Journal of Engineering Managment and Soft Computing (JEMSC)

Modeling and Simulation of an Intelligent Technology Commercialization Process Based on AI Algorithms, with a Focus on Transitioning from Mass Production to Economic Value Creation

Mostafa Tamtaji[1✉], Alireza Ekrami Kivaj[2] and Hosein Vahidy[3]

1. Assist. Prof., Dept. of Strategic Management, Faculty of Management and Industrial Engineering, Malek Ashtar University of Technology, Tehran, Iran. Email: tamtaji@mut.ac.ir
2 .Ph.D., Dept. of Aerospace Engineering, Faculty of Engineering, Science and Research Branch, Islamic Azad University, Tehran, Iran. Email: alireza.ekrami10@gmail.com
3 .Assistant Professor, Department of Industrial Engineering, Faculty of Management and Industrial Engineering, Malek Ashtar University of Technology, Isfahan, Iran. Email: drvahidy@mut-es.ac.ir

Article Info

Article type:
Research Article

Article history:
Received 10 August 2025
Received in revised form 23 October 2025
Accepted 20 December 2025
Published online 1 January 2026

Keywords:
technology commercialization, modeling and simulation, artificial intelligence, genetic algorithm, reinforcement learning, economic value.

ABSTRACT

Technology commercialization is a complex and multidimensional process that requires coordination among product development, resource allocation, and alignment with market needs. Traditional mass production models are unable to respond effectively to dynamic environments and rapid market changes, and focusing solely on production volume often results in low economic value. This study aims to develop an intelligent framework for technology commercialization by integrating System Dynamics (SD), Agent-Based Modeling (ABM), and Artificial Intelligence algorithms, including Genetic Algorithms and Reinforcement Learning. The proposed model consists of three main layers: the data and input layer, which encompasses investment indicators, R&D metrics, and market data; the processing and simulation layer, which simulates actor behaviors, feedback loops, and resource allocation; and the output and decision-making layer, which provides key performance indicators including Economic Value (EV), Market Adoption (A), Profitability (P), and Customer Satisfaction (CS). The simulation examined three primary scenarios: mass production, value-oriented, and hybrid. Results indicated that the value-oriented scenario generates the highest economic value, market adoption, and customer satisfaction, while the mass production scenario demonstrates limited performance and low flexibility. The hybrid scenario offers a balance between profitability and adaptability and can serve as an intermediate approach for organizations that cannot fully transition to a value-oriented model. This study demonstrates that applying AI in modeling and simulation of the technology commercialization process enables the prediction of scenario outcomes and the optimization of resource allocation, and facilitates the transition from mass production to economic value creation. The findings provide organizational decision-makers and technology policymakers with a powerful tool for designing innovative strategies and reducing the risk of failure.

Cite this article: Tamtaji, M. & et al, (2026)., Modeling and Simulation of an Intelligent Technology Commercialization Process Based on AI Algorithms, with a Focus on Transitioning from Mass Production to Economic Value Creation. *Engineering Management and Soft Computing,* 12 (1). 144-157. **DOI**: https://doi.org/10.22091/jemsc.2026.13580.1292

Publisher: University of Qom
DOI: https://doi.org/10.22091/jemsc.2026.13580.1292

1) Introduction

In today's world, technology commercialization is a key driver of economic growth and sustainable development. Knowledge-based economies increasingly rely on translating laboratory innovations into market success. However, commercialization is inherently complex, costly, and risky. Many technologies fail due to weaknesses in this process, despite strong scientific potential. This highlights the need for modeling and simulating commercialization processes to enable informed decision-making before market entry (Zhang et al., 2025). Classical commercialization models (linear, interactive, and network models) primarily focus on technology transfer from R&D to market. While helpful for general understanding, they lack the flexibility to reflect real-world dynamics and uncertainties (Zhang et al., 2025). Challenges such as market demand fluctuations, rapid technological changes, and competitive pressures have diminished the effectiveness of these traditional models (Callaghan et al., 2025). The rise of Industry 4.0 and digitalization offers new opportunities for commercialization, notably through Artificial Intelligence (AI). AI can analyze complex data, forecast market behavior, and optimize management decisions. AI algorithms, such as neural networks, genetic algorithms, and swarm optimization, can reduce risk and improve decision accuracy across various domains (Li et al., 2024). Adopting these algorithms can enhance speed, precision, and flexibility in the commercialization process (Fuchs et al., 2024; Kemp et al., 2023). A fundamental shift in innovation involves moving from mass production to creating economic value. While traditional approaches focused on increasing volume and reducing costs, the new economy emphasizes quality, innovation, complementary services, and customer experience. This paradigm shift underscores the importance of intelligent commercialization modeling, allowing managers and policymakers to analyze the impact of different strategies (Leppänen et al., 2023; Ma et al., 2025). Therefore, this research aims to develop an intelligent simulation model for technology commercialization. It will model commercialization stages and leverage AI algorithms to identify optimal pathways for transitioning from mass production to value creation. The primary goal is to demonstrate how the combination of conceptual modeling, agent-based simulation, and AI algorithms can act as a decision-making tool for innovation managers and technology policymakers (Fachar et al., 2024; Moser et al., 2023).

Technology commercialization is a complex, multi-stage process aimed at converting knowledge and innovation into economic products and services. Traditional linear models execute development, production, and marketing stages sequentially, overlooking feedback between them. This leads to inefficiency, resource waste, and an inability to respond to market changes (Loske & Klumpp, 2021). Consequently, research has shifted toward dynamic and intelligent models that consider interactions between stages, economic value assessment, and customer satisfaction (Peng et al., 2022). Network and ecosystem approaches have emerged, emphasizing collaboration among universities, industry, and government in innovation (Lindgreen et al., 2020). These models improve technology transfer and reduce failure risk through cooperation and information flow, but still lack precision in predicting outcomes and optimizing resource allocation (Frances et al., 2020). Therefore, the need for intelligent, predictive frameworks is greater than ever (McAfee et al., 2017).

