimizing customer orders by integrating SD and BSC. This approach supports informed decision-making and improved outcomes by leveraging investments across organizational capacity.

The structure and organization of the remaining sections of this paper are as follows:
Section 2 provides a literature review, categorized by key themes, methodologies, and outcomes. Section 3 introduces the modeling process, including key variables, archetype, dynamic hypotheses, subsystem, stock and flow maps, simulation model formulation, and model testing. Section 4 discusses the optimization of customer orders, including the analysis of several policies in response to key questions and their impact on customer orders, and also summarizes the results of these policies. Finally, Sections 5 and 6 conclude the paper and explore future research directions.

2. Literature review

The integration of SD with the BSC has received significant attention in academic and professional circles. This section reviews key studies that highlight the evolution and impact of this approach on improving customer orders. The papers are categorized and summarized by key trends, methodologies, and outcomes based on recent studies. Below is a categorized breakdown of the literature review, organized by key themes, methodologies, and outcomes:

2.1. Integration of SD with BSC for Enhanced Strategic Performance and Decision-Making

These papers focus on combining SD and BSC to address limitations in traditional BSC and improve strategic performance management:

Zhang (2012) integrated SD with BSC to create the Dynamic Balanced Scorecard (DBSC) model, addressing the limitations of the BSC by enhancing its causal relationships and dynamics. The model proposes specific implementation procedures for the DBSC, suggests future research directions, and emphasizes its practical value in enhancing strategic performance management in modern enterprises. Mostafavi (2019) argued that the value of combining SD with the BSC lies in addressing the limitations of the BSC, such as neglecting time dynamics, causal loops, and the lack of integration between strategic and operational levels. By using a causal loop diagram and dynamic modeling for each BSC perspective, this approach supports policymaking. Gunarsih et al. (2016) stated that integrating SD with the BSC addresses the latter's shortcomings, such as its lack of predictive capabilities and limited analysis of interactions among performance perspectives. By employing causal loop diagrams and dynamic modeling for each of the four BSC perspectives, this approach enhances the understanding of interdependencies and supports informed decision-making. Barnabè (2011) highlighted the development of a DBSC that integrates SD principles to improve strategic management decisions. This integration enhances complexity handling, feedback loop analysis, organizational learning, and policy design, especially through tools like management flight simulators. Supino et al. (2019) explored how integrating SD with the BSC model enhances decision-making, particularly for evaluating hypothetical scenarios and policy effects. By combining SD with statistical methods, the study demonstrates improved validation and reliability of the BSC system, enabling managers to more confidently forecast trends and assess both financial and non-financial indicators. Hu et al. (2017) highlighted the importance of strategy implementation over strategic planning, demonstrating that different management tools significantly influence decision-making and performance in strategy execution. By employing a closed-loop control task within a mortgage brokerage context, the research shows that tailored information presentation enhances the effectiveness of management performance measurement, offering valuable insights for both practitioners and scholars in strategic operational research and SD. Hristov et al. (2024) conducted a systematic literature review of the BSC in operations management, identifying key performance drivers (lead indicators) and outcome measures (lag indicators) across the four BSC perspectives, synthesizing their interrelationships using an SD approach. The findings reveal significant causal loops among these measures, culminating in the creation of a dynamic strategy map for operations management, thereby enhancing understanding for scholars and practitioners. Linard et al. (2002) critiqued the BSC for its inability to consistently align metrics with corporate strategy due to the absence of a rigorous methodology. This paper proposes an approach that uses cognitive mapping and hierarchical cluster analysis to identify and link metrics rationally to high-level organizational activities and strategy, serving as a foundation for a more effective BSC framework.

2.2. Application of DBSC Models to Specific Sectors or Problems

This category includes papers that apply the DBSC model to particular industries or operational challenges, integrating SD to improve outcomes in those contexts:

Costanza (2023) presented a DBSC model for social enterprises to create a flexible, multidimensional performance assessment tool. This approach addresses the limitations of BSC’s static structure by incorporating SD’s dynamic feedback loops, capturing complex interactions between financial and non-financial metrics. They apply this SD-driven model to a social cooperative focused on recycling and social reintegration, offering insights to enhance decision-making and stakeholder engagement. This work aims to fill a research gap on DBSC applications for social enterprises. Nahavandi and Bakhshi (2020) introduced a combined SD and BSC model to evaluate the performance of Company, addressing limitations of the traditional BSC by incorporating dynamic relationships and delays. This study proposes optimal policies through simulation and leverage point analysis. Ceresia and Montemaggiore (2010) developed an SD model for goal dynamics within a BSC framework, incorporating goal setting, management by objectives, and training as managerial tools to enhance workers' goal commitment and organizational performance. A case study of a wine company demonstrates how the DBSC, with a focus on the learning and growth perspective, helped management assess the impact of alternative policies. Todd and Palmer (2001) presented the development of a dynamic performance measurement system for Alpha District Council in New Zealand, which incorporates a pre-design and post-design phase to address concerns with traditional static measurement systems. By using rich visualization techniques and causal loop diagrams, the system filters relevant information and prioritizes key success loops, enabling more effective management and future-focused, 'what-if' analysis. Mayo-Alvarez et al. (2024) proposed the use of a DBSC methodology to improve industrial safety management in Peru's metallurgical mining sector, addressing the critical issue of fatal accidents through dynamic simulations and scenario analysis. By integrating SD and Soft Systems Methodology, the approach promotes organizational learning and proactive risk management, ultimately aiming to enhance safety standards and reduce workplace accidents, while acknowledging the need for further validation and the challenges that smaller organizations may face during implementation. Flores and Muñoz (2017) proposed an executive flight simulator (EFS) designed to aid new manufacturing companies in identifying and evaluating development strategies based on the BSC perspectives, thereby enhancing strategic planning and decision-making. By using SD, the EFS helps entrepreneurs understand the relationship between available resources, strategic objectives, and performance indicators, fostering a holistic approach to strategy development that adapts as the business evolves. Akkermans and Van Oorschot (2005) examined a case study in which SD modeling and simulation were applied to enhance the development of a BSC for a business unit of a Dutch insurer. The study revealed how management could better understand the interconnectedness of key performance measures such as customer satisfaction and employee productivity. It highlights that this SD approach not only facilitated a deeper analysis of the relevance and effectiveness of the BSC metrics but also provided insights into the dynamics of performance improvement initiatives, including the necessity of temporary performance drops before achieving significant gains. Theresia et al. (2016) discussed the use of an SD-based BSC to develop performance metrics for a university, focusing on the relationship between internal challenges and organizational strategy. The study found that while the university's performance from 2010 to 2012 emphasized business operations and financials, it neglected the human resources perspective. It recommends that future strategies focus on improving human resources, business operations, and market competitiveness using a resource-based view (RBV). Akkermans and Oorschot (2002) critiqued the BSC for its limitations, including its focus on unidirectional causality and insufficient integration of strategy with operational measures. They propose an SD approach to enhance BSC development, illustrated through a case study in the insurance sector, suggesting that this integration can improve stakeholder engagement and better address the systemic nature of organizational performance measurement. Capelo and Dias (2009) demonstrated that integrating strategy maps with the Balanced Scorecard (BSC) enhances managers' understanding of cause-and-effect relationships, leading to improved performance. They emphasized that active engagement with tools like causal diagrams promotes deeper learning and more effective decision-making, whereas passive use diminishes the BSC’s potential impact. Their research underscored the value of combining the BSC with system dynamics to refine mental models and drive better organizational outcomes.

