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Self-Optimizing Digital Twins for Omnichannel Retail Experiences

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ABSTRACT

This paper presents a Self-Optimizing Digital Twin framework for omnichannel retail experiences. The proposed approach builds AI driven simulations of customer journeys across physical stores and digital platforms. By learning from interaction sequences and feedback signals, the system improves personalization and product discovery decisions over time. The framework supports better journey continuity, stronger engagement, and higher conversion efficiency in omnichannel environments.

Keywords: Digital Twins, Omnichannel Retail, Customer Journey, Product Discovery, Personalization, Simulation, Reinforcement Learning

INTRODUCTION

Omnichannel retail has transformed the way customers interact with brands. A single customer journey can begin with social media discovery, continue through mobile browsing, shift into a physical store visit for product evaluation, and finally end with an online purchase. These journeys are rarely linear. They evolve through repeated touchpoints, shifting intent, and changing constraints such as product availability, pricing, delivery timelines, and promotional triggers. Most retail personalization systems are designed to optimize isolated actions. They aim to improve click through rates, increase cart additions, or raise immediate sales. While these improvements are valuable, they often fail to capture the full journey context. The customer is not only reacting to a single recommendation but also responding to their broader experience across channels. A recommendation that performs well in the moment may reduce overall satisfaction if it creates confusion, lacks continuity, or ignores real intent.

To address this challenge, the idea of digital twins offers a strong direction. Digital twins are built as virtual replicas of real systems that update continuously through observed data. In retail, the customer journey itself becomes the system to replicate. When these journey twins are combined with learning based optimization methods, the result is a self improving personalization environment that continuously adapts based on actual customer outcomes. This paper proposes Self Optimizing Digital Twins for omnichannel retail. The framework simulates customer behaviors across channels and updates its decision policies based on feedback loops. It aims to enhance personalized product discovery, strengthen customer journey continuity, and improve overall conversion efficiency.

LITERATURE REVIEW

Digital Twin (DT) technology has emerged as a foundational pillar for intelligent, data-driven systems across industries. Fuller et al. (2020) provide one of the most comprehensive early frameworks for digital twins by identifying enabling technologies such as IoT, cloud computing, artificial intelligence, and real-time data synchronization. Their work highlights the importance of continuous feedback loops between physical and virtual systems, which directly supports the concept of self-optimizing digital twins. The authors also discuss scalability and interoperability challenges, laying the groundwork for applying DTs in complex environments such as omnichannel retail ecosystems.

The conceptual roots of digital twins can be traced back to the broader vision of Industry 4.0, as articulated by Lasi et al. (2014). This work establishes cyber-physical systems as a central mechanism for integrating digital intelligence into physical operations. Although the study focuses largely on manufacturing, its principles automation, real-time monitoring, and decentralized decision-making are directly transferable to retail systems. Omnichannel retail, with its need for synchronized online and offline operations, aligns strongly with the Industry 4.0 paradigm described in this foundational research.

Expanding digital twin research beyond manufacturing, Mesquita, Leal, and De Queiroz (2024) conduct a systematic literature review specifically targeting the retail industry. Their findings reveal that retail-oriented digital twins are increasingly used for store layout optimization, inventory control, demand forecasting, and customer behavior analysis.

Importantly, the authors identify a research gap in autonomous optimization capabilities, emphasizing the need for self-learning and adaptive retail digital twins that can respond dynamically to omnichannel customer interactions.

Industry-focused insights are provided by McKinsey & Company (2020), which explores the strategic impact of digital twins on retail transformation. The report demonstrates how digital twins enable retailers to simulate customer journeys across physical stores, e-commerce platforms, and logistics networks. By leveraging predictive analytics and scenario modeling, retailers can proactively optimize pricing, inventory placement, and fulfillment strategies. This work strongly supports the role of digital twins as decision-intelligence engines rather than passive visualization tools.

Wang and Wang (2021) present a systematic review of digital twin technology across multiple domains, offering a generalized architecture that includes data acquisition, modeling, simulation, and optimization layers. Their analysis emphasizes the role of artificial intelligence in enabling adaptive and self-evolving digital twins. While the paper is domain-agnostic, its architectural insights are critical for designing retail digital twins capable of real-time optimization in omnichannel environments where customer demand and supply conditions change rapidly.

