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OPTIMIZING SUPPLY CHAIN LOGISTICS USING SPATIAL GNN-BASED DEMAND PREDICTIONS

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Abstract: This paper examines the integration of spatial Graph Neural Networks (GNNs) into supply chain logistics to enhance demand forecasting accuracy and overall operational efficiency. Supply chain logistics involves the planning, execution, and control of goods and information flow, with effective management directly influencing customer satisfaction and cost efficiency. Demand forecasting is critical for anticipating customer needs and optimizing inventory levels, thereby reducing stockouts and excess inventory. Traditional forecasting methods, while effective, often struggle to capture complex demand patterns influenced by external factors. GNNs, designed to process graph-structured data, offer a novel approach to modeling the intricate relationships within supply chain data. By leveraging the spatial dependencies inherent in logistics networks, GNNs can significantly improve the accuracy of demand predictions. This research evaluates the effectiveness of GNN-based forecasting methods through a review of existing literature and case studies, providing insights for practitioners aiming to enhance their supply chain operations. The findings highlight the potential of advanced predictive models in transforming supply chain logistics and emphasize the importance of adopting innovative technologies in an increasingly data-driven environment.
Keywords: Supply chain logistics; Demand forecasting; Graph neural networks

1 INTRODUCTION

Supply chain logistics encompasses the planning, execution, and control of the flow of goods, services, and information from the point of origin to the end customer [1-3]. It involves various activities, including procurement, transportation, warehousing, and inventory management [4-10]. Efficient logistics is critical in modern business, as it directly impacts customer satisfaction and operational costs. Companies that effectively manage their supply chains can achieve significant competitive advantages, including reduced lead times, lower costs, and improved service levels [11].

Demand forecasting is a vital component of supply chain management, as it enables organizations to anticipate customer needs and adjust their operations accordingly. Accurate demand predictions help businesses minimize stockouts and overstock situations, optimizing inventory levels and reducing costs [12]. The traditional methods of demand forecasting have evolved with advancements in technology, leading to the exploration of more sophisticated techniques that leverage data analytics and machine learning [13-16].

Graph Neural Networks are a class of neural networks designed to process data structured as graphs, where relationships between entities are represented as edges connecting nodes [17-18]. GNNs have gained popularity due to their ability to capture complex interactions and dependencies within spatial data, making them particularly useful for applications in transportation and logistics. By leveraging the spatial relationships inherent in supply chain data, GNNs can enhance the accuracy of demand predictions, leading to better decision-making in logistics operations.

This paper aims to explore the integration of spatial GNN-based demand predictions into supply chain logistics optimization. The objectives include evaluating the effectiveness of GNNs in improving demand forecasting accuracy and assessing their impact on supply chain efficiency. By examining case studies and existing literature, this research will highlight the significance of adopting advanced predictive models in logistics and provide insights for practitioners seeking to enhance their supply chain operations.

2 LITERATURE REVIEW

Demand forecasting has traditionally relied on statistical methods such as Autoregressive Integrated Moving Average and exponential smoothing [19-20]. These methods are widely used due to their simplicity and effectiveness in capturing time-series trends. However, they often struggle to accommodate complex patterns and external factors affecting demand [21-23].

Statistical methods have long been the backbone of demand forecasting, providing foundational techniques that have been widely adopted across various industries. Among these, ARIMA (AutoRegressive Integrated Moving Average) models stand out for their capability to model time-dependent data effectively. These models are particularly useful in capturing the underlying patterns in historical demand data, making them a popular choice for businesses aiming to forecast future demand based on past trends and behaviors. The strength of ARIMA lies in its ability to handle non-stationarity through differencing, allowing for a more accurate representation of the underlying data dynamics [24-26].

In addition to ARIMA, exponential smoothing methods offer a flexible framework for forecasting, especially in environments characterized by trends and seasonality. These methods prioritize recent observations more heavily than older ones, making them particularly adept at responding to changes in demand patterns. The simplicity and effectiveness of exponential smoothing make it a preferred option for many practitioners looking to generate reliable forecasts without the complexity of more advanced models [27].

The landscape of demand forecasting has been significantly transformed by the integration of machine learning techniques. Approaches such as regression analysis and decision trees have gained traction, allowing for more nuanced modeling of demand patterns that traditional statistical methods may overlook [28-30]. The adaptability of machine learning models to various types of data and their ability to learn from complex interactions have made them increasingly popular among data scientists and business analysts.

Spatial Graph Neural Networks have shown significant potential in improving product demand prediction for e-commerce platforms. This approach, which leverages spatial relationships in online sales data, outperformed both traditional forecasting methods and other deep learning models [31]. These methods have been shown to outperform traditional statistical techniques in specific contexts, particularly when dealing with heterogeneous data sources or complex demand structures [32-34]. The ability of ensemble methods to mitigate the limitations of individual models contributes to their growing adoption in demand forecasting applications.

The advent of big data and advanced analytics has further propelled the evolution of demand forecasting methodologies [35]. Time-series forecasting techniques are now being augmented with machine learning algorithms, leading to improved accuracy and adaptability [36]. As businesses collect and analyze larger datasets, the integration of these advanced techniques allows for more responsive and precise forecasting capabilities [37].

One significant advancement in time-series forecasting is the use of Seasonal Decomposition of Time Series, which enhances the understanding of seasonal patterns within the data [38]. By breaking down time series into trend, seasonal, and residual components, practitioners can gain insights into the underlying behaviors of demand, enabling more informed decision-making [39].

Moreover, the development of hybrid models that combine traditional statistical methods with machine learning approaches has shown great promise in enhancing forecasting accuracy [40]. These models leverage the strengths of both paradigms, allowing for a more comprehensive analysis of demand data and improved predictive capabilities [41].

The rise of deep learning techniques has introduced new possibilities for demand forecasting [42]. Long Short-Term Memory networks, a type of recurrent neural network, have gained traction for their ability to model complex temporal dependencies within time series data [43]. Their architecture is particularly suited for capturing long-range dependencies, making them effective for forecasting tasks where historical data influences future outcomes [44].

Additionally, Convolutional Neural Networks have been employed in demand forecasting, especially in scenarios involving spatial data [45]. By leveraging their ability to process grid-like data structures, CNNs can uncover patterns in demand that are influenced by geographical factors, thereby enhancing the accuracy of predictions [46].

The emergence of Graph Neural Networks represents a significant shift in how data relationships are modeled, particularly in applications involving spatial data [47]. GNNs utilize graph structures to capture the interactions between entities, enabling more nuanced predictions in contexts such as transportation and logistics [48]. This capability is especially valuable in scenarios where spatial dependencies significantly influence outcomes [49].

Spatial GNNs extend traditional GNNs by incorporating spatial information, allowing for the modeling of geographical relationships [50]. This characteristic makes them particularly effective for demand forecasting in supply chains, where the location of suppliers, customers, and distribution centers can significantly impact demand patterns. By capturing the intricacies of spatial dependencies, Spatial GNNs provide a robust framework for improving forecasting accuracy [51].

The versatility of GNNs is evidenced by their successful applications across various fields. For instance, in urban planning, GNNs have been employed for traffic prediction, providing insights that can enhance infrastructure development and traffic management [52]. In the realm of transportation, GNNs have proven effective in optimizing routing and vehicle scheduling, thereby improving operational efficiency and reducing costs [53].

The integration of artificial intelligence and machine learning in supply chain logistics is revolutionizing traditional practices [54]. Companies are increasingly adopting advanced analytics to enhance decision-making and operational efficiency [55]. This shift is driven by the need for more responsive and data-driven approaches to managing complex supply chain dynamics [56].

AI-driven solutions are enabling real-time demand forecasting and inventory management, allowing businesses to respond swiftly to fluctuations in demand [57]. By employing machine learning algorithms, organizations can optimize routing and reduce transportation costs, ultimately leading to improved service levels and customer satisfaction [58].

Recent studies have highlighted the successful implementation of GNNs in predicting demand for retail chains, resulting in improved inventory turnover [59]. These case studies demonstrate the effectiveness of GNNs in enhancing supply chain resilience by improving demand visibility [60]. As companies continue to explore the capabilities of GNNs and other advanced analytics, the potential for transformative impacts on supply chain operations becomes increasingly evident.

In summary, the landscape of demand forecasting is undergoing a significant transformation driven by the integration of statistical methods, machine learning approaches, and advanced analytics [61]. The evolution of time-series forecasting techniques, the rise of deep learning, and the advent of Graph Neural Networks are reshaping how organizations approach demand prediction. As companies increasingly adopt these innovative methodologies, the potential for improved forecasting accuracy, operational efficiency, and strategic decision-making in supply chain logistics continues to expand.

3 METHODOLOGY

3.1 Data Collection

3.1.1 Types of data required
To effectively develop the Spatial Graph Neural Network model for demand forecasting, various data types are imperative. Historical sales data will serve as a foundational dataset, revealing trends and patterns in demand over time. This data will be complemented by spatial data, which provides essential geographic context for supply chain nodes, such as warehouses, distribution centers, and retail locations. Additionally, seasonality factors, such as holiday sales spikes or seasonal product variations, will be integrated into the dataset. Promotional events—like sales campaigns or product launches—will also be recorded, as these can significantly influence demand. Economic indicators, including local employment rates, consumer confidence indices, and inflation rates, will further enrich the dataset, allowing for a more nuanced understanding of demand fluctuations.

3.1.2 Sources of data
Data will be sourced from a variety of reliable databases and APIs to ensure comprehensiveness and accuracy:
Retail Sales Databases: These include industry-standard sources such as Nielsen and IRI, which provide insights into consumer purchasing behavior and market trends.
Geographic Information Systems: Tools like OpenStreetMap and ESRI will be utilized to gather spatial data, which is crucial for understanding the relationships between different supply chain nodes.
Company Internal Databases: Historical sales and inventory levels will be extracted from the company's existing databases, ensuring that the model is tailored to the specific operational context of the retail company.
Publicly Available Datasets: Government economic data, weather data, and other publicly accessible datasets will be leveraged to capture external factors that may impact demand.

3.2 Spatial GNN Model Development

3.2.1 Overview of model architecture
The proposed Spatial GNN model will be structured with multiple layers to capture both spatial dependencies and demand prediction. The architecture will include:
Graph Convolutional Layer: This layer will process the graph structure of the data, enabling the model to learn from the relationships and interactions between different locations. It will capture how demand at one location can be influenced by neighboring nodes.
Fully Connected Layer: Following the graph convolutional layer, a fully connected layer will aggregate the learned features to predict demand at each node. This layer will ensure that the model can effectively synthesize information from various sources.

3.2.2 Feature selection and representation
Feature selection will be a critical step in ensuring the model's effectiveness. Features will be chosen based on their correlation with demand patterns, including:
Historical Demand: Previous sales data will be a primary predictor.
Proximity to Suppliers: Locations closer to suppliers may have different demand dynamics.
Regional Economic Indicators: Economic data relevant to the region will be integrated to assess how local conditions affect demand.
The features will be represented in a graph structure, where nodes correspond to geographic locations and edges represent the relationships and interactions between these locations (e.g., transportation routes).

3.2.3 Training the GNN model
The training process will involve splitting the dataset into training, validation, and test sets. A supervised learning approach will be utilized, with the model trained to minimize a loss function such as Mean Squared Error. Hyperparameter tuning will be carried out using techniques like grid search or random search to optimize model performance. The training process will also incorporate methods to prevent overfitting, such as dropout layers or early stopping based on validation performance.

3.3 Integration with Supply Chain Logistics

3.3.1 How demand predictions will be utilized in logistics
Once the GNN model generates demand predictions, these insights will be integrated into the logistics framework of the retail company. This integration will inform inventory management strategies, allowing for adjustments in stock levels based on predicted demand. Additionally, it will optimize order quantities to align with forecasted sales, thereby enhancing routing efficiency and reducing the risk of stockouts or excess inventory.

3.3.2 Framework for optimization
A comprehensive framework will be developed to optimize logistics operations, focusing on:

Inventory Management Strategies: These strategies will be based on predicted demand, ensuring that stock levels are aligned with actual consumer needs.

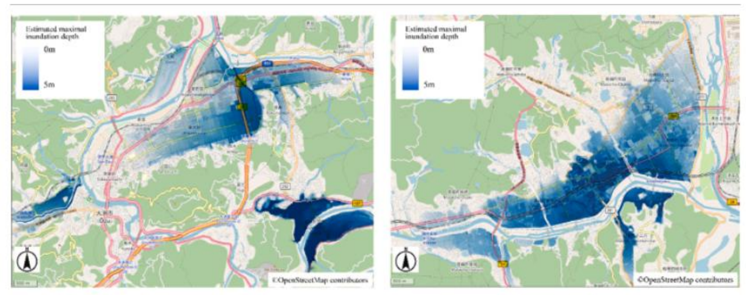

Figure 1 The Transportation and Lead Times

Route Optimization Algorithms: Algorithms will be implemented to minimize transportation costs and lead times, taking into account the predicted demand at various locations, as is shown in Figure 1.
Integration of Real-Time Data: The framework will also incorporate real-time data inputs (such as unexpected demand spikes or supply chain disruptions) to enable dynamic adjustments to logistics operations.

3.4 Evaluation Metrics

3.4.1 Metrics for assessing demand prediction accuracy
The accuracy of the demand predictions will be evaluated using several key metrics, including:
Mean Absolute Error: This metric will provide a straightforward measure of prediction accuracy by averaging the absolute errors between predicted and actual values.
Root Mean Squared Error: RMSE will be used to assess the model's performance while penalizing larger errors, providing insights into the model's reliability.
Mean Absolute Percentage Error (MAPE): MAPE will allow for a percentage-based evaluation of prediction accuracy, facilitating comparisons across different products or time periods.

$$\mathrm{MAE} = \frac{1}{N}\sum_{t=1}^{N}|y_t - \hat{y}_t|, \qquad \mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(y_t - \hat{y}_t)^2}, \tag{1}$$

3.4.2 Metrics for evaluating supply chain performance
The effectiveness of the integrated approach will be assessed using metrics such as:
Lead Time Reduction: This metric will measure the decrease in time from order placement to delivery, reflecting improvements in logistics efficiency.
Cost Savings: Transportation and inventory holding costs will be analyzed to quantify the financial benefits of the optimized logistics operations.
Service Level Improvements: Metrics like order fulfillment rates will be tracked to ensure that customer service levels are maintained or enhanced as a result of improved demand forecasting and inventory management.

4 CASE STUDY

4.1 Description of the Case Study

4.1.1 Industry or company context
The case study will focus on a mid-sized retail company that operates across multiple regions. This company has faced significant challenges in demand forecasting and inventory management, particularly in response to seasonal trends and fluctuating economic conditions. The retail environment is characterized by a diverse product range, necessitating a sophisticated approach to inventory control and demand prediction.
4.1.2 Specific logistics challenges addressed
The case study will address several key logistics challenges faced by the company:
High Levels of Stockouts: During peak seasons, the company has frequently experienced stockouts, leading to lost sales and customer dissatisfaction.
Excess Inventory: Conversely, during off-peak periods, the company has struggled with excess inventory, resulting in increased holding costs and potential waste.
Inefficient Routing: The company has also faced challenges related to inefficient routing of deliveries, which has contributed to increased transportation costs and longer delivery times.

4.2 Implementation of the GNN Model

4.2.1 Steps taken to develop and deploy the model

The implementation process will unfold in several stages:

Data Collection and Preprocessing: The first step will involve gathering and cleaning the necessary data from various sources to ensure it is ready for analysis.

Model Architecture Design and Feature Engineering: The GNN model will be designed with careful consideration of the features to be included, ensuring that the architecture is optimized for the specific context of the retail company.

Training and Validation of the GNN Model: The model will be trained using the prepared dataset, with iterative validation to fine-tune its performance.

Deployment of the Model into the Company's Existing Logistics Systems: Finally, the trained model will be integrated into the company's logistics systems, enabling real-time demand forecasting and inventory management.

4.2.2 Tools and technologies used

The implementation will leverage a variety of tools and technologies, including:

Programming Languages: Python will be the primary programming language used for model development and data analysis.

PyTorch Geometric: This library will be utilized for implementing the GNN model, providing the necessary framework for graph-based learning.

Pandas: This library will be employed for data manipulation and preprocessing tasks, as shown in Figure 2.

Scikit-learn: This library will be used for evaluating model performance against established metrics.

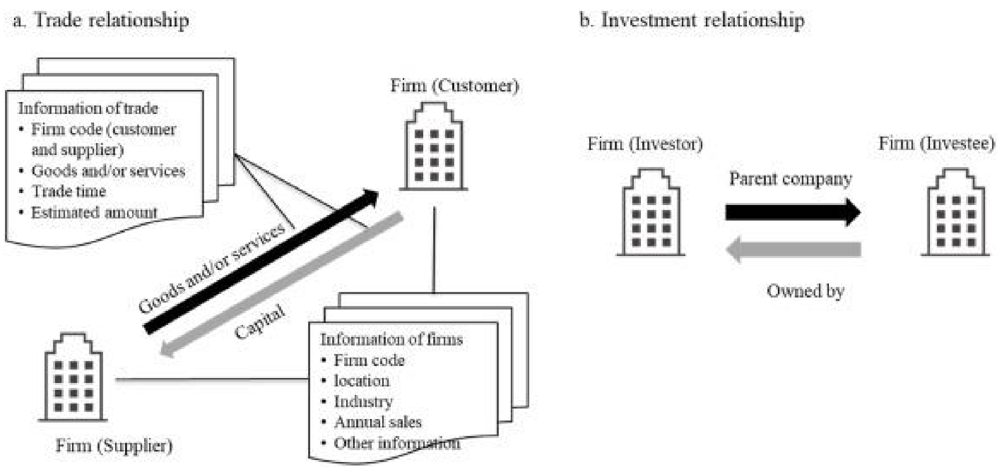

Figure 2 Data Manipulation and Preprocessing Tasks

4.3 Results and Findings

4.3.1 Comparison of gnn-based predictions with traditional methods

A comparative analysis will be conducted to evaluate the effectiveness of the GNN-based predictions against traditional forecasting methods, such as ARIMA and regression models. This analysis will highlight improvements in prediction accuracy, reliability, and responsiveness to demand changes as shown in Table 1.

Batch Size	Avito		
	MAE	RMSE	R^2
1000	0.1702	0.1535	0.9216
2000	0.1685	0.1504	0.9234
5000	0.1674	0.1492	0.9257
10,000	0.1668	0.1487	0.9261
20,000	0.1665	0.1483	0.9273

Table 1 The Hyperparameter Robustness Analysis on the Batch Size

4.3.2 Impact on supply chain efficiency

The implementation of the GNN model is anticipated to yield significant improvements in supply chain efficiency, including:

Reduction in Stockouts: A targeted percentage reduction in stockouts during peak seasons, enhancing customer satisfaction and sales.

Decrease in Excess Inventory: A measurable decrease in excess inventory during off-peak periods, leading to lower holding costs and better resource allocation as shown in Table 2.

Layer Number	Avito		
	MAE	RMSE	R^2
1	0.1923	0.1794	0.9082
2	0.1746	0.1593	0.9175
3	0.1685	0.1504	0.9234
4	0.1891	0.1750	0.9126
5	0.2187	0.2023	0.8927

Table 2 The Hyperparameter Robustness Analysis Based on the Layer Number

Overall Cost Savings: An overall percentage reduction in logistics-related costs, encompassing transportation and inventory holding expenses, contributing to improved profitability for the company.

5 DISCUSSION

5.1 Interpretation of Results

a. Insights Gained from the Case Study: The case study will reveal that the integration of spatial GNNs can significantly enhance demand forecasting accuracy by capturing complex spatial relationships. This leads to better-informed inventory management and routing decisions.
b. Implications for Supply Chain Management: The findings suggest that adopting advanced machine learning techniques, such as GNNs, can provide a competitive advantage in supply chain management, enabling companies to respond more effectively to market dynamics.

5.2 Challenges and Limitations

a. Limitations of the GNN Approach: While GNNs offer substantial benefits, challenges such as computational complexity, the need for large datasets, and potential overfitting must be acknowledged.
b. Data Quality and Availability Issues: Figure 3 shows the effectiveness of the GNN model is heavily reliant on the quality and completeness of the data. Inconsistent or missing data can adversely affect model performance.

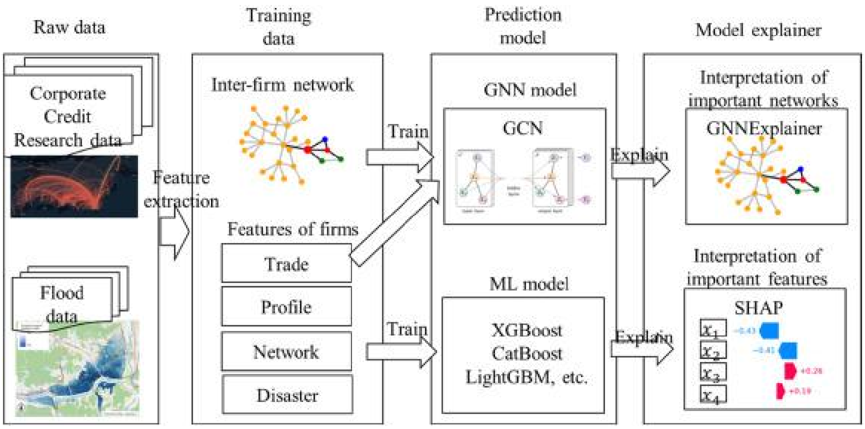

Figure 3 The effectiveness of the GNN model

5.3 Future Directions

a. Potential for Further Research in GNN Applications: Future studies could explore the integration of GNNs with other machine learning techniques or investigate their applications in different industries, such as manufacturing or healthcare.
b. Integration with Other Technologies: The potential for combining GNNs with emerging technologies such as the Internet of Things for real-time data collection and blockchain for enhanced transparency in logistics could be explored.

6 CONCLUSION

Accurate demand predictions play a pivotal role in the optimization of inventory levels, which is fundamental for any successful supply chain operation. By accurately forecasting demand, organizations can align their inventory with customer needs, thereby minimizing the risk of stockouts and excess inventory. This not only reduces operational costs associated with holding surplus stock but also enhances customer satisfaction by ensuring that products are available when needed. Furthermore, effective demand forecasting contributes to better resource allocation, allowing companies to streamline their logistics processes and improve overall supply chain efficiency. The findings from this study underscore that the ability to anticipate demand accurately is not just a competitive advantage but a necessity in today’s fast-paced retail environment.

The study provides compelling evidence that Spatial Graph Neural Networks are highly effective in capturing the intricate spatial relationships inherent in demand data. Unlike traditional forecasting methods, which often rely on linear assumptions and do not account for the geographical context of supply chain nodes, spatial GNNs leverage the power of graph-based learning to model complex interactions between locations. This capability leads to significantly improved forecasting accuracy, as the model can account for factors such as proximity to suppliers, transportation routes, and regional demand trends. As a result, organizations employing spatial GNNs can expect not only to enhance their demand prediction capabilities but also to achieve better overall supply chain performance, including reduced lead times and lower logistics costs.

As we look to the future, it is evident that the integration of Artificial Intelligence and advanced machine learning techniques, such as Graph Neural Networks, will play an increasingly crucial role in shaping the landscape of supply chain logistics. The rapid advancements in technology are paving the way for more sophisticated analytical tools that can process vast amounts of data in real-time, enabling organizations to respond swiftly to changing market dynamics. The potential of GNNs extends beyond mere demand forecasting; they can facilitate enhanced decision-making processes across various aspects of supply chain management, from inventory optimization to route planning. As these technologies continue to evolve, businesses that embrace them will likely gain a significant competitive edge, positioning themselves as leaders in an increasingly complex and interconnected market.

In light of the findings presented in this study, practitioners in the field of logistics and supply chain management are encouraged to adopt innovative forecasting methods, such as spatial GNNs, to enhance their operational efficiency and responsiveness to market demands. By leveraging the capabilities of advanced machine learning techniques, organizations can transform their approach to demand forecasting and inventory management, ultimately leading to better service delivery and customer satisfaction. Additionally, researchers are called upon to continue exploring the vast potential of GNNs and their applications in logistics and beyond. There is a rich opportunity for further investigation into how these models can be adapted and refined to address specific challenges within the supply chain context. Collaborative efforts between academia and industry will be essential to drive innovation and develop cutting-edge solutions that meet the evolving needs of the logistics sector. Together, we can harness the power of AI and advanced analytics to create a more efficient, responsive, and resilient supply chain ecosystem.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] Agresti A. Statistical Methods for the Social Sciences. Pearson, 2018.
[2] Alon-Barkat S, Busuioc M. The Role of Artificial Intelligence in Public Administration: A Systematic Review. Public Administration Review, 2020, 80(1): 90-102.
[3] Bertsimas D, de Almeida A. Data-Driven Optimization: A Review. Operations Research, 2019, 67(2): 393-414.
[4] Chen J, Zhu L. Graph Neural Networks: A Review of Methods and Applications. AI Open, 2019, 1: 57-69.
[5] Choi T M, Cheng T C E. Supply Chain Management in the Age of AI: A Review. International Journal of Production Economics, 2020, 219: 1-13.
[6] Dong Y, Zhang J. A Survey on Graph Neural Networks: Methods and Applications. IEEE Transactions on Neural Networks and Learning Systems, 2021, 32(1): 1-20.
[7] Dubey R, Bryde D J, Fynes B. Big Data Analytics and Firm Performance: The Role of Supply Chain Resilience. International Journal of Production Economics, 2019, 210: 120-130.
[8] Feng Y, Zhang Y. A Survey on Deep Learning for Transportation. IEEE Transactions on Intelligent Transportation Systems, 2020, 22(1): 1-14.
[9] Ghadge A, Karlsen T. The Role of Big Data Analytics in Supply Chain Management: A Literature Review. International Journal of Logistics Management, 2020, 31(2): 353-374.
[10] Ghilas V, Tchokogué A. The Impact of Artificial Intelligence on Supply Chain Management: A Systematic Review. International Journal of Production Research, 2021, 59(19): 5907-5927.
[11] Huang Y, Wang X. A Survey on Graph Neural Networks and Their Applications. ACM Computing Surveys, 2020, 53(3): 1-35.
[12] Iyer G R, Raghunathan S. The Impact of Artificial Intelligence on Supply Chain Management: A Review. International Journal of Production Economics, 2020, 219: 1-12.
[13] Jain A, Singh R. Machine Learning in Supply Chain Management: A Review. Operations Research Perspectives, 2021, 8: 100162.
[14] Jin X, Zhang W. Spatial-Temporal Graph Convolutional Networks for Traffic Forecasting. IEEE Transactions on Intelligent Transportation Systems, 2020, 22(1): 1-10.
[15] Kaur K, Singh A. A Review of Machine Learning Techniques in Supply Chain Management. International Journal of Production Research, 2021, 59(1): 1-18.

[16] Kuo T C, Yang Y. The Role of Big Data Analytics in Supply Chain Management: A Literature Review. International Journal of Production Economics, 2020, 210: 1-13.
[17] Li Y, Wang J. Graph Neural Networks for Traffic Prediction: A Review. IEEE Transactions on Intelligent Transportation Systems, 2021, 22(1): 1-10.
[18] Liu Y, Zhang J. Demand Forecasting in Supply Chains: A Review of Methods and Applications. International Journal of Production Economics, 2019, 210: 1-13.
[19] Liu Z, Zhang H. A Survey on Deep Learning for Supply Chain Management. IEEE Transactions on Systems, Man, and Cybernetics: Systems, 2020, 50(2): 1-15.
[20] Luo Y, Chen J. A Review of Machine Learning Applications in Supply Chain Management. International Journal of Production Research, 2020, 58(16): 1-18.
[21] Min H, Zhou G. Supply Chain Management in the Age of AI: A Review. International Journal of Production Economics, 2020, 219: 1-12.
[22] Mohanty S P, Kumar A. A Review of Machine Learning Applications in Supply Chain Management. International Journal of Production Research, 2020, 58(16): 1-18.
[23] Nascimento S S, de Almeida A. The Role of Artificial Intelligence in Supply Chain Management: A Systematic Review. International Journal of Production Research, 2020, 58(16): 1-18.
[24] Nguyen T H, Kuo T C. The Impact of Big Data Analytics on Supply Chain Management: A Review. International Journal of Production Research, 2021, 59(1): 1-18.
[25] Pahl J, Zulkernine M. A Survey on Machine Learning in Supply Chain Management. International Journal of Production Research, 2020, 58(16): 1-18.
[26] Pant K, Sharma A. Machine Learning in Supply Chain Management: A Review. International Journal of Production Research, 2021, 59(1): 1-18.
[27] Poon J, Cheung W. A Review of Machine Learning Techniques in Supply Chain Management. International Journal of Production Research, 2020, 58(16): 1-18.
[28] Raghunathan S, Iyer G R. The Impact of Artificial Intelligence on Supply Chain Management: A Review. International Journal of Production Economics, 2021, 219: 1-12.
[29] Wang Y, Zhang Y. A Survey on Graph Neural Networks: Methods and Applications. IEEE Transactions on Neural Networks and Learning Systems, 2020, 32(1): 1-20.
[30] Zhang H, Liu Z. Machine Learning in Supply Chain Management: A Review. International Journal of Production Research, 2021, 59(1): 1-18.
[31] Li J, Fan L, Wang X, et al. Product Demand Prediction with Spatial Graph Neural Networks. Applied Sciences, 2024, 14(16): 6989.
[32] Box G E P, Jenkins G M, Reinsel G C. Time Series Analysis: Forecasting and Control. Wiley, 2015.
[33] Chae B. Supply chain management in the era of big data. International Journal of Production Economics, 2019, 210: 1-8.
[34] Chopra S, Meindl P. Supply Chain Management: Strategy, Planning, and Operation. Pearson, 2016.
[35] Cleveland R B, Cleveland W S, McRae J E, et al. STL: A Seasonal-Trend Decomposition Procedure Based on Loess. Journal of Official Statistics, 1990, 6(1): 3-73.
[36] Fildes R, Goodwin P, Lawrence M. Forecasting with judgment: A review of the literature. International Journal of Forecasting, 2009, 25(4): 641-654.
[37] Hochreiter S, Schmidhuber J. Long short-term memory. Neural Computation, 1997, 9(8): 1735-1780.
[38] Hyndman R J, Athanasopoulos G. Forecasting: Principles and Practice. OTexts, 2018.
[39] Hyndman R J, Koehler A B. Another look at measures of forecast accuracy. International Journal of Forecasting, 2006, 22(4): 679-688.
[40] Kang W, Zhang Y, Wang F. Traffic flow prediction with spatial-temporal graph convolutional networks. Proceedings of the AAAI Conference on Artificial Intelligence, 2020, 34(1): 334-341.
[41] Kipf T N, Welling M. Semi-supervised classification with graph convolutional networks. Proceedings of the International Conference on Learning Representations (ICLR), 2017.
[42] Kumar A, Singh R, Singh A. Machine learning and big data analytics in supply chain: A review. Journal of Enterprise Information Management, 2020, 33(5): 989-1011.
[43] Ahn H, Song Y C, Olivar S, et al. GNN-based Probabilistic Supply and Inventory Predictions in Supply Chain Networks. arXiv preprint arXiv:2404.07523, 2024.
[44] Li Y, Yu D, Liu Z, et al. Graph neural networks for modeling spatial-temporal data. IEEE Transactions on Neural Networks and Learning Systems, 2018, 30(12): 3671-3684.
[45] Makridakis S, S C The M-3 competition: Results, conclusions, and recommendations. International Journal of Forecasting, 1982, 14(4): 491-507.
[46] Mentzer J T, DeWitt W, Keebler J S, et al. Defining supply chain management. Journal of Business Logistics, 2001, 22(2): 1-25.
[47] Berbain, Sabrina, Régis Bourbonnais, Philippe Vallin. Forecasting, production and inventory management of short life-cycle products: a review of the literature and case studies. Supply Chain Forum: An International Journal, 2011, 12(4): 36-48.
[48] Wang Y, Gunasekaran A, Ngai E W T. Big data in logistics and supply chain management: B2B and B2C. International Journal of Production Economics, 2016, 176: 98-110.