2.3. Enhancements in long-term planning and sustainability

These papers explore the development of new methodologies or frameworks within BSC or introduce SD to address long-term planning, and sustainability:

Nielsen and Nielsen (2018) advocated for enhancing the strategic learning process in companies through formalized models, particularly by integrating Business Analytics (BA) with the BSC framework to link long-term strategy with short-term actions through key performance indicators (KPIs). Their work emphasizes the role of SD Modeling in understanding the causal relationships among these KPIs, aiming to improve organizational competitiveness and performance in an increasingly complex global economy. Nielsen and Nielsen (2013) explored the integration of SD modeling into the BSC framework, focusing on the dynamic handling of cause-and-effect relationships over time. They demonstrate how SD modeling can help companies test and refine strategies before execution, offering insights into both short- and long-term financial impacts, thereby contributing to strategic learning and decision-making. Chaker et al. (2017) critically evaluated the construction methodologies and design architectures of the Sustainability Balanced Scorecard (SBSC), identifying key features and conceptual flaws in existing models. They suggest future research directions to develop a more holistic, adaptive, and strategic SBSC while addressing the limitations of mental models in dynamic system thinking. Shariat et al. (2020) presented a dynamic sustainability BSC model for strategic decision-making in turbulent environments by integrating environmental factors. The model explores three scenarios (optimistic, realistic, and pessimistic) and analyzes two internal policies (production and productivity maximization), showing that the preferred policy varies depending on the scenario, thus aiding managers in navigating uncertain environments.

The literature review discusses the integration of SD with BSC, focusing on enhancing performance measurement systems, strategic decision-making, and managing complexity through feedback loops and causal relationships. It highlights studies that apply SD-BSC models across various industries, demonstrating improvements in operational efficiency, organizational performance, and sustainability. These studies offer both theoretical insights and practical examples, showcasing how SD-BSC integration can optimize performance metrics from different organizational perspectives. Current research narrows this focus by specifically addressing the optimization of customer orders within the SD-BSC framework. While it shares commonalities with the broader literature in using SD to enhance decision-making, this research distinguishes itself by concentrating on customer orders as a key driver of organizational success. This specialized focus provides deeper insights for industries where managing customer orders is crucial to value creation, guiding optimal investment and policy decisions to improve customer order management.

The novelty of current paper lies in its focused application of SD and BSC to customer orders—an area that is underexplored in existing literature. By modeling feedback loops, time delays, and nonlinear relationships specific to customer orders, the study offers targeted insights and practical solutions for improving customer satisfaction and financial performance. Through simulation-based validation, this research provides actionable recommendations for optimizing policies and investments in customer orders, offering a more specialized contribution compared to the general performance improvement focus found in previous studies.

3. The Modeling Process

In this study, several steps and tools were used for modeling, including the model boundary chart, subsystem diagram, dynamic hypothesis, stock and flow map, formulation of a simulation model, model testing, and policy design.

3.1. Model Boundary Chart

A boundary chart for the model summarizes its scope, indicating which critical variables are endogenous, exogenous, and excluded (Sterman, 2002). Table 1 shows the model boundary chart for this study.

Table 1. Model boundary chart

Endogenous	Exogenous	Excluded
- Individual Knowledge - Organizational Knowledge - Ratio of New Technologies and Infrastructures - Ratio of New Organizational Culture Practices - Business Processes Productivity - Ratio of New Products and Services - Quality of Products and Services - Ratio of Sporadic Customers - Ratio of Loyal Customers - Ratio of Ambassador Customers - Ratio of Backlog of Orders - Financial Outcomes	- Proportion of Financial Outcomes in Investment - Proportion of Investment in Technologies and Infrastructures - Proportion of Investment in Organizational Culture Practices - Proportion of Investment in employee capabilities - Price	macroeconomic variables: - Inflation - Economic Growth - Competitors

3.2. Dynamic hypothesis

In this study, the dynamic hypothesis serves as the foundation for understanding the underlying relationships and structure of the observed problem. It identifies specific feedback loops and interactions that define how key variables influence the system's behavior over time. In this study, the dynamic hypothesis aligns with the 'limits to success' archetype. In the 'limits to success' archetype, the intended consequence of the positive feedback loop is that beneficial actions lead to improved outcomes. However, an unintended consequence of the negative feedback loop is that exceeding the desired outcome triggers a system reaction due to resource constraints. To address this issue, the solution loop involves adding resources to manage the system's response (Wolstenholme, 2003).

3.2.1. Reference Mode

In this model, the reference mode of customer orders over time is illustrated in Figure 2. The figure depicts the dynamic behavior of customer orders over time, represented by two states: state 1 (red curve) and state 2 (blue curve). Initially, state 1 exhibits exponential growth, likely driven by positive feedback mechanisms. However, this growth is short-lived. The curve peaks and then sharply declines due to negative feedback loops arising from organizational capacity constraints. Despite recovery efforts, customer orders continue to drop in this state.

In contrast, state 2 demonstrates an improved trajectory. Appropriate interventions, such as enhancing organizational capacity, successfully address the decline. As a result, customer orders stabilize at a higher equilibrium level. This emphasizes the importance of managing resources effectively through well-designed policies. The figure underscores the dynamic complexity of customer order management and the critical role of feedback loops in shaping outcomes.

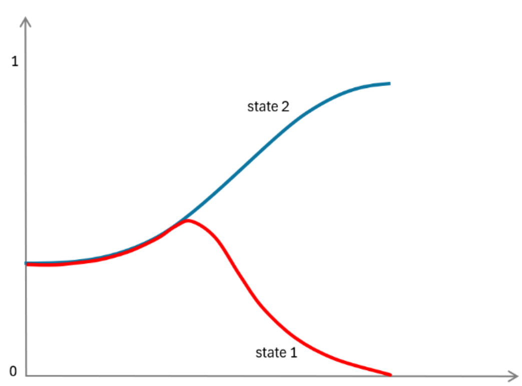


Figure 2. Reference Mode of Customer Orders over Time

3.2.2. Problem and Solution Archetype of the Study

In this study, as shown in Figure 3, the intended consequence is that value creation leads to an increase in customer orders (R1). However, the unintended consequence of this effort is that exceeding customer orders leads to a decrease in the adequacy of products and services due to organizational capacity, which in turn leads to a decrease in customer orders (B2).

To solve this problem, as shown in Figure 3, the solution loop involves adding new organizational capacity in response to the inadequacy of services and products to maintain customer orders. In other words, the balancing loop, which causes unintended consequences, is replaced by a reinforcing loop to sustain value (R3).

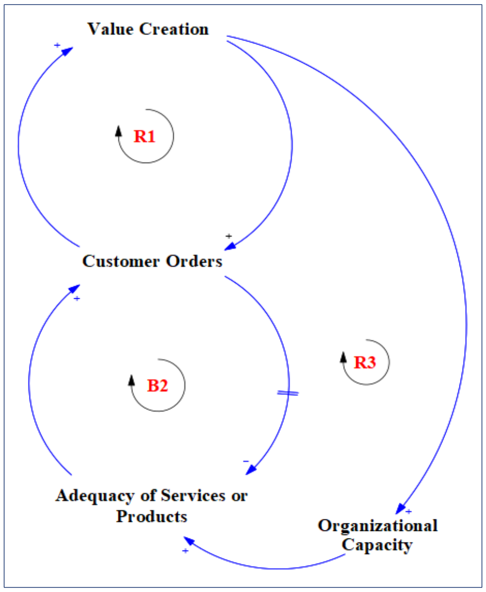


Figure 3. Limits to Success Archetype for Customer Orders

3.3. Subsystem diagram

There are subsystems based on the four perspectives of the Balanced Scorecard framework. As shown in Figure 4, the connections between these subsystems suggest a feedback loop, where each component interacts with the others, forming a dynamic system. Improvements in organizational capacity (including employee capabilities, infrastructure, technology, and organizational culture) enhance internal processes (such as processes, products and services), which subsequently impact customers. This, in turn, influences financial outcomes, leading to further investment in organizational capacity.