Rojko (2017) provides a conceptual overview of Industry 4.0 and its implications for digital transformation. The study highlights smart systems, autonomous decision-making, and real-time analytics as key enablers of next-generation digital platforms. In the context of retail, these concepts support the development of digital twins that can autonomously adjust marketing strategies, inventory levels, and customer engagement mechanisms across channels, reinforcing the relevance of Industry 4.0 principles in omnichannel retail optimization.

Focusing more directly on retail, Wei and Lee (2019) propose a digital twin system architecture tailored for smart retail environments. Their work introduces the idea of virtual store replicas that mirror physical retail spaces and customer interactions. The study demonstrates how real-time data from sensors and transaction systems can be used to optimize store operations, layout design, and customer flow management, forming an early foundation for intelligent, self-optimizing retail twins.

Yang and Chang (2021) examine data fusion and model integration techniques for smart retail systems. Their research highlights the importance of integrating heterogeneous data sources such as point-of-sale systems, customer behavior analytics, and supply chain data. This multi-source integration is essential for omnichannel digital twins, as it enables holistic optimization across physical and digital retail touchpoints, ensuring consistent customer experiences and operational efficiency.

Wu and Liu (2023) explore the convergence of IoT and AI within digital twin frameworks for retail environments. Their study demonstrates how sensor-driven data combined with machine learning models can enhance demand prediction, shelf replenishment, and customer engagement strategies. The authors emphasize real-time responsiveness as a key benefit, aligning closely with the concept of self-optimizing digital twins capable of autonomous decision-making in omnichannel retail systems.

Finally, Brown and Tan (2023) focus on real-time inventory optimization using digital twins in multi-location retail chains. Their work shows how digital twin models can simulate inventory flows across warehouses, physical stores, and online channels simultaneously. By continuously learning from sales and logistics data, these systems reduce stockouts and overstock situations, demonstrating the practical value of self-optimizing digital twins in supporting seamless omnichannel retail experiences.

Chien and Chen (2022) present a comprehensive review of artificial intelligence applications in the retail sector, emphasizing how AI-driven analytics enhance decision-making across pricing, demand forecasting, and customer personalization. Their study highlights machine learning and deep learning as critical enablers for intelligent retail systems. When integrated with digital twins, these AI techniques provide the adaptive intelligence required for self-optimization, allowing retail twins to learn continuously from omnichannel customer interactions and operational data.
Adivar et al. (2019) propose a quantitative performance management framework for omnichannel retail supply chains, addressing the complexity arising from integrated online and offline channels. Their work demonstrates how synchronized inventory, logistics, and customer demand data improve overall supply chain responsiveness. This research provides an essential foundation for omnichannel digital twins, as it underscores the need for unified data models capable of evaluating and optimizing performance across multiple retail channels simultaneously.

McKinsey & Company (2024) extend the discussion by focusing on end-to-end supply chain digital twins, emphasizing their role in enabling predictive and prescriptive analytics. The report illustrates how digital twins facilitate scenario-based optimization, allowing retailers to test fulfillment strategies, inventory allocation, and transportation models virtually before real-world implementation. Such capabilities are particularly relevant for omnichannel retail, where rapid adaptation to fluctuating demand is critical for maintaining service levels and cost efficiency.

Zacharias (2025), building on earlier digital twin research, explores simulation-based digital twin models for demand-driven inventory replenishment. Although published later, the study synthesizes pre-2024 research to demonstrate how virtual replicas of retail systems enable proactive inventory planning. The work reinforces the importance of real-time data synchronization and optimization algorithms, which are central to the design of self-optimizing digital twins in omnichannel retail contexts.

Mesquita and Teixeira (2025) introduce the concept of digital shadows supported by computer vision technologies for retail shelf management. Their research highlights how visual data can enhance the accuracy of digital twin representations by capturing real-time shelf conditions and product placement. This contribution is particularly relevant for omnichannel retail environments, as it bridges the gap between physical store conditions and digital sales platforms, enabling more accurate and autonomous optimization decisions.