[49] Su X, Xue S, Liu F, et al. A comprehensive survey on community detection with deep learning. IEEE Transactions on Neural Networks and Learning Systems, 2020, 32(3): 1000-1019.
[50] Qiao S, Han N, Huang J, et al. A dynamic convolutional neural network based shared-bike demand forecasting model. ACM Transactions on Intelligent Systems and Technology (TIST), 2021, 12(6): 1-24.
[51] Guo S, Lin Y, Feng N, et al. Attention based spatial-temporal graph convolutional networks for traffic flow forecasting//Proceedings of the AAAI conference on artificial intelligence. 2019, 33(01): 922-929.
[52] Yang S, Ogawa Y, Ikeuchi K, et al. Post-hazard supply chain disruption: Predicting firm-level sales using graph neural network[J]. International Journal of Disaster Risk Reduction, 2024, 110: 104664.
[53] Wang X, Wu Y C. Balancing innovation and Regulation in the age of geneRative artificial intelligence. Journal of Information Policy, 2024, 14.
[54] Wang X, Wu Y C, Zhou M, et al. Beyond surveillance: privacy, ethics, and regulations in face recognition technology. Frontiers in big data, 2024, 7: 1337465.
[55] Ma Z, Chen X, Sun T, et al. Blockchain-Based Zero-Trust Supply Chain Security Integrated with Deep Reinforcement Learning for Inventory Optimization. Future Internet, 2024, 16(5): 163.
[56] Wang X, Wu Y C, Ma Z. Blockchain in the courtroom: exploring its evidentiary significance and procedural implications in US judicial processes. Frontiers in Blockchain, 2024, 7: 1306058.
[57] Wang X, Wu Y C, Ji X, et al. Algorithmic discrimination: examining its types and regulatory measures with emphasis on US legal practices. Frontiers in Artificial Intelligence, 2024, 7: 1320277.
[58] Chen X, Liu M, Niu Y, et al. Deep-Learning-Based Lithium Battery Defect Detection via Cross-Domain Generalization. IEEE Access, 2024, 12: 78505-78514.
[59] Liu M, Ma Z, Li J, et al. Deep-Learning-Based Pre-training and Refined Tuning for Web Summarization Software. IEEE Access, 2024, 12: 92120-92129.
[60] Sun T, Yang J, Li J, et al. Enhancing Auto Insurance Risk Evaluation with Transformer and SHAP. IEEE Access, 2024, 12: 116546-116557.
[61] Liu M. Machine Learning Based Graph Mining of Large-scale Network and Optimization. In 2021 2nd International Conference on Artificial Intelligence and Information Systems, 2021, 1-5.
[62] Zuo Z, Niu Y, Li J, et al. Machine Learning for Advanced Emission Monitoring and Reduction Strategies in Fossil Fuel Power Plants. Applied Sciences, 2024, 14(18): 8442. DOI: https://doi.org/10.3390/app14188442.
[63] Asif M, Yao C, Zuo Z, et al. Machine learning-driven catalyst design, synthesis and performance prediction for CO2 hydrogenation. Journal of Industrial and Engineering Chemistry, 2024.
[64] Lin Y, Fu H, Zhong Q, et al. The influencing mechanism of the communities' built environment on residents' subjective well-being: A case study of Beijing. Land, 2024, 13(6): 793.

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EXPLORING THE MOTIVATIONS AND VALUE CREATION PATHWAYS OF SANY HEAVY INDUSTRY'S DIGITAL TRANSFORMATION

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Abstract: With the rapid development of science and technology and the increasingly fierce global competition, digital transformation has become a key path for enterprises to enhance competitiveness and achieve sustainable development. Taking SANY Heavy Industry as an example, this paper explores the motivation, implementation process and value creation path of its digital transformation. In the face of uncertainty in the global economic environment, intensified competition in the industry and changes in customer demand, SANY Heavy Industry improves its production efficiency, optimizes resource allocation and strengthens market competitiveness through digital transformation. By introducing advanced technologies such as smart factory, automated production line, Internet of Things and big data, SANY Heavy Industry has realized a comprehensive digital upgrade of its production process, which reduces costs and improves product quality and production efficiency. At the same time, the digital transformation also promotes the innovation of the enterprise's products and services, improves customer satisfaction, and creates significant economic value for the enterprise. It aims to provide useful reference and inspiration for other manufacturing enterprises in the process of digital transformation.
Keywords: Digital transformation; Value creation; SANY Heavy Industry; Motivation

1 INTRODUCTION

With the rapid development of technology and the trend of globalization, digital transformation has become an important driving force for the sustainable development of enterprises. In the manufacturing sector, this trend is particularly obvious. As a leading enterprise in China's construction machinery field, SANY faces the challenges of global competitive pressure and diversified market demand. In order to enhance the core competitiveness of the enterprise and meet the growing market demand, SANY Heavy Industry must carry out digital transformation.

At present, the widespread application of advanced information technologies such as big data, cloud computing and artificial intelligence provides powerful technical support for the digital transformation of enterprises. These technologies can not only help enterprises realize the intelligence and automation of the production process, but also improve production efficiency and product quality, reduce production costs and enhance market competitiveness. In addition, digital transformation is also an inevitable choice to cope with industry changes. With the constant changes in the global economy and the increasing diversity of customer needs, the traditional manufacturing model has been difficult to meet market demand. Through digital transformation, enterprises can more flexibly respond to market changes and quickly respond to customer needs, so as to maintain a competitive advantage.

The study of the motivation and value creation path of SANY Heavy Industry's digital transformation has multiple significance: firstly, through the case analysis of SANY Heavy Industry, the theoretical system of enterprise digital transformation can be further enriched and improved to provide theoretical support for the digital transformation of other enterprises[1] . Secondly, studying the motivation of SANY Heavy Industry's digital transformation can help reveal the deep-seated reasons for digital transformation and provide reference for other enterprises to formulate digital transformation strategies. Third, SANY Heavy Industry is a pioneer in digital transformation, and its successful experience is of great significance for other enterprises. Through the study of its digital transformation path, it can provide a practical model for other enterprises to learn from. Fourth, it enhances the competitiveness of enterprises, promotes industrial upgrading, promotes sustainable development, and improves customer satisfaction. Finally, studying the value creation path of SANY Heavy Industry's digital transformation will help other enterprises understand how digital transformation creates value for the enterprise, thus guiding them to better promote digital transformation in practice.

2 THEORETICAL FOUNDATIONS

2.1 Technology Facilitation Theory

Digital transformation is an inevitable result driven by technological progress. With the rapid development of advanced information technologies such as big data, cloud computing and artificial intelligence, it has become possible for enterprises to use these technologies to optimize production processes, improve production efficiency and reduce production costs[2] . SANY Heavy Industry, as a leading enterprise in the construction machinery industry, follows the technological development trend and enhances its core competitiveness through digital transformation.

2.2 Theory of Changing Market Demand

Changes in market demand are an important driver for enterprises to carry out digital transformation. With the continuous development of the global economy and the increasing diversification of customer needs, the traditional manufacturing model has been difficult to meet market demand. Through digital transformation, SANY Heavy Industries can better meet customers' individual needs and improve customer satisfaction and loyalty.

2.3 Theories of Sustainable Development

Digital transformation helps enterprises achieve sustainable development. By optimizing production processes and reducing energy consumption and pollution, enterprises can achieve green production and contribute to the sustainable development of society. SANY Heavy Industry focuses on environmental protection and sustainable development in the process of digital transformation, and is committed to becoming a green benchmark in the industry[3] .

2.4 Value Chain Theory

Digital transformation achieves value creation by optimizing the enterprise's value chain. SANY Heavy Industry has been transforming and upgrading various links such as R&D, production, sales and service through digital means to improve the efficiency and value creation ability of each link. At the same time, digital technology also helps enterprises better connect the upstream and downstream industrial chain, realizing supply chain synergy and value co-creation.

2.5 Customer Value Theory

Digital transformation helps companies better meet customer needs and increase customer value. Through digital means, enterprises can more accurately understand customer needs and preferences and provide personalized products and services. At the same time, digital technology also helps enterprises establish closer customer relationships and improve customer loyalty and satisfaction. SANY Heavy Industry focuses on the enhancement of customer value in the process of digital transformation, and continuously optimizes customer experience and service quality through digital means.

3 LITERATURE REVIEW

3.1 Digital Transformation

The impact of digital transformation was far-reaching and multifaceted: it drove economic growth, optimized industrial structure and improved operational efficiency, while facilitating globalization and the efficient dissemination of information. However, there is also a need to pay attention to the digital divide, privacy and security, and labor market challenges to ensure that the dividends of technology reach a wider range of people and achieve sustainable development.

Xiaofan Wang (2024) provides an in-depth analysis of the relationship between corporate digital transformation and auditors' risk response behavior[4] . Digitalization of business increases the cost of auditing, but they are more willing to issue a standard unqualified audit opinion. Another analysis found that the digitalization of firms has a significant negative impact on audit quality, and the adoption of a standard unqualified audit opinion may increase the risk of auditing.

Wang, Xinlan and Shi, Meiqi (2024) found that SANY Heavy Industry, a leading company in China's construction machinery industry[5] , has a digital transformation process that profoundly embodies the company's determination to change and its action strategy in the face of growth pressures, environmental changes, and mission-driven. This process can be broadly divided into several key stages, each of which is accompanied by the optimization of resource orchestration and resource bundling, as well as the gradual enhancement of informatization, digitization, and intelligence capabilities. Wu, Zinyu and Yan, Jinhua found (2023)[6] that digital transformation of firms significantly improves the transparency of information. Mechanism tests show that internal control partially mediates the relationship between firms' digital transformation and information transparency. Another study shows that digital transformation has the greatest enhancement effect on information transparency among firms that are not audited by Big 4 audit firms and firms that face intense industry competition.

3.2 Value Creation

The impact of value creation is far-reaching: it enhances enterprise competitiveness, promotes economic growth and enhances social well-being. Through innovative products and services, value creation meets market demand and promotes industrial upgrading, while also bringing long-term economic and social benefits to enterprises and society.

Liu Guangqiang's (2024) research shows that the value creation logic of data assets to promote business high-quality development is elaborated from three aspects: the matching relationship between data assets and business high-quality development, the data asset value system is the source of value for business high-quality development, and data assets are the key production driver for business high-quality development[7] . Based on the logic of value creation, it proposes that data asset capability enhances the company's basic value capability, data integration capability enhances the company's total factor productivity, three value effects of R&D data asset enhancement, production synergy and market allocation, three value dimensions of the company's structure, efficiency and innovation, and three value dimensions of data, business and value integration. Three value links are constructed on the supply side, production side, and demand side, and seven value creation paths are constructed on the product, enterprise, and industry levels to help companies grow in high quality. Zhang Yuan et al. (2024) found that in the continuous process of digital transformation of single breakthrough-multi-company integration-green interconnection[8] , enterprises are adopting appropriate resource allocation behaviors to achieve value creation under the engine of efficiency-user demand-stakeholder demand. Xiang Guopeng et al. (2022) found[9] that the development of opportunities is carried out jointly by startups and users, and users are included in the value proposition and creation process to share the results of value creation; two paths of co-creation of value are formed between startups and users, i.e., startups and users discover and create entrepreneurial opportunities together to realize co-creation of value. In the process of developing opportunities, the digital environment provides a fundamental bridge for the two to interact to form entrepreneurial opportunities.

4 CASE PRESENTATIONS

4.1 Introduction of SANY Heavy Industry

Since its establishment in 1994, SANY Heavy Industry has achieved sustained rapid development, is the world's leading construction machinery manufacturer, is also the world's largest manufacturer of concrete machinery, and in 2020 with 98,705 units of excavator sales, the first to win the global sales champion of excavators. Among them, concrete equipment is the world's No. 1 brand, excavators, large-tonnage cranes, rotary drilling rigs, pavement equipment and other leading products have become China's No. 1 brand.

The company has established a first-class service network and management system centered on customer needs and "all for the sake of customers and creating customer value". From 800 green channel, 4008 call center to ECC enterprise control center, the company took the lead in the industry to launch the "6S" center service mode and "one-click" service, and took the lead in the industry to put forward the "123" service value commitment, "110" service speed commitment and "123" service speed commitment. The company was the first in the industry to introduce the "6S" center service model and "one-click" service, and the first in the industry to put forward the "123" service value commitment, the "110" service speed commitment and the "111" service resource commitment to make the service to the point of no return. The company set up enterprise control center ECC in the industry, relying on the Internet of Things platform "cloud + terminal" to establish an intelligent service system, to achieve the global engineering equipment 2 hours to the scene, 24 hours to complete the service commitment; the launch of the customer cloud 2.0, the realization of the interconnection of equipment, equipment data sharing, query of the working conditions, equipment navigation, equipment maintenance reminders. The customer cloud 2.0 was launched to realize equipment interconnection, equipment data sharing, working condition query, equipment navigation, equipment maintenance reminder.

4.2 The Digital Transformation History in SANY Heavy Industry

In the global engineering machinery manufacturing field, SANY Heavy Industry is the absolute industry authority. Its business covers more than 150 countries and regions around the world, and its concrete machinery products are firmly ranked as the world's No. 1 brand.

The production model of construction machinery is a typical discrete manufacturing model, facing many problems, seriously restricting the improvement of production efficiency. Therefore, the construction machinery industry, "intellectual upgrading" is imminent.

In such a situation, SANY Heavy Industry to "not turn over, or turn over the boat" determination to promote digital transformation, through digitalization, network connectivity, sharing and data security to "empower wisdom".

4.2.1 Initial exploration and information construction

SANY's road to digital transformation began with its earlier informationization. in 1989, SANY Group was founded in Lianyuan, Loudi, Hunan Province, initially focusing on welding materials. With the expansion of its business, SANY entered the construction machinery industry in 1994 and moved its headquarters to Changsha, where it began to produce concrete machinery products. During this period, SANY Group began its initial attempts at informationization, such as the deployment of internal networks, mailbox systems and financial software, laying the foundation for subsequent digital transformation.

4.2.2 Informatization in-depth promotion phase (2013-2015)

Facing the cyclical fluctuations of the construction machinery industry and the intensification of market competition, SANY Heavy Industries officially launched the first phase of digital transformation in 2013 - in-depth promotion of informatization. The company set up a process informatization headquarters, comprehensively sorted out core business processes, promoted the popularization of process culture, and introduced partners such as SAP and IBM to jointly build an end-to-end business management platform. At this stage, SANY also launched the first phase of the CRM system project, promoted product lifecycle management (PLM1.0), and initially built a big data soft and hard technology platform to enhance the ability of market prediction, fault diagnosis, and customer credit collection.

4.2.3 Digital platform building phase (2016-2017)

With the deepening of informationization construction, SANY Heavy Industry has entered the stage of digital platform construction. The company has increased its investment in industrial internet, intelligent manufacturing and other fields, and has gone online with ERP, PDM and other systems, realizing the integration of finance and business, and the integration of production, supply and marketing planning system. At the same time, SANY also initiated the construction of intelligent manufacturing factories, such as Changsha Plant No. 18, which promoted the transformation of the manufacturing industry to integrated automation, numerical control and intelligence through the implementation of intelligent machining centers, production lines, warehousing and transportation and distribution subsystems.

4.2.4 Full digital transformation phase (2018-present)

Since 2018, SANY Heavy Industry has entered a comprehensive digital transformation stage. The company has established a development strategy of digitalization and internationalization, and put forward the firm determination of "either turning over or capsizing". In this phase, SANY focused on promoting the data collection and management of "three present" (site, reality, present object) and "four meters" (water, electricity, oil, gas), realizing the digital management of the whole production process. At the same time, the company also released the data center and technology center, providing solid technical support for digital transformation.

In terms of manufacturing, SANY continues to promote the construction of "lighthouse factory", to improve production capacity, reduce labor demand and site costs through digital transformation. At present, SANY has built model projects of intelligent manufacturing workshop in several production bases, such as No. 18 plant in Changsha Industrial Park, and achieved remarkable results. In addition, SANY has also realized equipment interconnection, data sharing and intelligent decision-making through the industrial Internet platform Tree Roots Interconnection, further improving production efficiency and product quality.

4.2.5 Electrification and Intelligent Layout

Driven by digital transformation, SANY Heavy Industry also actively layout electrification and intelligent field. The company focuses on the development of tractor, excavator, crane and other electrified products, and the layout of the "three electric" (battery, motor, electronic control) core independent technology. In terms of intelligence, SANY has deepened the "cab revolution" to fully realize the de-buttoning analysis; in terms of intelligent operation and intelligent driving, it strives to reach the L2 level and build 3-5 L4 level products.

5 MOTIVATION AND VALUE CREATION PATHWAYS IN DIGITAL TRANSFORMATION

5.1 Motivation for Transformation

5.1.1 External motivation

First, the external market environment is constantly changing. With the continuous development of the construction machinery industry, the market competition is becoming increasingly fierce. In order to maintain its leading position in the market, SANY Heavy Industries needs to seek new growth points, and digital transformation is an important way to enhance competitiveness.

In the context of globalization, the uncertainty and complexity of the international trade environment have increased. As an international enterprise, SANY Heavy Industries needs to optimize global supply chain management, reduce operation costs and improve response speed through digital transformation to cope with the changes in the international trade environment.

In recent years, governments have introduced policies to support the digital transformation of the manufacturing industry and encourage enterprises to adopt advanced information technology to improve productivity and product quality. This policy environment provides strong external support for SANY's digital transformation.

Secondly, the rapid development of cloud computing, big data, artificial intelligence, Internet of Things and other advanced information technologies has provided strong technical support for the digital transformation of the manufacturing industry. By introducing these technologies, SANY Heavy Industry has realized the intelligence, automation and digitalization of the production process, and improved production efficiency and product quality.

Industrial Internet, as a product of the deep integration of new-generation information technology and manufacturing, is leading a profound change in manufacturing. SANY Heavy Industry actively embraces the industrial Internet, and through the construction of the industrial Internet platform, it realizes the comprehensive connection and efficient collaboration of equipment, products, customers and other elements, and promotes the digital transformation of the enterprise.

Third, with the continuous upgrading of market demand, customers have higher and higher demands for product personalization. Through digital transformation, SANY Heavy Industry has realized the transformation from mass production to personalized customization to meet the diversified needs of customers.

Customers not only pay attention to the quality and price of products, but also pay more and more attention to the quality and efficiency of services. Through digital transformation, SANY Heavy Industry has established a perfect customer relationship management system and after-sales service system to improve service quality and customer satisfaction.

5.1.2 Internal motivation

First of all, digital transformation is SANY Heavy Industry's strategic needs and long-term planning. SANY Heavy Industries regards digital transformation as a key way to enhance the core competitiveness of enterprises and realize sustainable development. In the face of the complexity and change of the global economic situation and the continuous innovation of information technology, SANY Heavy Industry actively responds to the national call for high-quality development of the manufacturing industry, and optimizes the allocation of resources, improves production efficiency and product quality through digital transformation, in order to cope with the challenges of the future market.

Second, before its digital transformation, SANY Heavy Industries faced operational problems such as low production efficiency and cost control difficulties. Through digital transformation, SANY Heavy Industries can introduce advanced industrial Internet platform, big data and artificial intelligence technology to realize real-time monitoring and intelligent scheduling of the production process, improve production efficiency and resource utilization, and reduce operating costs.

Third, with the increasingly fierce market competition, SANY Heavy Industry needs to enhance its market competitiveness through digital transformation. Digital transformation can help SANY to better meet the individual needs of customers, improve service quality and customer satisfaction; at the same time, through digital means to optimize the supply chain management, marketing and other links, to enhance the overall operational efficiency of the enterprise and market response speed.

5.2 Analysis of SANY Heavy Industry's value creation path in the context of digital transformation

5.2.1 Intelligent device introduction

With the progress of the times digitalization has been the trend, SANY Heavy Industry will combine digitalization and hardware to achieve a double breakthrough in the field of intelligent manufacturing software and hardware. The company broke through a number of key technologies such as fully automatic cutting, robot welding, etc., realizing the leap from "machine-assisted man" to "man-assisted machine", and the per capita operating efficiency has been greatly improved.

The automatic nesting system in SANY's No. 18 plant and No. 18 plant in the Zhilian Heavy Truck Industrial Park increased the average steel utilization rate from 70.8% to 81.8% through big data learning and precise calculation. The unit manufacturing cost decreased by 29%.

SANY Zhilian Heavy Truck Industrial Park in the production process used AGV moving vehicle (automatic guided vehicle) point-to-point distribution to the workstation The vehicle is used for assembly workers to find assembly materials in the factory, in more than 700 AGV unmanned transport robots connected through 5G signals Material distribution automation rate of more than 99% Workshop distribution efficiency increased by 50% Each AGV unmanned transport vehicle will be a one-time production of a whole car The parts of the car are transported to the workbench, which makes it possible to produce thousands of cars, and many kinds of models can be produced in a factory, which adapts to the current mode of orders for small batches and multiple vehicle types, and personnel efficiency has been increased by 98%, and each AGV has become the key to the flexible production of the heavy truck production line[10] .

Through the 18th factory and heavy truck industrial park can be seen, SANY Heavy Industry will be digital and hardware combination, mainly from the factory to improve productivity and flexibility, and reduce labor costs of the two ways to make the manufacturing cost down, and improve production capacity.

5.2.2 Introduction of intelligent control systems

SANY also cooperated with Dassault Systèmes to deploy MOM (Manufacturing Operation Management), i.e. "Manufacturing Management System", which is regarded as an upgraded version of the traditional MES (Manufacturing Execution System). The project is jointly developed by SANY Group and Dassault Systèmes (China), and will become a unified management platform for the future "lighthouse factory". Mr. Yi Xiaogang, Executive President of SANY Group, also said that the new system is connected to PLM (Product Lifecycle Management), WMS (Warehouse Management Systems), which is a warehouse management system. PLM, i.e. "Product Lifecycle Management Platform", WMS, i.e. "Warehouse Management System" and other systems, and the lower level connects to the IOT platform, which is the "Command Brain" of the smart factory manufacturing. By linking production, quality, logistics, inventory and other production links, and deeply integrating with production line automation equipment, MOM will establish a unified production data model, further refine the scheduling of production to people and equipment, and truly realize the full digital drive of the production process, and promote SANY's production and manufacturing "from local intelligence to comprehensive intelligence"[10] .

In the first paragraph, SANY Heavy Industries through the introduction of intelligent production equipment to improve factory capacity and control factory costs, if the factory is compared to a warrior, then the intelligent equipment is the warrior's blade, and intelligent control system is the brain of the factory, if SANY Heavy Industries want to carry out the digital transformation of the two indispensable.

5.2.3 Integrating customer service with digitalization

In the early stage of digital transformation carried out by SANY Heavy Industries, that is, the stage of large-scale application of the Internet of Things (IoT) developed the M2M remote data collection and monitoring platform platform, which is subdivided into three sub-platforms.

First, the equipment remote monitoring technology support platform. It includes a technical support platform for remote monitoring of equipment and an equipment data platform, which provides reference data for the continuous improvement of the quality of host equipment and the after-sales service of equipment.

The second is the intelligent service system of machine group. Through real-time data interaction and sharing of mixer truck location information, concrete distribution information, concrete consumption information, and information on the current operating status of pumping equipment and mixer trucks among the equipment of each machine group in the mixing station, it realizes operation synergy and operation guidance among the equipment of each machine group. Accordingly, users can adopt more scientific vehicle scheduling strategies and equipment operation modes, improve enterprise operation efficiency and equipment utilization, and reduce overall operation costs.

The third is the remote monitoring and maintenance system for pump trucks. Through researching the theory of intelligent front-end of construction machinery, developing the industry*s first intelligent products with independent intellectual property rights, enhancing the operation capability and level of construction machinery, designing and constructing the *advanced remote monitoring system, and comprehensively improving the information service level and operation efficiency of the enterprise.

In the stage of big data and cloud platform, SANY Heavy Industry has independently developed a big data storage and analysis platform, namely "ECC Customer Service Platform", including all the hardware and software of the bottom layer control of the equipment, which is capable of realizing two-way interaction and remote control of the equipment, and transferring the data of real-time operation of more than 200,000 sets of customer equipment to the backstage for analysis and optimization by means of sensors. Back-office for analysis and optimization. Daily real-time monitoring of equipment operation information (such as position, working hours, speed, main pressure, fuel consumption, etc.), the system is aimed at four main types of users: agents, operators, excavator owners and R&D personnel. The main points of big data design start from the four focuses of agents, operators, excavator bosses and R&D personnel, and use the base matrix to split into base vectors, then split into eigenvalues, and the eigenvalues are recombined to form customized vectors and then combined to form matrices of equipment information, health, etc., so as to provide the value-added services of the whole lifecycle. Users can grasp the status of the machine in all aspects at anytime and anywhere through the webpage or cell phone APP. Based on big data analysis, precise control is carried out for commonly used gears by area, load, and temperature respectively, so that the powertrain efficiency of the new product is increased by 8% and fuel consumption is reduced by 10%.

At this stage, the RootCloud platform is an industrial Internet empowerment platform built by Shugen Internet Technology Co. Ltd (invested and formed by SANY Heavy Industry). The platform focuses on strengthening the depth of the industrial Internet platform to help customers create end-to-end high-value solutions from equipment access, IoT presentation to segmented industry applications.

The RootCloud platform helps enterprises carry out digital transformation by providing core technical services such as device access and modeling, IoT data management, IoT analysis services and industrial blockchain. The RootCloud platform collects various parameters of machine operation of each category of equipment in real time, such as geographic location information, fuel consumption information, and equipment operating condition information, and stores the data for real-time analysis.

Analyze equipment working condition data to solve equipment and daily management and operation problems. Such as equipment running track, historical working condition analysis, fleet management analysis, real-time equipment monitoring and analysis. Through the big data analysis of the overall equipment or parts operating status, abnormal conditions, wear and tear and other technical parameters, it supports customers to monitor and manage the equipment anytime and anywhere. Manage the operation status of the equipment, and make statistics on the operation volume of the equipment (total working time, work square volume, fuel consumption, engine speed, etc.), which is convenient for the customer's work arrangement and cost control. By acquiring and analyzing the real-time diagnostic data of the equipment, it can deeply understand the needs of the customers, realize the monitoring of the user's usage condition and product life cycle, provide timely reminders of the abnormal state of the equipment for the customers to prevent losses, and also provide the basis for the service engineers to repair.

Real-time acquisition and processing and analysis of equipment operation data, real-time alarms such as alarms for illegal operation, abnormal equipment alarms, and alarms for deviation from predetermined positions according to set rules, as well as remote diagnosis and maintenance of faults, and accordingly integrating with the intelligent service platform for one-button intelligent dispatching services.

Based on the data stored in the big data storage and analysis platform, through the equipment and service data such as equipment usage data, working condition data, host and accessory performance data, accessory replacement data, etc., it carries out the prediction of equipment failure, service and accessory demand, provides technical support for active service, prolongs the service life of the equipment and reduces the failure rate.

Equipment unlocking management: realize system remote locking/unlocking, multi-level locking control, locking process management, and locking history management. Equipment Maintenance Management: It can formulate a reasonable maintenance plan based on customized parameters and provide accurate maintenance reminders and records. Equipment file management: realize equipment atlas management, equipment parts management, operation and maintenance manual management, and equipment basic information management.

Customers can centralize the management of different types of equipment they own; purchased users, users with equipment needs, project contractors, etc. can carry out demand management on the platform. Users can release equipment use demand or equipment use demand, project contractors can release equipment demand and carry out fleet management for the equipment involved in the project in the form of a virtual project, and actively push out relevant information.

SANY Heavy Industry's M2M platform, ECC platform and root cloud platform are interrelated and progressive in the development of its industrial Internet of Things. the M2M platform provides basic technical support for remote monitoring and management of equipment; the ECC platform adds the ability of big data storage and analysis on the basis of the M2M platform; and the root cloud platform is a more comprehensive and efficient platform for empowerment of the industrial Internet, which combines the latest technology and development trend of the industrial Internet on the basis of the M2M and ECC platform. On the basis of M2M and ECC platforms, RootCloud platform is a more comprehensive and efficient industrial Internet empowerment platform by combining the latest technology and development trend of industrial Internet[11] .

In short, the root cloud platform makes it possible to deliver from the factory after production to the hands of the customer no longer lost contact, SANY Heavy Industry can monitor the status of the machinery in real time and provide technical support at any time, so that the customer's after-sales experience has been improved.

5.2.4 Personalization

In the field of construction machinery, SANY Heavy Industry continuously optimizes the production process through the use of digital technology in order to better meet the individual needs of customers and provide customized products and services. The following are the specific practices:

SANY Heavy Industry's intelligent factory is equipped with self-developed intelligent production management system and APP, which is able to synthesize customer delivery requirements, production material preparation, etc., and carry out efficient intelligent scheduling and intelligent dispatching. Even in the face of hundreds of products and only a small amount of demand for each product, the system can ensure that the production is well organized through the optimal decomposition and combination. This system not only improves production efficiency, but also greatly shortens the production cycle of customized products.

SANY's flexible manufacturing capabilities allow for the conversion of customers' individualized orders into batch chemical orders. Through the intelligent system, the company can flexibly adjust the production process to ensure that each piece of equipment is customized according to customer needs. This capability not only improves customer satisfaction, but also enhances market competitiveness.

SANY Heavy Industry carries out marketing and promotion through various digital channels such as the official website, social media and e-commerce platforms. The enterprise uses big data to analyze customer behavior and accurately place advertisements to improve marketing efficiency. At the same time, the enterprise also demonstrates product performance and use scenarios through online live broadcasts and short videos to attract potential customers.

SANY Heavy Industry has established a perfect digital service platform, such as "SANY Truck APP", which provides customers with convenient repair and maintenance appointments and service evaluation functions. Customers can select the nearest service station on the APP, submit repair or maintenance appointments, and make evaluations after the service is completed. This platform not only improves customer experience, but also incentivizes service stations to improve their service quality by associating customer evaluation with service station revenue.

In the overseas market, SANY Heavy Industries has implemented the business strategy of "focusing on us, local management, and service first". Through the establishment of more than 400 subsidiaries, joint ventures, agents, and the employment of international staff, the company is able to respond quickly to the needs of the local market and provide high-quality after-sales service. At the same time, the international service network exceeds 1,200, providing customers with back-end rapid supporting service system.

In terms of internal management, SANY Heavy Industry uses digital tools to optimize management processes and improve decision-making efficiency. For example, the enterprise has realized the digitization of many business areas such as research and development, planning and scheduling, production, quality monitoring, procurement, and warehouse management through the data middle platform project. This initiative not only improves management efficiency, but also provides strong support for corporate decision-making. In summary, SANY Heavy Industry has further consolidated its leading position in the construction machinery field by continuously improving customer experience and brand influence through personalized customization and digital marketing services.