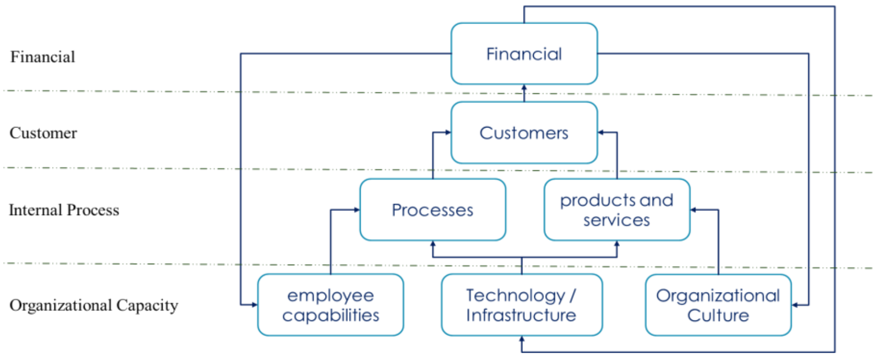


Figure 4. Subsystem

3.4. Stock and Flow maps

Stock and flow maps were drawn based on key variables, dynamic hypothesis, and literature review. In this section, we explain the stock and flow maps for four groups of Subsystems.

3.4.1. Organizational Capacity Subsystem

Figure 5 shows the ‘ratio of new technologies and infrastructures’ level, the ‘ratio of new organizational culture practices’ level, and an aging chain consisting of individual knowledge and organizational knowledge levels.

The 'ratio of new technologies and infrastructures' level represents the proportion of new technologies and infrastructures relative to the total (both new and old) technologies and infrastructures. Similarly, the 'ratio of new organizational culture practices' level represents the proportion of new organizational culture practices relative to the total of both new and old practices. The calculation of individual and organizational knowledge levels assesses both qualitative and quantitative metrics within an organization. These levels range from the lowest possible value (zero) to the highest possible score, which indicates excellence or perfection (equal to 1 or 100%).

Investment in increasing Organizational Capacity can be defined from three perspectives: employee capabilities, infrastructure and technology, and organizational culture. The proportion of investment across these perspectives can vary, and the sum of the proportions of investment in the three perspectives equals one (the proportions of investment are shown in orange in Figure 5). The effectiveness coefficient is illustrated in the graph, which shows the relationship between the input rate and the effective variables influencing it (effectiveness coefficients are shown in green in Figure 5).

As the levels of the ‘Ratio of New Technologies and Infrastructures,’ ‘Ratio of New Organizational Culture Practices’, ‘individual knowledge’, and ‘organizational knowledge’ increase, Organizational Capacity will also increase.

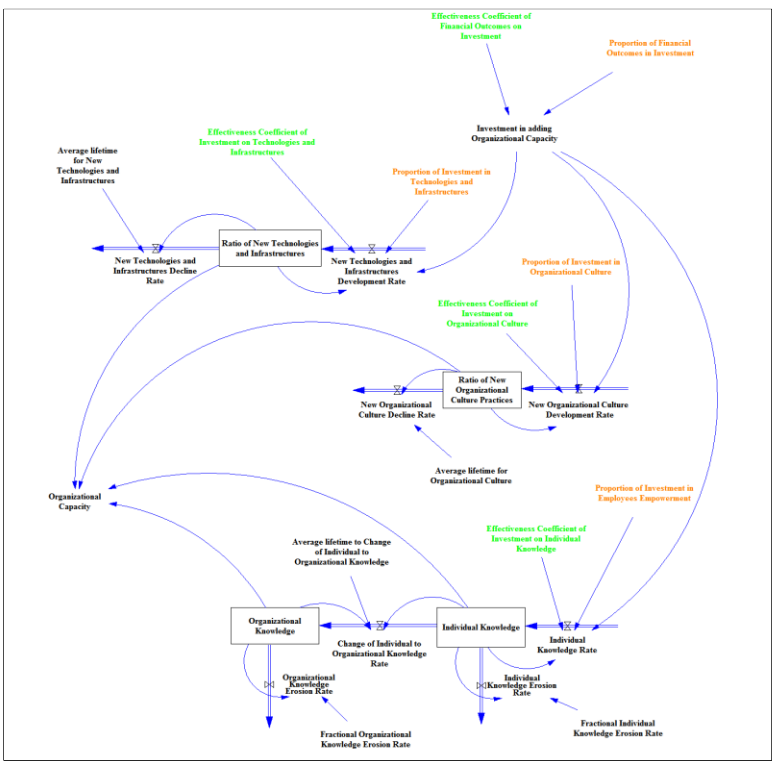


Figure 5. Organizational Capacity Subsystem

3.4.2. Internal Process Subsystem

Figure 6 presents the impact of organizational capacity on internal processes, including new products and services, business process productivity, and the quality of products and services. Organizational capacity is positioned centrally, with arrows indicating that it directly affects the change rates of these areas. Each change rate is influenced by an effectiveness coefficient of organizational capacity, signifying how well the organizational capacity can drive improvements in innovation, productivity, and quality.

The 'ratio of new products and services' level represents the proportion of new products and services relative to the total number of products and services, including both new and mature products and services. The assessment of productivity and quality levels considers both qualitative and quantitative metrics within an organization. These levels span from the lowest value (zero) to the highest score, which signifies excellence or perfection (equal to 1 or 100%).

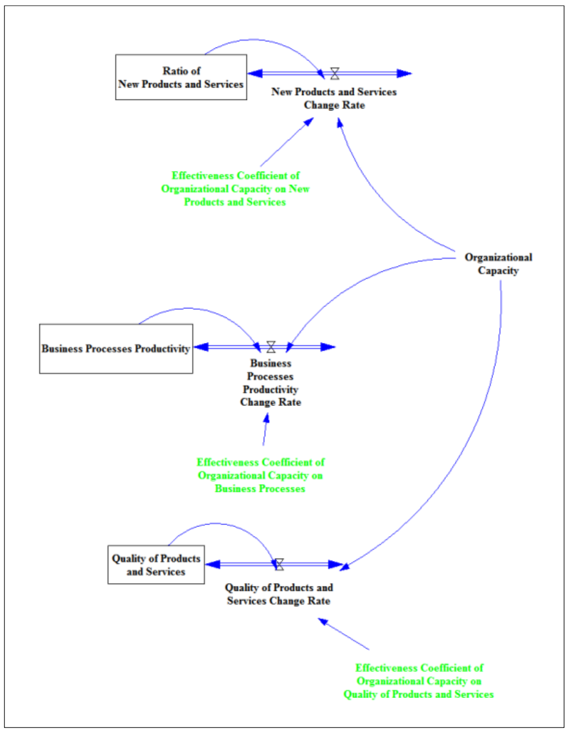


Figure 6. Internal Process Subsystem

3.4.3. Customer Subsystem

Figure 7 presents an aging chain consisting of customer segmentation levels, focusing on orders and illustrating the complex interplay among different customer groups—Sporadic, Loyal, and Ambassador customers. Each group is defined by its relationship with the organization: Sporadic customers purchase from both the organization and competitors; Loyal customers engage in repeat purchases and contribute through word-of-mouth marketing; and Ambassador customers are highly engaged and actively promote the organization's products. The model highlights feedback loops that influence transitions between these customer types, with factors such as promotion, word-of-mouth, and perceived value playing significant roles. Value for customers is shaped by elements such as the quality and novelty of products and services, pricing, order backlogs, and the organization's image—each of which impacts customer satisfaction and loyalty. As customer value improves, more sporadic customers transition to loyal and ambassador levels. This shift enhances word-of-mouth marketing from loyal customers, which in turn improves the organization's image and attracts more sporadic customers. Similarly, an increase in ambassador customers boosts promotion, further enhancing the organizational image and driving more sporadic customer changes. Effectiveness coefficients adjust the impact of 'value for customers' on different types of customers. The model also incorporates the 'ratio of backlog of orders', which balances customer orders with production volume to manage the flow of orders effectively.