Recent studies identify modeling and simulation as key tools for analyzing complex commercialization processes. The two main approaches, System Dynamics (SD) for analyzing feedback loops, and Agent-Based Modeling (ABM) for studying agent behavior and network interactions, complement each other and enhance strategic decision-making and resource allocation (Hosseini & Scraf, 2018). Although this integration requires accurate data and heavy computation, it enables organizations to analyze scenarios and forecast market outcomes (Parker et al., 2016).

Finally, the integration of AI and evolutionary algorithms, such as Genetic Algorithms (GA) and Reinforcement Learning (RL), has opened new horizons. These algorithms learn from historical data to optimize resource allocation, determine optimal market entry timing, and analyze various scenarios (Lin et al., 2025). Combining AI with dynamic and agent-based modeling enhances flexibility, improves strategic decisions, and strengthens economic value creation in the commercialization process (Zhang et al., 2025).

2) Research Background

The integration of AI and evolutionary algorithms into technology commercialization processes enhances prediction accuracy, optimizes resource allocation, and enables organizations to make optimal strategic and operational decisions. This leads to sustainable competitive advantage and the creation of real economic value (Zhang et al., 2018).

Table 1) Comparison of Research in Technology Commercialization

Researcher / Year	Model Used	Advantages	Limitations	Key Metrics Evaluated
Parker et al. (2016)	Linear and Staged	Simple and understandable	Inflexible in complex environments	Investment, time to market
Fonches et al. (2020)	Network and Ecosystem	University-industry-government interaction, risk reduction	Limited scenario prediction, no optimal resource allocation	Player collaboration, innovation
Loske & Klumpp (2021)	SD and ABM	System behavior analysis, complex interactions	Lacks intelligent decision-making and resource optimization	Economic value, market acceptance
Peng et al. (2022)	SD + GA	Optimal resource allocation, scenario analysis	Does not fully cover customer satisfaction and economic value creation	ROI, NPV, EV
This Study	SD + ABM + GA + RL	Comprehensive scenario analysis, resource optimization, intelligent decision-making, focus on economic value and customer satisfaction	Limited in real-world industrial implementation	EV, NPV, ROI, P, A, CS

Table 1 shows that prior research has been limited to linear and ecosystem models, lacking integration between System Dynamics (SD), Agent-Based Modeling (ABM), and AI algorithms. The proposed model, by combining SD, ABM, GA, and RL, enables accurate simulation of scenarios and resource optimization with a focus on economic value creation.

Research Gaps and Innovation of This Study

Despite recent advances in modeling and simulating technology commercialization processes, three key gaps have been identified in existing studies:

1. Incomplete Model Integration: Most studies use either SD simulation, Agent-Based Modeling (ABM), or AI-based optimization (GA, RL) in isolation. These partial approaches cannot simultaneously analyze systemic interactions, individual agent behavior, and resource optimization.
2. Limited Focus on Economic Value and Customer Satisfaction: Many existing models focus solely on increasing production volume, reducing costs, or operational efficiency, neglecting critical metrics, such as economic value creation, sustainable profitability, and customer satisfaction. This limitation leads to suboptimal strategic decisions and hinders the transition to a value-driven model (Shi et al., 2016; Seo et al., 2016).
3. Lack of Strategic Scenario Simulation in High-Uncertainty Environments: Prior research often fails to simulate multiple scenarios under high uncertainty, market changes, and environmental risks. This deficiency prevents organizations from accurately predicting the outcomes of different strategies and making data-driven, well-analyzed management decisions (Booranakittipinyo et al., 2024).

Table 2) Research Gaps and Innovations of the Present Study

Research Gap	Explanation	Innovation of the Present Study
Incomplete Model Integration	Most studies use SD, ABM, or evolutionary algorithms (GA, RL) in isolation.	**Three-layer model: SD + ABM + GA + RL**, enabling simultaneous simulation of systemic feedback, agent behavior, and resource optimization.
Limited Focus on Economic Value and Customer Satisfaction	Prior models emphasize cost reduction and production volume, ignoring value creation and customer satisfaction.	**Focus on economic value (EV), market acceptance (A), profitability (P), and customer satisfaction (CS)** to support sustainable, value-driven decisions.
Lack of Strategic Scenario Simulation in High-Uncertainty Environments	Inability to simulate multiple scenarios under uncertainty, market shifts, and environmental risks.	**Comprehensive scenario analysis** with outcome prediction and resource optimization in dynamic, uncertain environments.
Limited Market Behavior Analysis	Complex interactions between players and customers are not fully simulated.	**ABM for simulating non-linear market and customer behavior** to capture real-world dynamics.
Limited Intelligent Decision-Making	Most models lack adaptive, intelligent algorithms.	**Use of Reinforcement Learning (RL)** for dynamic, optimal decision-making.