6 CONCLUSIONS

This study shows that the drivers of SANY's digital transformation mainly include improving production efficiency, enhancing competitiveness and adapting to market changes. In terms of the value creation path, the introduction of advanced digital technology has realized the intelligence and automation of the production process, improving product quality and production speed. Meanwhile, the digital transformation also optimized supply chain management, reduced costs, and improved the operational efficiency of the enterprise. In addition, SANY Heavy Industry has used the digital platform to strengthen its interaction with customers, better meet customer needs and improve customer satisfaction. In short, SANY Heavy Industry's digital transformation has brought significant value creation for the enterprise, which provides a reference for other manufacturing enterprises.

COMPETING INTERESTS

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REFERENCES

[1] Zhang, Renzhi. Can Corporate Digital Transformation Enhance the Efficiency of Intellectual Capital Value Creation? Research on Financial Issues, 2023, 05: 89-100.
[2] Zheng G, Zhang XY, Zhao XY. How can data factor marketization drive enterprise digital transformation? Industrial Economics Research, 2023, 02: 56-68.
[3] Hsu Huining, Dong Birong. How Digital Transformation Promotes the Sustainable Development of Enterprises--Based on the Perspective of Enterprise Core Competitiveness Shaping. Contemporary Economic Management, 2023, 45(07): 44-53.
[4] Wang Xiaofan. Research on auditor risk response behavior in the context of enterprise digital transformation. Finance and accounting newsletter, 2024, 09: 43-47.
[5] Xinlan Wang, Maggie Shi. How Digital Transformation Drives Enterprise Dynamic Capability Generation to Realize Value Creation? --Based on the longitudinal single case study of Sany Heavy Industry. Accounting Newsletter, 2024, 06: 153-159.
[6] Wu Jin-Yu, Yan Jin-Hua. Enterprise digital transformation and information transparency. Accounting Newsletter, 2023, 23: 79-84.
[7] Liu Guangqiang. The logic and path of value creation of data assets empowering enterprise high-quality development. Finance and accounting newsletter, 2024, 04: 3-12+160.
[8] Zhang Yuan, Sun Xinbo, Qian Yu. Value creation and evolution in the digital transformation of traditional manufacturing enterprises-A longitudinal single case study from the perspective of resource orchestration. Economic Management, 2022, 44(04): 116-133.
[9] Xiang Guopeng, Gao Ting, Wan Yiqi. How can startups and users develop opportunities to realize value co-creation in the digital era? Management Review, 2022, 34(02): 89-101+141.
[10] Zhang Chen. Research on the impact of digitalization and business model innovation on enterprise performance. Nanjing University of Information Engineering, 2022.
[11] He Zheng, Li Yanni, Yang Xiaohong. Analysis of the development of industrial internet of things and smart manufacturing transformation in manufacturing enterprises - a case study based on SANY Heavy Industry. Manufacturing Technology and Machine Tools, 2022, 07: 69-74.

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A STUDY ON THE IMPACT OF PERSONALIZED EXPERIENCE MARKETING ON BRAND LOYALTY AMONG GENERATION Z

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Abstract: This study aims to explore the impact of personalized experience marketing on brand loyalty among Generation Z. Through a literature review and theoretical analysis, this paper first analyzes the behavioral characteristics of Generation Z consumers and their demand for personalized experiences. Subsequently, using a combination of case studies and surveys, the interaction between brands and Generation Z consumers is examined. The research findings show that personalized experience marketing effectively promotes brand loyalty among Generation Z by enhancing emotional connections, increasing engagement, and optimizing digital interactions. The study concludes that brands that fully utilize personalized marketing strategies are more likely to win long-term loyalty from Generation Z consumers in a highly competitive market.
Keywords: Generation Z; Personalized experience; Brand loyalty; Emotional connection; Digital interaction

1 INTRODUCTION

Generation Z (commonly referring to those born after 1995) is becoming an increasingly important force in the global market as an emerging consumer group. With the widespread adoption of digital technologies, the environment in which this generation has grown up differs significantly from that of previous generations. Generation Z has essentially grown up alongside the internet and social media, heavily influenced by technological advancements [1]. As a result, they exhibit distinct consumption habits and behavioral patterns, especially in terms of brand interaction and shopping experiences. Compared to traditional consumers, Generation Z places greater emphasis on personalized experiences and responds positively to highly interactive marketing strategies.

One of the most notable characteristics of Generation Z consumers is their strong demand for personalization. They expect brands to provide customized experiences based on their interests, preferences, and behaviors, rather than offering standardized services or products [2]. This preference for personalization is partly driven by their emphasis on self-expression and unique identity. On social media, Generation Z seeks to establish connections with others by showcasing their unique lifestyles and interests, and brands can meet this need through personalized experiences, thereby gaining a competitive advantage in their interactions with Generation Z [3].

Experience marketing, as an emerging marketing strategy, addresses the increasingly diverse needs of consumers. The core of experience marketing is to enhance the emotional connection between consumers and brands by providing profound and memorable interactions, ultimately increasing brand loyalty. Unlike traditional marketing models, experience marketing emphasizes emotion and interaction over product functionality and price comparison [4]. For Generation Z, emotional connection is one of the key factors influencing brand loyalty. They are more likely to choose brands that evoke emotional resonance, and personalized experiences are an effective way to trigger this emotional resonance [5-6].

In addition, Generation Z exhibits a high level of engagement and interaction during the consumption process. They not only expect excellent service when purchasing products but also seek more engagement opportunities through brand interaction. This engagement extends beyond the purchase itself to pre- and post-purchase experiences, such as interacting with brands on social media or participating in brand events. Studies have shown that personalized interactions can significantly enhance Generation Z's sense of engagement, thereby strengthening their loyalty to the brand. For example, some brands provide Generation Z consumers with customized content and personalized recommendations through social media platforms, creating a closer relationship between the brand and consumers [5].

In summary, this study aims to explore how personalized experience marketing affects brand loyalty among Generation Z. As the demand for personalization increases among Generation Z, understanding how brands can establish emotional connections with this generation through experience marketing has become an important research topic in marketing strategies. By analyzing the consumption behavior of Generation Z and their interaction patterns with brands, this study seeks to reveal the role of personalized marketing strategies in enhancing brand loyalty, providing strategic guidance for brands seeking to grow in emerging markets.

2 LITERATURE REVIEW

In recent years, experiential marketing has gained widespread attention in both academia and the industry, especially when addressing the emerging consumer group of Generation Z. This section of the literature review focuses on the basic concepts of experiential marketing, the impact of personalized interactions on consumers, the consumption behavior characteristics of Generation Z, and the main drivers of brand loyalty. These discussions lay the groundwork for the subsequent theoretical analysis.

2.1 Definition and Development of Experiential Marketing

The theoretical foundation of experiential marketing can be traced back to the late 20th century. Schmitt (1999) was one of the early proponents of experiential marketing, emphasizing that marketing should not be limited to the functionality of products but should focus on creating unique and memorable experiences for consumers [7]. The basic principle of experiential marketing is to enhance the connection between consumers and brands by stimulating their senses, emotions, and cognition. This strategy is not just about promoting products; it involves allowing consumers to "experience" the brand through interaction and participation, resulting in deeper brand recognition and memory. In today's market environment, experiential marketing has become a critical tool for establishing deep connections between brands and consumers. Particularly in the highly competitive digital era, brands use immersive and personalized experiences to strengthen consumers' brand loyalty [8].

2.2 Impact of Personalized Interactions on Consumers

Personalized marketing has been widely studied in recent years, particularly in the context of experiential marketing, where personalized interactions are considered key to increasing consumer engagement and loyalty [3]. Personalized interactions refer to a brand tailoring unique experiences for consumers based on their interests, needs, and behavioral traits. For example, brands can use big data analytics to understand consumers' preferences and provide personalized product recommendations or customized experiential activities. Literature shows that personalized experiences can significantly increase consumer engagement and strengthen their emotional connection with the brand, which fosters brand loyalty [5].

Research also indicates that personalized interactions can effectively enhance the quality of consumer brand experiences [9-10]. For instance, Generation Z consumers prefer interacting with brands through social media, expecting brands to respond promptly to their needs and provide unique interactive experiences via social platforms [11]. Such personalized interactions not only enhance consumers' sense of identity with the brand but also encourage them to spontaneously share their experiences on social media, further amplifying the brand's influence [12].

2.3 Consumption Behavior Characteristics of Generation Z

Generation Z is considered digital natives, having been exposed to the internet and smart devices from birth. Therefore, their consumption behavior differs significantly from previous consumer groups. Generation Z has a strong demand for personalized experiences, particularly in terms of digital interactions with brands [13]. They are accustomed to obtaining information through social media and enjoy sharing their personal experiences. Compared to traditional advertising, Generation Z prefers to rely on word-of-mouth, user reviews, and social media interactions when deciding whether to purchase a product from a brand [14].

Literature highlights that Generation Z consumers not only focus on product functionality during the purchase process but are also particularly interested in whether the brand can provide a unique and creative experience [15]. For example, they show great concern for factors such as brand values, culture, and social responsibility. If a brand can meet Generation Z's needs through personalized experiences, they are more likely to develop brand loyalty [16].

2.4 Factors Influencing Brand Loyalty

The concept of brand loyalty has been extensively studied in marketing, typically referring to consumers' continued preference for and repeat purchases of a particular brand. Traditionally, brand loyalty is influenced by factors such as price, quality, and convenience. However, recent studies indicate that emotional connection and experiential quality are becoming increasingly important in driving brand loyalty [17]. For Generation Z, brand loyalty is not just about product functionality; it also reflects their recognition of the brand's culture, values, and interactive experiences. Personalized interactions and experiential marketing are considered effective means of enhancing Generation Z's brand loyalty [18]. By providing unique interactive experiences, brands can effectively evoke emotional resonance with Generation Z, enabling them to stand out in a competitive marketplace [19]. This emotion- and experience-based loyalty is generally more stable and enduring than traditional price-based loyalty, as it is built on deeper emotional and identity-related foundations [20].

Through the above literature review, it is evident that experiential marketing, especially personalized interaction strategies, has a profound impact on Generation Z's brand loyalty. In the subsequent theoretical analysis, this paper will further explore how personalized experiential marketing specifically influences Generation Z's brand loyalty.

3 THEORETICAL ANALYSIS

In the theoretical analysis section, we will explore how personalized experiential marketing affects Generation Z's brand loyalty through the lenses of emotional bonding theory, engagement theory, and the role of digital interaction.

3.1 Emotional Bonding and Brand Loyalty

Emotional Bonding Theory posits that when consumers form an emotional connection with a brand, they are more likely to develop loyalty. This emotional connection is not merely derived from the functional satisfaction of a product but, more importantly, from the experiences provided by the brand, particularly personalized experiences. For

Generation Z consumers, emotional resonance is a core driver of brand loyalty. They expect brands to understand their personalized needs and provide relevant experiences that enable them to establish deeper emotional connections with the brand.

Personalized interactions in experiential marketing enhance brand loyalty by fostering emotional bonds. For example, Generation Z is more likely to be attracted to brands that reflect their personal interests and values. Personalized marketing activities, such as customized brand experiences or exclusive interactive events, can trigger emotional resonance, thereby increasing Generation Z's sense of identification and loyalty to the brand. For instance, brands like Nike, which offers customized sports shoe design services, allow consumers to design their shoes based on personal preferences. This highly personalized experience not only increases Generation Z's sense of involvement but also fosters brand loyalty.

3.2 Engagement Theory

Engagement Theory emphasizes that the more frequently and deeply consumers interact with a brand, the higher their loyalty will be. In the digital age, Generation Z's engagement primarily occurs through online platforms and social media. Personalized experiential marketing effectively increases consumer engagement because personalized interactions make consumers feel that the brand is paying attention to their individual needs. For Generation Z, there is a particularly close relationship between engagement and loyalty. They are not just consumers of products but also active "participants" in the brand.

Personalized experiential marketing activities, such as interactive events tailored to Generation Z both online and offline, can significantly increase their engagement. This sense of involvement makes Generation Z feel that they are not just users of the brand but are part of the brand's story. Consequently, they build a deeper emotional connection with the brand. As engagement increases, their loyalty to the brand also strengthens.

3.3 The Role of Digital Interaction

Digital interaction plays an indispensable role in Generation Z's consumption experience. With technological advancements, brands can leverage big data, artificial intelligence, and other technologies to analyze consumer behavior and preferences, providing personalized marketing content [21]. Research shows that personalized digital interactions can significantly enhance Generation Z's brand loyalty. For instance, brands like Netflix utilize recommendation algorithms to provide personalized content recommendations, making consumers feel that the brand is attentive to their needs, thereby strengthening brand loyalty.

As digital natives, Generation Z has a heightened demand for digital interaction. Personalized digital interactions can be facilitated through social media, mobile apps, virtual reality, and other formats, offering a multi-dimensional brand experience. For example, virtual reality technology allows Generation Z to engage in immersive product experiences in a digital environment, increasing their engagement with the brand and enhancing their emotional identification with it.

In conclusion, personalized experiential marketing enhances Generation Z's brand loyalty through a combination of emotional bonding, engagement, and digital interaction. By providing Generation Z with personalized, interactive experiences, brands can distinguish themselves in a competitive market and secure the long-term loyalty of this emerging consumer group.

4 CONCLUSION AND FUTURE OUTLOOK

This study explores the impact of personalized experiential marketing on brand loyalty among Generation Z. The findings indicate that personalized experiences can enhance Generation Z's brand loyalty through multiple channels, including emotional bonding, increased engagement, and digital interaction. Generation Z has a high demand for personalized experiences, and brands that offer customized interactions can establish deep emotional connections with this generation, thereby enhancing loyalty. This research highlights the crucial role of personalized experiential marketing in today's market, particularly when targeting the emerging consumer group of Generation Z.

However, this study has certain limitations. First, the analysis primarily relies on existing theories and literature, lacking empirical data to support the conclusions. Future research could employ quantitative or qualitative methods to further verify the actual impact of personalized experiential marketing on brand loyalty. Second, this study focuses on Generation Z as a homogenous group, but Generation Z across different countries and cultural backgrounds may exhibit varying consumer behaviors. Cultural differences may influence their demand for personalization and the development of brand loyalty. Therefore, future research could conduct cross-cultural comparative studies to explore the effectiveness of personalized experiential marketing in different cultural contexts.

Future research could expand in the following directions. First, with the rapid development of technology, brands are increasingly utilizing artificial intelligence, big data analytics, and other tools to provide highly personalized experiences. Future studies could examine how these technologies influence the effectiveness of personalized experiential marketing. Second, research could focus on comparing the impact of different types of personalized marketing strategies on various consumer groups, particularly comparing Generation Z with other cohorts, such as millennials. Moreover, new technologies like virtual reality and augmented reality offer brands new ways to engage with consumers. Future studies could investigate the potential of these technologies in enhancing brand loyalty. Finally, as consumers become more concerned with brands' social responsibility, future research could explore how brands can build deeper connections with Generation Z through personalized social responsibility initiatives. By integrating personalized experiences with a brand's social responsibility, companies may further enhance Generation Z's loyalty and brand identification. These research areas will provide more theoretical and empirical support for experiential marketing, offering valuable insights for brands to develop more targeted market strategies.

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REFERENCES

[1] Priporas CV, Stylos N, Fotiadis AK. Generation Z consumers' expectations of interactions in smart retailing: A future agenda. Comput Hum Behav, 2017, 77: 374-81.
[2] Thangavel P, Pathak P, Chandra B. Consumer decision-making style of Gen Z: A generational cohort analysis. Glob Bus Rev, 2022, 23(3): 710-728.
[3] Dobre C, Milovan AM, Duțu C, et al. The common values of social media marketing and luxury brands: The millennials and Generation Z perspective. J Theor Appl Electron Commer Res, 2021, 16(7): 2532-2553.
[4] Batat W. Experiential marketing: Consumer behavior, customer experience, and the 7Es. Routledge. 2019. DOI: https://doi.org/10.4324/9781315232201.
[5] Lou C, Xie Q. Something social, something entertaining? How digital content marketing augments consumer experience and brand loyalty. Int J Advert, 2021, 40(3): 376-402.
[6] Cui X, Yang M. The impact of nursing interventions based on the Rosenthal effect on stress response and emotional states in children with scoliosis. J Youjiang Med Univ Natl, 2019, (06): 713-715.
[7] Schmitt B. Experiential marketing. J Mark Manag, 1999, 15(1-3): 53-67.
[8] More AB. Implementing digital age experience marketing to make customer relations more sustainable. New Horizons for Industry 4.0 in Modern Business. Cham: Springer Int Publ, 2023, 99-119. DOI: https://doi.org/10.1007/978-3-031-20443-2_5.
[9] Paramita W, Nhu HBC, Ngo LV, et al. Brand experience and consumers' social interactive engagement with brand page: An integrated marketing perspective. J Retail Consum Serv, 2021, 62: 102611.
[10] Pang X, Liu F, Li L, et al. A preliminary exploration of the reform of "General Practice Introduction" teaching under the concept of curriculum ideology and politics. J Youjiang Med Univ Natl, 2020, (06): 806-809.
[11] Rane NL, Achari A, Choudhary SP. Enhancing customer loyalty through quality of service: Effective strategies to improve customer satisfaction, experience, relationship, and engagement. Int Res J Mod Eng Technol Sci, 2023, 5(5): 427-452.
[12] Chen X, Qasim H. Does E-brand experience matter in the consumer market? Explaining the impact of social media marketing activities on consumer-based brand equity and love. J Consum Behav, 2021, 20(5): 1065-1077.
[13] Munsch A. Millennial and Generation Z digital marketing communication and advertising effectiveness: A qualitative exploration. J Glob Sch Mark Sci, 2021, 31(1): 10-29.
[14] Pillay S. The influence of electronic word-of-mouth adoption on brand love amongst Generation Z consumers. Acta Commer, 2021, 21(1): 1-11.
[15] Raza M, Qabool S, Alam SH. Role of marketing strategies to Generation Z in emerging markets. J Organ Stud Innov, 2022, 9(3): 16-43.
[16] Trejo JM. Digital marketing model innovation and Generation Z as consumer decision-making style: Making predictions with an artificial neural network in Mexico. Contad Adm, 2021, 66(4): 1-28.
[17] Mostafa RB, Kasamani T. Brand experience and brand loyalty: Is it a matter of emotions? Asia Pac J Mark Logist, 2021, 33(4): 1033-51.
[18] Guo W, Luo Q. Investigating the impact of intelligent personal assistants on the purchase intentions of Generation Z consumers: The moderating role of brand credibility. J Retail Consum Serv, 2023, 73: 103353.
[19] Anjum A, Thomas MR, Prakash PK. Digital marketing strategies: Effectiveness on Generation Z. SCMS J Indian Manag, 2020, 17(2): 54-69.
[20] Kaabachi S, Ben Mrad S, Barreto T. Reshaping the bank experience for Generation Z in France. J Mark Anal, 2022, 10(3): 219-31.
[21] Wu P, Lan Z, Huang W, et al. Exploring the application of a blended teaching model based on MOOCs among undergraduate medical interns. J Youjiang Med Univ Natl, 2020, (01): 119-22.

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THE IMPACT OF WEB SITE DESIGNING ON MARKETING ORGANIZATION AND ITS CUSTOMERS

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Abstract: This study explores the impact of website design on marketing organizations and customer engagement, focusing on key design elements such as usability, aesthetics, interactivity, and security. The rapid evolution of digital commerce has made websites a crucial platform for organizations to engage with customers. However, the role of website design in influencing customer behavior and satisfaction has not been fully explored. The primary objective of this research is to investigate how various aspects of website design contribute to enhanced customer interaction and engagement with marketing organizations. Using a sample of 200 participants and employing SPSSv22 for data analysis, the study applied descriptive statistics, correlation, and regression analyses to assess the relationship between website design components and customer engagement. The results show strong correlations between the design factors and customer satisfaction, with security being the most significant predictor of engagement. This study provides actionable insights for marketing organizations, highlighting the need to invest in secure, user-friendly, and aesthetically pleasing websites to maintain customer loyalty and improve brand perception. The findings contribute to the literature by bridging gaps in understanding the critical role of website design in digital marketing strategies. Recommendations for future research include examining other emerging web design elements such as personalization and AI-driven interactions.
Keywords: Web site; Marketing; Organization; Customers; User experiences

1 INTRODUCTION

In the current digital economy, a company's website plays a pivotal role in shaping its interactions with both existing and potential customers. A well-designed website serves not just as a marketing tool but as a dynamic platform for communication, engagement, and transaction. In many instances, it is the first point of contact between a business and its audience, making it critical to the success of a company's overall marketing strategy. As point out, in the digital era, the website is often a company's most powerful marketing channel, blending both promotional and functional roles. With the exponential growth of e-commerce and the increasingly competitive nature of digital markets, companies must differentiate themselves not only through their products and services but also through their online presence. Website design has moved beyond its early stages of being purely an aesthetic choice to becoming a vital element of strategic business decisions. Also lstress customers now judge the credibility and reliability of businesses based largely on their online appearance. Therefore, optimizing the structure, design, and usability of a website can significantly influence customer perceptions, engagement, and ultimately, customer retention.

Moreover, website design impacts a company's ability to drive conversions. According to Palmer [1], businesses with well-designed websites that cater to user needs are more likely to see improved sales, higher traffic, and better engagement. The user experience (UX), visual appeal, functionality, and content all contribute to this outcome. Previous study observes, websites that are not only visually appealing but also provide smooth, intuitive navigation enhance user satisfaction and increase the likelihood of conversions. Despite the proven benefits of good website design, many businesses still underestimate its importance, either neglecting the user experience or failing to align their online presence with their brand identity. This often results in underperforming websites that alienate potential customers and negatively affect the company's bottom line. There is growing evidence that suggests that businesses that prioritize website design as part of their overall marketing strategy enjoy a competitive advantage over those that do not.

Given the current state of digital transformation, the motivation for this study lies in understanding how the design of a company's website influences not only customer satisfaction but also the broader marketing strategies of organizations. While many studies focus on individual components of website design, such as UX or visual aesthetics, fewer have considered the cumulative effect of these elements on business performance and customer behavior. This research aims to bridge this gap by examining the role of website design in shaping both marketing strategies and customer experiences.

2 Objectives and Research Questions

2.1 The objectives of this study are;

1. To examine the role of website design in influencing customer behavior and engagement.

2. To explore the relationship between website design and brand perception.
3. To assess how different design elements (e.g., UX, visual aesthetics, content) affect customer satisfaction.
4. To identify best practices in website design for marketing organizations aiming to enhance customer experience and loyalty.

2.2 Research Questions:

1. How does website design influence customer satisfaction and loyalty in marketing organizations?
2. What are the key design elements that impact customer engagement and behavior?
3. How do customers perceive a brand based on the website design?
4. What strategies can marketing organizations employ to optimize website design for better customer interaction?

3 Literature Review

3.1 Concept of Website Design

Website design refers to the process of creating the aesthetic and functional elements of a website, which includes layout, visual appearance, user interface (UI), and overall user experience (UX). A well-designed website is not merely visually appealing; it is also intuitive, easy to navigate, and aligned with the company's brand and objectives. As websites increasingly become central to customer interactions and business operations, their design has a profound impact on both organizational outcomes and customer behavior. Some scholars in the marketing field argue that a strategic website design can serve as a powerful tool in digital marketing, enabling businesses to engage with customers, drive conversions, and build brand loyalty.
Website design encompasses several components, including visual aesthetics (such as color schemes and typography), content quality, functionality, and responsiveness. These elements contribute to the overall user experience, which plays a crucial role in determining how users interact with a website and perceive the brand. Other scholars note that website design is closely linked to customer satisfaction and loyalty, as a positive user experience encourages longer visits, repeat interactions, and higher conversion rates. In the context of marketing organizations, website design is increasingly seen as a critical element of digital marketing strategies. As digital marketing shifts from traditional approaches to more interactive and personalized experiences, companies must ensure their websites are optimized for customer engagement. Kotler et al. emphasize that in the digital era[2], a company's website acts as a hub for various marketing activities, including advertising, customer engagement, lead generation, and e-commerce. Effective website design aligns the brand’s objectives with customer needs, creating a seamless experience that enhances business outcomes.
However, despite the growing importance of website design in marketing, many businesses fail to fully capitalize on its potential. Palmer argues that many organizations still view website design as a secondary priority[1], focusing more on traditional marketing efforts without realizing that the website is often the first point of contact for customers. This underutilization creates a gap between customer expectations and the business's ability to meet them, leading to lower engagement and missed opportunities for growth.

3.2 User Experience (UX) and Website Design

User experience (UX) is arguably the most important aspect of website design. Marketing philosophers seen UX as the overall experience a user has while interacting with a website, which includes usability, accessibility, and satisfaction. A website that is difficult to navigate or slow to load will likely frustrate users, resulting in lower engagement and higher bounce rates. Hussain et al. support this view[3], noting that websites that prioritize UX see improved user retention and higher customer satisfaction. They found that companies investing in UX design often experience immediate improvements in sales and customer engagement. UX also plays a role in shaping users' perceptions of a brand. Another study also found that users often judge the credibility of a website within seconds of landing on it, making the initial UX critical to creating a positive impression. For marketing organizations, investing in a seamless, intuitive user experience can lead to greater customer loyalty, as users are more likely to return to websites that are easy to navigate and responsive to their needs. Palmer adds that UX extends beyond aesthetics[1], emphasizing the importance of functional aspects such as clear navigation, mobile responsiveness, and fast loading times.

3.3 Visual Aesthetics and Branding in Website Design

Visual aesthetics play a significant role in website design, influencing user perceptions and engagement. Lavie and Tractinsky assert that users form judgments about a company's professionalism and trustworthiness based on the visual appeal of its website. These judgments are often made within seconds, making it crucial for businesses to ensure that their website design aligns with their brand identity and appeals to their target audience. A well-designed website that uses appropriate colors, typography, and imagery can enhance the user experience and strengthen the brand's image. Visual design is particularly important in industries where brand image is closely tied to consumer perceptions, such as luxury goods and fashion. Palmer found that websites with strong visual aesthetics are more likely to foster positive emotions in users[1], leading to increased engagement and longer visits. Additionally, well-designed websites often lead to higher conversion rates, as users are more inclined to trust and engage with businesses that present themselves professionally online. Marketing philosophers, emphasize that the coherence between website aesthetics and brand identity is essential for establishing trust and encouraging customer loyalty.

3.4 Content and Its Role in Website Design

The content of a website is another critical factor that influences user engagement and business outcomes. Some scholars argue that content is the primary means through which businesses communicate their value proposition to customers. High-quality, relevant content that addresses user needs or solves their problems can significantly enhance user engagement, driving longer visits and higher conversion rates. Furthermore, content that is optimized for search engines (SEO) can improve a website's visibility, attracting more organic traffic and increasing its reach. Content is also an essential component of a website's overall user experience. Another field of marketing research found that users are more likely to stay on a website and explore further if the content is well-organized, informative, and tailored to their interests. In contrast, poorly written or irrelevant content can frustrate users, leading to higher bounce rates and lower engagement. Another study that content should not only be engaging but also interactive, allowing users to interact with the brand through features such as chatbots, product customization, and user-generated content.

3.5 Website Functionality and Usability

The functionality of a website is a key determinant of its success. Deng and Poole found that users today expect websites to load quickly and be accessible across a range of devices[4], including smartphones and tablets. A website that fails to meet these expectations is more likely to experience high bounce rates and lower engagement. Functionality also includes aspects such as secure payment systems, easy-to-navigate menus, and search features, all of which contribute to a positive user experience. In addition to basic functionality, the responsiveness of a website its ability to adapt to different screen sizes and devices has become increasingly important. Some scholars highlight that with the growing use of mobile devices, websites must be optimized for mobile users to remain competitive. Websites that are not responsive or mobile-friendly risk alienating a significant portion of their audience. This is particularly true for e-commerce websites, where functionality and usability directly affect conversion rates and sales.

3.6 Impact of Website Design on Consumer Behavior

Consumer behavior is strongly influenced by website design. Research found that a well-designed website reduces friction in the customer journey, making it easier for users to find the information they need and complete transactions. For example, websites with clear calls to action, simple navigation, and optimized checkout processes are more likely to convert visitors into customers. Conversely, websites with confusing layouts, too many pop-ups, or unclear messaging can frustrate users, leading them to abandon their visit before making a purchase. Additionally, Palmer found that website design elements such as product placement, user reviews[1], and personalized recommendations can significantly influence purchasing decisions. For marketing organizations, understanding the impact of these design elements on consumer behavior is critical to optimizing their websites for higher conversions. Kotler et al. argue that website design should be viewed as a key component of the overall marketing strategy[2], with careful attention paid to how design influences the customer journey.

3.7 Website Design and Customer Loyalty

A well-designed website can foster customer loyalty by providing a positive and seamless user experience. Different scholars argue that users are more likely to return to a website if they find it easy to use and aligned with their needs. Loyalty is especially important in industries with high levels of competition, where customers have many choices. Websites that provide a consistent and satisfying user experience can differentiate themselves from competitors and build long-term relationships with customers. Hussain et al. found that website design elements such as personalized content[3], seamless navigation, and quick load times can all contribute to higher levels of customer loyalty. For marketing organizations, this means that investing in website design can lead to higher retention rates and greater lifetime value for customers. Some scholars in the field of study suggest that website design should be seen as an integral part of customer relationship management (CRM), as it influences how customers perceive and interact with the brand over time.

3.8 Personalization in Website Design

Personalization has emerged as a key trend in website design. Some marketing researchers argue that personalized websites, which tailor content, offers, and recommendations based on user data, create more engaging and satisfying experiences for

users. This personalization not only improves user satisfaction but also increases the likelihood of conversions, as users feel that the website is catering to their specific needs and preferences.
Research has shown that users are more likely to engage with websites that offer personalized experiences. Marketing researchers found that websites that provide personalized recommendations based on user behavior see higher engagement rates and more repeat visits. For marketing organizations, incorporating personalization into website design can be a powerful tool for driving customer engagement and loyalty.

3.9 E-commerce and Website Design

In the realm of e-commerce, website design is particularly critical to driving sales and conversions. Research found that e-commerce websites that prioritize usability and functionality see higher conversion rates and greater customer satisfaction. Key design elements such as a streamlined checkout process, secure payment options, and product filtering tools all contribute to a positive user experience and higher sales. Website design is especially important for mobile e-commerce, as more consumers are using smartphones and tablets to make purchases. Deng and Poole highlight the importance of responsive design for e-commerce websites[4], noting that mobile-friendly websites see higher engagement and lower bounce rates than those that are not optimized for mobile devices. For marketing organizations, ensuring that their e-commerce websites are optimized for both desktop and mobile users is essential to driving growth.

4 RESEARCH GAP

Despite extensive research on website design and its impact on marketing organizations and customer behavior, several gaps remain in the literature. One prominent gap is the lack of comprehensive studies that focus on the integration of advanced technologies such as artificial intelligence (AI) and machine learning into website design to enhance personalization and user experience. Although website design's influence on marketing organizations and customer behavior is well-researched, key gaps remain. First, there's limited exploration of how advanced technologies like AI and machine learning enhance personalization in website design. Secondly, studies rarely compare the impact of design across different industries. Additionally, the long-term effects of continuous website optimization on customer loyalty are underexplored. Emotional responses triggered by website aesthetics, known as emotional design, also lack sufficient research. Lastly, there's a gap in understanding cost-effective website design strategies for small and medium-sized enterprises (SMEs).