The 'ratio of sporadic customers' represents the proportion of sporadic customers in the organization relative to the desired customer level (which equals 1). The 'ratio of loyal customers' represents the proportion of loyal customers relative to the desired level (also equals 1). Likewise, the 'ratio of ambassador customers' represents the proportion of ambassador customers relative to the desired level (which equals 1).

The 'ratio of backlog of orders' represents the proportion of the backlog relative to the highest possible backlog level. These levels range from the minimum value (zero) to the maximum possible score, which is equal to 1 or 100%.

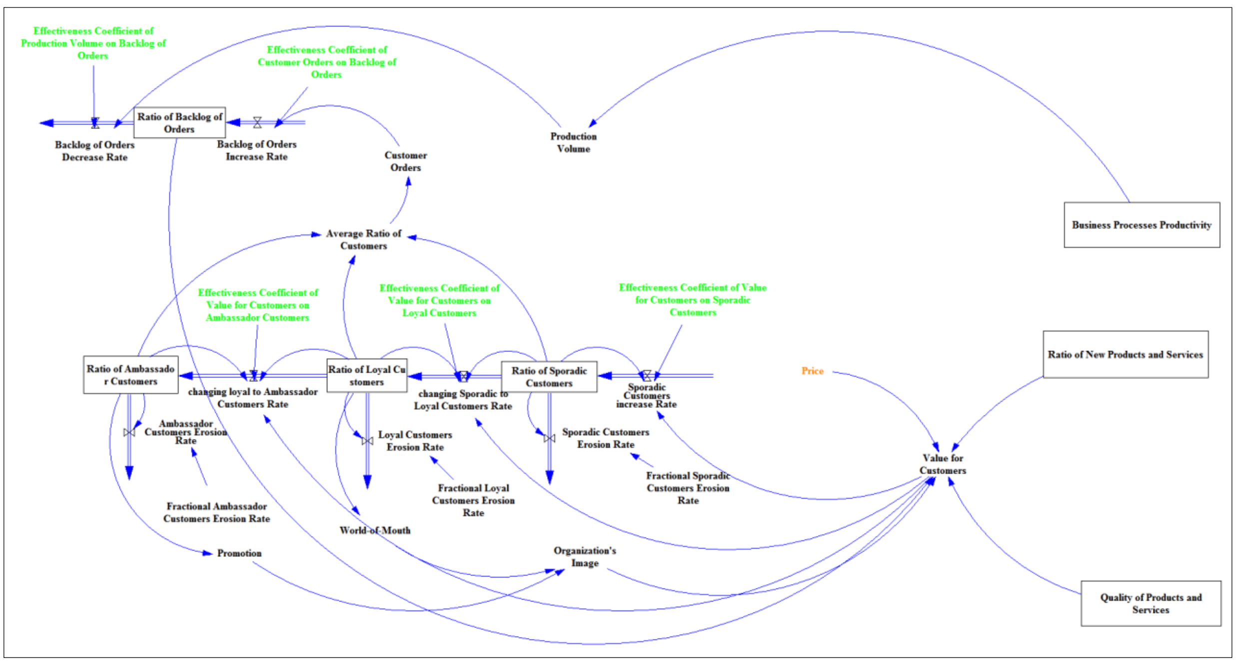


Figure 7. Customer Subsystem

3.4.4. Financial Subsystem

Figure 8 illustrates the interplay among customer orders, production efficiency, investment, and financial outcomes. Business process productivity drives production volume, which, in turn, affects the cost per product and ultimately impacts financial outcomes. Positive financial outcomes can, in turn, fuel further investment in organizational capacity. The 'Effectiveness Coefficient' parameter quantifies the influence of financial outcomes on investment in organizational capacity. The 'Proportion of Financial Outcomes in Investment' suggests that a portion of financial outcomes is allocated to organizational capacity. Additionally, price adjustments directly impact financial outcomes.

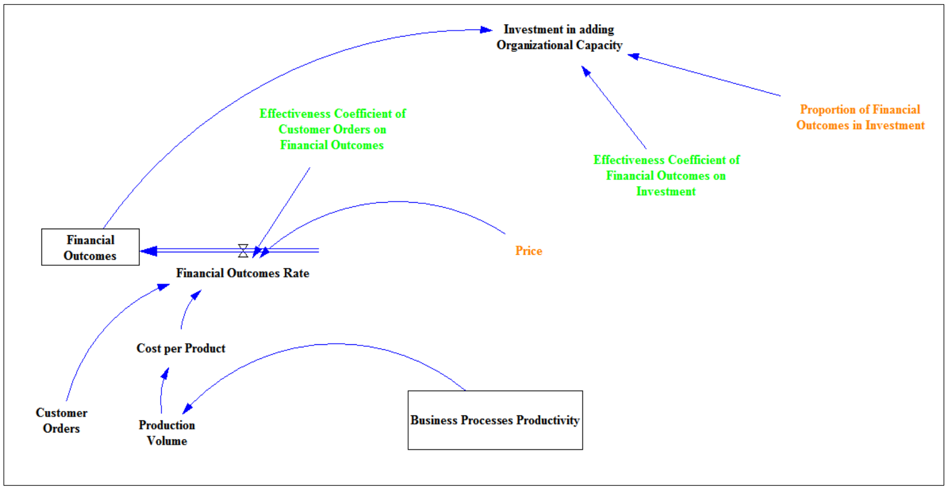


Figure 8. Financial Subsystem

3.4.5. Overall SD Model

Figure 9 presents an SD model designed to optimize customer orders within the BSC framework. Each part of the model demonstrates how different BSC aspects interact, creating reinforcing or balancing feedback loops that impact overall performance.

The model's variables are linked through feedback loops that illustrate their interrelationships. For example, an increase in customer orders can positively affect financial outcomes. However, if orders exceed business process capacity, operational inefficiencies may arise, ultimately reducing the value provided to customers. This model highlights the complexity of managing organizational performance, showing how changes in one area can have unintended consequences in others.

The model includes feedback loops that either reinforce or balance changes within the system. Reinforcing loops amplify changes, such as increased investment in employee capabilities, which improves organizational knowledge, boosts productivity, and potentially attracts more customers. Conversely, balancing loops act to stabilize the system; for instance, an overemphasis on employee investment without technological upgrades can lead to stagnation, balancing growth in orders for new products and services. These loops reveal the model's adaptive mechanisms, allowing the organization to self-correct and avoid overextension or underperformance, ensuring long-term sustainability.

A major portion of the model focuses on customer-related variables, underscoring the BSC's customer perspective. Metrics such as the rate of sporadic, loyal, and ambassador customers and their orders highlight the importance of customer behavior in organizational performance. These variables capture not only order volume but also customer loyalty and retention, both critical for sustainable revenue. Additionally, metrics like the "Effectiveness Coefficient of Value Creation in Customers" gauge how customers perceive value, influencing their loyalty and likelihood of repeat orders. This approach aligns with a customer-centered strategy, directly linking customer orders to financial outcomes.

The model integrates views essential for long-term adaptability and growth, including new technologies, emerging cultural practices, and employee capabilities (individual and organizational knowledge). These views support the organizational capacity perspective, fostering the development of other BSC perspectives. As organizational capacity strengthens, it enhances productivity, quality and novelty of products and services, ultimately boosting customer satisfaction and financial outcomes. Several effectiveness coefficients are also incorporated to represent factors influencing the impact of various elements.

Overall, this SD model provides a complex, interconnected approach that aligns with the BSC framework. It illustrates how all perspectives are interdependent, with each component's success impacting others through feedback loops. This interconnectedness underscores the need for strategic balance across perspectives, enabling sustainable growth and adaptability to evolving customer orders.