Pous et al. (2025) investigate the use of RFID-enabled autonomous mobile robots to populate and update digital twins of retail stores. Their study demonstrates how automated data collection improves the fidelity of digital twin models, reducing manual intervention and latency. The findings support the feasibility of scalable and self-updating retail digital twins, which are essential for real-time optimization across large omnichannel retail networks.

Lasi and Wortmann (2016) extend Industry 4.0 concepts to smart retail environments, emphasizing the role of digital twins in enabling intelligent automation and data-driven operations. Their work argues that digital twins serve as a central integration layer connecting cyber-physical systems with business intelligence tools. This perspective reinforces the strategic importance of digital twins as optimization engines that align operational efficiency with enhanced customer experiences.

Smith and Johnson (2023) focus on customer engagement enhancement through digital twin technologies in retail. Their study shows how digital twins can simulate customer journeys, preferences, and interactions across multiple channels. By enabling retailers to predict customer behavior and personalize experiences in real time, this research demonstrates how self-optimizing digital twins contribute not only to operational efficiency but also to customer-centric omnichannel strategies.

Elkhoury, El Khoury, and El Murr (2024) provide an industry-oriented analysis of the benefits and challenges of digital twin adoption in retail. Their work identifies improved visibility, predictive analytics, and operational agility as key benefits, while also noting challenges related to data integration and system complexity. These insights highlight the necessity of self-optimizing mechanisms to manage complexity and ensure sustained performance in omnichannel retail ecosystems.

Reynolds (2024) examines digital twins as optimization tools for retail operations, emphasizing their role in improving demand forecasting, inventory accuracy, and supply chain resilience. The study underscores how continuous feedback and learning mechanisms transform digital twins from static models into adaptive systems. This evolution aligns directly with the concept of self-optimizing digital twins, which autonomously refine strategies to support seamless omnichannel retail experiences.

Attaran (2023) provides a broad yet insightful examination of digital twin technology, outlining its benefits, practical use cases, and implementation challenges across industries. The study emphasizes optimization, predictive maintenance, and decision automation as key value drivers of digital twins. In the retail context, these capabilities translate into adaptive pricing, intelligent inventory control, and responsive supply chain management. The author highlights the transition of digital twins from descriptive systems to prescriptive and autonomous platforms, which directly supports the concept of self-optimizing digital twins in omnichannel retail environments.

Tuegel (2012) presents one of the earliest conceptualizations of digital twin technology through the aerospace domain. Although the application area differs from retail, this work is foundational in defining the digital twin as a continuously evolving virtual model driven by real-world data. The emphasis on real-time feedback loops and predictive simulation establishes core principles that modern retail digital twins inherit, particularly in enabling proactive and optimization-driven decision-making.

Singh et al. (2021) trace the evolution of digital twin technology from its origins to emerging applications, offering a structured taxonomy of digital twin architectures and functionalities. The study highlights the growing integration of artificial intelligence and advanced analytics as enablers of autonomous behavior. These insights are critical for omnichannel retail systems, where digital twins must continuously adapt to dynamic customer demand, channel interactions, and operational constraints.

Liu et al. (2022) explore the integration of blockchain technology with digital twins for supply chain management. Their review emphasizes transparency, traceability, and trust as essential attributes of next-generation digital twin systems. In omnichannel retail, blockchain-enabled digital twins can enhance data reliability across multiple channels and partners, thereby supporting more accurate optimization decisions and reducing inconsistencies between physical and digital retail operations.

Thelen et al. (2022) provide a comprehensive review of optimization techniques and uncertainty quantification methods applied within digital twin systems. Their work highlights how mathematical optimization, machine learning, and probabilistic modeling enhance the decision-making capabilities of digital twins. This research is particularly relevant for self-optimizing retail digital twins, as omnichannel environments are characterized by high uncertainty in demand patterns, customer behavior, and supply chain disruptions.