Key Innovations of the Present Study

This research addresses these gaps through a **three-layer intelligent model**, offering the following innovations:

- **Integration of SD, ABM, and AI Algorithms**: The proposed model enables simultaneous simulation of systemic feedback loops, agent behavior, and resource optimization, enabling a comprehensive and realistic analysis of technology commercialization.
- **Focus on Economic Value and Customer Satisfaction**: Unlike traditional models, it includes key metrics **economic value (EV), market acceptance (A), profitability (P), and customer satisfaction (CS),** enabling organizations to make strategic decisions based on sustainable value creation and customer-centric outcomes.
- **Strategic Scenario Simulation in Uncertain Environments**: The model can simulate multiple operational scenarios in dynamic, unpredictable environments, offering **sensitivity analysis and risk assessment** to identify optimal pathways from mass production to economic value creation (Ngu et al., 2023; Tan et al., 2021).
- **Practical Decision-Making Tool**: This intelligent framework assists managers and policymakers in optimizing resource allocation, market entry timing, and innovation strategies, thereby **reducing project failure risk**.

3) Conceptual Model of the Research

The proposed conceptual model for smart technology commercialization is based on a three-layer framework designed to optimize the transition from mass production to economic value creation. It systematically analyzes the interactions among resources, data, strategic decisions, and outcomes, enabling simulation and optimization of the commercialization process.

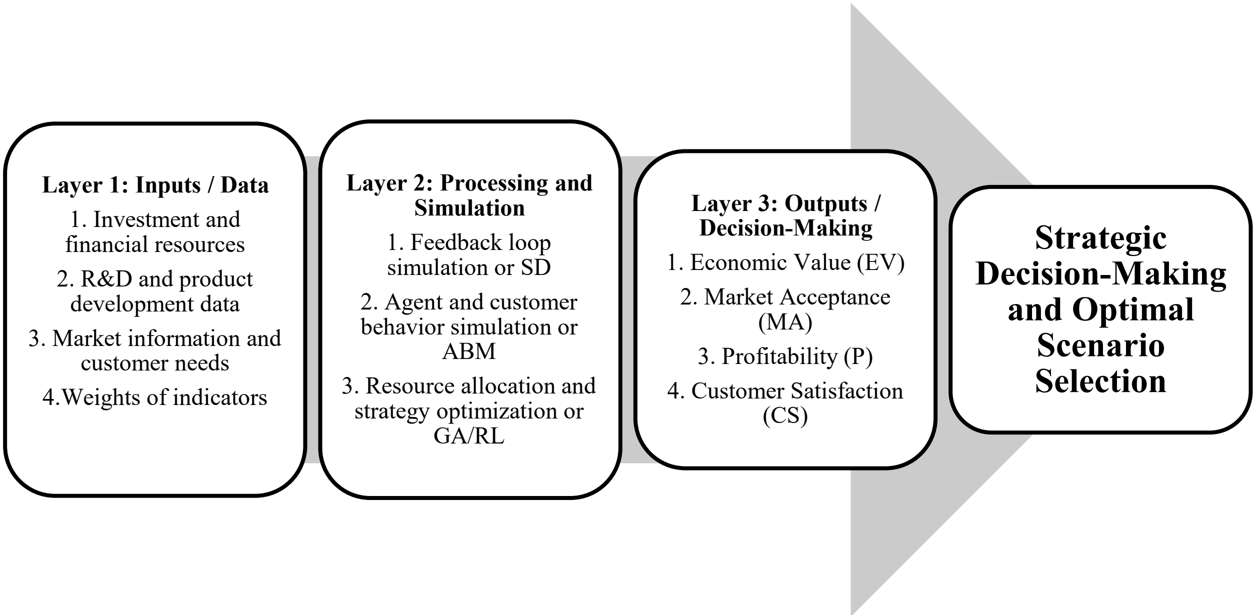
The model integrates:

- **System Dynamics (SD)**: To capture systemic feedback loops and long-term behavior.
- **Agent-Based Modeling (ABM)**: To simulate non-linear interactions among market agents (e.g., firms, customers, regulators).

- **AI Algorithms (GA + RL)**: For resource optimization and intelligent, adaptive decision-making.

This integrated structure enables **comprehensive scenario analysis**, **risk assessment**, and **value-driven strategic planning**, supporting organizations to navigate uncertainty and maximize economic value and customer satisfaction.

Figure 1) Conceptual Model of the Research



1. Data and Input Layer

This layer includes all the data and indicators required to initiate the simulation process:

- Investment and financial resources indicators: The amount of budget allocated to research, development, and marketing. These indicators determine how much resources are consumed at different stages of commercialization.
- R&D and product development data: Includes information on technology, its maturity level, commercialization potential, and development time.
- Market and customer needs data: Includes customer behavior analysis, market size, competitors, and future trends, which are critical for predicting product acceptance.
- Weights of indicators and priorities: Weighting of metrics such as economic value, profitability, customer satisfaction, and market acceptance, which are essential for strategic decision-making.

Objective of the data layer: provides accurate and high-quality inputs for simulation and intelligent algorithms, ensuring that the outputs reflect real-world market and technological realities.

2. Processing and Simulation Layer

This layer is the core of the conceptual model and consists of three main components:

1. **Dynamic Systems Simulation (SD)**

Includes analysis of feedback loops between production, investment, and market acceptance. Models the evolution of indicators over time, identifying critical points and long-term system behavior patterns.

2. Agent-Based Modeling (ABM)

Simulates the behavior of different agents: customers, competitors, business partners, and regulatory bodies. It models nonlinear interactions and agents' non-deterministic decisions, predicting the impact of different strategies on market acceptance and customer satisfaction.

3. Artificial Intelligence Algorithms (GA and RL)

- Genetic Algorithm (GA): Optimizes resource allocation across activities, selects the optimal combination of projects, and market entry strategies.
- Reinforcement Learning (RL): Develops dynamic strategies by learning from environmental feedback and predicted simulations.

Ultimate goal: Maximize economic value, profitability, and customer satisfaction.