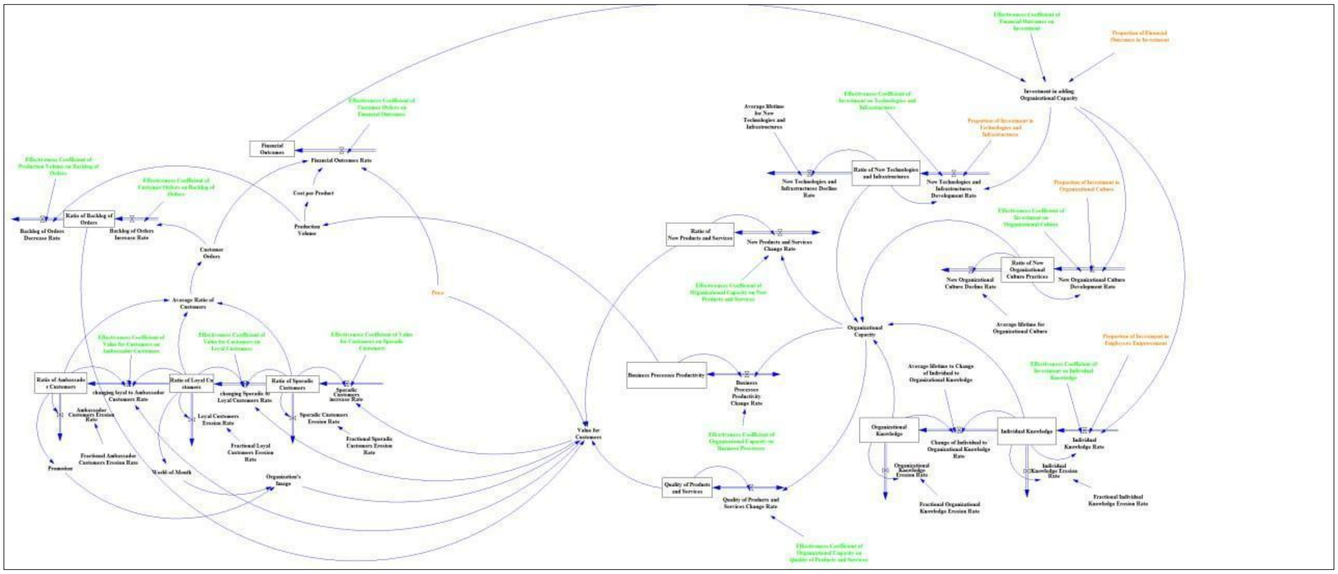


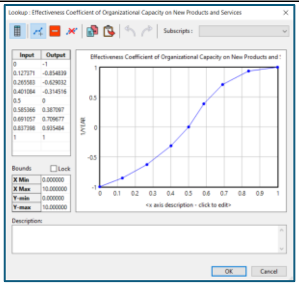
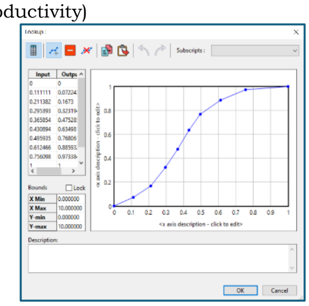
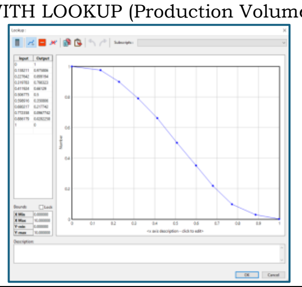
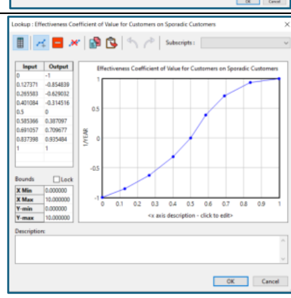
Figure 9. Overall SD Model

3.5. Formulation of a Simulation Model

The developed model is implemented in a profit-driven business and industry organization as a case study and executed using Vensim software. In this study, the time unit is defined in years, with the model running over a duration of 10 years, starting in 2024. The time step for integration is 0.25 years. All initial variable values are based on performance assessments, ranging from 0 percent to 100 percent. Table 2 shows the equations for some of the variables in the model.

Table 2. Some equations for the variables

Row	Variable	Equation	Meaning
1	Investment in adding Organizational Capacity	Proportion of Financial Outcomes in Investment* Effectiveness Coefficient of Financial Outcomes on Investment(Financial Outcomes)	The formula calculates the proportion of financial outcomes by multiplying it with an effectiveness coefficient, illustrating the relationship between financial outcomes and investments in enhancing organizational capacity.
2	New Technologies and Infrastructures Development Rate	(1-New Technologies and Infrastructures) * Effectiveness Coefficient of Investment on New Technologies and Infrastructures (Investment in adding Organizational Capacity*Proportion of Investment in New Technologies and Infrastructures)	The formula for new technologies and infrastructures calculates the gap between the desired (100%) and actual level by using (1−new technologies and infrastructures) multiplied by an effectiveness coefficient. This coefficient illustrates how the rate of new technology and infrastructure development is influenced by the product of the investment in organizational capacity and the proportion allocated to new technologies and infrastructures.
3	New Technologies and Infrastructures Decline Rate	New Technologies and Infrastructures/Average lifetime for New Technologies and Infrastructures	This phrase refers to an assessment of how long new technologies and infrastructures are expected to remain functional before needing replacement or significant upgrades.
4	Organizational Capacity	(Organizational Knowledge+ Individual Knowledge+ Ratio of New Organizational Culture Practices+ Ratio of New Technologies and Infrastructures)/4	The equation suggests that organizational capacity is the average of these views of organizational capacity based on the Balanced Scorecard framework.