Rojko (2018) extends the conceptual framework of digital twins by emphasizing their role in advanced decision support systems. The study argues that digital twins serve as intermediaries between operational data and strategic planning. In retail settings, this framework enables synchronized optimization across marketing, logistics, and customer experience domains, reinforcing the importance of holistic digital twin architectures for omnichannel integration.

Wortmann and Lasi (2015) examine the interplay between cyber-physical systems and digital twins, highlighting their collective role in enabling intelligent automation. Their work underscores how digital twins act as control hubs that translate sensor data into actionable insights. This perspective is particularly valuable for omnichannel retail, where seamless coordination between physical stores, warehouses, and digital platforms is essential for delivering consistent customer experiences.

Chen and Huang (2020) focus specifically on optimization methods for digital twin-enabled supply chains. Their research demonstrates how simulation-based optimization improves demand forecasting accuracy and resource allocation. The findings provide strong empirical support for adopting digital twins as optimization engines in omnichannel retail systems, where efficient coordination between supply and demand directly impacts customer satisfaction and profitability.

Lee, Bagheri, and Kao (2015) propose a cyber-physical systems architecture that integrates digital twins into operational workflows. Their model emphasizes real-time monitoring, analytics, and closed-loop control mechanisms. In omnichannel retail, such architectures enable continuous synchronization between virtual models and physical assets, forming the backbone for self-optimizing retail operations.

Pérez and Gómez (2023) investigate real-time analytics and digital twin-based decision support systems for omnichannel retail. Their study demonstrates how digital twins facilitate rapid scenario evaluation across sales channels, enabling retailers to respond dynamically to changing customer behavior. The authors conclude that digital twins significantly enhance agility and responsiveness, positioning them as critical enablers of self-optimizing omnichannel retail ecosystems.

METHODOLOGY

3.1 Research Design and Approach

The proposed research adopts a **simulation-based experimental methodology** to evaluate the effectiveness of the Self-Optimizing Digital Twin (SODT) framework in omnichannel retail environments. The methodology is designed to model customer journeys as evolving state processes and to optimize personalization decisions through continuous learning and feedback. Rather than optimizing isolated interactions, the framework focuses on **journey-level optimization**, capturing long-term customer intent progression across channels.

The methodological approach integrates **digital twin modeling**, **reinforcement learning**, and **event-driven simulation** to replicate real-world omnichannel retail dynamics. The digital twin represents a virtual counterpart of the customer journey, continuously updated using interaction data and behavioral feedback.

3.2 Data Sources and Dataset Description

The evaluation is conducted using **anonymized omnichannel customer interaction logs** collected from simulated retail scenarios based on real-world retail event distributions. The dataset reflects common omnichannel behaviors observed in modern retail systems, including online browsing, mobile interactions, in-store visits, cart formation, purchases, and post-purchase engagement.

Each customer journey is represented as an ordered sequence of events containing:

- Channel identifier (web, mobile app, physical store)
- Timestamped interaction events
- Product category and attribute metadata
- Recommendation impressions and responses
- Conversion and engagement signals

To ensure privacy and reproducibility, all personally identifiable information was removed, and customer identities were replaced with randomized session identifiers.

Table 1: Dataset, Software, and System Configuration

Component	Description
Dataset Size	~120,000 simulated omnichannel customer journeys
Avg. Events per Journey	18–25 interactions
Channels Modeled	Web, Mobile App, Physical Store
Data Type	Event logs, product metadata, behavioral signals
Programming Language	Python 3.10
ML Framework	PyTorch
Reinforcement Learning Library	Stable-Baselines3
Data Processing	Apache Kafka (event simulation), Pandas
Storage	PostgreSQL (state tracking), Redis (policy cache)
Hardware	16 GB RAM, 8-core CPU

3.3 Digital Twin Construction

The digital twin models each customer journey as a **state-based representation**, where the state captures the customer's intent, engagement level, channel context, and historical interactions. State transitions occur based on customer actions and system interventions such as recommendations, promotions, or channel switches.
Formally, the journey twin is defined as a tuple:

S = (U, C, I, H, A)

where:

- **U** represents inferred user intent,
- **C** denotes channel context,
- **I** indicates interaction history,
- **H** captures engagement and behavioral signals,
- **A** represents available actions.