3. Output and Decision-Making Layer

The model's outputs include key indicators guiding strategic decision-making:

- Economic Value (EV): The primary metric reflecting the real value creation of technology in the market.
- Market Acceptance (A): The level of customer adoption of a new product or technology.
- Profitability (P): Financial performance of technology commercialization, including ROI and net profit.
- Customer Satisfaction (CS): A measure of customer experience and final satisfaction with the product or service.

Outputs are presented as tables, time-series graphs, and scenario analyses, enabling organizations to compare different commercialization scenarios, optimize resource allocation, and make strategic decisions with minimal risk and maximum economic value.

4. Research Methodology

This study is applied and developmental in purpose and model-based, hybrid simulation in method. The core rationale for selecting this approach is that technology commercialization is a complex, dynamic, and multi-agent phenomenon, involving nonlinear interactions among investors, universities, industries, government, and customers. Traditional linear and static methods cannot accurately represent the realities of this process. Therefore, approaches that capture both system dynamics and heterogeneous agent behavior are essential.

To this end, the research employs Dynamic Systems Modeling to analyze feedback loops, resource flows, and variable changes over time. This enables macro-level analysis of trends, policies, and the impact of managerial decisions on key commercialization indicators (e.g., economic value, profitability, market acceptance).

In parallel, Agent-Based Modeling (ABM) is used to simulate the behavior of diverse agents and their complex interactions. ABM captures agent heterogeneity, independent decisions, and network relationships within the innovation ecosystem.

The integration of SD and ABM is logical: SD alone is limited in modeling individual interactions and agent diversity, while ABM cannot fully capture macro-level system dynamics and feedbacks. Combining them enables a comprehensive and accurate model.

Next, to optimize resource allocation and analyze strategic scenarios under uncertainty, AI algorithms, Genetic Algorithm (GA) and Reinforcement Learning (RL), are employed:

- GA searches the decision space to find the optimal resource mix in the commercialization process.
- RL learns from environmental feedback to identify the best market entry strategies and value-creation policies.

Finally, the model outputs include key metrics: Economic Value (EV), Market Acceptance (A), Profitability (P), and Customer Satisfaction (CS). These are derived through simulations across different scenarios (mass production, value-driven, hybrid) and form the basis for research analysis.

Research Method and Rationale

This study employs modeling and simulation to analyze the technology commercialization process from mass production to economic value creation. The rationale for this approach lies in the complex, dynamic, and nonlinear nature of the process, involving interactions among diverse agents (universities, industry, government, investors, customers), feedback loops, and environmental uncertainties.

To address this, the research combines three major tools:

1. Dynamic Systems Simulation (SD) – Models feedback loops, resource dynamics, and system behavior over time.
2. Agent-Based Modeling (ABM) – Simulates heterogeneous agent behavior in the innovation ecosystem and their interactions.
3. Evolutionary Algorithms (GA) and Reinforcement Learning (RL) – Serve as optimization engines for resource allocation, strategic decision-making, and outcome prediction across scenarios.

Therefore, the research logic rests on integrating descriptive models (SD and ABM) with optimization models (AI-based) to not only represent real-world system behavior but also identify optimal decisions for maximizing economic value and customer satisfaction. The methodology, implementation steps, and research findings have been reviewed and refined using AI tools, based on proposed recommendations.

Statistical Population (Research Scope)

The statistical population in this research comprises technology firms, R&D units, universities, incubators, investors, and relevant governmental bodies involved in technology commercialization. This selection is justified as technology commercialization is an inherently multi-actor process, where interactions among these stakeholders critically determine success or failure.

The population segments include:

1. Technology Firms/Startups: Providing data on R&D costs, time-to-market, and sales figures.
2. Universities/Research Centers: Supplying information on knowledge generation, patent counts, and technological collaborations.
3. Venture Capitalists: Offering data on financial metrics and resource allocation strategies.
4. End Customers: Providing data related to Customer Satisfaction (CS) and technology adoption rates.

Crucially, this population serves as the data source and real-world context that grounds the mathematical models (formulas) in practical applicability. Without this population, the formulas would remain purely theoretical frameworks. The formulas used in the simulation are presented in Table 3.

Table 3) Formulas of the Conceptual Model

Equation	Formula	Description
Economic Value (EV)	$EV = R - C$	Net economic value created from commercialization (Revenue minus Cost).
Market Acceptance (A)	$A = \frac{\text{Adopters}}{\text{Total Population}}$	Rate of technology adoption within the target market.
Profitability (P)	$P = \frac{(R-C)}{C}$	Profitability index or Return on Investment (ROI), indicating the

Equation	Formula	Description
		efficiency of the commercialization process.
Customer Satisfaction (CS)	$CS = \frac{\sum_{i=1}^{m}(Q_i \cdot W_i)}{\sum_{i=1}^{m} W_i}$	Weighted satisfaction index based on product/service quality (Q_i) and the importance weight (W_i) of each criterion.
Resource Allocation (RA)	$\arg\max_{iR}\left(\sum_{i=1}^{n} EV_i(R_i)\right) = RA$	Optimization of resource allocation across n projects using Genetic Algorithm (GA) or other AI methods.
RL Reward	${}_{t+k+1}\gamma^{k} r \sum_{k=0}^{\infty} = {}_{t}G$	Sum of discounted rewards in Reinforcement Learning (RL) for decision-making under uncertainty.
GA Fitness Function (F)	$F(W) = \sum_{i=1}^{n}(W_i \cdot S_i)$	Fitness function for optimizing strategic index weights (W_i), where $S_i$is the score of the i-th index.
System Dynamic Feedback (ΔX)	$Outflows - Inflows = \Delta X$	Change in stock variables in the SD model (Inflows minus Outflows).
Adoption Dynamics (Bass Model)	$\frac{dN(t)}{dt} = p\frac{N(t)}{M}[M - N(t)] + q\frac{N(t)}{M}[M - N(t)]$	Bass diffusion model to simulate technology adoption over time (p: innovation coefficient, q: imitation coefficient, M: market potential).