5	Effectiveness Coefficient of Organizational Capacity on New Products and Services		The graph illustrates the impact of organizational capacity on the effectiveness of introducing new products and services. When organizational capacity is below 0.5, the effectiveness coefficient remains low or negative, indicating that the organization lacks the necessary resources to support new projects. This constraint hinders innovation and limits the organization's ability to expand its offerings. However, as organizational capacity increases beyond 0.5, the effectiveness coefficient begins to rise. This suggests that a higher level of capacity enables the organization to better manage and execute innovation initiatives. In other words, when capacity is insufficient, the organization struggles to introduce new products and services effectively. Conversely, as capacity improves, the organization becomes more capable of successfully launching innovations, leading to greater overall effectiveness in product and service development.
6	New Products and Services Change Rate	IF THEN ELSE((Effectiveness Coefficient of Organizational Capacity on New Products and Services(Organizational Capacity))>=0, (1-New Products and Services)*Effectiveness Coefficient of Organizational Capacity on New Products and Services(Organizational Capacity), New Products and Services*Effectiveness Coefficient of Organizational Capacity on New Products and Services(Organizational Capacity))	(1-New Products and Services): Represents the difference between the desired and actual new products and services, where the desired is set to 1 or 100%. Effectiveness Coefficient: The effectiveness coefficient shows how the 'new products and services change rate' is affected by the 'organizational capacity'. To normalize the score of the level of new products and services between 0 and 1, an 'if-then-else' condition is used. If the effectiveness coefficient of organizational capacity on new products and services is positive or neutral (≥ 0), the formula multiplies the effectiveness coefficient by '1 - new products and services,' thus it functions as an input rate. On the other hand, if the coefficient is negative (< 0), the formula multiplies the effectiveness coefficient by 'new products and services,' thus it functions as an output rate.
7	Production Volume	WITH LOOKUP (Business Processes Productivity) 	Production Volume: This variable represents the normalized score of production, ranging between 0 and 1. WITH LOOKUP (Business Processes): This indicates that the value of Production Volume is determined based on a lookup operation involving Business Processes. The graph shows an S-shaped curve: •At the beginning, increases in the Business Processes lead to minimal increases in the production volume. •In the middle portion of the curve, there's a rapid increase. As the input increases, the output grows significantly. Thus, the business processes are highly efficient within this range. •Toward the end, the curve flattens out, meaning that further increases in the input lead to decreasing returns on the output. Thus, the processes have reached a saturation point where additional improvement in business processes no longer results in significant improvements in production volume efficiency.
8	Value for Customers	(New Products and Services + Products and Services Quality + Organization's Image+(1-Backlog of Orders)+(1-Price))/5	The formula averages various components that contribute to customer value, assuming that each factor is equally important in determining the value customers perceive from the organization. Lower backlog and price, combined with higher quality, new products and services, and a strong image, result in greater perceived value for customers.
9	Cost per Product	WITH LOOKUP (Production Volume) 	Cost per Product: This represents how much it costs to produce one unit of a product. WITH LOOKUP (Production Volume): This calculates the cost per product based on a lookup of the production volume. The graph shows an S-shaped curve where, as 'production volume' increases, the 'cost per product' decreases. This demonstrates the inverse relationship between the two variables.
10	Effectiveness Coefficient of Value for Customers on Sporadic Customers		The graph illustrates the impact of the value provided to customers on the effectiveness of converting potential customers into sporadic customers. When the perceived value for customers is low, the effectiveness coefficient remains low or negative, indicating that the organization struggles to attract and retain potential customers. This limitation reduces the likelihood of converting them into sporadic customers. However, as the value for customers increases, the effectiveness coefficient begins to rise. This suggests that higher perceived value enhances the organization's ability to convert potential customers into sporadic ones. In other words, when customers perceive little value, their engagement remains minimal, making conversion difficult. Conversely, as the value they receive improves, they are more likely to transition into sporadic customers, strengthening the organization's customer base.
11	Sporadic Customers Rate	IF THEN ELSE((Effectiveness Coefficient of Value for Customers on Sporadic Customers(Value for Customers))>=0, (1-Sporadic Customers)*Effectiveness Coefficient of Value for Customers on Sporadic Customers(Value for Customers), Sporadic Customers*Effectiveness Coefficient of Value for Customers on Sporadic Customers(Value for Customers))	(1-Sporadic Customers): Represents the difference between the desired and actual sporadic customers, where the desired is set to 1 or 100%. Effectiveness Coefficient: The effectiveness coefficient shows how the 'sporadic customers rate' is affected by the 'value for customers'. To normalize the score of the level of sporadic customers between 0 and 1, an 'if-then-else' condition is used. If the effectiveness coefficient of value for customers on sporadic customers is positive or neutral (≥ 0), the formula multiplies the effectiveness coefficient by '1 - sporadic customers', thus it functions as an input rate. On the other hand, if the effectiveness coefficient is negative (< 0), the formula multiplies the effectiveness coefficient by 'sporadic customers', thus it functions as an output rate.

3.6. Testing the model

SD uses various testing methods to identify and address weaknesses in models. These tests evaluate accuracy, reliability, and behavior, helping modelers refine the model's structure and predictions. By employing these approaches, modelers can ensure that the model aligns with real-world dynamics and effectively meets its intended purpose.

3.6.1. Integration Error

This test is used to determine whether the results are sensitive to the choice of the time step. In this test, the time step of 0.25 year is halved to 0.125 year, and changes in behavior are examined to investigate any potential effects. After running the model with the adjusted time step, all variables exhibited the same behavior as before, indicating that the model is not sensitive to the choice of the time step. In Figure 10, State 1 shows the behavior with the default 0.25-year time step; State 2 shows the behavior with the halved 0.125-year time step. Both curves are directly overlapping.

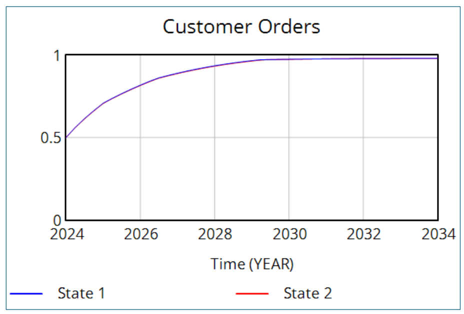


Figure 10. The behavior of customer orders in the Integration Error Test

3.6.2. Sensitivity Analysis

In this test, input variable values were altered over a short period to evaluate system stability. In stable systems, the model initially responds to changes but eventually returns to its original state or reaches a new equilibrium. This study employed PULSE and STEP functions, both of which confirmed the model's stability.

- <u>PULSE Function:</u>

  PULSE (Change start time, Duration of change)

  Proportion of Financial Outcomes in Investment = 0 + 0.25 * PULSE (2025, 1)

This function temporarily increases the Proportion of Financial Outcomes in Investment from zero to 0.25 in 2025 for a duration of one year, after which it returns to its original value.

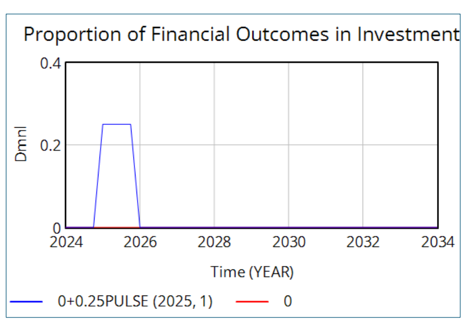


Figure 11. Sensitivity Analysis Test using the PULSE Function

Following a sudden parameter change, the system reacts but eventually returns to its initial state, demonstrating model stability.

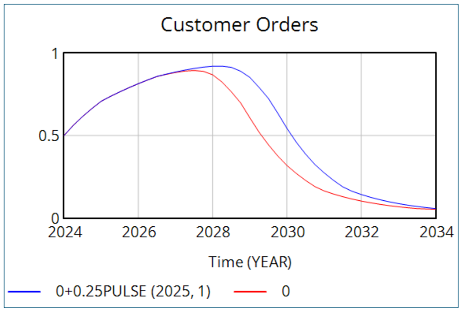


Figure 12. Behavior of customer orders based on the PULSE function

- <u>STEP Function:</u>
  STEP (Amount of change, Change start time)

Proportion of Financial Outcomes in Investment = 0 + STEP (1, 2025)

This function permanently increases the Proportion of Financial Outcomes in Investment from zero to one starting in 2025.

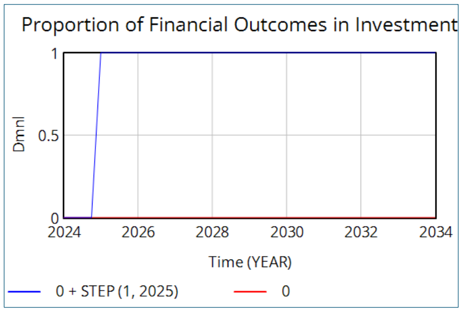


Figure 13. Sensitivity Analysis Test using the STEP Function

After the parameter change, the system stabilizes at a new state where the Proportion of Financial Outcomes in Investment remains at 1, confirming model stability.

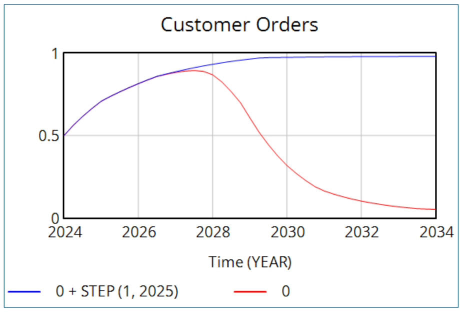


Figure 14. Behavior of customer orders based on the STEP function

3.6.3. Reality Check:

The Vensim 'Reality Check' feature was used to validate all level variables in the model against predefined constraints. According to the performance assessment, each level should range from 0 to 1, with no negative values allowed. Logical conditions, defined as Level ≥ 0 and Level ≤ 1, were applied to each variable using the Reality Check tool. The test was then executed to ensure the model met these constraints. The results confirmed that all variables adhered to the specified criteria, demonstrating the model's consistency and validity.

3.6.4. Structure and Behavior Consistency

This test examines whether the system's behavior aligns with its structure. Based on the dynamic hypothesis, the expected behavior in this study is goal-seeking. After running the simulation, the results confirmed that the behavior of the levels was indeed goal-seeking.