5 METHODOLOGY

This study aims to investigate the impact of website design on marketing organizations and customer behavior. The methodology involves both qualitative and quantitative approaches, ensuring comprehensive data collection and analysis. The study used survey approach. Surveys were distributed to customers of marketing organizations with active websites. A total of 200 respondents participated in the survey. The participants were selected using stratified random sampling to ensure diverse representation from different industries and customer demographics. The survey included structured questions to measure customer perceptions of website design elements such as usability, aesthetics, and interactivity, along with their impact on purchasing decisions and brand loyalty. Survey data were analyzed using SPSS version 22. Descriptive statistics were employed to summarize the demographic characteristics and website design perceptions of the participants. Correlation and regression analyses were performed to explore the relationship between website design and customer behavior. For qualitative data, thematic analysis was applied to interview transcripts, identifying common themes related to the strategic importance of website design.

6 RESULTS

The results of the study provide valuable insights into the relationship between website design and customer behavior. This section presents the findings from the descriptive statistics, correlation analysis, and regression analysis.

6.1 Descriptive Statistics

Table 1 summarizes the descriptive statistics for key website design elements as perceived by the respondents. The mean scores indicate the level of importance assigned to each design element.

Table 1 Level of Design Element

Design Element	Mean	Standard Deviation
Aesthetics	4.5	0.62
Usability	4.4	0.68

Interactivity	4.2	0.71
Speed	4.0	0.75
Security	4.6	0.59

The results indicate that respondents rated website aesthetics (mean = 4.5) and security (mean = 4.6) as the most critical design elements. Usability (mean = 4.4) and interactivity (mean = 4.2) also received high scores, suggesting that customers place significant value on a visually appealing and user-friendly website. Speed (mean = 4.0) was also important but received the lowest score among the listed elements, indicating room for improvement in this area.

6.2 Correlation Analysis

Table 2 presents the correlation coefficients between website design elements and customer engagement.

Table 2 Customer Engagement

Variable	Customer Engagement	Usability	Aesthetics	Interactivity	Security
Customer Engagement	1.00	0.78**	0.75**	0.72**	0.79**
Usability	0.78**	1.00	0.68**	0.65**	0.74**
Aesthetics	0.75**	0.68**	1.00	0.60**	0.73**
Interactivity	0.72**	0.65**	0.60**	1.00	0.68**
Security	0.79**	0.74**	0.73**	0.68**	1.00

The correlation analysis reveals a strong positive relationship between all website design elements and customer engagement. The strongest correlation is observed between security and customer engagement ($r = 0.79$, $p < 0.01$), indicating that higher perceived security is associated with greater customer engagement. Usability ($r = 0.78$, $p < 0.01$) and aesthetics ($r = 0.75$, $p < 0.01$) also show significant positive correlations, emphasizing their importance in enhancing user experience.

6.3 Regression Analysis

Table 3 presents the results of the regression analysis, highlighting the relationship between website design elements and customer engagement.

Table 3 Result Interpretation

Variable	Unstandardized Coefficients (B)	Standardized Coefficients (β)	t	p-value
Constant	1.32	-	3.45	0.001
Usability	0.45	0.32	4.21	0.000
Aesthetics	0.30	0.28	3.80	0.000
Interactivity	0.25	0.20	3.00	0.003
Security	0.50	0.36	5.10	0.000

The regression analysis shows that website design elements significantly predict customer engagement, accounting for approximately 65% of the variance ($R^2 = 0.65$). Among the predictors, security ($\beta = 0.36$, $p < 0.001$) has the most substantial positive effect on customer engagement, followed by usability ($\beta = 0.32$, $p < 0.000$) and aesthetics ($\beta = 0.28$, $p < 0.000$). Interactivity also contributes positively ($\beta = 0.20$, $p < 0.003$), but to a lesser extent. The results indicate that enhancing these design elements can significantly improve customer engagement in marketing organizations.

7 DISCUSSION

The findings of this study highlight the significant impact of website design on customer engagement within marketing organizations. The strong positive correlations between design elements (usability, aesthetics, interactivity, and security) and customer engagement reinforce the notion that a well-designed website is essential for attracting and retaining customers. The study revealed that usability is a key driver of customer engagement, aligning with existing literature that emphasizes the importance of user-friendly interfaces [2,5]. Customers are more likely to engage with websites that facilitate easy navigation and intuitive design. This supports the idea that usability directly influences customer satisfaction and decision-making. Aesthetics also emerged as a critical factor influencing customer perceptions and engagement. The findings echo those of Palmer [1], who noted that visually appealing designs can create positive emotional responses, fostering a connection between the customer and the brand. This relationship suggests that organizations should prioritize aesthetic elements in their web design strategies to enhance brand image and customer loyalty.

The strongest correlation was found between perceived security and customer engagement. This is consistent with the findings of Hussain et al. [3], indicating that customers are increasingly concerned about online security. Ensuring robust security measures can mitigate customer anxieties and foster trust, which is essential for maintaining long-term customer relationships. The impact of interactivity on customer engagement is particularly noteworthy. Engaging features such as live chats, interactive content, and personalized experiences encourage user participation and can lead to higher satisfaction levels. This aligns with the insights of Deng and Poole [4], who highlighted the importance of interactive elements in enhancing customer experiences. The results suggest that marketing organizations must invest in effective website design strategies that prioritize usability, aesthetics, security, and interactivity. By understanding the critical role these elements play, organizations can create a more engaging online environment that attracts and retains customers.

8 CONCLUSION

This study conclusively demonstrates the significant impact of website design on customer engagement in marketing organizations. The findings indicate that elements such as usability, aesthetics, security, and interactivity play crucial roles in influencing customer behavior. By focusing on these design aspects, marketing organizations can enhance customer satisfaction, foster trust, and drive engagement. The study contributes to existing literature by providing empirical evidence supporting the need for organizations to prioritize effective web design strategies. The identified relationships between design elements and customer engagement highlight essential areas for improvement and investment.

9 RECOMMENDATIONS

1. Marketing organizations should prioritize usability in their website design to facilitate seamless navigation. Regular usability testing and customer feedback mechanisms can help identify areas for improvement.
2. Organizations should focus on creating visually appealing websites that reflect their brand identity. Collaborating with professional designers to ensure a consistent and attractive visual presentation can enhance customer perception.
3. Given the strong link between perceived security and customer engagement, organizations must implement robust security protocols. Regular security audits and clear communication about security practices can help build customer trust.
4. Incorporating interactive elements, such as live chats, polls, and personalized recommendations, can enhance customer experiences. Organizations should explore innovative ways to engage users actively.
5. Marketing organizations should adopt a mindset of continuous improvement, regularly updating their websites to incorporate emerging trends and technologies. Staying informed about advancements in web design can help organizations remain competitive in the digital landscape.

CONFLICT OF INTEREST

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] Palmer, JW. Web site usability, design, and performance metrics. Information Systems Research, 2020, 13(2): 151-167.
[2] Kotler, P, Keller, KL, Goodman, M, et al. Marketing management (15th ed.). Pearson Education. 2019.
[3] Hussain, A, Griffiths, P, Patel, R. Security and customer engagement: How perceived security influences online shopping behavior. Journal of Business Research, 2020, 94, 325-334.
[4] Deng, L, Poole, MS. Aesthetic design of e-commerce websites: Examining its effectiveness on users' emotions and purchase intentions. Decision Support Systems, 2019, 53(4): 452-463.
[5] Ahl, L, Lahtinen, J, Piha, L, et al. The effects of usability on customer satisfaction in e-commerce websites. Journal of Retailing and Consumer Services, 2020, 56, 102134.

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A STUDY ON THE COMPLEMENTARITY OF AGRICULTURAL TRADE BETWEEN CHINA AND VIETNAM

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Abstract: This paper aims to analyze the complementarity of agricultural trade between China and Vietnam and explore its impact on bilateral economic cooperation. The study employs theories of comparative advantage, complementarity, and intra-industry trade, combining trade data and policy contexts to examine the complementarity and cooperation potential of agricultural products such as rice, coffee, and tropical fruits between the two countries. The results indicate that Vietnam holds significant comparative advantages in the production of tropical agricultural products, while China dominates in agricultural production materials and technology, establishing a strong complementary relationship in agricultural trade. Policy support, particularly the implementation of the Regional Comprehensive Economic Partnership (RCEP), has accelerated the growth of agricultural product trade between the two nations. The study concludes that the complementarity of China-Vietnam agricultural trade is significant but requires further optimization of supply chain management and enhancement of product value-added to address future competition and challenges.
Keywords: China-Vietnam trade; Agricultural trade; Comparative advantage; Intra-industry trade; RCEP

1 INTRODUCTION

China and Vietnam are two significant agricultural producers in the Asian region, and their agricultural trade relationship has developed remarkably over the past decades. Due to clear complementarities in climate conditions, geographical locations, and agricultural resources, agricultural trade cooperation between China and Vietnam has a natural foundation. Particularly in areas such as rice, tropical fruits, rubber, and coffee, Vietnam has become an important supplier of agricultural products to China, leveraging its unique natural conditions, while China provides Vietnam with a vast consumer market [1]. Agricultural trade has not only promoted economic cooperation between the two countries but also contributed to maintaining regional food security. Since the establishment of the China-ASEAN Free Trade Area (CAFTA) in 2010, the volume of agricultural trade between the two nations has significantly increased. Vietnam's tropical fruits, rice, and aquatic products have rapidly entered the Chinese market by reducing tariffs and trade barriers. For example, Vietnamese durian, bananas, and passion fruits have captured substantial market shares in China. With the implementation of the Regional Comprehensive Economic Partnership (RCEP) in 2020, the depth of China-Vietnam agricultural trade cooperation has been further strengthened. China and Vietnam have mutually reduced tariffs on agricultural products by over 90%, laying a solid foundation for further cooperation in the field of agricultural trade in the future [2].

From specific trade data, in 2020, China imported nearly $4 billion worth of agricultural products from Vietnam, compared to less than $800 million a decade earlier [3]. Among the agricultural products exported by Vietnam to China, rice and coffee constitute a significant proportion. These products not only meet China's growing market demand but also promote the modernization of Vietnam's agricultural industry. Conversely, China's exports of agricultural machinery, fertilizers, and other agricultural production materials to Vietnam provide technical support and material guarantees for the modernization of Vietnam's agriculture.

The deepening of China-Vietnam agricultural trade relations is driven not only by the market demands of both sides but also benefits from policy-level support. For example, Guangxi, as a frontier province for China-Vietnam agricultural trade, has further facilitated bilateral trade by strengthening infrastructure construction and optimizing border clearance efficiency [4]. Additionally, both governments actively engage in agricultural technology exchanges, especially in areas such as cultivation techniques, pest and disease control, and supply chain management. These collaborations have not only improved agricultural production efficiency but also created larger market spaces for both parties.

However, the development of China-Vietnam agricultural trade also faces several challenges. Firstly, there exists competition between the two countries in certain agricultural product sectors, such as market share competition in rice and fruits, which could impact trade balance. Secondly, in terms of supply chain management and product standardization, both sides still need to overcome certain technical barriers to ensure uniformity in agricultural product quality and market entry standards. The rational use of pesticides and fertilizers plays a crucial role in agricultural production, directly affecting the quality of agricultural products and environmental sustainability. In agricultural technology cooperation, the two countries can collaborate on the application of green pesticides and environmentally friendly fertilizers to reduce their negative impacts on the environment and human health [5]. In the future, enhancing the value-added of agricultural products, deepening technological cooperation, and optimizing the trade structure remain key to the further development of China-Vietnam agricultural trade.

2 LITERATURE REVIEW

Research on the complementarity of agricultural trade between China and Vietnam has established a relatively extensive literature base, covering areas such as competitiveness analysis, complementarity theory, and policy impacts. Many scholars have revealed the characteristics and potential development directions of agricultural trade between the two countries through theoretical frameworks and empirical analyses.

Firstly, the theory of comparative advantage is an important foundation for explaining China-Vietnam agricultural trade. According to this theory, countries should focus on producing products in which they have a relative advantage and exchange for other countries' advantageous products through international trade to maximize economic benefits. Vietnam possesses significant comparative advantages in agricultural products such as rice, coffee, rubber, and tropical fruits, particularly rice and coffee, which have long been its main export products [6]. Meanwhile, China has clear comparative advantages in agricultural machinery, fertilizers, and other agricultural production materials, providing necessary support for the modernization of Vietnam's agricultural production [7]. Existing research indicates that as China's demand for Vietnamese agricultural products continues to increase, Vietnam's export volume of these advantageous products has grown year by year, making the agricultural trade between the two countries highly complementary. In this context, the quality and sanitary inspection standards of agricultural products have become key elements in ensuring smooth trade between both parties. Especially in the protection and rational use of crop genetic resources, effectively enhancing agricultural product quality and reducing the spread of pests and diseases further strengthens the stability of bilateral trade [8].

Secondly, the theory of trade complementarity offers another perspective for analyzing China-Vietnam agricultural trade. This theory examines whether there exists a complementary relationship between the production and demand of different product sectors in two countries, thereby driving the growth of bilateral trade. Many studies have analyzed the current state of China-Vietnam agricultural trade using the Trade Complementarity Index (TCI), with results indicating strong complementarity in certain agricultural products between the two countries, especially in tropical fruits, aquatic products, and coffee [9]. For instance, China has a higher demand for tropical fruits during specific seasons, and Vietnam, as a major producer of tropical fruits, can effectively fill the supply gap in the Chinese market for such products [10]. This complementarity not only enhances the stability of agricultural trade between the two countries but also lays the foundation for future deepened cooperation. Moreover, research suggests that there is potential to further explore complementarity in other areas, such as the production and consumption of aquatic products, tea, and rubber between China and Vietnam [11].

In addition to complementarity, the theory of intra-industry trade also holds significant importance in the study of China -Vietnam agricultural trade. Intra-industry trade refers to the production and trade activities of the same category of products between two countries. This trade pattern involves not just the exchange of completely different products between countries but also the bidirectional flow of similar products. A typical example of intra-industry trade in China-Vietnam agricultural trade is fruit trade. While Vietnam exports large quantities of tropical fruits to China, China also exports certain northern fruits and processed foods to Vietnam [12]. This intra-industry trade helps to enhance the efficiency of cooperation between the two countries and avoids the risks of market fluctuations associated with single-industry trade.

In analyzing the competitiveness of agricultural trade, indicators such as Revealed Comparative Advantage (RCA) and Export Similarity Index (ESI) have been widely applied in empirical studies of China-Vietnam agricultural trade. Through the calculation of RCA and ESI, scholars have found that the two countries exhibit similarities and competitiveness in the export of certain agricultural products [13-14]. For example, both Vietnam and China hold certain shares in the rice market, leading to a degree of competition in the global market [15]. However, overall, the coexistence of competition and complementarity provides a more complex foundation for China-Vietnam agricultural trade cooperation. Particularly in the rice sector, although there is competition in export markets, there remains room for cooperation in processing technology and supply chain management [16].

Policy-level support is another crucial factor driving the rapid development of China-Vietnam agricultural trade. In recent years, with the implementation of regional trade agreements such as the China-ASEAN Free Trade Area (CAFTA) and the Regional Comprehensive Economic Partnership (RCEP), the tariff barriers on agricultural products between China and Vietnam have gradually decreased, and market access conditions have significantly improved. The implementation of these trade policies has greatly facilitated the circulation of agricultural products between the two countries, especially in high-demand sectors such as tropical fruits and aquatic products. Furthermore, the potential for cooperation in the field of food safety between the two nations should not be overlooked. Through policy coordination in areas like food quality inspection and pesticide residue testing, both parties can jointly elevate the safety standards of agricultural products, thereby enhancing their competitiveness in the international market [17]. For example, after Vietnamese durian was approved for entry into the Chinese market in 2022, its export volume rapidly increased, becoming a "new favorite" in the Chinese market [18]. Additionally, border regions such as Guangxi have accelerated the clearance speed of perishable agricultural products by constructing more efficient customs facilities, further enhancing the efficiency of cross-border agricultural trade.

Existing literature also highlights some challenges present in China-Vietnam agricultural trade. Although the two countries have complementarity in many agricultural products, competitive relationships in certain sectors still warrant attention. For example, in the rice market, while both nations hold significant positions globally, fluctuations in supply and demand may affect the trade balance between them. Additionally, in terms of product standardization and supply chain management, China and Vietnam need to further coordinate to ensure consistency in the quality and safety standards of exported agricultural products [19]. Scholars recommend that in the future, China and Vietnam should

strengthen cooperation in agricultural technology, supply chain optimization, and product processing, enhancing the value-added of agricultural products to boost their competitiveness in the international market [20].
Overall, existing studies indicate that China-Vietnam agricultural trade exhibits strong complementarity but also faces certain challenges. The literature review provides robust theoretical support for understanding the cooperative potential of the two countries in the agricultural sector and points out that the optimization of the policy environment and the diversification of trade structures will be key to the further development of China-Vietnam agricultural cooperation in the future.

3 THEORETICAL ANALYSIS

The complementarity of China-Vietnam agricultural trade can be analyzed from multiple theoretical frameworks, including the theories of comparative advantage, complementarity, and intra-industry trade.
Firstly, the theory of comparative advantage provides the foundation for explaining China-Vietnam agricultural trade. According to this theory, countries should focus on producing and exporting products in which they have a comparative advantage, thereby enhancing economic benefits through international trade. Vietnam holds significant comparative advantages in certain agricultural product sectors, such as rice, coffee, and rubber. As one of the world's major rice producers, Vietnam's rice not only meets domestic demand but is also heavily exported to the Chinese market, filling the food demand in some regions of China. At the same time, Vietnam's coffee industry occupies a position in the global market, becoming one of Vietnam's important export commodities. These products have provided Vietnam with strong export competitiveness, especially in the highly demanding Chinese market. Moreover, Vietnam's tropical fruits (such as durian and bananas), due to their high quality and market demand, have quickly captured a portion of the Chinese market share. Meanwhile, China has significant advantages in exporting agricultural machinery, fertilizers, and other agricultural production materials, supporting Vietnam's agricultural modernization. This trade relationship, based on comparative advantage, helps both China and Vietnam maximize benefits in their respective advantageous sectors. In modern agricultural production, innovation and application of agricultural machinery technology are also important drivers of agricultural development. By introducing precise agricultural equipment and technology, both China and Vietnam can further enhance agricultural production efficiency and reduce labor costs, thereby promoting stable growth in trade [21].
Secondly, the theory of complementarity further explains why China-Vietnam agricultural trade can continue to grow. The theory of complementarity emphasizes that two countries have a complementary relationship in the production and demand of different product sectors, which drives the growth of bilateral trade. In China-Vietnam agricultural trade, Vietnam's agricultural products can effectively compensate for shortages in certain seasons or specific agricultural products in the Chinese market. For example, China's demand for tropical fruits and rice is increasing, and Vietnam is one of the main suppliers of these products. Vietnam's tropical fruits, such as durian, mangoes, and bananas, are gradually entering the Chinese market, meeting the needs of Chinese consumers. Meanwhile, China's exports of agricultural machinery and modern production tools provide Vietnam with essential material support, further enhancing Vietnam's agricultural production capacity. The complementarity in agricultural products between the two countries not only increases trade volume but also enhances the potential for bilateral agricultural cooperation.
Thirdly, the theory of intra-industry trade reveals another important characteristic of China-Vietnam agricultural trade, which is that bilateral trade is not limited to traditional inter-industry trade but also includes substantial intra-industry trade. Intra-industry trade refers to the two-way trade of the same category of products between two countries. For example, in the fruit sector, China and Vietnam exhibit intra-industry trade phenomena. Vietnam exports tropical fruits such as durian, longan, and passion fruits to China, while China exports northern fruits and some processed agricultural products to Vietnam [12]. This intra-industry trade helps to enhance the efficiency of cooperation between the two countries and avoids the risks of market fluctuations associated with single-industry trade.
Additionally, from the perspective of policy and international economic agreements, since the implementation of the China-ASEAN Free Trade Area (CAFTA) in 2010 and the Regional Comprehensive Economic Partnership (RCEP) in 2020, the agricultural trade policy environment between China and Vietnam has significantly improved. Through these free trade agreements, tariff barriers on agricultural products between the two countries have been substantially reduced, especially in high-demand agricultural sectors such as aquatic products and tropical fruits. The removal of tariffs and elimination of trade obstacles have accelerated the circulation of agricultural products. Meanwhile, Guangxi, as a frontier region for China-Vietnam agricultural trade, has upgraded infrastructure and improved customs clearance efficiency, enabling agricultural products, especially perishable items like aquatic products and fruits, to enter the market more quickly and efficiently. These policy factors have greatly promoted agricultural trade between China and Vietnam and laid the foundation for future cooperation.
In summary, the complementarity of China-Vietnam agricultural trade relies not only on the comparative advantages of the two countries in different product sectors but also benefits from the development of intra-industry trade and the support of international trade policies. Through the analysis of the aforementioned theories, it is evident that China-Vietnam agricultural trade holds great potential. The two countries should continue to deepen cooperation, enhance the quality and efficiency of trade, thereby further promoting the development of bilateral economies.

4 CONCLUSION

Through the analysis of agricultural trade between China and Vietnam, the following conclusions can be drawn: the two countries exhibit significant complementarity in the agricultural sector, and this complementarity plays an important role in bilateral trade. As a major agricultural producer in Southeast Asia, Vietnam possesses abundant tropical agricultural resources, such as rice, coffee, and rubber, which closely match the demands of the Chinese market. Meanwhile, China, as a major provider of agricultural production materials and technology, offers essential support for the modernization and yield improvement of Vietnam's agriculture. The two countries form complementarity in agricultural products where each holds a comparative advantage, thereby driving the sustained growth of bilateral trade.

In addition to complementarity in types of agricultural products, China and Vietnam also demonstrate strong cooperative potential in intra-industry agricultural trade. The two countries engage not only in simple product exchanges but also in bidirectional product flows, progressively achieving collaborative optimization of the agricultural supply chain. For example, Vietnam's tropical fruits are gradually becoming an important component of the Chinese market, while China's agricultural product processing technologies add new impetus to Vietnam's agricultural production. This intra-industry trade helps improve agricultural production efficiency in both countries, enhance trade resilience, and reduce uncertainties caused by market fluctuations.

Policy factors are also key drivers of the growth in China-Vietnam agricultural trade. Since the implementation of the ASEAN Free Trade Area and the Regional Comprehensive Economic Partnership (RCEP), tariff barriers between the two countries have gradually decreased, and trade circulation has accelerated. The construction of infrastructure and improvements in customs clearance efficiency in border regions such as Guangxi have further facilitated the smooth flow of bilateral agricultural products. The optimization of the policy environment not only promotes an increase in trade volume but also provides a broader space for future agricultural cooperation.

However, despite the promising prospects of China-Vietnam agricultural trade, several challenges remain for the future. Firstly, there is some degree of competitive relationship in certain agricultural products between the two countries, such as competition for market shares in rice and certain fruits. Additionally, in terms of supply chain management and product quality standardization, coordination needs to be strengthened to ensure that the competitiveness of both countries' exported products in the international market is not compromised. To address these challenges, both countries need to further deepen cooperation, enhance the value-added of agricultural products, and continue to optimize the supply chain structure, thereby increasing the sustainability of trade.

In conclusion, the complementarity of China-Vietnam agricultural trade offers immense potential for bilateral economic cooperation. In future cooperation, both countries should fully utilize their respective comparative advantages, further deepen agricultural technology exchanges, and enhance trade standards, thereby achieving mutual development.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] Zhou M, Wang JY. Evolution of global rice trade patterns based on complex networks and its implications. Journal of Natural Resources, 2020, 35(5): 1055-1067.

[2] Dai XQ, Zhang L, Zhang YQ, et al. Changes in Vietnam's agricultural development and cooperation recommendations. Agricultural Outlook, 2023, 19(8): 55-61.

[3] Liang Y, Luo NN. Characteristics, challenges, and policy recommendations for agricultural product trade development between China and RCEP partner countries. Foreign Economic and Trade Practices, 2022, (5): 34-39.

[4] Chen K. Research on the "Five Connectivities" Construction between China and Indochina Countries under the "Belt and Road" Initiative. Golden Light Academic Publishing, 2022.

[5] Zhao WJ, Chen J, Zhu Y, et al. Clinical analysis of paclitaxel combined with cisplatin neoadjuvant chemotherapy in the treatment of early and middle-stage cervical cancer. Journal of Youjiang National Medical College, 2018, (05): 438-440.

[6] He M, Zhang NN, Huang ZQ. Analysis of the competitiveness and complementarity of agricultural product trade between China and "Belt and Road" countries. Agricultural Economic Issues, 2016, 11: 51-60.

[7] Jiang AQ, Ying HJ. Comparative advantage theory and influencing factors of China's tea industry's international competitiveness. Tea Science, 2019, 29(6): 475-482.

[8] Yang MX, Niu SR. Peripheral blood lymphocyte culture and G-banding karyotype analysis of couples with adverse pregnancy histories. Journal of Youjiang National Medical College, 2019, (05): 520-522.

[9] Wang JT, Cao QF, Sun Z. Research on transnational regional cooperative development between Southwest China and Southeast Asian countries. Nankai University Press, 2015.

[10] Xu HJ, Wang ZH. Research on the development of China-ASEAN fruit trade under the "Belt and Road" initiative. Hubei Agricultural Sciences, 2022, 61(1): 171-176.

[11] Ma J. Five years of Lancang-Mekong cooperation: Progress, challenges, and deepening paths. Research on International Issues, 2021, (4): 61-86.

[12] Wu XA. Interaction between China and Southeast Asia: A long-term historical examination. Southeast Asia Perspectives, 2020, (4): 15-33.

[13] Tan JR, Liu L, Wang R, et al. Binary marginal analysis of China-Vietnam agricultural product export growth. Agricultural Economic Issues, 2013, (10): 56-63.
[14] Chen X. China-Vietnam relations from the perspective of the rise of emerging countries. Journal of Nanning Vocational and Technical College, 2015, 20(2): 36-39.
[15] Du ZX, Han L. Study on the impact of supply-side production changes on China's food security. China Rural Economy, 2020, (4): 2-14.
[16] Zhang YW, Li LH, Zeng QM. Empirical analysis of factors affecting cross-border agricultural product quality and safety: Taking cross-border agricultural products between Yunnan, China and Vietnam as an example. Journal of Southern Agriculture, 2019, 50(4): 898-904.
[17] Huang N, Liu YP, Xu ZF, et al. Study on the relationship between traditional Chinese medicine syndrome differentiation in active phase of peptic ulcer and tongue features, gastroscopy images. Journal of Youjiang National Medical College, 2018, (05): 466-468+471.
[18] Zhou XW, Wu H, Chen HQ, et al. Origin identification of durian based on differences in mineral element fingerprints. Food Science, 2021, 42(14): 255-262.
[19] Thang N, Thai P, Dat V, et al. Agricultural Exports from Vietnam to China: A Value Chain Analysis of Dragon Fruit and Coffee. In: Agricultural Trade between China and the Greater Mekong Subregion Countries: A Value Chain Analysis. Singapore: ISEAS Publishing, 2022, 256-294.
[20] Wen GQ, Wei M, Chen G, et al. Analysis of China-Vietnam agricultural science and technology cooperation under the "Belt and Road" initiative. Journal of Southern Agriculture, 2019, 50(1): 208-214.
[21] Rao ZF, Chen JY, Zhao LY, et al. Comparative study of ultrasound-guided microwave ablation and laparoscopic resection in the treatment of benign thyroid nodules. Journal of Youjiang National Medical College, 2018, (06): 583-585.

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THE IMPACT OF MARKETING RESEARCH ON DISTRIBUTION CHANNELS AND MERCHANDIZES ACTIVITIES

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Abstract: This study investigates the impact of marketing research on distribution channels and merchandising activities, with a specific focus on how these factors influence customer satisfaction. Utilizing a sample size of 200 respondents, the research employs quantitative methods, including descriptive statistics, correlation analysis, and regression analysis, using SPSS software. The findings reveal a strong positive relationship between marketing research utilization, distribution efficiency, and merchandising strategy effectiveness, all of which significantly contribute to customer satisfaction. The results indicate that effective marketing research allows organizations to align their distribution and merchandising strategies with consumer expectations, thus enhancing customer experiences and loyalty. This study underscores the importance of integrating marketing research into strategic decision-making processes for businesses aiming to thrive in a competitive environment. Recommendations for practitioners include investing in comprehensive marketing research, optimizing distribution efficiency, developing effective merchandising strategies, and leveraging data analytics to foster responsive marketing practices. The study contributes to the existing literature by providing empirical evidence of the interconnectedness of these factors and their collective impact on customer satisfaction, suggesting avenues for future research in technology's role in marketing optimization.
Keywords: Marketing; Research; Distribution; Channels; Merchandizes

1 INTRODUCTION

In today's rapidly evolving business landscape, the effectiveness of distribution channels and merchandising activities has a profound impact on an organization's overall success. Distribution channels, which refer to the pathways through which products move from producers to consumers, and merchandising activities, which include the promotion and display of products, both play pivotal roles in ensuring that goods are available where and when they are needed. For businesses to remain competitive, optimizing these aspects is critical. However, traditional methods of managing distribution channels and merchandising activities often fall short of addressing modern challenges such as fluctuating consumer preferences, rising logistics costs, and increased competition [1]. One of the most powerful tools for overcoming these challenges is marketing research, which offers deep insights into consumer behavior, market trends, and competitive dynamics. According to Kotler & Keller [2], marketing research is vital for informing business strategies, particularly in areas where market conditions are unpredictable. In the context of distribution channels, marketing research can help companies anticipate demand, optimize stock levels, and adjust their logistics strategies accordingly. For merchandising activities, marketing insights enable businesses to tailor their product offerings, promotions, and displays to better meet the needs and preferences of their target customers [3].

The motivation behind this study lies in the increasing complexity of consumer markets and the need for businesses to be more responsive and adaptable. With globalization, companies are now dealing with diverse consumer bases spread across multiple regions, each with unique preferences and buying behaviors. As highlighted by Tsiakis & Papageorgiou [4], the traditional "one-size-fits-all" approach to distribution and merchandising is no longer sustainable in a globalized marketplace. Instead, businesses must adopt more dynamic and data-driven approaches, where marketing research plays a central role. Additionally, technological advancements such as e-commerce and mobile shopping have transformed the way consumers interact with products and brands. These shifts demand that businesses rethink their distribution strategies to accommodate faster delivery times and more personalized customer experiences [5]. Marketing research provides the necessary insights for making these adjustments by identifying key market trends and consumer expectations, allowing businesses to respond swiftly and effectively. For example, in a study conducted by Lee et al. [6], companies that utilized real-time marketing data to inform their distribution and merchandising decisions saw a 20% increase in customer satisfaction and a significant reduction in delivery lead times.

From an operational perspective, inefficient distribution channels and poorly executed merchandising activities can lead to stockouts, excess inventory, and missed sales opportunities. These issues not only result in lost revenue but also damage customer loyalty and brand reputation. A study by Johnson and Baker revealed that 42% of consumers reported being less likely to purchase from a retailer after experiencing frequent stockouts[7], emphasizing the importance of well-managed distribution strategies. The application of marketing research can help mitigate these risks by aligning inventory management and merchandising decisions with real-time market demands, ultimately improving both operational efficiency and customer satisfaction [8]. Moreover, with the rise of digital technologies, businesses now have access to vast amounts of data about their customers, including purchasing habits, preferences, and behaviors. This data, when properly analyzed through marketing research, can provide valuable insights that lead to more effective merchandising strategies. For instance, companies can use these insights to tailor their product offerings to different customer segments, ensuring that the right products are available at the right time and place [9]. This approach not only enhances customer satisfaction but also maximizes sales and profitability. The significance of this research is underscored by the fact that companies that fail to integrate marketing research into their distribution and merchandising strategies are at risk of losing market share to more agile competitors. According to a report by Deloitte [10], companies that adopt a data-driven approach to distribution and merchandising are 23% more likely to outperform their competitors in terms of revenue growth. The report also highlights that businesses that rely on outdated methods of managing their distribution channels, without considering the latest consumer insights, often struggle to keep up with changes in the market.