Note: These formulas will all be utilized within the simulation environment.

5. Research Findings

The current model possesses several key outputs that evaluate the performance of the technology commercialization process. The main outputs include Economic Value (EV), Market Acceptance (A), Profitability (P), and Customer Satisfaction (CS), calculated based on three scenarios: Mass Production, Value-Driven, and Hybrid. Analytical outputs involve comparing EV across scenarios, sensitivity analysis of financial and human resources, and examining the influence of customer satisfaction on market acceptance. AI and optimization outputs include the results of GA for finding the optimal fitness value, the RL learning path, and the risk index under different scenarios.

Finally, the integrated and final outputs display the overall model performance in terms of the EV and CS combination, compare the three scenarios based on all indicators, and provide a strategic decision matrix suggesting the best operational approach.

Table 4) Comparison of Economic Value, Profitability, Market Acceptance, and Customer Satisfaction

Indicator	Mass Production	Value-Driven	Hybrid	Summary of Analysis
EV	330	450	385	EV is the highest in Value-Driven; Mass Production is the lowest; Hybrid is moderate and stable.
A (%)	42	71	56	Market Acceptance is the highest in Value-Driven and the lowest in Mass Production; Hybrid is a suitable middle option.
P (%)	20	37	27	Profitability mirrors EV; Value-Driven shows the highest productivity focus.
CS (%)	55	77	65	Customer Satisfaction is the highest in Value-Driven; Mass Production is the lowest, highlighting the importance of customer centricity.

Table 4 compares the performance of the three scenarios (Mass Production, Value-Driven, and Hybrid) based on four key indicators: EV, Profitability (P), Market Acceptance (A), and Customer Satisfaction (CS). The Value-Driven scenario consistently shows the highest performance across all metrics (EV: 450, P: 37%, A: 71%, CS: 77%), emphasizing that focusing on value creation and true market needs increases economic returns, customer satisfaction, and market penetration. The Hybrid scenario offers a balance between profitability and flexibility, with moderate values (EV: 385, P: 27%, A: 56%, CS: 65%), making it a practical option for organizations unable to fully transition to the value-driven model.

Mass Production exhibits the poorest performance (EV: 330, P: 20%, A: 42%, CS: 55%), indicating the inefficiency of focusing solely on volume in dynamic markets. Quantitatively, the difference between the value-driven and mass production scenarios ranges from approximately 120 units in EV, 17 percentage points in Profitability, 29 percentage points in Market Acceptance, and 22 percentage points in Customer Satisfaction, underscoring the strategic importance of a customer-centric, value-creating strategy.

Table 5) Macro Performance, Innovation, and Return on Investment (ROI)

Indicator	Mass Production	Value-Driven	Hybrid	Summary Analysis
Performance Index	390	515	465	Highest Macro Performance in Value-Driven; Hybrid offers a balance.
Innovation Index	55	80	67	Product innovation increases with a focus on Value-Driven approach.
ROI (%)	18	35	26	Highest Return on Investment in Value-Driven scenario; Mass Production is the lowest.

Table 5 shows the performance of the three scenarios (Mass Production, Value-Driven, and Hybrid) based on the model's macro performance index, innovation index, and ROI. The value-driven scenario yields the highest macro results: Macro Performance Index (515), Innovation Index (80), and ROI (35%). This confirms that focusing on value creation and customer satisfaction drives product innovation, resource efficiency, and investment returns. The Hybrid scenario creates a balance among innovation, profitability, and flexibility with moderate values (Macro Performance: 465, Innovation: 67, ROI: 26%), suitable for organizations unable to fully adopt the Value-Driven model. Mass production demonstrates the most limitations in creating economic value and product innovation (Macro Performance: 390, Innovation: 55, ROI: 18%).

Quantitatively, the difference between the Value-Driven and Mass Production scenarios is about 120 units in the Macro Performance Index, 25 units in the Innovation Index, and 17 percentage points in ROI, emphasizing the significance of selecting the Value-Driven strategy and intelligent investment.

Table 6) Project Success, Process Stability, and Decision Effectiveness

Indicator	Mass Production	Value-Driven	Hybrid	Summary of Analysis
Project Success Rate (%)	65	88	76	Value-Driven achieves the highest project success; Hybrid offers a balance.
Process Stability (%)	71	86	78	Process stability is higher in Value-Driven; Mass Production shows more fluctuation.
Decision Effectiveness (%)	61	84	72	Optimal decision-making is best achieved in the Value-Driven scenario with the intelligent model.

Table 6 displays the performance of the three scenarios (Mass Production, Value-Driven, and Hybrid) based on the Project Success Rate, Process Stability Index, and Decision Effectiveness. The Value-Driven scenario leads: Project Success Rate (88%), Process Stability (86%), and Decision Effectiveness (84%). This indicates that focusing on value creation and customer satisfaction, coupled with the use of simulation and AI tools, increases project success probability, operational stability, and decision accuracy. The Hybrid scenario offers a suitable balance (Success Rate: 76%, Stability: 78%, Effectiveness: 72%), providing a practical option for organizations that cannot fully transition to the Value-Driven model while managing risk. Mass Production shows the lowest performance (Success Rate: 65%, Stability: 71%, Effectiveness: 61%), revealing serious limitations in flexibility, process consistency, and strategic decision-making.