3.6.5. Extreme Conditions

This test evaluates the model's robustness by subjecting it to extreme conditions. In this study, extreme values were applied to the 'Proportion of Financial Outcomes in Investment' as an input variable, with the lower bound set to 0% and the upper bound to 100%. After running the model under these conditions, all variables exhibited reasonable behavior, confirming the model's robustness.

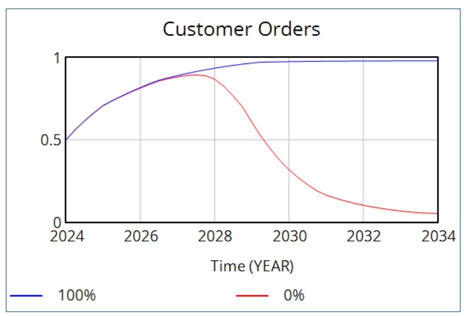


Figure 15. Behavior of customer orders based on extreme conditions

4. Optimizing Customer Orders

To optimize customer orders, it is essential to determine the optimal values for input variables, which act as decision-making levers. These variables include the 'Proportion of Financial Outcomes in Investment' and its dimensions including 'Proportion of Investment in Technologies and Infrastructures', 'Proportion of Investment in Organizational Culture Practices', 'Proportion of Investment in employee capabilities'. Additionally, price plays a significant role in this process. (Input variables are shown in orange in Figure 9.)

4.1. Policy Design

In this study, several policies are designed to determine the optimal values for key input variables. These policies are then analyzed to address critical questions and assess their impact on Customer Orders within the BSC framework.

4.1.1. Question 1: What proportion of the financial outcomes should be invested in organizational capacity?

To answer this question, two policies are defined for the "Proportion of Financial Outcomes to Invest":

- Policy 1: No investment (0%)
- Policy 2: Full investment of financial outcomes (100%)

These policies are implemented in the software. Figure 16 illustrates the behavior of customer orders under these policies, showing that Policy 2 leads to an increase in customer orders over time, while Policy 1 results in a decline. This indicates that investing in organizational capacity is more beneficial than making no investment.

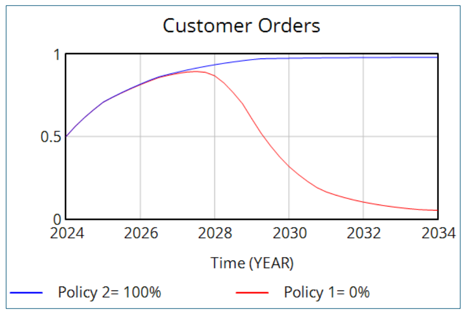


Figure 16. Customer orders behavior in response to Question 1

4.1.2. Question 2: How does the behavior of 'customer orders' vary across different values of the 'Proportion of Financial Outcomes in Investment' from 0% to 100%?

To answer this question, sensitivity analysis in Vensim software is used, setting the 'Proportion of Financial Outcomes in Investment' within a range of 0 to 1. This analysis helps determine how 'customer orders' change over time based on different investment levels.

Figure 17 illustrates that within this range, some values lead to an increase in customer orders, while others result in a decline. This highlights the significant impact of investment variations on customer orders and emphasizes the importance of identifying the optimal investment level. The goal is to determine the minimum 'Proportion of Financial Outcomes in Investment' required to drive growth in customer orders.

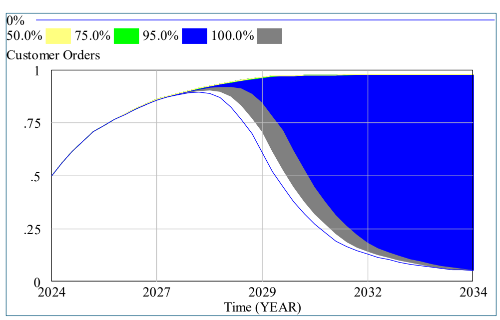


Figure 17. Customer orders behavior in response to Question 2

4.1.3. Question 3: What is the minimum value of the 'Proportion of Financial Outcomes in Investment' required to increase 'Customer Orders'?

To answer this question, the SyntheSim option in Vensim software is used, which allows adjustments to the values of input variables to observe the resulting trends in customer orders over time. In this study, the minimum value of the 'Proportion of Financial Outcome in Investment' is tested, starting at zero percent and increasing in one percent increments until it reaches eleven percent.

Figure 18 illustrates the projected trends of customer orders from 2024 to 2034 across these percentages, ranging from 0 to 11 percent. Only an 11 percent increase results in a rise in customer orders. Therefore, when comparing these percentages, only an 11 percent increase yields acceptable outcomes. In conclusion, the minimum value for the 'Proportion of Financial Outcome in Investment' required to increase customer orders is 11 percent. Based on this minimum value, the next question is presented.

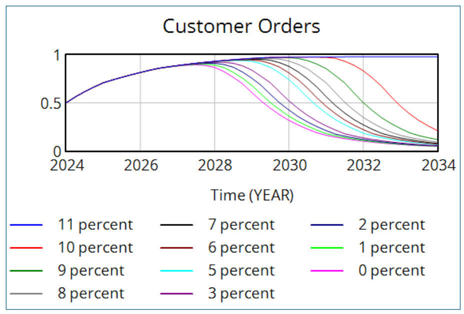


Figure 18. Customer orders behavior in response to Question 3

4.1.4. Question 4: How does the behavior of 'customer orders' vary across a range of values from 11% to 100% of the 'Proportion of Financial Outcomes in Investment'?

To answer this question, the sensitivity analysis option in Vensim software is used, with the 'Proportion of Financial Outcomes in Investment' ranging from 11% to 100%. This analysis helps determine how changes in this proportion affect the behavior of 'customer orders' over time.

Figure 19 shows that, across this range, all values contribute to an increase in 'customer orders.' However, the figure also reveals that the changes in 'customer orders' are quite small across the 11% to 100% range of the 'Proportion of Financial Outcomes in Investment.'

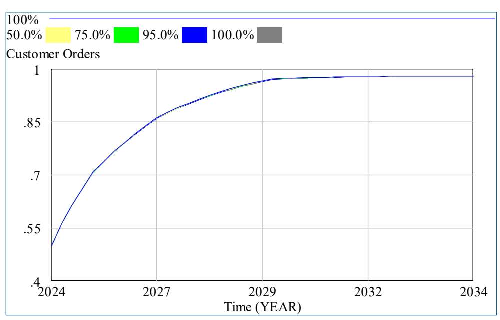


Figure 19. Customer orders behavior in response to Question 4

4.1.5. Question 5: What is the optimal value of the ‘Proportion of Financial Outcomes in Investment’ for optimizing ‘Customer Orders’?

According to Figure 19, the behavior of customer orders has not changed significantly between 11% and 100%. This indicates that the patterns or trends in customer orders remain relatively stable across this range. Due to this stability, the recommended investment level for strategies aimed at improving order behavior is set at 11%. Investing more than this amount is considered unnecessary, as it does

not lead to a proportionate increase in effectiveness or positive results. Essentially, there is a point of diminishing returns, where further investments do not yield better outcomes for customer orders.
With the optimal value of 11% established for the 'Proportion of Financial Outcomes in Investment,' the next step is to determine how this investment in organizational capacity should be distributed among the three key dimensions: technologies and infrastructures, culture, and employee capabilities.

4.1.6. Question 6: How does the behavior of 'customer orders' change with varying proportions of investment in 'Employee Capabilities', 'Culture', and 'Technologies and Infrastructures'?