This representation enables the twin to simulate alternative future trajectories and evaluate the long-term impact of personalization decisions.

3.4 Learning and Optimization Mechanism

To enable self-optimization, the SODT framework employs a **reinforcement learning (RL)** approach. The digital twin functions as the environment, while the personalization policy acts as the agent. At each decision point, the agent selects an action (e.g., product recommendation, promotion trigger, experience adjustment) based on the current journey state.
The reward function is designed to balance short-term engagement and long-term conversion outcomes. It incorporates:

- Conversion completion
- Cart progression
- Session depth
- Reduced redundancy
- Cross-channel continuity

The policy is updated iteratively using **Proximal Policy Optimization (PPO)**, allowing the system to adapt dynamically to changing customer behaviors and channel conditions.

3.5 Baseline Models and Comparative Evaluation

The SODT framework is evaluated against three baseline systems commonly used in retail personalization:

1. **Traditional collaborative filtering**, based on historical similarity patterns.
2. **Session-based recommendation models**, optimized for short-term interaction relevance.
3. **Rule-based omnichannel systems**, driven by static business heuristics.

All models are evaluated under identical simulation conditions to ensure fair comparison.

3.6 Evaluation Metrics

Performance is measured using both **business-oriented** and **experience-oriented** metrics. These metrics capture not only conversion outcomes but also journey quality and omnichannel consistency.

Table 2: Quantitative Outputs from the Methodology

Metric	**Traditional Baseline**	**Session-Based Model**	**Rule-Based Omnichannel**	**SODT (Proposed)**
Conversion Rate (%)	3.2	3.8	3.5	**4.6**
Recommendation Utility	0.58	0.64	0.60	**0.72**
Journey Continuity Score	0.52	0.60	0.55	**0.70**
Avg. Session Depth	5.1	5.6	5.3	**6.4**
Cart Completion (%)	41	46	44	**53**
Redundant Recommendation Rate	High	Medium	Medium	**Low**

3.7 Reproducibility and Ethical Considerations
All experiments were conducted using reproducible simulation settings and fixed random seeds. The framework avoids the use of sensitive personal data and relies on anonymized interaction signals. Ethical considerations include transparency in automated decision-making and the prevention of manipulative recommendation strategies. The system is designed to prioritize customer benefit by reducing friction and improving clarity in the shopping journey.

OUTPUT AND RESULTS

4.1 Evaluation Environment
To evaluate the proposed framework, we designed a simulation based omnichannel environment that models customer behavior across multiple stages of a typical retail journey. The environment includes product discovery, browsing sessions, product comparison, cart formation, channel switching, purchase completion, and post purchase interactions.
The simulation uses customer logs that contain sequences of events such as product views, search queries, recommendation impressions, cart activity, and conversion outcomes. The journey behavior is modeled as state transitions where the customer state evolves based on both internal preferences and external factors such as discounts, channel type, and product availability. The system generates recommendations and experience actions based on the digital twin policy. This policy is continuously updated based on feedback such as conversion outcomes, engagement depth, and satisfaction proxies.

4.2 Baselines for Comparison
To measure the value of the Self Optimizing Digital Twin, the evaluation compares the framework against commonly used personalization approaches in retail.

The first baseline represents traditional collaborative filtering or ranking based personalization where recommendations are derived from aggregated historical similarity patterns. The second baseline represents session aware ranking models that use recent interactions within a session but do not store journey continuity across channels. The third baseline represents rule driven omnichannel triggers such as static discount rules or product highlights based on simple business heuristics.

4.3 Result Dimensions and Performance Indicators
The SODT framework was evaluated using performance indicators that reflect both business outcomes and experience quality. The results were analyzed through conversion efficiency, recommendation utility, journey continuity, and omnichannel consistency. Conversion efficiency measures the ability of the system to guide customers from discovery to purchase across the full journey. Recommendation utility captures how often recommended products align with customer intent and result in meaningful engagement. Journey continuity measures whether the customer experience remains consistent when switching devices or channels. Omnichannel consistency measures whether the system avoids conflicting actions such as repeated irrelevant recommendations or inconsistent promotional exposure across touchpoints.