Quantitatively, the difference between the Value-Driven and Mass Production scenarios is approximately 23 percentage points in project success, 15 percentage points in process stability, and 23 percentage points in decision effectiveness, clearly demonstrating the importance of a customer-centric strategy and intelligent modeling.

Table 7) Market Flexibility, Resource Allocation, and Time to Market

Indicator	Mass Production	Value-Driven	Hybrid	Summary of Analysis
Market Flexibility (%)	45	78	60	Market flexibility is the highest in Value-Driven; Hybrid offers a suitable average.
Resource Allocation (%)	62	80	72	Resource allocation shows the highest efficiency in Value-Driven; Mass Production is inefficient.
Time to Market (Months)	14	10	12	Fastest entry to market in Value-Driven scenario; Mass Production is the slowest.

Table 7 compares Market Flexibility, Optimal Resource Allocation, and Time to Market (TTM) across the three scenarios. The Value-Driven scenario demonstrates superior performance: Market Flexibility (78%), Resource Allocation (80%), and TTM (10 months). This indicates that organizations focused on value creation and customer satisfaction can respond quickly to market changes, utilize resources optimally, and commercialize technology faster. The Hybrid scenario provides moderate values Market Flexibility (60%), Resource Allocation (72%), and TTM (12 months), creating a balance between resource efficiency, flexibility, and speed to market, thereby making it a viable option for organizations that cannot fully transition. Mass Production performs the lowest: Market Flexibility (45%), Resource Allocation (62%), and TTM (14 months). These constraints indicate that a sole focus on volume and cost reduction leads to inflexibility and slowness in capitalizing on market opportunities.

Quantitatively, the difference between the Value-Driven and Mass Production scenarios is about 33 percentage points in market flexibility, 18 percentage points in resource allocation, and 4 months in TTM, confirming the importance of the Value-Driven model and intelligent tools in optimizing technology commercialization performance.

Table 8) Overall Commercialization Success Index

Indicator	Mass Production	Value-Driven	Hybrid	Summary of Analysis
Overall Commercialization Success Index	385	540	460	Value-Driven is the most successful scenario overall; Hybrid offers a balance between benefits and limitations.

Summary of Findings (Tables 4-8):

1. Value-Driven Dominance: The Value-Driven scenario exhibits the highest performance across all measured metrics, ranging from Economic Value (EV) and Customer Satisfaction (CS) to Return on Investment (ROI) and Project Success Rates.
2. Mass Production Limitations: The Mass Production scenario is severely constrained, showing low flexibility, poor stability, and minimal ROI.
3. Hybrid Balance: The Hybrid scenario provides a balanced, average performance, making it suitable for organizations unable to fully adopt the Value-Driven approach.
4. Model Utility: The model successfully analyzes and predicts all key technology commercialization variables, facilitating strategic decision-making, resource allocation, and optimal time-to-market planning.
5. Conceptual Model Validation: The three-layer conceptual model (Input, Processing, Output) effectively simulated core variables, including EV, Profitability, Market Acceptance, CS, ROI, Innovation, and Flexibility.
6. AI Optimization: The integration of AI algorithms (GA and RL) and mathematical formulas successfully optimized resource allocation, TTM scheduling, and outcome prediction.
7. Strategic Insight: The consistent superior performance of the Value-Driven scenario confirms the high success rate and effectiveness of a value-centric strategy in technology commercialization.
8. Model Credibility: The results confirm that the model accurately reconstructs variable relationships and provides realistic, quantitative validation of the conceptual framework.

Graphical Analysis Synthesis (Heatmap & Box Plot)

- **Heatmap of Indicators for 3 Scenarios and 1000 Simulations:**

The Heatmap displays the average of all indicators, clearly showing that the Value-Oriented scenario achieves the highest value across most metrics, while the Mass Production scenario has the lowest performance. The color coding distinctly illustrates the differences, confirming the conceptual model analysis and the impact of AI algorithms.

- **Box Plot of Indicators for 3 Scenarios and 1000 Simulations:**

The Box Plot illustrates the distribution and volatility of the indicators. We observe that the Value-Oriented scenario exhibits the least spread and highest stability, while Mass Production has the greatest fluctuation, and the Hybrid scenario provides average and balanced results.