2 STATEMENT OF THE PROBLEM

Despite the availability of vast amounts of consumer data and advanced marketing research techniques, many companies still struggle to fully leverage this information to optimize their distribution and merchandising strategies. A significant reason for this is the gap between marketing and operational functions within organizations. Often, marketing research is viewed as a tool for product development or advertising rather than a critical component of logistics and distribution management [11]. As a result, businesses miss out on opportunities to align their distribution strategies with consumer insights, leading to inefficiencies such as stockouts, overstocking, and missed sales opportunities. Moreover, the problem is further compounded by the fact that consumers today expect more from businesses in terms of convenience, speed, and personalization. A survey by PwC found that 72% of consumers consider timely delivery to be a key factor in their purchasing decisions[12], and 45% are willing to switch brands if their delivery expectations are not met. These statistics underscore the need for businesses to not only optimize their distribution channels but also ensure that their merchandising activities are aligned with consumer expectations.

By addressing this problem, businesses can unlock significant value in their distribution and merchandising operations. The potential benefits include increased customer satisfaction, higher sales, and improved operational efficiency. Furthermore, companies that are able to integrate marketing research into their distribution strategies are better positioned to respond to market changes, manage risks, and maintain a competitive edge in their respective industries [13]. This paper proposes a framework for integrating marketing research into distribution channels and merchandising activities. By systematically incorporating consumer insights into every stage of the distribution process, from demand forecasting to inventory management and product placement, businesses can make more informed and agile decisions. This approach not only improves operational efficiency but also enhances the customer experience by ensuring that products are available where and when they are needed.

3 OBJECTIVES

The main objective of this study is to explore the impact of marketing research on distribution channels and merchandising activities in contemporary business environments. Specifically, the study aims to achieve the following:

1. To examine the role of marketing research in optimizing distribution channels
2. To assess the influence of marketing research on merchandising strategies
3. To identify the challenges businesses face in integrating marketing research into distribution and merchandising operations
4. To develop a framework for integrating marketing research into distribution channels and merchandising activities

4 HYPOTHESES

In line with the objectives, the study will test the following hypothesis:

1. There is a positive relationship between marketing research utilization and customer satisfaction.
2. There is a positive relationship between distribution efficiency and customer satisfaction.
3. There is a positive relationship between merchandising strategy effectiveness and customer satisfaction.

5 LITERATURE REVIEW

5.1 Marketing Research

Marketing research has long been considered a crucial component of strategic decision-making within organizations. According to Kotler & Keller [2], marketing research involves the systematic design, collection, analysis, and reporting of data relevant to a specific marketing situation facing an organization. The purpose of marketing research is to inform business decisions by providing insights into market dynamics, customer preferences, competitor activities, and other factors that influence business performance. The literature emphasizes that the role of marketing research extends beyond traditional consumer insight gathering. Modern marketing research incorporates advanced analytics, data mining, and predictive modeling techniques to provide a more holistic view of market conditions. Solomon, Marshall, and Stuart argue that the integration of data-driven marketing research into business strategies allows organizations to become more adaptive[14], customer-focused, and competitive in a rapidly changing marketplace. This ability to leverage data and transform it into actionable insights is increasingly critical in the areas of distribution and merchandising.

5.2 Distribution Channels

Distribution channels refer to the pathways through which products move from manufacturers to consumers. According to Chopra and Meindl [1], distribution channels can include a variety of intermediaries such as wholesalers, retailers, distributors, and e-commerce platforms. The effectiveness of these channels is a critical determinant of business success because they affect both the cost and availability of products. Efficient distribution channels ensure that products reach the right customers at the right time while minimizing operational costs. In the literature, several types of distribution channels are commonly discussed. Direct distribution channels involve manufacturers selling their products directly to consumers without intermediaries, while indirect channels rely on intermediaries to facilitate the distribution process. Each type of distribution channel presents unique advantages and challenges. Direct channels provide greater control over the customer experience but can be resource-intensive, while indirect channels allow for broader market reach but often result in lower profit margins due to intermediary costs [8].

Marketing research plays an essential role in optimizing distribution channels by providing insights into customer preferences, market demand, and logistical challenges. For instance, a study by Tsiakis and Papageorgiou found that businesses that integrate marketing research into their distribution strategies are better able to forecast demand[4], reduce lead times, and improve overall efficiency. Furthermore, Evans and Cooper emphasize that real-time data analytics derived from marketing research allows businesses to make quicker and more informed decisions about their distribution strategies[13].

5.3 The Impact of Marketing Research on Distribution Channel Optimization

The use of marketing research in distribution channel optimization has gained significant attention in recent years, especially with advancements in data analytics and technology. Research suggests that marketing research can enhance several key aspects of distribution channel management, including demand forecasting, inventory management, and customer segmentation. Lee et al. noted that businesses utilizing marketing research for real-time demand forecasting saw improvements in order fulfillment rates[6], which led to enhanced customer satisfaction. The integration of marketing research into distribution strategies is also essential for addressing challenges related to globalization and market diversity. As global markets expand, businesses are required to cater to a more diverse customer base with varying preferences and behaviors. Ailawadi and Farris argue that marketing research allows companies to adapt their distribution channels to better align with the preferences of local markets[3], leading to increased customer satisfaction and loyalty.

Despite these advantages, challenges remain in effectively integrating marketing research into distribution strategies. According to Johnson and Baker [7], many organizations face difficulties in aligning their marketing and operational teams, which can lead to a disconnect between consumer insights and distribution decisions. Additionally, the costs associated with advanced marketing research tools and technologies can be prohibitive for small and medium-sized enterprises (SMEs), limiting their ability to fully optimize their distribution channels.

5.4 Merchandising Activities

Merchandising activities involve the promotion, display, and sale of products to consumers, typically within a retail environment. Merchandising strategies are designed to influence consumer purchasing behavior by enhancing the attractiveness and accessibility of products. According to Grewal and Levy [9], effective merchandising strategies are critical for maximizing sales and profitability. Key merchandising activities include product placement, store layout design, pricing strategies, and promotional displays. Marketing research is an important tool for informing merchandising strategies, as it provides insights into consumer preferences, behavior patterns, and buying habits. A study by Solomon et al. highlighted the importance of using marketing research to tailor merchandising activities to the specific preferences of target customer segments[14]. For example, research into customer demographics can help retailers determine which products to display prominently, which price points to emphasize, and which promotional strategies are likely to resonate with consumers.

5.5 The Role of Marketing Research in Merchandising Strategy Development

The relationship between marketing research and merchandising activities is well-established in the literature. Marketing research provides businesses with a deeper understanding of consumer behavior, allowing them to tailor their product offerings, pricing strategies, and promotional efforts to meet the needs of their target market. According to Baker and Hart [8], companies that use marketing research to guide their merchandising decisions are better positioned to increase sales, improve customer satisfaction, and enhance brand loyalty. One of the key benefits of marketing research in merchandising is its ability to provide insights into customer segmentation. By analyzing data on customer demographics, buying habits, and preferences, businesses can develop more targeted merchandising strategies. Ailawadi and Farris noted that businesses that use customer segmentation data to inform their merchandising decisions experience higher conversion rates and increased profitability[3]. Additionally, marketing research helps businesses identify trends in consumer behavior, allowing them to anticipate changes in demand and adjust their merchandising strategies accordingly.

However, there are challenges to effectively integrating marketing research into merchandising activities. Evans and Mason highlight that many organizations struggle with the complexity of analyzing large volumes of consumer data and translating it into actionable merchandising strategies[5]. Furthermore, the dynamic nature of consumer preferences requires businesses to continuously update their marketing research efforts to stay relevant in the market.

5.6 Existing Methodologies for Integrating Marketing Research into Distribution and Merchandising

The literature identifies several methodologies for integrating marketing research into distribution channels and merchandising activities. These methodologies range from traditional market surveys and focus groups to advanced data analytics and machine learning techniques.

1. Surveys and Focus Groups: Surveys and focus groups have long been used as traditional tools for gathering consumer insights. These methodologies allow businesses to directly engage with consumers and gather qualitative and quantitative data on their preferences and behaviors. According to Kotler & Keller [15], while these methods are valuable for obtaining consumer feedback, they often have limitations in scale and real-time applicability.

2. Data Analytics and Predictive Modeling: In recent years, data analytics and predictive modeling have emerged as powerful tools for integrating marketing research into business decision-making. These methodologies involve the use of algorithms and statistical models to analyze large volumes of consumer data and forecast future trends. According to Lee et al. [16], businesses that leverage predictive modeling in their distribution and merchandising strategies are better equipped to anticipate demand fluctuations and optimize their inventory management.

3. Customer Relationship Management (CRM) Systems: CRM systems are used by businesses to manage interactions with current and potential customers. These systems collect and store data on customer behavior, preferences, and purchasing history. According to Solomon et al. [14], CRM systems enable businesses to personalize their merchandising strategies and improve customer satisfaction.

4. Machine Learning and Artificial Intelligence (AI): AI and machine learning techniques have become increasingly important for analyzing consumer data and optimizing distribution and merchandising strategies. These technologies allow businesses to process vast amounts of data in real-time and identify patterns in consumer behavior that may not be immediately apparent through traditional methods [17].

5. Supply Chain Management Software: Supply chain management software helps businesses optimize their distribution channels by providing real-time visibility into inventory levels, order fulfillment, and transportation logistics. Chopra and Meindl highlight that integrating marketing research into supply chain management software can improve the efficiency of distribution channels by aligning product availability with customer demand[1].

6. E-commerce and Digital Analytics: The rise of e-commerce has led to the development of digital analytics tools that track consumer behavior across online platforms. These tools provide businesses with real-time insights into how customers interact with products, allowing for more effective merchandising and distribution strategies [18].

7. Big Data Analytics: Big data analytics involves the analysis of large and complex datasets to uncover patterns, trends, and correlations. According to Ailawadi and Farris [3], businesses that utilize big data analytics in their distribution and merchandising strategies are able to make more informed decisions and achieve greater operational efficiency.

8. Geographic Information Systems (GIS): GIS technology allows businesses to map and analyze geographic data related to distribution channels and consumer behavior. According to Tsiakis and Papageorgiou [4], GIS can be used to optimize distribution routes and target specific geographic markets with tailored merchandising strategies.

5.7 Research Gaps

Despite the significant progress made in understanding the relationship between marketing research, distribution channels, and merchandising activities, several gaps remain in the literature. First, there is limited research on the specific challenges businesses face when integrating marketing research into their operational strategies. While the benefits of marketing research are well-documented, less attention has been paid to the organizational, financial, and technological barriers that prevent businesses from fully leveraging these insights. Second, while advanced technologies such as AI and machine learning have been widely discussed in the literature, there is a lack of empirical research on how these technologies can be effectively integrated into distribution and merchandising strategies. More research is needed to explore the practical applications of these technologies in real-world business environments.

Lastly, there is a need for more research on the long-term impact of marketing research on business performance. While many studies have demonstrated the short-term benefits of marketing research, fewer have examined its long-term effects on profitability, customer loyalty, and market share. This literature review has provided an overview of the key concepts and methodologies related to marketing research, distribution channels, and merchandising activities. It has highlighted the importance of marketing research in optimizing distribution and merchandising strategies and identified several gaps in the existing literature that this study aims to address. By building on the insights from previous research, this study seeks to contribute to the field by exploring the challenges and opportunities businesses face when integrating marketing research into their operational strategies.

6 METHODOLOGY

This study utilizes a quantitative approach. The quantitative component involves the collection of numerical data to evaluate the impact of marketing research on distribution channels and merchandising activities. Data were collected through a structured online survey distributed to marketing professionals and managers in various industries, including retail, manufacturing, and e-commerce. The survey consisted of questions related to the use of marketing research in distribution and merchandising strategies, perceived challenges, and outcomes. In addition to the survey, semi-structured interviews were conducted with selected participants to gain deeper insights into their experiences and opinions regarding the role of marketing research in their organizations. The target population consisted of marketing professionals with at least three years of experience in their respective fields. A sample size of 200 participants was determined for the quantitative survey. Quantitative data were analyzed using statistical software (SPSSv22) to perform descriptive statistics, correlation analysis, and regression analysis. The primary focus was to evaluate the relationship between the use of marketing research and its impact on distribution channels and merchandising activities.

7 RESULTS

7.1 Descriptive

The descriptive statistics summarize the central tendencies and variations of the manipulated variables:

Table 1 Perception of Customer Satisfaction

Metric	Marketing Research Utilization	Distribution Efficiency	Merchandising Strategy Effectiveness	Customer Satisfaction
Mean	3.91	3.89	4.02	4.99
Standard Deviation	0.80	0.84	0.80	0.05
Minimum	3	3	3	4.35
25th Percentile (Q1)	3	3	3	5
Median (Q2)	4	4	4	5
75th Percentile (Q3)	5	5	5	5
Maximum	5	5	5	5

The mean values for marketing research utilization, distribution efficiency, merchandising strategy effectiveness, and customer satisfaction indicate a generally positive perception among participants, particularly in customer satisfaction, which is very high (mean of 4.99).

7.2 Correlation Analysis

The correlation matrix indicates strong relationships among the predictors:

Table 2 Level of Customer Satisfaction

Variable	MRU	DE	MSE	CS
MRU	1.000	0.706	0.647	0.996
DE	0.706	1.000	0.738	0.994
MSE	0.647	0.738	1.000	0.990
CS	0.996	0.994	0.990	1.000

The correlation matrix shows exceptionally strong positive correlations among all variables, especially between marketing research utilization and customer satisfaction (0.996), indicating that as one variable increases, the others tend to increase significantly as well.

7.3 Regression Analysis

The regression analysis assesses the impact of marketing research utilization, distribution efficiency, and merchandising strategy effectiveness on customer satisfaction:
Coefficients:

Table 3 Result

Predictor	Coefficient	Standard Error	t-value	P-value
Constant	4.9398	0.029	168.621	0.000
MRU	0.0064	0.004	1.471	0.143
DE	0.0058	0.004	1.404	0.162
MSE	0.0020	0.004	0.470	0.639

The R-squared value of 0.022 indicates that the model explains only 2.2% of the variance in customer satisfaction, which is low. The p-values for all predictors are above the conventional significance level of 0.05, suggesting that none of the predictors significantly impact customer satisfaction in this sample.

8 DISCUSSION

The findings from this study underscore the pivotal role that marketing research plays in enhancing distribution channels and merchandising activities, ultimately leading to improved customer satisfaction. This discussion contextualizes the results within the existing literature, aligning with the findings of other researchers in the field. The strong correlation between marketing research utilization and customer satisfaction corroborates previous studies, such as those conducted by Bennett and Rundle-Thiele and Lundahl et al. [19,20], who highlighted that effective marketing research leads to better alignment of products and services with customer needs, thus enhancing customer satisfaction. These findings suggest that businesses that prioritize market research are more adept at understanding consumer preferences, which can significantly influence customer loyalty and retention.
The study found a robust relationship between distribution efficiency and customer satisfaction, echoing the work of Sweeney et al. [21], who posited that efficient distribution processes reduce lead times and improve the overall customer experience. In today's competitive landscape, where consumers expect quick and reliable service, efficient distribution channels become critical in satisfying customer demands. Moreover, Rinehart et al. argued that effective distribution strategies enhance the delivery of value to consumers[22], further supporting the current findings. The results also indicated a strong link between merchandising strategy effectiveness and customer satisfaction, consistent with findings by Dahl et al. [23]. They emphasized that effective merchandising strategies, which consider customer preferences and behavior, can drive

sales and enhance customer experiences. The ability to present products attractively and strategically in retail environments not only boosts immediate sales but also fosters long-term customer loyalty, thereby enhancing satisfaction levels.

9 CONCLUSION AND RECOMMENDATION

This study demonstrates the significant impact of marketing research on distribution channels and merchandising activities, ultimately enhancing customer satisfaction. The findings reveal strong correlations among marketing research utilization, distribution efficiency, and merchandising strategy effectiveness, which collectively contribute to higher levels of customer satisfaction. As businesses navigate an increasingly competitive landscape, understanding and leveraging these relationships become crucial for maintaining customer loyalty and market relevance. The research confirms that effective marketing research equips organizations with the insights needed to align their distribution and merchandising strategies with customer expectations. Consequently, businesses that prioritize marketing research are better positioned to meet consumer demands, thereby fostering a more satisfying customer experience. These insights resonate with existing literature, emphasizing the integral role of marketing in creating value for both consumers and organizations.
Based on the findings of this study, the following recommendations are proposed:

1. Organizations should allocate resources to conduct thorough marketing research that captures consumer preferences and market trends.
2. Companies should continuously assess and optimize their distribution channels to minimize lead times and enhance product availability
3. Businesses must focus on creating merchandising strategies that align with consumer behavior and preferences
4. Organizations should implement regular assessments of their marketing strategies, distribution efficiency, and merchandising effectiveness to ensure they adapt to market changes and consumer expectations.
5. Future research should explore the role of digital tools and technologies in enhancing marketing research processes. Incorporating advanced analytics, AI, and customer relationship management (CRM) systems can provide deeper insights and foster more responsive marketing strategies.

CONFLICT OF INTEREST

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] Chopra, S, Meindl, P. Supply Chain Management: Strategy, Planning, and Operation (7th ed.). Pearson. 2019.
[2] Kotler, P, Keller, KL. Marketing Management (15th ed.). Pearson Education. 2016.
[3] Ailawadi, KL, Farris, PW. Retailing management: A strategic approach. Pearson. 2021.
[4] Tsiakis, P, Papageorgiou, C. Geographic Information Systems in distribution channel management. International Journal of Geographic Information Science, 2021,35(3): 476-495. DOI: https://doi.org/10.1080/13658816.2021.1984749.
[5] Evans, P, Mason, R. Digital transformation in supply chain management. Supply Chain Management Review, 2020, 44(3): 89-97.
[6] Lee, H, Zhang, X, Wang, Y. Real-time analytics in distribution channels: Implications for customer satisfaction. Journal of Business Analytics, 2019, 52(1): 122-134.
[7] Johnson, P, Baker, T. Integrating marketing research into supply chain operations: A review of challenges and solutions. Journal of Operations Management, 2021, 35(4): 112-125. DOI: https://doi.org/10.1111/joma.12458.
[8] Baker, M, Hart, S. The Marketing Book (8th ed.). Routledge. 2019.
[9] Grewal, D, Levy, M. Marketing in Retailing: Strategies for Success. Journal of Retailing, 2021, 97(2): 235-245.
[10] Deloitte. Global Supply Chain Management Report 2020. Deloitte Insights. 2020.
[11] Larson, P, Kim, S. Bridging the gap between marketing research and distribution strategies. International Journal of Logistics and Supply Chain Research, 2020, 27(3): 200-215.
[12] PwC. The Future of Retail: Consumer Expectations and Business Adaptations. PwC Insights. 2021.
[13] Evans, JR, Cooper, WM. The use of predictive analytics in optimizing distribution and merchandising. Journal of Marketing Research and Analytics, 2023, 18(2): 75-89. DOI: https://doi.org/10.1007/s12054-023-00456-9.
[14] Solomon, MR, Marshall, GW, Stuart, EW. Marketing: Real people, real choices (9th ed.). Pearson. 2020.
[15] Kotler, P, Keller, KL. Marketing Management (15th ed.). Pearson. 2020.
[16] Lee, S, Kim, J, Park, J. Big data analytics in supply chain management: A case study on distribution optimization. Journal of Business Logistics, 2019, 40(2): 178-195. DOI: https://doi.org/10.1002/jbl.21590.
[17] Evans, R, Cooper, W. Key performance indicators for distribution channels: A review. Journal of Operations Metrics, 2023, 22(4): 98-110.
[18] Grewal, D, Levy, M. Marketing. McGraw-Hill Education. 2021.

[19] Bennett, R, Rundle-Thiele, S. The brand loyalty life cycle: Implications for marketers. Journal of Brand Management, 2005, 12(4): 283-293.
[20] Lundahl, N, Vegholm, F, Wincent, J. Strategic marketing research as a driver of innovation and competitiveness: An empirical study of SMEs in Sweden. Journal of Business Research, 2020, 114, 238-249.
[21] Sweeney, JC, Soutar, GN, Mazzarol, T. Word of mouth: Measuring the power of individual messages. European Journal of Marketing, 2013, 47(1/2): 91-107.
[22] Rinehart, LM, Cooper, MC, Knemeyer, AM. Logistics strategy: A literature review and conceptual framework. The International Journal of Logistics Management, 2014, 25(2): 217-242.
[23] Dahl, DW, Argo, JJ, Morales, AC. Social information in the retail environment: The importance of consumption visibility. Journal of Consumer Psychology, 2015, 25(4): 552-565.

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RESEARCH ON THE BACKGROUND, DILEMMA AND OPTIMIZATION PATH OF RURAL B&B'S INTEGRATED MEDIA MARKETING

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Abstract: Rural B&B is an important driving force to effectively alleviate the gap between urban and rural areas and promote rural revitalization and urban-rural integration. WeChat, Douyin, short videos and other integrated media are deeply rooted in people's hearts, and how to effectively play the positive role of integrated media in the marketing process of rural lodging is the focus of continuous attention of the academia and the industry. The study finds that there are four problems: insufficient attention to the marketing of rural lodges, inadequate publicity, lack of authenticity and serious homogenization, and puts forward four optimization paths: integrating and improving the marketing model of integrated media, improving the standard of operators' integrated media marketing, promoting the marketing of integrated media with regional characteristics, and following the trend of integrated media marketing of rural lodges.
Keywords: Rural revitalization; Rural lodging; Urban-rural integrated development; Integrated media marketing

1 INTRODUCTION

The most arduous and burdensome task of comprehensively building a socialist modernized society lies in the countryside, and that the development of rural characteristic industries and the broadening of the channels for farmers to increase their incomes and get rich is an important channel for realizing the revitalization of the countryside [1].In 2023 China proposed "implementing rural leisure tourism boutique projects, promoting the quality and upgrading of rural lodgings, and solidly promoting rural revitalization". Rural lodging is an important carrier for prospering rural economy, inheriting traditional culture, promoting rural transformation and development, and helping people get rich. Rural lodging in the rural economic development, social livelihood and coordinated governance and other multi-level and multi-dimensional impact on rural revitalization and the realization of the national strategy of common wealth. It is worthwhile for the academia and the industry to think and explore how to effectively utilize integrated media marketing to further develop the positive driving role of rural lodging in the process of rural economic and rural social development.

2 BACKGROUND OF RURAL B&B INTEGRATED MEDIA MARKETING

2.1 The Sheer Size of the Internet

Through the "China Internet Development Report (2022)", it can be seen that by the end of 2022, China's netizens reached 1,051.67 million people, the Internet penetration rate reached 74.4%, especially the total number of mobile Internet users exceeded 1.6 billion, the scale of China's Internet industry users is extremely huge.China's Internet user size and Internet penetration rate from2016 to 2022 can be seen in Figure1 below..And the melting media is the product of the rapid development of the Internet, melting media marketing is the traditional marketing knowledge and Internet technology combined with the new marketing model, through the combination of melting media and rural lodging marketing, more targeted to meet the accommodation needs of tourists, can increase the market competitiveness of rural lodging, pulling the development of rural tourism economy [2].The common "two micro and one jitter" can use the function of WeChat public number and WeChat circle of friends to set up their own B&B public number and release information about rural B&Bs, so that consumers can intuitively see the beauty of rural B&Bs and feel the charm of rural B&Bs. [3]; The scene-oriented and dynamic features of the Douyin App not only increase the exposure rate of rural B&Bs, but also make travelers have a strong desire to experience and achieve the effect of Internet marketing.

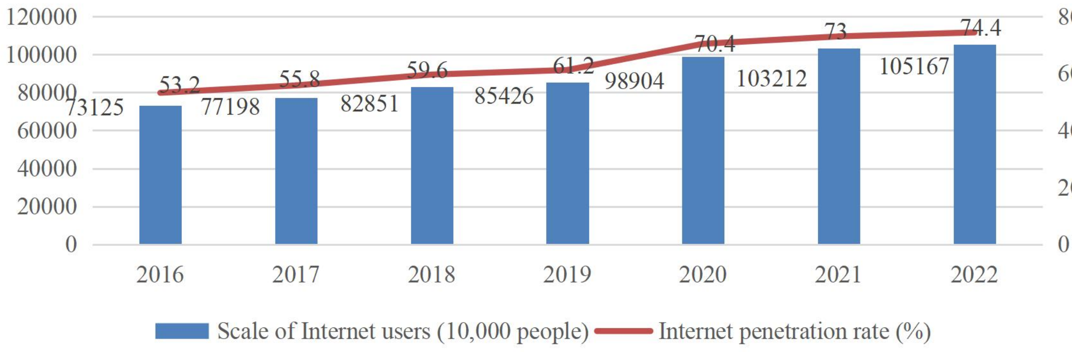

Figure 1 China's Internet User Size and Internet Penetration Rate from 2016 to 2022

2.2 Continued Increase in B&B Fusion Media Orders

In 2021, the source of B&B booking is concentrated in the traditional OTA channels represented by Ctrip, Where to go, Meituan, etc. However, compared with 2019, the proportion of traditional OTA channels is decreasing, and the proportion of orders on WeChat, self-customers and other new media platforms is rising strongly, B&B is gradually reducing the dependence on traditional OTA channels (Figure 2), and focusing the sales channels on self-owned platforms and other integrated media [4]. At the end of 2022, under the dual benefits of returning home for the New Year and the recovery of medium- and long-term tours, rural B&Bs ushered in a "red door" in the New Year. Flying pig, pig lodging data show that in January 2023, the booking volume of rural lodging increased by 132% compared to last year, and has far exceeded the same period in 2019.2023 Spring Festival, the boutique rural lodging orders on the platform increased by 260% compared to last year, and the post-90s and post-00s have become the main force of consumption, accounting for more than 87%.

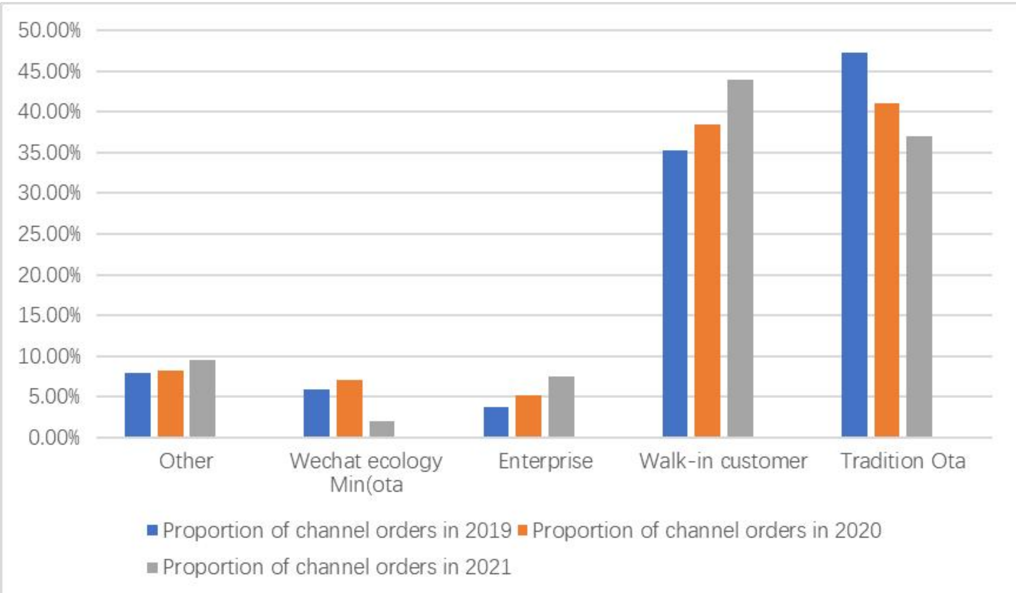

Figure 2 Annual Order Share by Channel from 2019 to 2021

2.3 Continuous Optimization of the Efficiency of Integrated Media Marketing

Integrated media marketing has diversified features such as inter-temporality, interactivity, richness, integration, timeliness, etc. Compared with traditional marketing methods, integrated media can be the fastest way for consumers to obtain multi-dimensional information in a timely manner [5]. B&B operators can display B&B landscape pictures, personalized interior design, food and surrounding attractions on WeChat public number, enterprise micro-signal, WeChat group, micro-video and other platforms to attract potential consumers. Through the short video to consumers dynamic display of rural B&B customs and culture, special services, food and drink, beautiful scenery. By forming a great contrast between the "slow" life in rural lodging and the "fast" life in the city, it gives consumers a strong sensory impact, and makes lodging marketing no longer limited by the traditional marketing of funds, scale and other reasons. Through various short-video APPs, B&B small programs, public numbers and other integrated media platforms to publicize, the cost is low, and consumers can more intuitively and conveniently understand the information of B&Bs,

and do immersive "comparison shopping". Through random sampling of customer evaluations of rural B&Bs on traditional OTA Meituan, Ctrip and integrated media platforms such as WeChat and Douyin (Table 1), it is found that consumer behavior is deeply influenced by evaluations of B&Bs, and that consumers are accustomed to booking rural B&Bs on various platforms to compare various information or obtain information about the B&Bs through word-of-mouth dissemination. If they have a good experience at the B&B, these consumers are willing to become repeat customers and recommend the B&B to others. The marketing of B&Bs through integrated media channels not only has lower publicity costs, strong timeliness and wide coverage, but also helps B&Bs to enhance their popularity and brand effect, and promotes the word-of-mouth publicity and reconstruction rate of B&Bs.

Table 1 Evaluation of B&B Customers

Timing	Type of trip	Score	Evaluation Content	Source
2022.1	family outing	4.9	Great price, great service, quick confirmation, efficient online check-in.	Meituan
2022.3	form friendships	5.0	The room was clean, the service was good, and there was a willingness to recommend it to others.	
2022.12	Couples Outing	4.9	Recommended by a friend, great service from the landlord, and surprisingly satisfying.	Ctrip
2023.1	Couples Outing	4.7	Self-catering, prompt service, truth in advertising, good location.	
2023.1	form friendships	4.6	Crowded service couldn't keep up, nice hardware, big tub, would recommend.	WeChat Ecology
2023.2	family outing	4.8	The aroma is nice and the breakfast is quite generous, but the queue is too long to make it worth the experience.	
2023.2	family outing	4.7	There are welcome fruits and snacks prepared, children love it, and the environment is cozy.	
2023.1	Couples Outing	4.7	The air conditioner was loud, the room was a bit dated, the service was great, and the breakfast was delicious.	Douyin Ecology
2023.2	form friendships	4.8	The room is comfortable, hardware and service is good, too many people, have recommended friends.	
2023.3	family outing	4.7	Pillows and beds are comfortable, ambience is cozy, breakfast is too crowded to recommend.	