To answer this question, the sensitivity analysis option in Vensim software is used, testing a range of values between 0 and 1 for the 'Proportion of Investment in Technologies and Infrastructures,' 'Proportion of Investment in Organizational Culture,' and 'Proportion of Investment in Employee Capabilities.' This analysis helps determine how different investment allocations influence the behavior of 'customer orders' over time.
Figure 20 shows that certain investment proportions contribute to an increase in customer orders, while others lead to a decline. The figure also indicates that 50% of the values fall within the yellow area, 75% within the combined green and yellow areas, and 95% within the combined blue, green, and yellow areas. In conclusion, customer order behavior varies significantly based on investment distribution. Therefore, identifying the optimal proportion for each investment dimension is essential to maximizing effectiveness in increasing customer orders.

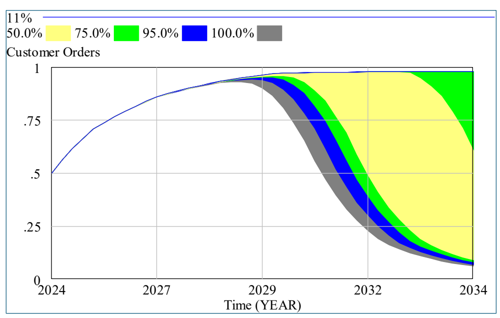


Figure 20. Customer orders behavior in response to Question 6

4.1.7. Question 7: How does the behavior of 'customer orders' vary across a range of values from 0% to 100% of 'Price'?

To answer this question, the sensitivity analysis option in Vensim software is used, setting 'Price' within a range of values from 0 to 1. This analysis helps observe how changes in price influence the behavior of 'customer orders' over time.
Figure 21 shows that across the range from 0 to 1, some values lead to an increase in customer orders, while others result in a decrease. In conclusion, customer order behavior varies significantly across this range, highlighting the need to determine the optimal price. To achieve this, it is essential to identify the price point that maximizes customer orders.

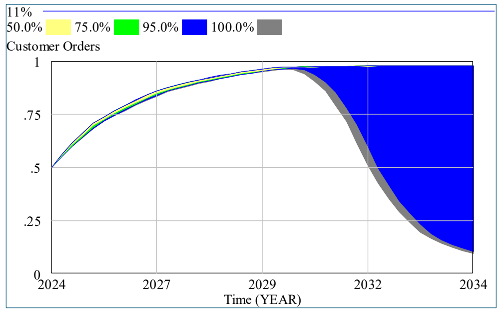


Figure 21. Customer orders behavior in response to Question 7

4.1.8. Question 8: What is the optimal proportion of investment in 'Employee Capabilities', 'Culture', and 'Technologies and Infrastructures' and the optimal price to optimize customer orders?

To answer this question, the optimization feature in Vensim software is used to determine the optimal values for maximizing customer orders. After running the model, the optimal allocation is as follows:

* Proportion of Investment in Technologies and Infrastructures: 45%
* Proportion of Investment in Employee Capabilities: 33%
* Proportion of Investment in Organizational Culture: 22%
* Price: 12%

These allocations reflect a strategic prioritization among the three investment areas. The 45% allocation to technologies and infrastructures suggests that enhancing technological capabilities is the most critical factor for efficiency and customer attraction, likely yielding the highest impact on customer orders. The 33% investment in employees highlights the role of human resources in managing increased demand and enhancing service quality. The 22% allocation to organizational culture, the smallest proportion, suggests that while culture is essential for long-term alignment and sustainability, its immediate impact on order volume is lower compared to technology and employee development.

The model suggests that setting the price at 12% of the maximum market price leads to the highest number of customer orders. While this may seem counterintuitive, a lower price increases demand, attracting more customers and maximizing order volume. This strategy focuses on quantity over per-unit revenue, making it especially effective in competitive, volume-driven markets.

Though the primary goal is to optimize customer orders rather than financial outcomes, financial sustainability is inherently part of the process. If maximizing orders causes financial strain, investment in organizational capabilities will decrease, undermining innovation, service quality, and product excellence. As a result, customer value declines, leading to fewer customers and lower order volume. Thus, this optimization strategy naturally balances investment, innovation, and long-term customer retention to ensure financial stability.

4.2. Summary of Results

Table 3 presents the optimal values for each input variable required to maximize 'customer orders'.

Table 3. The Optimal Values for Input Variables

Input Variables	optimal Value
Proportion of Financial Outcomes in Investment	11 %
• Proportion of Investment in Technologies and Infrastructures	45 %
• Proportion of Investment in Employee Capabilities	33 %
• Proportion of Investment in Organizational Culture	22 %
Price	12 %

Table 3 outlines the optimal investment allocation and pricing strategy. The ideal investment in organizational capacity is set at approximately one-tenth of financial outcomes, meaning that about 10% of financial resources should be allocated to this area. Within this allocation, investments in technologies and infrastructures take priority due to their larger share, followed by employee capabilities as a secondary focus. Organizational culture, though a tertiary priority, still plays a crucial role in enhancing overall organizational capacity. Additionally, the recommended pricing strategy sets the price at roughly one-tenth of the maximum market value, ensuring competitiveness, meeting market expectations, and optimizing customer orders.

5. Conclusions

This paper concludes by synthesizing the integration of the BSC and SD frameworks to optimize customer orders. Key findings include:

- **Integration of BSC and SD**: Merging BSC's strategic perspectives (financial, customer, internal processes, and capacity) with SD's dynamic analysis enables a deeper understanding of interactions and feedback loops within an organization. This integrated approach allows organizations to simulate the impact of strategy changes on customer orders over time.
- **Resource Allocation and Prioritization**: The model emphasizes the importance of balanced investment, with a significant portion dedicated to 'Technologies and Infrastructure,' followed by 'Employee Capabilities,' and a smaller allocation to 'Organizational Culture.' This ensures a holistic approach to enhancing organizational capacity and optimizing customer orders.
- **Optimal Pricing Strategy**: The pricing strategy recommends setting prices competitively in relation to market value to align with customer expectations, without undervaluing offerings. This approach helps maintain customer orders while supporting broader organizational goals.
- **Customer Focus**: The integrated framework enables organizations to adjust strategies based on market changes and internal dynamics. By focusing on technology, employees, culture, and competitive pricing, companies can effectively increase customer orders and ensure long-term financial sustainability. Financial strain could reduce investments in organizational capabilities, weakening customer value and order volume. The strategy maintains a balance between investment, innovation, and customer retention for stability.

In summary, the integration of BSC and SD offers a powerful framework for optimizing customer orders, supporting long-term success, and ensuring adaptability in changing market conditions. This research provides a foundation for building more resilient order management systems.

6. Future studies

Building upon the insights gained from this study, future research can explore several avenues to enhance the robustness, adaptability, and applicability of the integrated BSC and SD framework. Key areas for future exploration include:

- **Exploring Industry-Specific Investment Prioritization**: Future studies could examine how the optimal allocation of investments varies across different industries. The findings could reveal how industries with distinct characteristics, such as rapid technological advancements or market maturity, require differing focuses in terms of 'technologies and infrastructures,' 'employee capabilities,' and 'organizational culture.' A deeper understanding of industry-specific needs could guide more tailored strategies for optimizing customer orders.

- **Impact of External Factors on Strategic Decision-Making and Resilience**: The effect of external factors such as economic downturns, changes in customer behavior, and competitive shifts on pricing and investment strategies should be explored. Integrating these factors into scenario analysis and feedback loops will enable the model to adapt to real-world conditions, improving its resilience and predictive power. This will provide actionable strategies for optimizing customer orders in dynamic environments and ensuring long-term sustainability.
- **Customization for Different Organizational Structures**: Future research should apply the integrated BSC-SD framework across organizations of varying sizes and structures, including small and medium enterprises (SMEs) versus large corporations. Examining how geographic scope, organizational complexity, and business model influence the prioritization of investments in key areas like technology, employee capabilities, and culture could offer valuable insights into the scalability and flexibility of the framework.

By expanding on these areas, future research can enhance the integrated BSC and SD framework, making it more adaptable to different industries, market conditions, and organizational types, while ensuring its practical application in optimizing customer orders and sustaining long-term growth.

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