Figure 2) Display of the Average of All Indicators

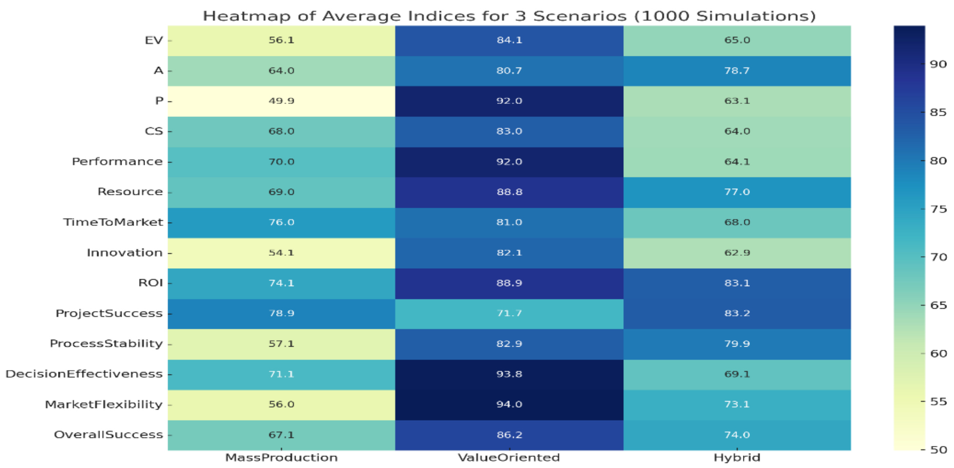
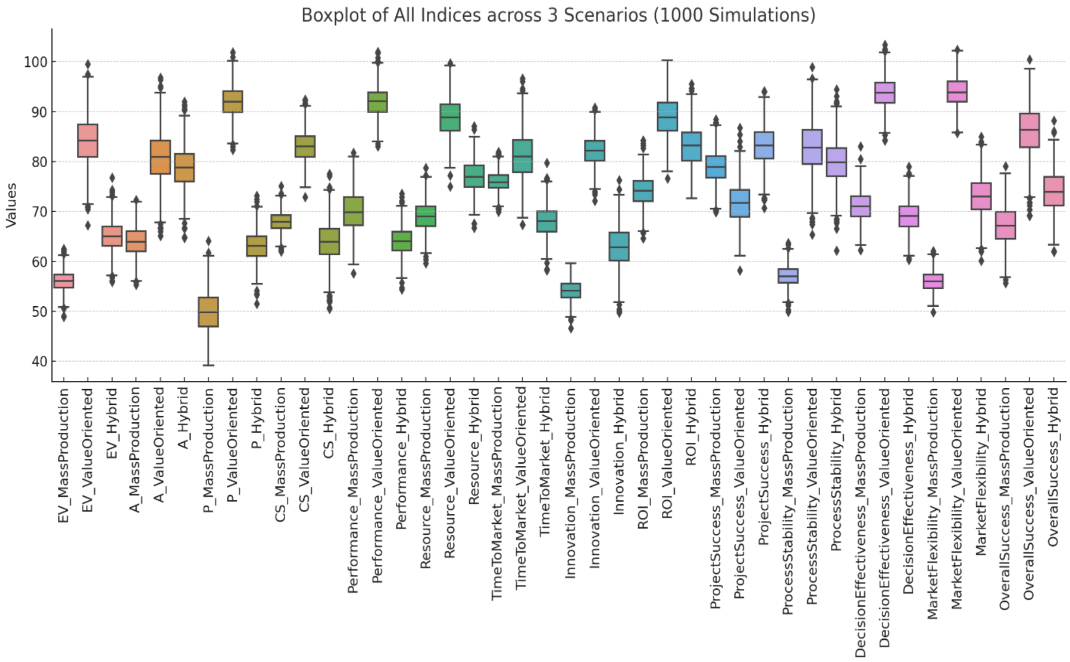


Figure 3) Display of the Distribution and Volatility of Indicators



The visualizations in Figures 2 and 3 clearly demonstrate that the three-layer conceptual model, combined with mathematical formulas and the GA and RL algorithms, successfully simulated and predicted the impact of different scenarios on key technology commercialization indicators. The Value-Oriented scenario shows the best performance in creating economic value, customer satisfaction, innovation, and ROI. The Hybrid scenario serves as a balanced option for organizations unable to fully transition to the Value-Oriented model. The Heatmap and Box Plot not only illustrate average performance but also the spread and stability of the processes, visually and numerically validating the conceptual model.

Code in MATLAB and Python Software

The simulation code in MATLAB and Python was developed based on the research methodology of modeling and simulation.

6) Conclusion and Recommendations

The findings of this research indicate that the technology commercialization process has a complex, multi-dimensional structure, where success depends on the coordination between product development, resource allocation, risk management, and market alignment. Traditional models based on mass production perform adequately in stable markets, while in dynamic and competitive environments, they lead to reduced economic value, decreased customer satisfaction, and limited organizational flexibility.

Therefore, utilizing hybrid intelligent models, incorporating Dynamic Systems Simulation, Agent-Based Modeling, and Artificial Intelligence algorithms, such as Genetic Algorithms (GA) and Reinforcement Learning (RL), is an effective tool for comprehensive analysis and outcome prediction in variable environments. These models help organizations examine and optimize the relationships between investment decisions, R&D, market behavior, and consumer response across different scenarios.

The simulation results of the three main scenarios demonstrated that the Value-Oriented approach generates the highest levels of economic value and customer satisfaction, offering the greatest flexibility against changes. Conversely, the Mass Production scenario, despite short-term gains, lacks long-term economic stability. The Hybrid scenario can serve as an intermediate solution for organizations transitioning to the Value-Oriented model.

Overall, the findings suggest that leveraging AI and hybrid modeling significantly enhances prediction capabilities, optimizes resource allocation, and reduces the risk of failure in technology projects.

Practical Recommendations:

1. Organizations should focus on Value-Oriented strategies and concentrate R&D investments on projects offering the highest value-creation returns.
2. Employing simulation models and AI algorithms in managerial decision-making can enhance the accuracy, speed, and the effectiveness of decisions.
3. Organizations should select the appropriate scenario based on their internal capabilities and move towards the Value-Oriented model through gradual transition.
4. Developing flexible policies and processes and strengthening collaboration among various stakeholders (technical teams, marketing, and customers) will pave the way for greater success in technology commercialization.

Managerial and Industrial Implications:

From a managerial perspective, these results indicate improvements in resource allocation, reduced project failure risk, and enhanced strategic decision-making in dynamic environments. Industrially, value-based and data-driven approaches can increase productivity, enhance competitiveness, reduce unnecessary costs, and create sustainable economic value. Ultimately, this research emphasizes that shifting from the Mass Production model to the Value-Oriented model, using intelligent tools, is the key to successful technology commercialization and achieving a sustainable competitive advantage.