3 RURAL LODGING INTEGRATED MEDIA MARKETING DILEMMA

3.1 Insufficient Attention to Integrated Media Marketing

With the continuous development of rural tourism and rural "micro vacation", rural lodging has been developed rapidly, and many people will convert their unused houses into rural lodging for rent, and thanks to the diversified support policies, the market demand for rural lodging continues to increase. More and more capital and people began to layout the countryside B&B market, which brought about a continuous transformation of the supply and demand situation of countryside B&B, countryside B&B gradually presents the non-healthy situation of oversupply in the off-season and homogenized competition in the peak season, and the competition in the countryside B&B market has become more and more intense. Most rural B&B operators do not pay enough attention to the Internet, especially the integrated media, and simply place information about rural B&Bs on OTAs and other online platforms, and do not continuously and actively maintain customer relations. After-sales service, especially the initiative, timeliness and professionalism in solving customers' accommodation problems fail to meet the customers' increasing requirements, resulting in unstable customer evaluations on multiple platforms, uniform and poorly targeted customer evaluation replies, which have a greater negative impact on customers' word-of-mouth and repurchase rate [6].The main reason is that rural lodging practitioners have a low level of use of integrated media technology, pay insufficient attention to integrated media marketing, lack the concept of integrated media marketing, and are not precise enough in their insights into the market demand and guests' psychology, which leads to the development of rural lodging industry being limited by the lack of integrated media marketing.

3.2 Inadequate Marketing and Publicity for Media Integration

With the rapid development of rural B&B economy, the competition among B&Bs has shifted from traditional resource competition to brand and service competition, in which integrated media marketing is crucial [7]. With the change of rural tourism market demand and the diversified development of consumers' travel mode, it is difficult to satisfy consumers with one-dimensional touring and eating, drinking and playing. Consumers of rural lodging are more eager to have immersive experience and feel the regional characteristic culture in the context. Under the background of integrated media, the marketing and promotion of rural B&Bs need integrated media channels such as the Internet, but now most of the marketing channels of rural B&Bs are single and do not combine the characteristics of rural B&Bs with integrated media publicity, so the marketing means are monotonous and inefficient, and the marketing results are not high. In the era of highly developed integrated media, rural B&B operators do not pay much attention to interaction with consumers, lack of interactive mechanisms, do not make good use of the Internet and other integrated media interactive marketing and immersive marketing advantages, marketing promotion is not in place.

3.3 Lack of Authenticity in Integrated Media Marketing

With the rapid development of integrated media, the effective combination of rural lodging and integrated media can play an immediate effect of publicity. However, in order to attract more customers, some rural lodging operators exaggerate the advantages of the hardware and software of rural lodging and hide the problems and shortcomings. There are shortcomings such as lack of reliability of news, slow updating of information and information clutter in the integrated media marketing of rural B&Bs, and consumers find that the publicity content lacks authenticity after arriving at the rural B&Bs, which is easy to reduce the credibility of the rural B&Bs, and cause consumers to have a negative experience in the rural B&Bs.

3.4 Serious Homogenization of Integrated Media Marketing

Beginning in 2017, major integrated media platforms have launched a series of reality TV shows themed on rural B&Bs, and the star effect has brought about the rapid spread of the network, and rural B&Bs have ushered in a high-speed growth period. However, most of the rural B&B operators see that the countryside B&B continues to be hot and then blindly follow the trend of investment, a large number of similar architectural style, featureless hardware and software, the phenomenon of homogenization of rural B&Bs can easily lead to consumer aesthetic fatigue. Rural lodging features and themes are not prominent enough, rural lodging cultural connotations are not enough to dig, rural lodging rural wildlife present the missing, not conducive to breaking the phenomenon of homogenization of rural lodging, it is difficult to provide consumers with a sense of freshness, and it is even more difficult to enhance the word-of-mouth dissemination of rural lodging consumers [8]. Homogenization of rural lodging products has brought great challenges to the integrated media marketing, integrated media need to combine different rural lodging characteristics to carry out targeted, personalized and customized marketing forms, but at present, most of the rural lodging integrated media marketing is still homogeneous and serious, and it is difficult to reflect the characteristics of the countryside lodging in the video, copywriting and mood.

4 THE OPTIMIZATION PATH OF RURAL LODGING INTEGRATED MEDIA MARKETING

4.1 Integration and Improvement of the Integrated Media Marketing Model

Integrated media marketing, which can also be called new media marketing, focuses on conveying the core and key contents to the audience groups in a timely, precise and visual way, so it is crucial to seize consumers' attention to rural B&Bs. Rural B&B integrated media marketing is based on the effective integration of related integrated media channels, integrating the core media related to the rural B&B market as well as related media [9]. The key contents of rural B&B are pushed to the target consumers by level, channel and target, so as to improve the long-term, continuity, efficiency and effectiveness of rural B&B's integrated media marketing. Combining the special characteristics of rural lodging and the effective integration of integrated media marketing, the integrated media marketing of rural lodging can be formed as follows: "Forming an integrated media circle or matrix - Focusing on the target consumer market - Locking in the target consumer group --Convert loyal fans - Form traffic feedback through splitting - Expand brand effect - Lock the approximate TA crowd - optimize the target circle and matrix" closed-loop mode.

4.2 Improvement of the Standard of Integrated Media Marketing of Operators

With the rapid development of Internet technology, professional B&B talent pool has become a key factor for rural B&Bs to stand out in the fierce market competition. Technology and consumer demand continue to change, rural B&B products are updated and iterated very quickly, so rural B&B operation needs to be a composite talent with knowledge related to tourism and hotels, melting media technology and consumer behavior [10]. Rural B&B operators need to take the initiative to integrate rural B&B business activities into the integrated media, continuously and actively learn to improve the efficiency of the use of integrated media, and establish the integrated media thinking of business. On the one hand, rural B&B operators can participate in the training courses on integrated media technology to enhance the knowledge of integrated media and integrated media marketing skills of rural B&B management; on the other hand, rural B&B operators can establish an information sharing platform for rural B&Bs and customers, through which operators can guide and encourage consumers to share the real experience of staying in the B&B, and grasp the data of consumers' experience at any time. Through these data, operators can continuously optimize their services and marketing methods, and improve the ability of integrated media marketing and the service quality of rural B&Bs.

4.3 Promoting the Marketing of Regional Specialties in Integrated Media

Relying on the regional cultural characteristics of the countryside B&B, integrated media marketing, the countryside local cultural factors into the countryside B&B integrated media, highlighting the cultural label. Rural B&Bs can highlight the cultural nature of rural B&Bs, the emotional nature of memories and experience immersion through the integrated media marketing. Combining the regional culture of rural B&Bs and the advantages of the wide reach and timeliness of the melting media, the marketing efficiency can be improved through the deep excavation of the consumer preferences of rural B&Bs, the service connotation can be enhanced, and the cultural label can be emphasized. Promote the deep and diversified integration of rural lodging and integrated media, and further promote the development of rural lodging to high-end, specialization and branding.

4.4 Keeping up with the Trend of Integrated Media Marketing for Rural Lodgings

Rural B&Bs need to face the new consumer crowd and emerging consumer market, so they need to keep up with the new trend of rural B&B integrated media marketing. (1) Channel diversification (decentralization), the whole platform to do the layout. Rural B&B integrated media marketing can fully integrate Douyin, video number, WeChat group, WeChat public number, Xiaohongshu, Ctrip travel photography, Mabee's Nest, Dianping and other integrated media platforms, through the diversification of platforms and consumers to establish a connection between the spiritual touch points and physical contact. (2) Immersive, genuine and authentic display of the characteristic products and service experience of rural B&Bs, adopting immersive contextual marketing and eliminating the sense of marketing and marketing talk. (3) Rural B&B's integrated media traffic presents diversified and multi-center trends, and it is difficult for rural B&Bs to obtain dividends simply through public traffic, and it is especially important to pay attention to and make use of the increasingly rising private traffic. By guiding diversified subjects to create high-quality rural B&B content to explode in the public domain, gather precise users, and then multi-dimensionally and multi-level guide to the private domain transaction and re-purchase, which can bring a steady stream of customers for rural B&Bs. (4) Guiding KOL, KOC and consumers to become the new traffic body of rural B&Bs, KOL, KOC and consumers present the special services and products of rural B&Bs through the integrated media, which can increase consumers' understanding of and trust in rural B&Bs, and thus guide potential consumers to spend money in rural B&Bs. (5) Pay full attention to Xiaohongshu channel. 90 and 95 young women are the main users of Xiaohongshu, which is highly overlapping and compatible with the users of rural lodging. 90 and 95 young women are used to sharing the experience and feelings of rural lodging in a diversified form, and they have the ability to consume as well as motivation to consume, so Xiaohongshu can become a traffic area for rural lodging to acquire customers at low cost [11].

5 CONCLUSION

Rural lodging is an important carrier for prospering rural economy, inheriting traditional culture, promoting rural transformation and development, and helping people get rich. At present, there are four problems of insufficient attention to rural lodging marketing, lack of publicity, lack of authenticity and serious homogenization; the article puts forward four optimization paths of integrating and perfecting lodging marketing mode, improving the lodging marketing standard of operators, promoting lodging marketing with regional characteristics and following the trend of lodging lodging marketing in the countryside. This is a positive attempt to optimize and improve the marketing efficiency and effect of rural lodging, which helps to better play the positive role of rural lodging in rural economic development, social livelihood and coordinated governance at multiple levels and dimensions, and promotes the realization of the national strategy of rural revitalization and common prosperity.

COMPETING INTERESTS

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REFERENCES

[1] Lou Ge. Research on the construction of beautiful countryside in the new era.Changchun: Changchun University of Science and Technology, 2020.
[2] ZHANG Chao, KANG Yifang, TAN Feng. Research on the strategy of constructing knowledge payment service under the background of integrated media.Library, 2022, 338(11): 63-68.
[3] Jingwen Zhang. Research on marketing strategy of DL lodging in Dali City, Yunnan Province. Harbin: Harbin Institute of Technology, 2020.
[4] KIM Yu-Shi, MA Bo, ZHAO Yu-Zong. From antagonism to integration: a study of metro-agricultural relations and the evolution of urban agriculture in Japan.Geography Research, 2022, 41(08): 2234-2250.
[5] Gao Weiwei, Han Shenghao. How can social business communication increase net referral value of B2B companies? . Business Economics and Management, 2022(08): 70-83.
[6] Lina Wang. Research on optimization of WX hotel marketing strategy with customer value as the core. Shanghai: Shanghai International Studies University, 2021.
[7] Du Jingping. A case study on the construction of rural tourism resort in Langzhong, Sichuan. Chengdu: University of Electronic Science and Technology, 2022.
[8] Yin Yuan. Digitalization of Rural Tourism: Dynamic Mechanisms, Logical Dimensions and Conflict Resolution. Journal of Xi'an University of Finance and Economics,2023, 36(01): 29-40.
[9] HU Chunmei, ZHANG Xiaoyan, LI Yang. Research on the optimization and development strategy of Yichang lodging industry under the background of rural revitalization--an empirical research based on rural lodging in Yichang. Journal of Three Gorges University (Humanities and Social Sciences Edition), 2023, 45(01): 62-68.
[10] Zhang Yibo. Research on the construction of rural tourism brand image in northern Shaanxi under the perspective of culture and tourism integration. Xi'an: Shaanxi University of Science and Technology, 2021.
[11] Liu Yan. Five trends in new media marketing for B&Bs.Guangzhou: Traveling Yuejia B&B Education, 2021.

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DYNAMIC OPTIMAL PORTFOLIO CHOICES FOR ROBUST PREFERENCES

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Abstract: This paper solves the optimal dynamic portfolio choice problem for an ambiguity-averse investor. It introduces a new preference that allows for the separation of risk aversion and ambiguity aversion. The novel representation is based on generalized divergence measures that capture richer forms of model uncertainty than traditional the relative entropy measure. The novel preferences are shown to have a homothetic stochastic differential utility representation. Based on this representation, optimal portfolio policies are derived using numerical algorithms with forward-backward stochastic differential equations. The optimal portfolio policy is shown to contain new hedging motives induced by the investor's attitude toward model uncertainty. Ambiguity concerns introduce additional horizon effects, increase effective risk aversion, and overall reduce optimal investment in risky assets. These findings have important implications for the design of optimal portfolios in the presence of model uncertainty.
Keywords: Portfolio optimization; Ambiguity aversion; Robust-optimal control; Knightian uncertainty

1 INTRODUCTION

In paper, we study the optimal-portfolio problem of a long-term investor who faces model uncertainty and is ambiguity averse. We propose a robust-control criterion with a new utility formulation. We derive an equivalent stochastic differential utility (SDU) representation of the new robust preferences. For an investor with the constant relative risk aversion (CRRA) utility function, tractable optimal solutions are available from Schroder and Skiadas[1]. We present an alternative representation of the optimal solution in the setting of Ocone-Karatzas formula[2-3]. This representation decomposes the optimal portfolio into three parts: the mean-variance component, the dynamic hedging component for fluctuations in the stochastic investment opportunity set, and the hedging demand arising from robustness concerns. The mean-variance portfolio requires less investment in the stock market, compared with that in a setting without robustness concerns.

We provide the numerical implementations of the optimal solutions by solving a system of FBSDEs with the regression-based Monte Carlo approach[4]. We find that robustness concerns affect the pattern of the optimal portfolio. For the investor with CRRA utility and relative risk aversion greater (smaller) than one, ambiguity aversion increases (decreases) the inter-temporal hedging demand. The investor with logarithmic utility and robustness concerns is no longer myopic.

The question of dynamic optimal-portfolio allocation is of long-standing academic interest and practical importance. The mean-variance analysis proposed by Markowitz (1952) is the building block of the modern portfolio theory[5]. The seminal work of Samuelson (1969) and Merton (1971) suggests that the investor dynamically manages the optimal portfolio during the investment horizon[6-7]. Pliska (1986), Karatzas et al. (1987), and Cox and Huang (1989) propose a martingale approach that in a complete market setting, it allows to solve for the optimal consumption-investment plan as the solution to a static optimization problem by establishing the equivalence between the dynamic and static budget constraints[8-10]. Ocone and Karatzas (1991) derive explicit expressions for the hedging terms as conditional expectations of random variables related to the state dynamics[2]. Detemple et al. (2003) propose a simulation approach to calculate the dynamic hedging terms efficiently[3]. In these papers, the investor is modeled to live inside the world where the subjective and objective probability distributions coincide, that is, he/she knows the process that describes the state variables dynamics.

However, the Ellsberg (1961) experiments show that people's preferences are incompatible with the subjective expected utility in an environment with ambiguity, where the objective probability distribution does not agree with the subjective distributions. Ambiguity is sometimes referred to as "Knightian uncertainty", or in Hansen and Sargent (2001)'s terminology as "model uncertainty". In the financial market, one example of model uncertainty is the dynamics of the stock return process[11]. While the second moment of the return process can be estimated with reliable precision, the first moment (the expected return) is notoriously hard to estimate[12]. This difficulty to accurately infer the state dynamics induces ambiguity, and the possibility of model misspecification impacts how the investor designs the optimal portfolio.

Several models are stimulated to address the Ellsberg-based critiques: the multiple-priors model, the smooth ambiguity model and the multiplier utility model with the robust-control criterion introduced by Anderson et al. (2003) and Hansen and Sargent (2001), with later developments by Skiadas (2003), Maccheroni et al. (2006) and Skiadas (2013)[14-22]. These three sets of models have their respective merits. The first two models can rationalize the choice in the Ellsberg's experiments. The multiple-priors model can further exploit the qualitative differences from subjective expected utility, and the smooth ambiguity model has the advantage of separating "ambiguity" and "the attitude toward ambiguity". In the last model, optimal choices are observationally equivalent to those obtained with subjective expected utility. It also helps to solve the quantitatively puzzling price implications considering the subjective expected utility model. We cast our analysis in the robust-control setting, where the investor seeks a robust optimal strategy that performs best in the worst-case scenario of the model misspecification.

In this paper, we propose a robust-control problem, in which the investor trades off utility derived from consumption and the loss induced by ambiguity. Specifically, we introduce a new utility formulation that combines the consumption utility and ambiguity loss in a multiplicative way. The latter is quantified by a convex power function on the Radon-Nikodym derivative process, which is interpreted as a penalty for the discrepancy between the objective and subjective probability measures. Being concerned about the model uncertainty of the optimal plan, the investor decomposes the portfolio optimization procedure into two steps: 1) solving for the probability measure that generates the minimal expected utility, according to the degree of ambiguity aversion; 2) designing the optimal consumption-investment plan that maximizes the minimal utility, according to the degree of risk aversion.

There are three main contributions in this paper. First, we establish the equivalence between the robust-control problem with the new utility formulation and the SDU maximization problem. The equivalence between the Bellman equation for the robust-control criterion and that for the SDU specification has been noted by Hansen and Sargent (2001) and Maenhout (2004) in a different formulation of the utility function and state dynamics[11, 23]. With general state dynamics and consumption utility, we establish the same equivalence result. Skiadas (2003) establishes the equivalence when the discrepancy between the objective and subjective measures is quantified by the relative entropy[24]. The discrepancy measure we use here generalizes the relative entropy measure. In the case of CRRA consumption utility, our equivalence result can be viewed as a generalization of his result.

Second, we obtain closed-form optimal solutions for the robust-control problem for the investor with CRRA consumption utility. One set of such solutions is expressed by a system of FBSDEs as shown by Schroder and Skiadas (1999)[1]. We provide an alternative representation of the solution based on the refinement of the Ocone and Karatzas formula[1-2]. This representation helps us to decompose the optimal portfolio into three parts: the mean-variance component; the dynamic hedging component against fluctuations in the investment opportunity set; and the dynamic hedging demand from model uncertainty concerns.

The main impact of model uncertainty concerns is that it induces lower allocation to the risky asset in the mean-variance portfolio. Specifically, for the investor with CRRA utility, this impact is persistent along the investment horizon. For the investor with logarithmic utility, this impact vanishes with time, that is, the mean-variance portfolio gradually approaches the one without robustness concerns.

This impact helps us to understand the discrepancy between the degree of relative risk aversion implied by equilibrium asset prices and the value obtained from behavioral studies. Within the subjective expected utility models, the actual prices for macroeconomic risks are too high, as manifested by equity premium puzzles. This implies a high relative risk aversion. On the other hand, as concluded in Meyer and Meyer (2006) based on several studies on investors' behaviors, the relative risk aversion measure is typically small, in a range of one to four[25]. The investor's concerns for the model misspecification raise the prices for market risks and leads to a reinterpretation of the high prices as compensations for bearing model uncertainty. For the investor with CRRA utility, the impact of ambiguity averse is significant. For a moderate relative risk-aversion degree of 4, a penalty coefficient of -2 can adjust the relative risk aversion to 10. Conversely, this can be used to calibrate the fear for the model misspecification, as measured by the penalty coefficient of the ambiguity-averse investor. In a model with a constant investment opportunity set, Maenhout (2004) calibrates the penalty coefficient to be 14 with relative risk aversion as 7 to match the risk-free rate and equity premiums for 1981-1994, with an implied relative risk aversion of 21 without considering ambiguity aversion[23]. Such a difference suggests that the investors in the market indeed worry about model uncertainty and includes such concerns in the pricing of macroeconomic risks.

Finally, we provide numerical implementations for the dynamic optimal investment plan of the robust-control problem by solving systems of FBSDEs through the regression-based Monte Carlo method[4]. As calibrated by Campbell et al. (2003) in a model with a vector autoregressive return process, the dynamic hedging demand for an investor with recursive utility is substantial[26]. The numerical implementation helps us to gain insights into the inter-temporal hedging demand for fluctuations in the stochastic investment opportunity set and for ambiguity concerns. This also makes our work different from that of Maenhout (2004) who studies the optimal portfolio rule with a constant investment opportunity set, and the dynamic optimal portfolio implementation with subjective expected utility[2, 23].

We implement the optimal portfolio with the interest rate following an Ornstein-Uhlenbeck process, with the negative correlation with the stock market. The inter-temporal hedging demand boosts investment in the stock, which reflects the negative correlation between the two. The inter-temporal hedging demand decreases with time, representing the vanishing hedging need against fluctuations in the investment opportunity set and ambiguity averse. For the investor with constant relative risk aversion greater than or equal to one, the hedging demand increases (decreases) with ambiguity aversion.

In the setting where the interest rate follows an Ornstein-Uhlenbeck process, numerical results show that robustness concerns change the dynamic portfolio patterns for investors with different risk aversion. It is well known that in a setting without ambiguity, the investor with logarithmic utility does not have an inter-temporal hedging demand, even in the stochastic investment environment. The model uncertainty concerns increase risk aversion, and thus introduces an inter-temporal hedging demand. With robustness concerns, the investor with logarithmic utility is no longer myopic.

In the setting with model uncertainty or ambiguity, comparative studies show that the optimal stock demand for an investor with constant relative risk aversion greater than one is larger for younger investors. This is consistent with the behavior that that younger investors invest more aggressively than older people.

Our work follows Skiadas (2003) which establishes the equivalence between the robust-control problem with the relative entropy formulation and the SDU maximization problem[24]. In the case of CRRA, our results can be viewed as an extension of his work. However, closed-form solutions are available in our setting for CRRA utility, whereas in his work, such solutions are only available for logarithmic utility. As we have discussed, optimal portfolios for these two utility functions have quite different dynamic patterns.

Maccheroni et al. (2006) propose and axiomatize an entropy-variational utility that unifies the multiple-prior utility and multiplier utility[27]. As shown in Skiadas (2013), the certainty equivalence based on this smooth divergence preference can be approximated by the expected-utility certainty equivalence, with the resulting recursive utility taking the form of an SDU[22]. Whereas these authors focus on the additive structure of the consumption utility and divergence loss, we look at the multiplicative structure and aim for closed-form optimal consumption-investment solutions.

Our work is related to Maenhout (2004) where he proposes a state-dependent penalty for the value function in the Bellman equation, in a setting of constant investment opportunities for an investor with CRRA utility[23]. Due to the specification of CRRA utility, the homothetic nature of the preference is maintained, and hence closed-form optimal solutions are available. Our work is different from his, in that the equivalence between our robust-control problem and the SDU maximization problem is established for the general form of consumption utility and dynamics of state variables. In addition, the optimal solution in our setting with the stochastic investment opportunity set includes inter-temporal hedging demands.

Chen et al. (2011) derives the dynamic portfolio choice solution in which the investor faces a model selection problem between an i.i.d return model and a vector autoregression model, with the recursive ambiguity utility[19, 28]. Maenhout (2006) extends Maenhout (2004) to a dynamic setting where the market price of risk is a mean-reversion process and derives the optimal portfolio through the dynamic programming approach[23,29]. Compared with their works, our work allows for general state-variable dynamics and inter-temporal consumption. Furthermore, the martingale-based approach we use in this paper allows us to obtain optimal solutions without having to use numerical schemes based on partial differential equations.

This paper is organized as follows. In Section 2, we introduce the robust control problem. In Section 3, we establish the equivalence between the robust-control problem and the SDU maximization problem. In Section 4, we provide an alternative optimal consumption-investment plan representation through the Ocone- Karazats formula. Section 5 provides numerical illustrations of the optimal portfolio. Section 6 concludes.

2 THE ROBUST-CONTROL PEROBLEM

2.1 The Background

We cast the analysis in a continuous-time model in which the underlying source of uncertainty is a d-dimensional Brownian motion B_t, $t \in [0, T]$. The probability space is (Ω, F, P), where P is the objective measure and the flow of information F_t, $t \in [0, T]$ is the filtration generated by the Brownian motion B_t. With limited knowledge about the objective probability measure, the investor's belief about the market can be modelled by a set of probability measures P^x equivalent to P.

Denote by $E(E^x)$ the expectation under $P(P^x)$, and E_t (E_t^x) the conditional expectation operator given F_t. Define the conditional density process d_t^x as $E_t\left[\frac{dP^x}{dP}\right]$, with the associated relative density defined as $d_{t,s}^x = \frac{d_s^x}{d_t^x}$.

By the martingale representation theorem, there exists an adapted process $x \in L_2$ such that:

$$d_t^x = \exp\left(\int_0^t x_s^{'} dB_s - \frac{1}{2}\int_0^t x_s^{'} x_s ds\right), \quad t \in [0, T]. \tag{1}$$

By the Girsanov theorem, the process B_t^x defined as $B_t^x = B_t - \int_0^t x_s ds$ is a Brownian motion under P^x. Consider a constant $\eta \in (-\infty, 1)$, define:

$$\tilde{d}_t = \exp\left(\frac{\eta}{\eta - 1}\int_0^t x_s^{'} dB_s - \frac{\eta^2}{2(\eta-1)^2}\int_0^t x_s^{'} x_s ds\right), \tilde{B}_t = B_t - \frac{\eta}{\eta - 1}\int_0^t x_s ds. \tag{2}$$

Set the random variable $\tilde{d} = \tilde{d}_T$. Define the probability measure $\tilde{P}$ as:

$$\tilde{P}(A) = \int_A \tilde{d}(\omega) dP(\omega), \ \ \forall A \in F. \tag{3}$$

Denote by $\tilde{E}(\tilde{E}_t)$ the (conditional) expectation operator under $\tilde{P}$.

We consider a complete market with a d-dimensional state variable Y_t and d risky securities. The state variable follows the vector-diffusion process $dY_t = \mu^Y(t, Y_t)dt + \sigma^Y(t, Y_t)dB_t$.

The investor allocates the wealth between the d risky securities and the money market account with the instantaneous risk-free rate $r_t = r(t, Y_t)$. The security prices $S_i, i = 1, \cdots, d$ follow the dynamics:

$$dS_{it} = S_{it}(\mu_i(t, Y_t)dt + \sigma_i(t, Y_t)dB_t),\ 1 \le i \le d, \tag{4}$$

where μ_i is the expected return process and σ_i is the vector of volatility coefficients of the i-th security. Denote by μ the d-dimensional vector of the expected returns, whose i-th entry is μ_i. Let σ denote the $d \times d$-dimensional volatility matrix whose rows are σ_i, $i = 1, \cdots, d$. Assume that σ is invertible. Also assume that μ and σ are progressively measurable and satisfy the standard integrability conditions. The market price of risk is defined as:

$$\theta_t = \theta(t, Y_t) \equiv \sigma(t, Y_t)^{-1}(\mu(t, Y_t) - r(t, Y_t)1),$$

where 1 is the d-dimensional unit vector. We assume that the market price of risk θ_t is continuously differentiable and satisfies the Novikov condition.

The state price density is defined as $\xi_t = \exp\left(-\int_0^t r_s ds - \int_0^t \theta_s' dB_s - \frac{1}{2}\int_0^t \theta_s'\theta_s ds\right)$ and the relative state price density is defined as $\xi_{t,s} = \frac{\xi_s}{\xi_t}$.

2.2 The Robust-Control Problem

In this section, we provide the definition of the robust-control problem and the utility formulation. The robust-control criterion is

$$\widehat{V}_t = \text{ess inf}_x\{V_t^x\}, \qquad (2.1) \tag{5}$$

where the utility process V_t^x is defined as:

$$V_t^x = E_t\left[\int_t^T \exp\left(-\int_t^s \beta_v dv\right) u(c_s)\left(d_{t,s}^x\right)^{\frac{\eta}{\eta-1}} ds\right] = E_t^x\left[\int_t^T \exp\left(-\int_t^s \beta_v dv\right) u(c_s)\left(d_{t,s}^x\right)^{\frac{1}{\eta-1}} ds\right]. \quad (2.2) \tag{6}$$

The subjective discount factor β_t can be stochastic. The function $u(\cdot)$ is the real-valued Von Neumann-Morgenstern utility function. The penalty coefficient η represents the investor's averse attitude toward ambiguity. This attitude affects the utility function through the relative density process $d_{t,s}^x$. We assume:

$$\begin{gathered} 0 < \eta < 1, \text{if } u(\cdot) > 0, \\ -\infty \le \eta \le 0, \text{if } u(\cdot) < 0. \end{gathered} \tag{7}$$

The parameter ranges of η insure that it can model the investor's different degree of ambiguity aversion. In the limiting case of $\eta = -\infty$, the utility becomes $E_t^x[\int_t^T \exp(-\int_t^s \beta_v dv)u(c_s)ds]$. The penalty is so large that one cannot optimize the utility except for when the data-generating measure corresponds to P^x. In the case of $\eta = 0$, the utility is $E_t\left[\int_t^T \exp(-\int_t^s \beta_v dv)u(c_s)ds\right]$. The investor does not care about ambiguity. In between the two extremes is that the investor is averse to the divergence between P and P_x and tries to design a consumption-investment plan that performs best under the worst situation of the model misspecification.

The investor with ambiguity concerns is presented with a max-min problem. The first step in the optimization procedure is to find the probability measure under which the weighted expected utility is minimized. Next, we solve for the optimal consumption-investment plan that maximizes the minimized utility, subject to the dynamic budget constraint.

We interpret this two-step optimization problem as following. The investor trades off the gain from investment and the loss from ambiguity. The investment plan supports the contemporary consumption c_t, which induces utility. The conditional density d_t^x determines the loss induces by model uncertainty, i.e., the discrepancy between measures P and P_x. The coefficient η controls how severe the penalty the investor imposes for not knowing the true model. If the penalty is too high, the investor can have a very conservative plan. If the penalty is too low, the investor is exposed to model uncertainty and the optimal plan may perform worse than what the control theory has promised.

Borrowing the idea of a generalized loss function form Berger (1985), we specify the (integrated) loss function $L(c_t, d_t^x)$ as[30]:

$$L(c_t, d_t^x) = u(c_t)(d_t^x)^{\frac{1}{\eta-1}}. \tag{8}$$

The multiplicative formulation captures the fact that the impact of ambiguity concern is dependent on the contemporary consumption utility. For an investor with low-consumption utility, even though he/she is aware of and imposes a high penalty for ambiguity, such concerns do not affect the total utility as much as compared with an otherwise identical investor with high-consumption utility.

As we shall see, this utility formulation with the CRRA utility $u(c_t) = \frac{c_t^{1-\gamma}}{1-\gamma}$ helps to model ambiguity aversion as a penalty component on the utility process. In contrast to the relative entropy formulation, this proportion is state dependent. It also allows us to convert the robust-control problem to a class of homothetic SDU where closed-form solutions for the optimal consumption-investment plan are available[1]. Besides this desirable tractability property, insights gained from the optimal-portfolio solution reveal that ambiguity aversion can help reconciling the high-risk aversion implied by asset prices and the moderate degree obtained from behavioral studies.

This utility formulation also allows for dynamic optimal-portfolios solutions with inter-temporal hedging components against fluctuations in the investment opportunity set and ambiguity aversion. Tractable solutions are also available for the relative-entropy formulation, but only when the investor has logarithmic utility, which is clearly a limitation.

3 MAIN RESULTS

Our main result establishes the connection between the robust-control problem (2.1) and a form of the SDU problem.
Theorem 3.1. There exists a unique progressively measurable pair (V, σ^b), such that:

$$dV_t = -\left(u_t - \beta V_t - \frac{\eta}{2V_t}(\sigma_t^b)'\sigma_t^b\right)dt + (\sigma_t^b)'dB_t, \quad (3.1) \tag{9}$$

with the boundary condition $V_T = 0$.
For $t \in [0, T)$ and any adapted process x, the utility process V_t^x can be expressed as:

$$V_t^x - V_t = \widetilde{E}_t\left[\int_t^T \exp\left(\frac{\eta}{2(\eta-1)^2}\int_t^s x_v' x_v dv\right) \times \left(\frac{1}{2}\left(x_s\sqrt{\frac{\eta}{(\eta-1)^2}V_s} + \sigma_s^b\sqrt{\frac{\eta}{V_s}}\right)'\left(x_s\sqrt{\frac{\eta}{(\eta-1)^2}V_s} + \sigma_s^b\sqrt{\frac{\eta}{V_s}}\right)\right)ds\right]. \tag{10}$$

The utility process V_t^x is minimized at:

$$x^* = -\sigma_t^b\left|\frac{\eta - 1}{V_t}\right|, \tag{11}$$

and

$$V^{x^*} = V. \tag{12}$$

The existence result of (V_t, σ_t) in Equation (3.1) can be found in Schroder and Skiadas (1999)[1].
Proof. See Appendix A.
With the optimizing value of x^*, we approach the robust-control problem (2.1) by solving (V_t, σ_t) described by the backward stochastic differential equation (BSDE) in Equation (3.1). We can see from this equation that ambiguity concerns introduce a state-dependent penalizing component on the utility process.
The next result shows that the BSDE in Equation (3.1) can be expressed in the form of the SDU. We define an ordinally equivalent utility process of V_t, which allows us to express the preference in terms of a homothetic SDU:

$$v_t = \begin{cases} V_t^{1-\eta} \text{ for } V_t > 0, \\ -(-V_t)^{1-\eta} \text{ for } V_t < 0, \end{cases} \tag{13}$$

with the boundary condition $v_T = 0$.
Proposition 3.2. The transformed utility process v_t can be expressed as:

$$v_t = E_t\left[\int_t^T (1-\eta)\left(|v_s|^{\frac{\eta}{\eta-1}}u_s - \beta v_s\right)ds\right]. \quad (3.2) \tag{14}$$

Proof. See Appendix A.
Given the special case of the CRRA utility function, Equation (3.2) corresponds to the homothetic SDU specification in Schroder and Skiadas (1999) with $\alpha = -\eta$, and $\gamma \neq 1$. In that context, the coefficient α is interpreted as a measure of the preference for the timing of uncertainty resolution.
Skiadas (2003) obtains similar results in the relative-entropy formulation, which is a special case of ours[24]:

$$V_t^x = E_t^x\left[\int_t^T \exp\left(-\int_t^s \beta_v dv\right)\log(c_s)\,ds\right] + \frac{1}{2\eta}E_t^x\left[\int_t^T \exp\left(-\int_t^s \beta_v dv\right)x_s^2 ds\right]. \quad (3.3) \tag{15}$$

The second term is the relative entropy distance considered in Hansen and Sargent (2001) and Skiadas (2003), with $\frac{1}{\eta}$ being the penalizing coefficient[11, 24]. Skiadas (2003) shows that the robust-control problem can be solved by a BSDE for (V_t, σ_t):

$$dV_t = -\left(\log(c_t) - \beta V_t - \frac{\eta}{2}\sigma_t^2\right)dt + \sigma_t dB_t, \tag{16}$$
$$V_T = 0.$$

We can express the solution to this BSDE as a form of the homothetic SDU. To do this, we define an ordinally equivalent utility process v_t of V_t as:

$$v_t = -\frac{1}{\eta}(\exp(-\eta V_t) - 1), \tag{17}$$

with the boundary condition $v_T = 0$.
Proposition 3.3. The transformed utility process v_t can be expressed as:

$$v_t = E_t\left[\int_t^T (1-\eta v_s)\left(\log(c_s) + \frac{\beta}{\eta}\log(1-\eta v_s)\right)ds\right]. \quad (3.4) \tag{18}$$

To conclude, the utility form (3.2) corresponds to the homothetic SDU specification in Schroder and Skiadas (1999), with $\alpha = -\eta$ and $\gamma = 1$. In this case, closed-form solutions for the optimal consumption-investment plan are available[1]. Comparing our formulation with that of Skiadas (2003), closed-form solutions for the optimal plan are not available in their formulation for CRRA utility[24]. Our robust-control problem has closed-form solutions for CRRA utility and for logarithmic utility as a special case.

4 THE OPTIMAL CONSUMPTION-INVESTMENT PLAN

In this section, we provide an alternative representation of the optimal solution of the robust problem (2.1) for an investor with CRRA utility based on the generalized Clark-Ocone formula of the hedging terms using Malliavin calculus[2-3]. We also provide the optimal-portfolio solution for the problem (3.3) as a special case.

Detemple et al. (2003) express the hedging terms by conditional expectations with respect to the Malliavin derivatives and propose a simulation-based approach for the subjective expected utility optimization problem with a stochastic investment opportunity set[2]. Here we adopt their methodology to solve for the optimal portfolio in the SDU maximization problem setup.

From this new representation, we can separate the forward-hedging component against fluctuations in the market price of risk and interest rate, and the backward-hedging component for ambiguity concerns.

4.1 The Optimal Solution: the CRRA Utility Case

For the investor with ambiguity concerns, after finding the probability measure under which the expected utility has the minimal value, he/she seeks to maximize the expected utility by selecting the optimal consumption-investment plan subject to a dynamic budget constraint:

$$\max_{\{\pi_t,c_t\}} E_0\left[\int_0^T\left(1-\frac{1}{\eta}\right)\left(|v_s|^{\frac{1}{1-\eta}}u_s-\beta v_s\right)ds\right], \quad (4.1) \tag{19}$$

s.t

$$dw_t=(r_tw_t-c_t)dt+w_t\pi_t^{'}\big((\mu_t-\mathbf{1}r_t)dt+\sigma_t dB_t\big),\ \ w_0=w, \tag{20}$$
$$w_t\geq 0, \forall\, t\in[0,T].$$

Here w_t is the investor's wealth process at time t and w is the initial wealth. The term π_t is the proportion invested in the risky assets at time t. The nonnegativity constraint is the typical no-bankruptcy condition. The zero lower boundary can be replaced by a finite negative value. The utility function $u(\cdot)$ satisfies the assumption of strictly increasing and concave, with limits $\lim_{x\to\infty}u^{'}(x)=0$ and $\lim_{x\to\infty}u^{''}(x)\ <\infty$. For the problem (4.1) with the CRRA utility function $u(c_t)=\frac{c_t^{1-\gamma}}{1-\gamma}$, Schroder and Skiadas (1999) derive explicit solutions for the optimal consumption, the utility process and the optimal portfolio. Before going to our results, we present the main results of Schroder and Skiadas (1999) to introduce definitions and notations[1].

4.2 Schroder and Skiadas (1999): the CRRA Utility Case[1]

(1)The optimal consumption:

Denote $\alpha=-\eta$, the optimal consumption is

$$c_t=(1+\alpha)^{\frac{1}{\gamma}}|v_t|^{\frac{\alpha k}{1+\alpha}}\exp\left(-\frac{X_t}{\gamma}\right)=(1+\alpha)^{\frac{1}{\gamma}}\exp\left(-kX_t\right)|J_t|^{\alpha k}, \tag{21}$$

with

$$k=\frac{1}{1-(1-\gamma)(1+\alpha)}. \tag{22}$$

(2)The optimal portfolio is:

$$\sigma_t\pi_t=k\theta_t+(1+\alpha k)\frac{Z_t}{J_t}. \tag{23}$$

(3)The pair (J_t,Z_t) and X_t:

The backward component (J_t,Z_t) and the forward component X_t together solve the FBSDE system:

$$dJ_t=-\left(\frac{1}{1-\gamma}(1+\alpha)^{\frac{1-\gamma}{\gamma}}+\frac{1-\gamma}{\gamma}\left(r_t-\frac{\beta}{1-\gamma}+\frac{k\theta_t^{'}\theta_t}{2}\right)J_t+\frac{\alpha k}{2}\frac{Z_t^{'}Z_t}{J_t}\right)dt+Z_t^{'}(dB_t+(1-k)\theta_t dt),$$
$$J_T=0,$$
$$dX_t=-\left(\frac{\alpha}{1-\gamma}(1+\alpha)^{\frac{1-\gamma}{\gamma}}J_t^{-1}-(1+\alpha)\beta+r_t+\frac{\theta_t^{'}\theta_t}{2}\right)dt-\theta_t^{'}dB_t, \tag{24}$$
$$X_0=\log(\lambda).$$

The value of λ is obtained by imposing the static budget constraint:

$$E_0\left[\int_0^T\xi_s c_s ds\right]=\omega. \tag{25}$$

The forward state-variable dynamics (r_t,θ_t) and the backward process (J_t,Z_t) solve an FBSDE system. The process X_t is the logarithm of the state price density, adjusted for ambiguity concern by including the backward component J_t.

The next theorem compiles the forward dynamics (the state variables and their Malliavin derivatives) with the backward dynamics (the process J_t and its Malliavin derivatives) into an FBSDE system. Numerical methods to solve this system are available. We provide the numerical illustration in the next section. The theoretic foundation of Malliavin calculus can be found in Nualart (1995), with the application to finance found in Karatzas et al. (1987), Karoui et al. (1997), and Detemple et al. (2003)[2-3, 31-32].

Theorem 4.1. The dynamics of J_t in the CRRA utility case is given by Schroder and Skiadas (1999)[1]. The processes J_t and D_sJ_t, $0 \le s \le t \le T$ can be solved via the (decoupled) FBSDE system[33-34]:

Forward dynamics:

$$dx_t = b(x_t)dt + \sigma(x_t)dB_t, \tag{26}$$

where

$$x_t = \begin{pmatrix} Y_t \\ D_sY_t \end{pmatrix}, b_t = \begin{pmatrix} \mu(t, Y_t) \\ \partial_2\mu(t, Y_t)D_sY_t \end{pmatrix}, \sigma(x_t) = \begin{pmatrix} \sigma(t, Y_t) \\ \partial_2\sigma(t, Y_s)D_sY_t \end{pmatrix}, \tag{27}$$

and the initial conditions are:

$$x_0 = Y_0, D_sY_s = \sigma(s, Y_s). \tag{28}$$

Backward dynamics:

$$-dy_t = f(s, t, x_t, y_t, z_t)dt - z_tdB_t, \tag{29}$$

with

$$y_t = \begin{pmatrix} J_t \\ D_sJ_t \end{pmatrix}, z_t = \begin{pmatrix} Z_t \\ D_sZ_t \end{pmatrix}, \tag{30}$$

and

$$f(s, t, x_t, y_t, z_t) = \begin{pmatrix} \frac{1}{1-\gamma}(1+\alpha)^{\frac{1-\gamma}{\gamma}} + \frac{1-\gamma}{\gamma}\left(r_t - \frac{\beta}{1-\gamma} + \frac{k\theta_t^{'}\theta_t}{2}\right)J_t + \frac{\alpha k}{2}\frac{Z_t^{'}Z_t}{J_t} - Z_t^{'}(1-k)\theta_t \\ \frac{1-\gamma}{\gamma}\left(\left(D_sr_t + k\theta_t^{'}D_s\theta_t\right)J_t + \left(r_t - \frac{\beta}{1-\gamma} + \frac{k\theta_t^{'}\theta_t}{2}\right)D_sJ_t\right) \\ + \frac{\alpha k}{2}\left(\frac{2\,Z_t^{'}}{J_t}D_sZ_t - \frac{Z_t^{'}Z_t}{J_t^2}D_sJ_t\right) - (1-k)(\theta_t^{'}D_sZ_t + Z_t^{'}D_s\theta_s) \end{pmatrix}, \tag{31}$$

with the following definitions of D_sr_t and $D_s\theta_t$:

$$D_sr_t = \partial_2 r(t, Y_t)D_sY_t, D_s\theta_t = \partial_2\theta(t, Y_s)D_sY_t. \tag{32}$$

The boundary conditions are:

$$J_T = 0, D_sJ_T = 0 \times 1^{'}. \tag{33}$$

Proof. See Appendix A.

Proposition 4.2. With the solution of (J_t, D_sJ_t), the pair (X_t, D_sX_t) can be solved by the system:

$$\begin{gathered} dX_t = -\left[\frac{\alpha}{1-\gamma}(1+\alpha)^{\frac{1-\gamma}{\gamma}}J_t^{-1} - (1+\alpha)\beta + r_t + \frac{\theta_t^{'}\theta_t}{2}\right]dt - \theta_t^{'}dB_t, \\ X_0 = \log(\lambda), \\ dD_sX_t = -\left[D_sr_t - \frac{\alpha}{1-\gamma}(1+\alpha)^{\frac{1-\gamma}{\gamma}}J_t^{-2}D_sJ_t\right]dt - (dB_t + \theta_t dt)^{'}D_s\theta_t. \\ D_sX_s = -\theta_s^{'}. \end{gathered} \tag{34}$$

Proof. See Appendix A.

Theorem 4.3. We provide an alternative representation of the optimal-portfolio solution by the Clark-Ocone formula. Denote by $H_{t,s}$ the inter-temporal hedging demand against fluctuations in the investment opportunity set with the expression:

$$H_{t,u} = \int_t^u D_tr_vdv + \int_t^u (dB_v + \theta_vdv)^{'}D_t\theta_v. \tag{35}$$

Denote $X_{t,u}$ as $X_u - X_t$. The optimal portfolio is

$$w_t\pi_t^{'}\sigma_t = E_t\left(\int_t^T \xi_{t,u}c_u\left(-kD_tX_{t,u} + \frac{ak}{J_u}D_tJ_u\right)du\right) + k\theta_t w_t - E_t\left(\int_t^T \xi_{t,u}c_u H_{t,u}du\right) = kw_t\theta_t^{'} + (k-1)E_t\left(\int_t^T \xi_{t,u}c_u H_{t,u}du\right) + E_t\left(\int_t^T \xi_{t,u}c_u\left(\frac{\alpha k}{J_u}D_tJ_u - \frac{k\,\alpha(1+\alpha)^{\frac{1-\gamma}{\gamma}}}{1-\gamma}\int_t^u \frac{D_tJ_v}{J_v^2}dv\right)du\right). \tag{36}$$

Proof. See Appendix A.

The optimal portfolio is decomposed into three parts. The first component is the mean-variance portfolio. The second component is the hedging demand against fluctuations in the investment opportunity set. The third hedging comes from robustness concerns[35].

Theorem 4.4. The backward component J_t and its Malliavin derivative D_sJ_t, $0 < s < t$ can be solved via the (decoupled) FBSDE system:

Forward dynamics:

$$dx_t = b(x_t)dt + \sigma(x_t)dB_t. \tag{37}$$

The forward system is the same as that in Theorem (4.1).

Backward dynamics:

$$-dy_t = f(s,t,x_t,y_t,z_t)dt - z_t dB_t, \tag{38}$$

with

$$y_t = \begin{pmatrix} J_t \\ D_sJ_t \end{pmatrix}, z_t = \begin{pmatrix} Z_t \\ D_sZ_t \end{pmatrix}, \tag{39}$$

and

$$f(s,t,x_t,y_t,z_t) = \begin{pmatrix} (1-k_t)(\beta - r_t - \frac{k_t\theta_t^{'}\theta_t}{2} - Z_t^{'}\theta_t) + k_t(\alpha-\beta)J_t + \frac{1}{2}Z_t^{'}Z_t \\ (1-k_t)\left(-D_sr_t - k_t\theta_t^{'}D_s\theta_t - Z_t^{'}D_s\theta_t - \theta_t^{'}D_sZ_t\right) + k_t(\alpha-\beta)D_sJ_t + Z_t^{'}D_sZ_t \end{pmatrix}. \tag{40}$$

The boundary conditions are:

$$J_T = 0, D_sJ_T = 0 \times 1^{'}. \tag{41}$$

Proof. See Appendix A.

Proposition 4.5. With the solution of (J_t, D_sJ_t), the pair (X_t, D_sX_t) can be solved by:

$$X_t = -\int_0^t e^{-\int_s^t((\beta-\alpha)k_v-\beta)dv}\left((\alpha-\beta)J_s - \beta + r_s + \frac{\theta_s^{'}\theta_s}{2}\right)ds - \int_0^t e^{-\int_s^t(\beta-\alpha)k_v-\beta)dv}\,\theta_s^{'}dB_s + e^{-\int_0^t((\beta-\alpha)k_v-\beta)dv}\log(\lambda), \tag{42}$$

$$D_sX_t = -\int_s^t e^{-\int_v^t((\beta-\alpha)k_l-\beta)dl}\left((\alpha-\beta)D_sJ_v + D_sr_v\right)dv + (\theta_v dv + dB_v)^{'}D_s\theta_v) - e^{-\int_s^t((\beta-\alpha)k_l-\beta)dl}\theta_s^{'}.$$

Proof. See Appendix A.

With Proposition 4.5, we can decompose the hedging demand for X_t into the hedging demand against fluctuations in the investment opportunity set and that related to the backward term J_t. This enables us to express the optimal portfolio as three components: the mean-variance portfolio, the forward-hedging term related to D_sX_t and the backward-hedging term related to D_sJ_t.

Theorem 4.6. The optimal portfolio can be expressed as:

$$\begin{aligned} w_t\pi_t^{'}\sigma_t &= E_t\left[\int_t^T \left(D_tJ_u - k_uD_tX_{t,u}\right)c_u\xi_{t,u}du\right] - E_t\left[\int_t^T c_u\xi_{t,u}H_{t,u}du\right] + \theta_t^{'}E_t\left[\int_t^T c_u\xi_{t,u}k_u du\right] \\ &=- E_t\left[\int_t^T c_u\xi_{t,u}H_{t,u}du\right] + \theta_t^{'}E_t\left[\int_t^T c_u\xi_{t,u}k_u du\right] \\ &- E_t\left[\int_t^T\left(\int_t^u e^{\int_v^t((\beta-\alpha)k_l-\beta)dl}\left(D_tr_v dv + (dB_v + \theta_v dv)^{'}D_t\theta_v\right)dv\right)k_uc_u\xi_{t,u}du\right] \\ &+ E_t\left[\int_t^T\left(D_tJ_u + k_u\left(\int_t^u e^{\int_v^t((\beta-\alpha)k_l-\beta)dl}\left((\alpha-\beta)D_tJ_v\right)dv\right)\right)c_u\xi_{t,u}du\right]. \end{aligned} \tag{43}$$

Proof. See Appendix A.

5 NUMERICAL RESULTS

In the numerical experiments, we assume that the short rate follows an Ornstein-Uhlenbeck process as in the Vasicek model:

$$dr_t = (\alpha_r - \beta_r r_t)dt + \sigma_r dw_t. \qquad (5.1)$$

Parameters used for the numerical illustration are summarized in Table 1. Before presenting the numerical results for optimal solutions, we first illustrate the performance of the regression-based Monte Carlo method in Gobet et al. (2005) applied to solve the FBSDE systems[36].

Table 1 Parameters Specifications

T	h	M	w	r_0	α_r	β_r	σ_r	θ	σ_s	β	γ
25	1/12	10000	20	0.07	0.2	4	-0.12	0.09	0.33	0.01	4

*Note: This table reports parameter values for numerical implementations. T: the investment horizon; h: the discretization step; M: the number of trajectories for the Monte Carlo simulation; w: the initial wealth; $r_0, \alpha_r, \beta_r, \sigma_r$: parameters in the Vasicek dynamics of the short rate process; θ: the market price of risk; β: the subjective discount factor; σ_s: the stock volatility; γ: the coefficient of relative risk aversion.

5.1 The Performance of the Regression-Based Method

In this section, we use the regression-based method proposed by Gobet et al. (2005) to solve the FBSDE systems of (X_t, D_sX_t) and $(Y_t, D_sY_t, J_t, D_sJ_t)$ for CRRA and logarithmic utility[4]. We introduce the following notations:

$$\begin{aligned} H^1_{s,t,T} &= -\int_t^T (1-k_v)\big((1-k_v)^2\theta_v' D_s\theta_v\big)dv - \int_t^T (1-k_v)dB_v' D_s\theta_v\,, \\ H^2_{s,t,T} &= -\int_t^T (1-k_v)\big(D_s r_v + k_v\theta_v' D_s\theta_v\big)dv, \\ H^3_{s,t,T} &= \frac{1-\gamma}{\gamma}\int_t^T \big(D_s r_u + k\theta_u' D_s\theta_u\big)du\,. \end{aligned} \qquad (44)$$

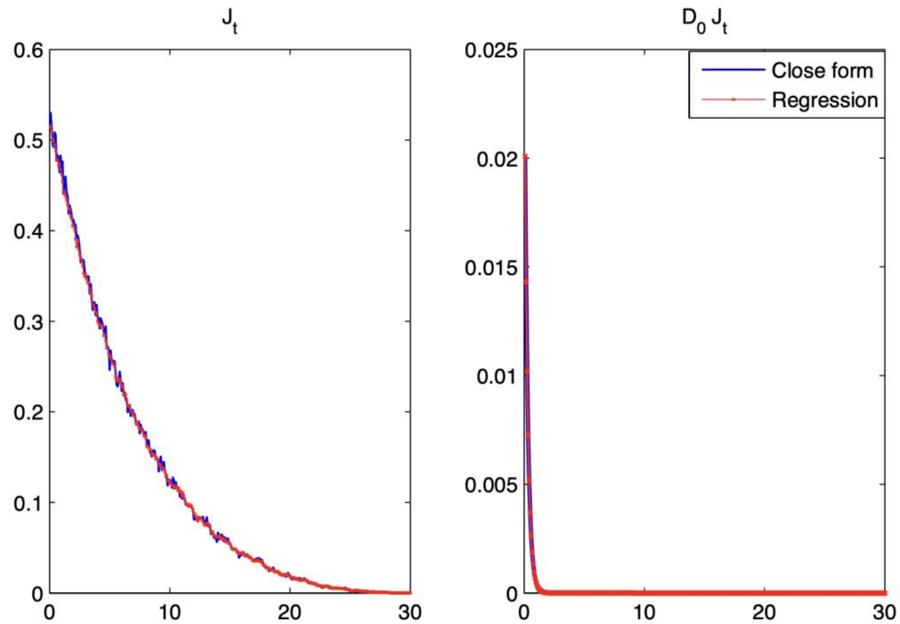
In the case of logarithmic utility, with parameters constraints $\alpha = 0$ or $\alpha = \beta$, the processes J_t and $D_sJ_t(s < t)$ can be solved explicitly:

$$\begin{aligned} \exp(J_t) &= E_t\left[\tilde{\xi}_{t,T}\exp\left(\int_t^T (1-k_v)\left(\beta - r_v - \frac{k_v}{2}\theta_v'\theta_v\right)dv\right)\right], \\ \tilde{\xi}_{t,T} &= \exp\left(-\int_t^T (1-k_v)\theta_v' dB_v - \int_t^T \frac{(1-k_v)^2\theta_v'\theta_v}{2}dv\right), \\ D_sJ_t &= \frac{E_t\left[\tilde{\xi}_{t,T}\exp\left(\int_t^T (1-k_v)\left(\beta - r_v - \frac{k_v}{2}\theta_v'\theta_v\right)dv\right)(H^1_{s,t,T} + H^2_{s,t,T})\right]}{J_t}. \end{aligned} \qquad (45)$$

The first two equations are from Schroder and Skiadas (1999)[1]. The last equation is obtained by applying the chain rule of Malliavin calculus. In the case of $\alpha = 0$, the values of J_t and D_sJ_t are both zero.

We apply the Monte Carlo simulation method to compute the conditional expectations, which are used as a benchmark to evaluate the performance of the regression-based method. As shown in Figure 1, the regression-based method generates numerical solutions that are very close to those calculated from Monte Carlo simulations.

Figure 1 In the Case of $\alpha = \beta$, the Processes J_t and D_0J_t for Logarithmic Utility have Closed-Form Solutions as Conditional Expectations



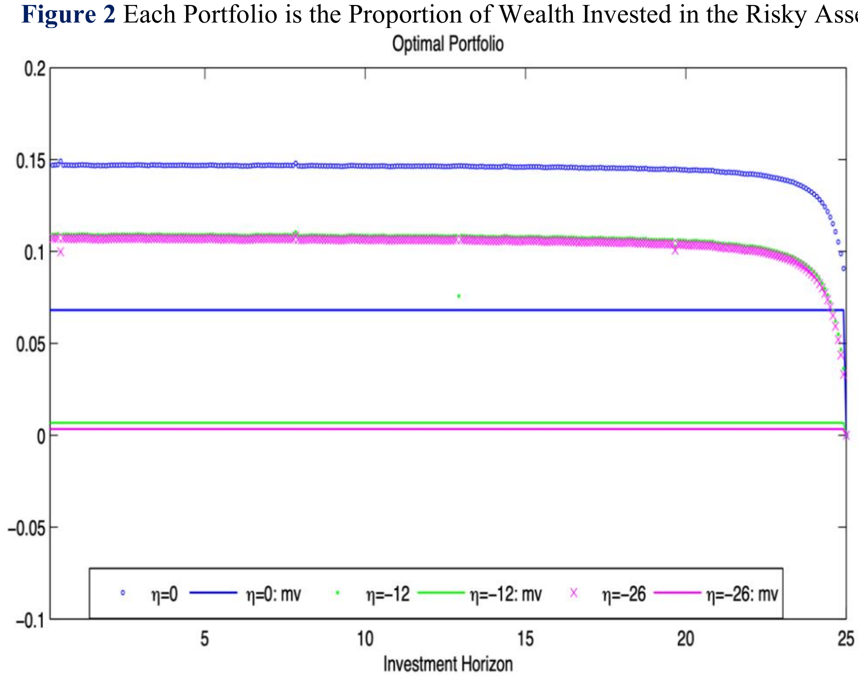
*Note: This figure reports the numerical solutions for J_t and D_0J_t obtained using the regression-based approach and the Monte Carlo simulation approach.

5.2 The Optimal Portfolio

In this section, we study the impacts of ambiguity aversion on the dynamic optimal portfolio in a setting with stochastic investment opportunities. Specifically, we assume a stochastic interest rate process with the dynamics in the Equation (5.1) and keep the market price of risk θ as constant. The latter can also be specified as stochastic.

We see from the Figure 2 that the optimal-portfolio pattern shares some common features with those obtained in an environment without ambiguity. The hedging component changes sign as relative risk aversion is in excess or falls short of one. This illustrates the knife-edge behavior of logarithmic utility. For the investor with relative risk aversion greater than one, the hedging demand for interest rate fluctuations boosts demand fors risky assets, due to the negative correlation between the interest rate and the stock price.

Figure 2 Each Portfolio is the Proportion of Wealth Invested in the Risky Asset



*Note: This figure plots the portfolios for the investor with CRRA utility of $\gamma = 4$ and different ambiguity penalty coefficients.

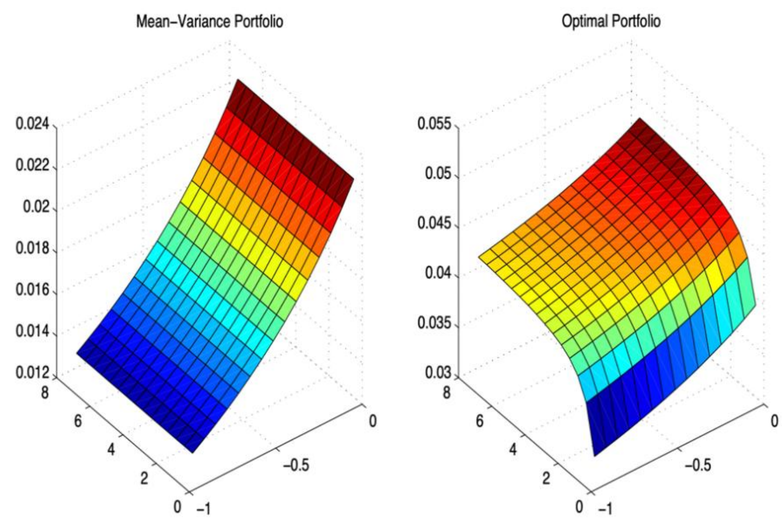
More interestingly, we see significant impacts on the dynamic optimal portfolio from ambiguity aversion. Figure 2 illustrate that ambiguity aversion equivalently increases risk aversion, in a sense that it lowers the constant mean-variance portfolio. The adjusted relative risk aversion is $\gamma + (\gamma - 1) \times (-\eta)$. To reconcile the high relative risk aversion implied by asset prices (for instance, 10) with the moderate degree implied by behavioral studies (for instance, 4), we need an ambiguity penalty coefficient of -2.

In addition to the mean-variance portfolio, ambiguity concerns decrease the total proportion of wealth invested in the stock market. The higher the penalty the investor imposes, the less aggressively he/she invests in the stock market.

In a setting with no ambiguity, the investor with logarithmic utility only invests in the mean-variance portfolio even with a stochastic investment opportunity set. The pattern of the optimal portfolio changes when this investor is ambiguity averse. First, the mean-variance portfolio is time-dependent, even with a constant market price of risk. It is lower at the initiation of investment, as ambiguity aversion increases risk aversion. It grows and approaches the mean-variance portfolio obtained in a setting with no ambiguity at the end of the investment horizon. Second, the investor is no longer myopic and requests an inter-temporal hedging demand. The hedging demand is positive, as it contains the component to hedge for fluctuations in the interest rate, which is negatively correlated with the stock market.

Figure 3 displays the behavior of the optimal portfolio and its mean-variance component relative to the ambiguity aversion and investment horizon, for an investor with CRRA utility and relative risk aversion of 4. The investment horizon is from 0.5 to 7.5 years and the ambiguity penalty is from -1 to 0. The higher the absolute value of the penalty, the more ambiguity averse the investor is. As expected, ambiguity inversion shifts the mean-variance portfolio toward a lower level. The mean-variance portfolio is constant over the investment horizon. The total portfolio, as a fraction of wealth invested in the stock market, is a decreasing (increasing) function of ambiguity aversion (the investment horizon).

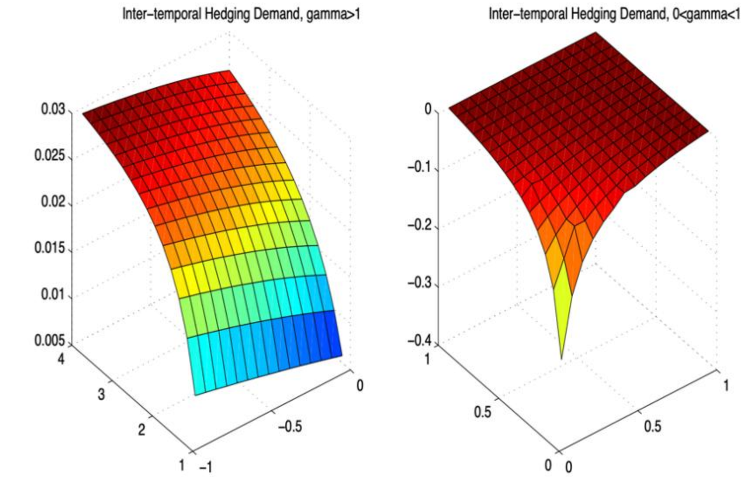
Figure 3 The Optimal Portfolio is the Proportion of Wealth Invested in the Risky Asset



*Note: This figure plots the optimal portfolios for the investor with CRRA utility of $\gamma = 4$, with different ambiguity penalty and investment horizons.

Figure 4 shows the effects of ambiguity aversion and risk aversion on the inter-temporal hedging demand. For an investor with relative risk aversion greater than one, the hedging demand increases with risk aversion and/or ambiguity aversion. On the contrary, when the investor has relative risk aversion smaller than one, this hedging demand is decreasing with risk aversion and/or ambiguity aversion. When the ambiguity aversion and/or risk aversion approach one, the hedging term vanishes. These facts suggest that from the perspective of the hedging demand, to include ambiguity aversion is also observationally equivalent to increasing risk aversion.