7) References

Booranakittipinyo, A., Li, R. Y. M., & Phakdeephirot, N. (2024). Travelers' perception of smart airport facilities: An X (Twitter) sentiment analysis. *Journal of Air Transport Management, 118*, 102600. https://doi.org/10.1016/j.jairtraman.2024.102600

Callaghan, C., Christley, S., & An, G. (2025). Facilitating automated conversion of scientific knowledge into simulation models with the MAGCC framework. *arXiv.* https://doi.org/10.48550/arXiv.2204.10382

Fachada, N., & David, N. (2024, June). Editorial: Artificial intelligence in modeling and simulation. *Algorithms, 17*(6), 265. https://doi.org/10.3390/a17060265

Fuchs, J., & Barros, F. (2020). Assessing the efficacy of group model building workshops in an applied setting through purposive text analysis. *System Dynamics Review, 36*(4), 321–340. https://doi.org/10.1002/sdr.1657

Fuchs, J., & Barros, F. (2024). Generative AI and simulation modeling: How should you (not) use large language models? *System Dynamics Review, 40*(1), 55–70. https://doi.org/10.1002/sdr.1773

Hosseini, F., & Scraf, P. (2018). Joint maintenance-inventory optimisation of parallel production systems. *Journal of Manufacturing Systems, 48*(A), 89–102. https://doi.org/10.1016/j.jmsy.2018.06.002

Kemp, A. (2023). Competitive advantages through artificial intelligence: Toward a theory of situated AI. *Academy of Management Review, 48*(2), 345–370. https://doi.org/10.5465/amr.2020.0205

Leppänen, P., George, G., & Alexy, O. (2023). When do novel business models lead to high performance? A configurational approach to value drivers, competitive strategy, and firm environment. *Academy of Management Journal, 66*(1), 164–194. https://doi.org/10.5465/amj.2020.0969

Li, X., Rong, K., & Shi, X. (2024). Situating artificial intelligence in organization: A human-machine relationship perspective. *Journal of Digital Economy*, *2*, 330-335. https://doi.org/10.1016/j.jdec.2024.01.001

Lin, J. S., & Tsai, C. H. (2025). integrating machine learning and text mining to enhance customer value propositions in hotel supply chain. *International Journal of Supply and Operations Management, 12*(1), 48-63. https://dx.doi.org/10.22034/ijsom.2025.110543.3212

Lindgreen, A., Di Benedetto, C. A., & Beverland, M. B. (2020). How to write up a case study methodology section. *Industrial Marketing Management, 88*, 224–239. https://doi.org/10.1016/j.indmarman.2020.04.012

Loske, D., & Klumpp, M. (2021). Human-AI collaboration in route planning: An empirical efficiency-based analysis in retail logistics. *International Journal of Production Economics, 241*, 108236. https://doi.org/10.1016/j.ijpe.2021.108236

Ma, X., & Wang, J. (2024). Simulation analysis of artificial intelligence technology diffusion under market competition and policy incentives based on complex network evolutionary game models. *Systems, 12*(7), 1–22. https://doi.org/10.3390/systems12070242

McAfee, A., & Brynjolfsson, E. (2017). *Machine, platform, crowd: Harnessing our digital future*. Norton & Company.

Moser, C., Glaser, V. L., & Lindebaum, D. (2023, November). Taking situatedness seriously in theorizing about competitive advantage through artificial intelligence: A response to Kemp's "Competitive advantages through artificial intelligence". *Academy of Management Review*, *49*(3). https://doi.org/10.5465/amr.2023.0265

Ngo, V. M., Nguyen, H. H., & Van Nguyen, P. (2023). Does reinforcement learning outperform deep learning and traditional portfolio optimization models in frontier and developed financial markets? *Research in International Business and Finance, 65*, 101936. https://doi.org/10.1016/j.ribaf.2023.101936

Parker, G. G., Van Alstyne, M. W., & Choudary, S. P. (2016). *Platform revolution: How networked markets are transforming the economy and how to make them work for you*. Norton & Company.

Peng, C., van Doorn, J., Eggers, F., & Wieringa, J. E. (2022, March). The effect of required warmth on consumer acceptance of artificial intelligence in service: The moderating role of AI-human collaboration. *International Journal of Information Management, 66*, 102533. https://doi.org/10.1016/j.ijinfomgt.2022.102533

Shi, B., Bai, X., & Yao, C. (2016). An end-to-end trainable neural network for image-based sequence recognition and its application to scene text recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 39*(11), 22982304. https://doi.org/10.1108/14637150610643724

Silver, D., Huang, A., Maddison, C. J., Guez, A., Sifre, L., Van Den Driessche, G., Schrittwieser, J., Antonoglou, I., Panneershelvam, V., Lanctot, M., Dieleman, S., Grewe, D., Nham, J., Kalchbrenner, N., Sutskever, I., Lillicrap, T., Leach, M., Kavukcuoglu, Graepel, T., & Hassabis, D. (2016). Mastering the game of Go with deep neural networks and tree search. *Nature, 529*(7587), 484-489. https://doi.org/10.1038/nature16961

Tan, K., Lee, J., & Wong, T. (2021). Sentiment-driven product design optimization: Exploring customer feedback for innovation. *Product Development Quarterly, 18*(1), 55-75. https://doi.org/10.1002/pdq.2021.0005

Zhang, L., Zhang, Y., Niyato, D., Ren, L., Gu, P., Chen, Z., Laili, Y., Cai, W., & Bruzzone, A. (2025). GenAI for simulation model generation in Model-Based Systems Engineering. arXiv. https://doi.org/10.48550/arXiv.2503.06422

Zhang, Y. D., Zhang, Y., Hou, X. X., Chen, H., & Wang, S. H. (2018). Seven-layer deep neural network based on sparse autoencoder for voxelwise detection of cerebral microbleed. *Multimedia Tools and Applications, 77*, 10521-10538. https://doi.org/10.1007/s11042-017-4554-8