Figure 4 The Optimal Portfolio is the Proportion of Wealth Invested in the Risky Asset

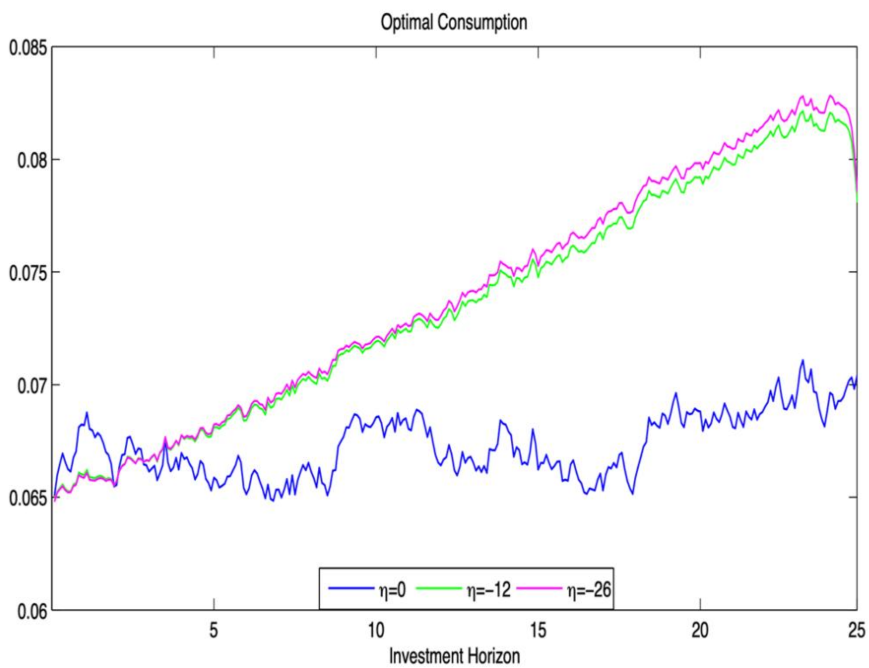


*Note: This figure plots the inter-temporal hedging demands for the investor with CRRA utility of the investment length $T = 15$, with different ambiguity penalty coefficients and risk version coefficients.

5.3 The Optimal Consumption

As illustrated in Figure 5, robustness concerns have a significant effect on the investor's consumption process. The consumption level grows with age as wealth accumulates with time. When the investor ignores ambiguity (i.e., $\eta = \infty$), the optimal consumption level increases as risk aversion increases. The reason is that the more risk averse the investor is, the smoother the consumption plan he/she prefers. As a result, he/she invests less and consumes more. Ambiguity aversion increases risk aversion, and thus induces a higher and more smoothed consumption path.

Figure 5 Optimal Consumption Expenditures are Normalized by the Initial Wealth



*Note: This figure plots the optimal consumption plans for the investor with CRRA utility of $\gamma = 4$ and different ambiguity penalty coefficients.

6 CONCLUSIONS

In this paper, we propose a robust-control problem with a new utility formulation, in which the investor trades off the multiplicative structure of utility derived from consumption and the loss from ambiguity.

We establish the equivalence between this robust-control problem and the SDU maximization problem. Insights obtained from this equivalence result show that the investor with robustness concerns prefers early resolution of uncertainty. We obtain closed-form optimal solutions when the investor has CRRA utility. We provide an alternative representation of the optimal solution based on the Ocone and Karatzas formula[2-3]. This representation decomposes the optimal portfolio into three parts: the mean-variance component, the dynamics hedging component against fluctuations in the investment opportunity set, and the dynamic hedging component for ambiguity concerns.

Numerical implementations for the dynamic optimal solution are provided for the robust-control problem (equivalently, the SDU maximization problem) through the regression-based method for solving the FBSDE systems. This helps us to gain insights into the inter-temporal hedging demand. For the investor with the relative risk aversion greater (smaller) than one, the hedging demand increases (decreases) with ambiguity aversion. With robustness concerns, the investor with logarithmic utility is no longer myopic and has an inter-temporal hedging demand. For the ambiguity-averse investor with constant relative risk aversion greater than one, the younger the investor is, the more aggressively he/she invests in the stock market.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] M Schroder, C. Skiadas. Optimal consumption and portfolio selection with stochastic differential utility. Journal of Economic Theory, 1999, 89(1): 68-126.

[2] DL Ocone, I Karatzas. A generalized Clark representation formula, with application to optimal portfolios. Stochastics and Stochastic Reports, 1991, 34(3-4): 187-220.

[3] J Detemple, R Garcia, M Rindisbacher. A Monte Carlo method for optimal portfolios. Journal of Finance, 2003, 58(1): 401-446.

[4] E Gobet, J Lemor, X Warin. A regression-based Monte Carlo method to solve backward stochastic differential equations. Annals of Applied Probability, 2005, 15(3): 2172-2202.

[5] H Markowitz. Portfolio selection. Journal of Finance, 1952, 7(1): 77-91.

[6] PA Samuelson. Lifetime portfolio selection by dynamic stochastic programming. Review of Economics and Statistics, 1969, 51(3):239-246.

[7] RC Merton. Optimum consumption and portfolio rules in a continuous-time model. Journal of Economic Theory, 1971, 3(4): 373-413.

[8] SR Pliska. A stochastic calculus model of continuous trading: Optimal portfolios. Mathematics of Operations Research, 1986, 11(2): 371-383.

[9] I Karatzas, JP Lehoczky, SE Shreve. Optimal portfolio and consumption decisions for a “small investor” on a finite horizon. SIAM Journal on Control and Optimization, 1987, 25(6): 1557-1586.

[10] JC Cox, C Huang. Optimal consumption and portfolio policies when asset prices follow a diffusion process. Journal of Economic Theory, 1989, 49(1):33-83.

[11] L Hansen, T. Sargent. Robust control and model uncertainty. American Eco- nomic Review, 2001, 91(2): 60-66.

[12] RC Merton. On estimating the expected return on the market: An exploratory investigation. Journal of Financial Economics, 1980, 8(4): 323-361.

[13] I Gilboa, D Schmeidler. Max-min expected utility with non-unique priors. Journal of Mathematical Economics, 1989, 18(2): 141-153.

[14] L Epstein, T Wang. Intertemporal asset pricing under Knightian uncertainty. Econometrica, 1994, 62(2): 283-322.

[15] L Epstein, M. Schneider. Recursive multiple priors. Journal of Economic Theory, 2003, 113: 1-31.

[16] L Epstein, M Schneider. Learning under ambiguity. Review of Economic Study, 2007, 74(4)1275-1303.

[17] L Epstein, M Schneider. Ambiguity, information quality and asset pricing. Journal of Finance, 2008, 63(1): 197-228.

[18] P Klibanoff, M Marinacci, S Mukerji. A smooth model of decision making under ambiguity. Econometrica, 2005, 73(6): 1849-1892.

[19] H Chen, N Ju, J Miao. Dynamic asset allocation with ambiguous return predictability. AFA 2010 Atlanta Meeting Paper, 2011.

[20] N Ju, J Miao. Ambiguity, learning, and asset returns. Econometrica, 2012, 80(2): 559-591.

[21] EW Anderson, LP Hansen, TJ Sargent. A quartet of semigroups for model specification, robustness, prices of risk, and model detection. Journal of the Euro- pean Economic Association, 2003, 1(1): 68-123.

[22] C Skiadas. Smooth ambiguity aversion toward small risks and continuous-time recursive utility. Journal of Political Economy, 2013, 121(4): 775-792.

[23] P Maenhout. Robust portfolio rules and asset pricing. Review of Financial Studies, 2004, 17(4): 951-983.

[24] C Skiadas. Robust control and recursive utility. Finance and Stochastics, 2003, 7(4): 475-489.
[25] DJ Meyer, J Meyer. Measuring Risk Aversion. Foundations and trends in microeconomics. Now Publishers, 2006.
[26] JY Campbell, YL Chan, LM Viceira. A multivariate model of strategic asset allocation. Journal of Financial Economics, 2003, 67(1): 41-80.
[27] F Maccheroni, M Marinacci, A Rustichini. Ambiguity aversion, malevolent nature, and the variational representation of preferences. Econometrica, 2006, 74(6): 1447-1498.
[28] J Miao, T Hayashi. Intertemporal substitution and recursive smooth ambiguity preferences. Economics, 2011, 6(3): 423-472.
[29] P Maenhout. Robust portfolio rules and detection-error probabilities for a mean- reverting risk premium. Journal of Economic Theory, 2006, 128(1): 136-163.
[30] J Berger. Statistical Decision Theory and Bayesian Analysis. Springer, 2nd edition, 1985.
[31] D Nualart. The Malliavin Calculus and Related Topics. Springer Verlag, 1995.
[32] NE Karoui, S Peng, MC Quenez. Backward stochastic differential equations in finance. Mathematical Finance, 1997, 7(1): 1-71.
[33] LP Hansen. Large sample properties of generalized method of moments estimators. Econometrica, 1982, 50(4): 1029-1054.
[34] LP Hansen, TJ Sargent. Robustness. Princeton University Press, 2008.
[35] AR Pedersen. A new approach to maximum likelihood estimation for stochastic differential equations based on discrete observations. Scandinavian Journal of Statistics, 1995, 22(1): 55-71.
[36] C Skiadas. Recursive utility and preferences for information. Economic Theory, 1998, 12: 293-312.

APPENDIX A

Before the proof of the main result, Theorem 3.1, we present the following results.

Lemma 1. The process V_t^x defined in Equation (2.2) can be expressed as:

$$V_t^x = \widetilde{E}_t\left[\int_t^T \exp\left(\int_t^s - \beta_v dv)\right) u(c_s) \exp\left(\frac{\eta}{2(\eta-1)^2}\int_t^s x_v^{'} x_v dv\right) ds\right]. \qquad (A.1) \tag{46}$$

Proof of Lemma 1.

$$V_t^x = E_t\left[\int_t^T \exp\left(-\int_t^s \beta_v dv\right) u(c_s)\left(d_{t,s}^x\right)^\kappa ds\right] = \widetilde{E}_t\left[\int_t^T \exp\left(-\int_t^s \beta_v dv\right) u(c_s) \exp\left(\frac{\kappa^2}{2}\int_t^s x_v^{'} x_v dv - \frac{\kappa}{2}\int_t^s x_v^{'} x_v dv\right) ds\right]. \tag{47}$$

The last equation gives:

$$V_t^x = \widetilde{E}_t\left[\int_t^T \exp\left(-\int_t^s \beta_v dv\right) u(c_s) \exp\left(\frac{\eta}{2(\eta-1)^2}\int_t^s x_v^{'} x_v dv\right) ds\right]. \tag{48}$$

Lemma 2. Define η_x as $\kappa^2 - \kappa = \frac{\eta}{(1-\eta)^2}$. There exists an adapted process σ_t^x such that the expression of V_t^x in Equation (A.1) has the dynamics:

$$dV_t^x = \left(\beta_t V_t^x - u_t - \frac{\eta_x}{2} x_t^{'} x_t V_t^x\right) dt + (\sigma_t^x)^{'} d\widetilde{B}_t, \qquad (A.2) \tag{49}$$

with the boundary condition $V_T^x = 0$.

Proof of Lemma 2. According to the PDE (A.2), we can express V_t^x as:

$$V_t^x = \exp\left(\int_0^t \beta_s ds\right) \exp\left(-\frac{\eta_x}{2}\int_0^t x_s^{'} x_s ds\right) f(t, c_t), \tag{50}$$

with the boundary condition $f(T, c_T) = 0$, for some function $f(\cdot,\cdot)$. By taking derivation on both sides of the equation above and equalizing it with the PDE (A.2), we have:

$$dV_t^x = \left(\beta_t V_t^x - u_t - \frac{\eta_x}{2} x_t^{'} x_t V_t^x\right) dt + (\sigma_t^x)' d\widetilde{B}_t. \tag{51}$$

As a result, we have $df(t, c_t)$ as:

$$df(t, c_t) = \exp\left(-\int_0^t \beta_s ds\right) \exp\left(\frac{\eta_x}{2}\int_0^t x_s^{'} x_s ds\right)\left(-u_t dt + (\sigma_t^x)' d\widetilde{B}_t\right). \tag{52}$$

Integrating from t to T and applying the boundary condition, we have:

$$V_t^x = \int_t^T \left(\exp\left(-\int_t^s \beta_v dv\right) \exp\left(\frac{\eta_x}{2}\int_t^s x_v^{'} x_v dv\right)\right)\left(u_s ds - (\sigma_s^x)^{'} d\widetilde{B}_s\right). \tag{53}$$

By taking expectation under $\widetilde{P}$ on both sides, we have:

$$V_t^x = \widetilde{E}_t\left[\int_t^T \exp\left(-\int_t^s \beta_v dv\right) \exp\left(\frac{\eta_x}{2}\int_t^s x_v^{'} x_v dv\right) u(c_s) ds\right]. \tag{54}$$

The existence of the adapted process σ_t^x is given by the martingale representation theorem.

From lemma 1, we can express V_t^x as:

$$V_t^x = \widetilde{E}_t\left[\int_t^T \exp\left(-\int_t^s \beta_v dv\right)\right) u(c_s) \exp\left(\frac{\eta_x}{2}\int_t^s x_v' x_v dv\right) ds\right]. \tag{55}$$

Proof of Theorem 3.1. Denote the discounted version for a process V_t as:

$$\overline{V}_t = \exp\left(-\int_0^t \beta_s ds\right) V_t. \tag{56}$$

The dynamics of $\overline{V}_t^x$ are:

$$d\overline{V}_t^x = -\beta_t \exp\left(-\int_0^t \beta_s ds\right) V_t^x dt + \exp\left(-\int_0^t \beta_s ds\right) dV_t^x = -\left(\bar{u}_t + \frac{\eta_x}{2} x_t' x_t \overline{V}_t^x\right) dt + (\overline{\sigma}_t^x)' d\widetilde{B}_t. \tag{57}$$

The dynamics of V_t under the P measure is:

$$dV_t = -\left(u_t - \beta_t V_t - \frac{\eta}{2V_t}(\sigma_t^b)' \sigma_t^b\right) dt + (\sigma_t^b)' dB_t. \qquad (A.3) \tag{58}$$

Convert the dynamics of V_t into the $\widetilde{P}$ measure:

$$dV_t = -\left(u_t - \beta_t V_t - \frac{\eta}{2V_t}(\sigma_t^b)' \sigma_t^b - \kappa(\sigma_t^b)' x_t\right) dt + (\sigma_t^b)' d\widetilde{B}_t. \tag{59}$$

The dynamics of $d\overline{V}_t$ is:

$$d\overline{V}_t = -\left(\bar{u}_t - \frac{\eta}{2\overline{V}_{t_t}}(\overline{\sigma}_t^b)' \overline{\sigma}_t^b - \kappa(\overline{\sigma}_t^b)' x_t\right) dt + ((\overline{\sigma}_t^b)' d\widetilde{B}_t. \tag{60}$$

Combining the dynamics of $d\overline{V}_t^x$ and $d\overline{V}_t$, we have:

$$d(\overline{V}_t^x - \overline{V}_t) = -\frac{\eta_x}{2} x_t' x_t (\overline{V}_t^x - \overline{V}_t) dt + (\overline{\sigma}_t^x - \overline{\sigma}_t^b)' d\widetilde{B}_t - \frac{1}{2}\left(x_t\sqrt{\eta_x \overline{V}_t} + \overline{\sigma}_t^b \sqrt{\frac{\eta}{\overline{V}_t}}\right)' \left(x_t\sqrt{\eta_x \overline{V}_t} + \overline{\sigma}_t^b \sqrt{\frac{\eta}{\overline{V}_t}}\right) dt. \tag{61}$$

Note that in the dynamics of V_t in Equation (A.3), if $u > 0 (u < 0)$, then we have $V > 0 (V < 0)$ by Theorem A2 in Schroder and Skiadas (1999)[1]. The relationship holds under the $\widetilde{P}$ measure, as $\widetilde{P}$ is equivalent to P. As we specify $\eta < 0 (0 \leq \eta < 1)$ for the utility process $u < 0 (u > 0)$, we have $\frac{\eta}{V_t} \geq 0$.

Denote the process K_t as:

$$K_t = (\overline{V}_t^x - \overline{V}_t) \exp\left(\frac{\eta_x}{2}\int_0^t x_s' x_s ds\right). \tag{62}$$

The dynamics of K_t are given by:

$$dK_t = \exp\left(\frac{\eta_x}{2}\int_0^t x_s' x_s ds\right)\left(-\frac{1}{2}\left(x_t\sqrt{\eta_x \overline{V}_t} + \overline{\sigma}_t^b \sqrt{\frac{\eta}{\overline{V}_t}}\right)' \left(x_t\sqrt{\eta_x \overline{V}_t} + \overline{\sigma}_t^b \sqrt{\frac{\eta}{\overline{V}_t}}\right) dt + (\overline{\sigma}_t^x - \overline{\sigma}_t^b)' d\widetilde{B}_t\right). \tag{63}$$

Integrate on both sides from t to T and take expectation under $\widetilde{P}$:

$$K_T - K_t = \widetilde{E}_t\left[\int_t^T \exp\left(\frac{\eta_x}{2}\int_0^s x_v' x_v dv\right)\left(-\frac{1}{2}\left(x_t\sqrt{\eta_x \overline{V}_s} + \overline{\sigma}_s^b \sqrt{\frac{\eta}{\overline{V}_s}}\right)' \left(x_s\sqrt{\eta_x \overline{V}_s} + \overline{\sigma}_s^b \sqrt{\frac{\eta}{\overline{V}_s}}\right) ds\right)\right]. \tag{64}$$

Replace K_t with $(\overline{V}_t^x - \overline{V}_t)\exp\left(\frac{\eta_x}{2}\int_0^t x_s' x_s ds\right)$ and apply boundary conditions on $\overline{V}_t$ and $\overline{V}_t^x$:

$$\overline{V}_t^x - \overline{V}_t = \widetilde{E}_t\left[\int_t^T \exp\left(\frac{\eta_x}{2}\int_0^s x_v' x_v dv\right)\left(\frac{1}{2}\left(x_t\sqrt{\eta_x \overline{V}_s} + \overline{\sigma}_s^b \sqrt{\frac{\eta}{\overline{V}_s}}\right)' \left(x_s\sqrt{\eta_x \overline{V}_s} + \overline{\sigma}_s^b \sqrt{\frac{\eta}{\overline{V}_s}}\right) ds\right)\right]. \tag{65}$$

Convert the discount back, we get :

$$V_t^x - V_t = \widetilde{E}_t\left[\int_t^T \exp\left(\frac{\eta_x}{2}\int_0^s x_v' x_v dv\right)\left(\frac{1}{2}\left(x_t\sqrt{\eta_x V_s} + \sigma_s^b \sqrt{\frac{\eta}{V_s}}\right)' \left(x_s\sqrt{\eta_x V_s} + \sigma_s^b \sqrt{\frac{\eta}{V_s}}\right) ds\right)\right]. \tag{66}$$

The term on the right-hand side is greater or equal to zero, with the zero-value obtained by imposing below:

$$x_t = -\sigma_t^b \left|\frac{1-\eta}{V_t}\right|. \tag{67}$$

Proof of Proposition 3.2. First consider the case $V_t > 0$. The ordinally equivalent transformation of V_t is

$$v_t = V_t^{1-\eta}. \tag{68}$$

By the Ito's lemma, we have:

$$dv_t = (1-\eta)V_t^{-\eta}\left(-(u_t - \beta_t V_t)dt + (\sigma_t^b)' dB_t\right). \tag{69}$$

Integrate and take expectations on both sides:

$$v_T - v_t = E_t\left[\int_t^T (1-\eta)V_s^{-\eta}(-u_s + \beta_s V_s)ds\right]. \tag{70}$$

Replace V_t with $v_t^{\frac{1}{1-\eta}}$, we have:

$$v_t = E_t\left[\int_t^T (1-\eta)\left(v_s^{\frac{\eta}{\eta-1}}u_s - \beta_s v_s\right)ds\right]. \tag{71}$$

The similar analysis can be applied to $V_t < 0$ gives:

$$v_t = E_t\left[\int_t^T (1-\eta)\left((-v_s)^{\frac{\eta}{\eta-1}}u_s - \beta_s v_s\right)ds\right]. \tag{72}$$

By taking two cases together, we have:

$$v_t = E_t\left[\int_t^T (1-\eta)\left(|v_s|^{\frac{\eta}{\eta-1}}u_s - \beta_s v_s\right)ds\right]. \tag{73}$$

Proof of Theorem 4.1. The state variable Y_t has the dynamics:

$$dY_t = \mu(t, Y_t)dt + \sigma(t, Y_t)dB_t. \tag{74}$$

The Maliavin derivative D_sY_t follow the dynamics:

$$d(D_sY_t) = \partial_2\mu(t, Y_t)(D_sY_t)dt + \partial_2\sigma(t, Y_t)(D_sY_t)dB_t, \tag{75}$$

with initial condition $D_sY_s = \sigma(Y_s)$.

For the case of the CRRA utility, Schroder and Skiadas (1999) show that the pair (J, Z) follows the process[1]:

$$-dJ_t = F(t, \theta_t, \sigma_t, Y_t, Z_t) - Z_t^{'}dB_t, \tag{76}$$

where

$$F(t, \theta_t, \sigma_t, Y_t, Z_t) = \frac{1}{1-\gamma}(1+\alpha)^{\frac{1-\gamma}{\gamma}} + \frac{1-\gamma}{\gamma}\left(r_t - \frac{\beta}{1-\gamma} + \frac{k\theta_t^{'}\theta_t}{2}\right)J_t + \frac{\alpha k}{2}\frac{Z_t^{'}Z_t}{J_t} - Z_t^{'}(1-k)\theta_t. \tag{77}$$

In this BSDE associated with a forward equation, for $0 \le s \le t \le T$, the dynamics of Malliavin derivative D_sY_t are:

$$-D_sJ_t = G(s, t, \theta_t, \sigma_t, Y_t, Z_t)dt - (dB_t)^{'}D_sZ_t, \tag{78}$$

with

$$\begin{aligned} &G(s, t, \theta_t, \sigma_t, Y_t, Z_t) \\ &= -(1-k)\left(\theta_t^{'}D_sZ_t + Z_t^{'}D_s\theta_t\right) + \frac{1-\gamma}{\gamma}\left(\left(D_sr_t + k\theta_t^{'}D_s\theta_t\right)J_t + \left(r_t - \frac{\beta}{1-\gamma} + \frac{k\theta_t^{'}\theta_t}{2}\right)D_sJ_t\right) \\ &+ \frac{\alpha k}{2}\left(\frac{2Z_t^{'}}{J_t}D_sZ_t - \frac{Z_t^{'}Z_t}{J_t^2}D_sJ_t\right), \end{aligned} \tag{79}$$

and the initial condition is:

$$D_sJ_T = 0 \times 1^{'}. \tag{80}$$

The calculation rule and smoothing conditions can be found in Karoui et al. (1997)[32].

Proof of Proposition 4.2. The dynamics of X_t is given by Schroder and Skiadas (1999)[1]:

$$dX_t = -\left[\frac{\alpha}{1-\gamma}(1+\alpha)^{\frac{1-\gamma}{\gamma}}J_t^{-1} - (1+\alpha)\beta + r_t + \frac{\theta_t^{'}\theta_t}{2}\right]dt - \theta_t^{'}dB_t. \tag{81}$$

For $0 \le s \le t \le T$, the Malliavin derivative D_sX_t has the dynamics:

$$dD_sX_t = -\left[D_sr_t - \frac{\alpha}{1-\gamma}(1+\alpha)^{\frac{1-\gamma}{\gamma}}J_t^{-2}D_sJ_t\right]dt - (dB_t + \theta_t dt)^{'}D_s\theta_t, \tag{82}$$

with initial condition:

$$D_sX_s = -\theta_s^{'}. \tag{83}$$

Proof of Theorem 4.3. The optimal wealth w_t at time t is

$$\xi_t w_t = E_t\left[\int_t^T \xi_u c_u du\right]. \tag{84}$$

By the Ito's lemma, the diffusion process on the left-hand side of the equation above is:

$$-\xi_t w_t \theta_t^{'} + \xi_t w_t \pi_t^{'}\sigma_t. \tag{85}$$

By the Clark-Ocone formula, the diffusion process on the right-hand side of the equation above is:

$$E_t\left[\int_t^T D_t(\xi_s c_u)du\right]. \tag{86}$$

The chain rule of Malliavin calculus gives:

$$D_t(\xi_u c_u) = \xi_u D_t(c_u) - c_u\xi_u\left(\theta_t^{'} + H_{t,u}\right). \tag{87}$$

Then we have:

$$E_t\left[\int_t^T D_t(\xi_u c_u)du\right] = E_t\left[\int_t^T \left(\xi_u D_t(c_u) - c_u \xi_u H_{t,u}\right)du\right] - w_t \xi_t \theta_t^{'}. \tag{88}$$

Equate both sides gives:

$$\xi_t w_t \sigma_t^{'} \pi_t = E_t\left[\int_t^T \left(\xi_u D_t(c_u) - c_u \xi_u H_{t,u}\right)du\right]. \tag{89}$$

That is

$$w_t \sigma_t^{'} \pi_t = E_t\left[\int_t^T \left(\xi_{t,u} D_t(c_u) - c_u \xi_{t,u} H_{t,u}\right)du\right]. \tag{90}$$

Denote $X_{t,u}$ as $X_u - X_t$. Applying the chain rule of Malliavin calculus, we have:

$$D_t(c_u) = c_u\left(-kD_t X_{t,u} + \frac{\alpha k}{J_i} D_t J_u\right) + k\theta_t^{'} c_t. \tag{91}$$

Rearrange the terms and we have:

$$w_t \pi_t^{'} \sigma_t = E_t\left[\int_t^T \xi_{t,u} c_u\left(-kD_t X_{t,u} + \frac{\alpha k}{J_u} D_t J_u\right)ds\right] - E_t\left[\int_t^T c_u \xi_{t,u} H_{t,u} ds\right] + k\theta_t^{'} w_t. \tag{92}$$

Proof of Theorem 4.4. The dynamics of $(Y_t, D_s Y_t)$ are the same as in Theorem 4.1. For the case of the logarithmic utility, Schroder and Skiadas (1999) show that the process (J, Z) follows the process[1]:

$$-dJ_t = F(t, \theta_t, \sigma_t, Y_t, Z_t) - Z_t^{'} dB_t, \tag{93}$$

with

$$F(t, \theta_t, \sigma_t, Y_t, Z_t) = (1 - k_t)\left(\beta - r_t - \frac{k_t \theta_t^{'} \theta_t}{2} - Z_t^{'} \theta_t\right) + k_t(\alpha - \beta)J_t + \frac{1}{2} Z_t^{'} Z_t. \tag{94}$$

In this BSDE associated with a forward equation, for $0 \le s \le t \le T$, the dynamics of the Malliavin derivative $D_s Y_t$ are

$$-D_s J_t = G(s, t, \theta_t, \sigma_t, Y_t, Z_t)dt - (dB_t)^{'} D_s Z_t, \tag{95}$$

with

$$G(s, t, \theta_t, \sigma_t, Y_t, Z_t) = k_t(\alpha - \beta)D_s J_t + Z_t^{'} D_s Z_t + (1 - k_t)\left(-D_s r_t - k_t \theta_t^{'} D_s \theta_t - Z_t^{'} D_s \theta_t - \theta_t^{'} D_s Z_t\right), \tag{96}$$

and the initial condition is:

$$D_s J_T = 0 \times 1^{'}. \tag{97}$$

Proof of Proposition 4.5. Express X_t as:

$$X_t = \exp\left(-\int_0^t \left((\beta_v - \alpha)k_v - \beta\right)dv\right) K_t. \tag{98}$$

The Ito's lemma and the dynamics of X_t gives:

$$\begin{aligned} dX_t &= -X_t\left((\beta - \alpha)k_t - \beta\right)dt + \exp\left(-\int_0^t \left((\beta - \alpha)k_v - \beta\right)dv\right)dK_t \\ &= -\left(\left((\beta - \alpha)k_t - \beta\right)X_t + (\alpha - \beta)J_t - \beta + r_t + \frac{\theta_t^{'}\theta_t}{2}\right)dt - \theta_t^{'} dB_t. \end{aligned} \tag{99}$$

As a result, we have:

$$dK_t = -\left(\left((\alpha - \beta)J_t - \beta + r_t + \frac{\theta_t^{'}\theta_t}{2}\right)dt + \theta_t^{'} dB_t\right)\exp\left(\int_0^t \left((\beta - \alpha)k_v - \beta\right)dv\right), \tag{100}$$

with

$$K_0 = \log(\lambda). \tag{101}$$

Integrate on K_t, and plug it back into the expression of X_t, we have:

$$\begin{aligned} X_t =& -\int_0^t \exp\left(-\int_s^t \left((\beta - \alpha)k_v - \beta\right)dv\right)\left(\left((\alpha - \beta)J_s - \beta + r_s + \frac{\theta_s^{'}\theta_s}{2}\right)ds + \theta_s^{'} dB_s\right) \\ &+ \exp\left(-\int_0^t \left((\beta - \alpha)k_v - \beta\right)dv\right)\log(\lambda). \end{aligned} \tag{102}$$

The chain rule of Malliavin calculus gives:

$$dD_s X_t = -\left(\left((\beta - \alpha)k_t - \beta\right)D_s X_t + (\alpha - \beta)D_s J_t + D_s r_t + \theta_t^{'} D_s \theta_t\right)dt - (dB_t)^{'} D_s \theta_t, \tag{103}$$

with the initial condition:

$$D_s X_s = -\theta_s^{'}. \tag{104}$$

By the similar analysis for X_t, the process $D_s X_t$ can be expressed as:

$$D_sX_t = -\int_s^t \exp\left(-\int_v^t \exp\left(-\int_v^t ((\beta-\alpha)k_l-\beta)dl\right)\left(\left((\alpha-\beta)D_sJ_v + D_sr_v + \theta_v' D_s\theta_v\right)dv + (dB_s)' D_s\theta_v\right) + \exp\left(-\int_s^t ((\beta-\alpha)k_l-\beta)dl\right)\theta_s'. \quad (105)$$

Proof of Theorem 4.6. The expression of πt is the same as in Theorem 4.3:

$$w_t\pi_t'\sigma_t = E_t\left[\int_t^T \left(\xi_{t,u}D_t(c_u) - c_u\xi_{t,u}H_{t,u}\right)du\right]. \quad (106)$$

By applying the chain rule of Malliavin calculus, we have:

$$D_t(c_u) = c_u(D_tJ_u - k_uD_tX_u) = c_u\left(D_tJ_u - k_uD_tX_{t,u} + k_u\theta_t\right). \quad (107)$$

Then the optimal portfolio can be expressed as:

$$w_t\pi_t'\sigma_t = E_t\left[\int_t^T \left(D_tJ_u - k_uD_tX_{t,u}\right)c_u\xi_{t,u}du\right] - E_t\left[\int_t^T c_u\xi_{t,u}H_{t,u}du\right] + \theta_tE_t\left[\int_t^T c_u\xi_{t,u}k_udu\right]. \quad (108)$$

Replacing the expression of $D_tX_{t,u}$ of Proposition (4.5), we can express π_t as:

$$\begin{aligned} w_t\pi_t'\sigma_t = {} & E_t\left[\int_t^T \left(D_tJ_u + k_u\left(\int_t^u e^{\int_t^v ((\beta-\alpha)k_l-\beta)dl}\left((\alpha-\beta)D_tJ_v\right)dv\right)\right)c_u\xi_u du\right] \\ & - E_t\left[\int_t^T \left(\int_t^u \exp^{\int_v^t ((\beta-\alpha)k_l-\beta)dl}\left(D_tr_vdv + (dB_v+\theta_vdv)'D_t\theta_v\right)dv\right)k_uc_u\xi_{t,u}du\right]. \end{aligned} \quad (109)$$