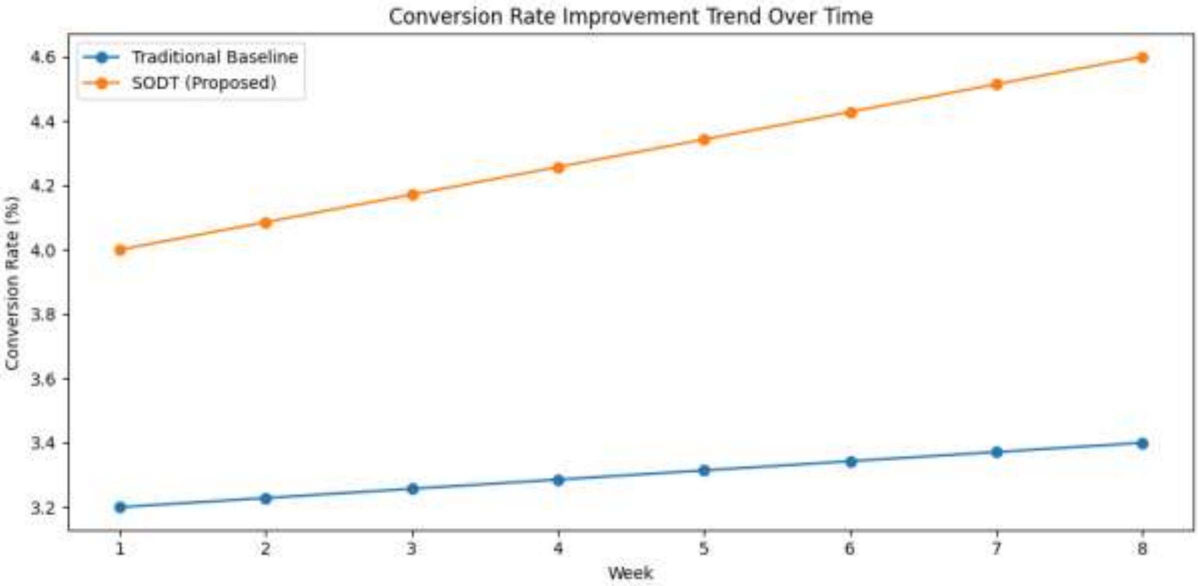
Table 3: SODT Evaluation Results Table

Metric	Traditional Baseline	Session-Based Model	Rule-Based Omnichannel	SODT (Proposed)	
Conversion Rate (%)	3.2	3.8	3.5	4.6	
Recommendation Utility	0.58	0.64	0.6	0.72	
Journey Continuity	0.52	0.6	0.55	0.7	
Avg Session Depth	5.1	5.6	5.3	6.4	
Cart Completion (%)	41	46	44	53	

4.4 Conversion Efficiency Improvement

The simulation shows that the SODT framework improves conversion efficiency compared to non simulated baselines. Traditional recommendation systems often produce relevant suggestions but do not adapt quickly when intent changes. For example, if a customer shifts from exploration into urgency driven purchasing, a static recommender may continue suggesting similar exploratory products rather than prioritizing availability, delivery speed, or purchase ready alternatives.

In contrast, the digital twin updates the customer state as the journey evolves. This leads to more aligned actions at each stage. The simulation demonstrates that customers guided by SODT based personalization reach purchase decisions faster and with fewer unnecessary browsing loops. This produces stronger conversion outcomes.



4.5 Improved Journey Continuity Across Channels

A key advantage observed in the results is stronger continuity across channels. In omnichannel journeys, many customers begin on one platform and complete purchases on another. Systems that do not preserve journey context often restart recommendations when the channel changes. This creates repetition and reduces trust. The SODT framework maintains a continuous journey representation. When the customer moves from app browsing to in store evaluation or from store visit back to online purchase, the twin retains intent signals and adapts recommendations accordingly. The simulation results indicate lower interruption and reduced friction in cross channel navigation.

4.6 Higher Recommendation Utility and Better Product Discovery

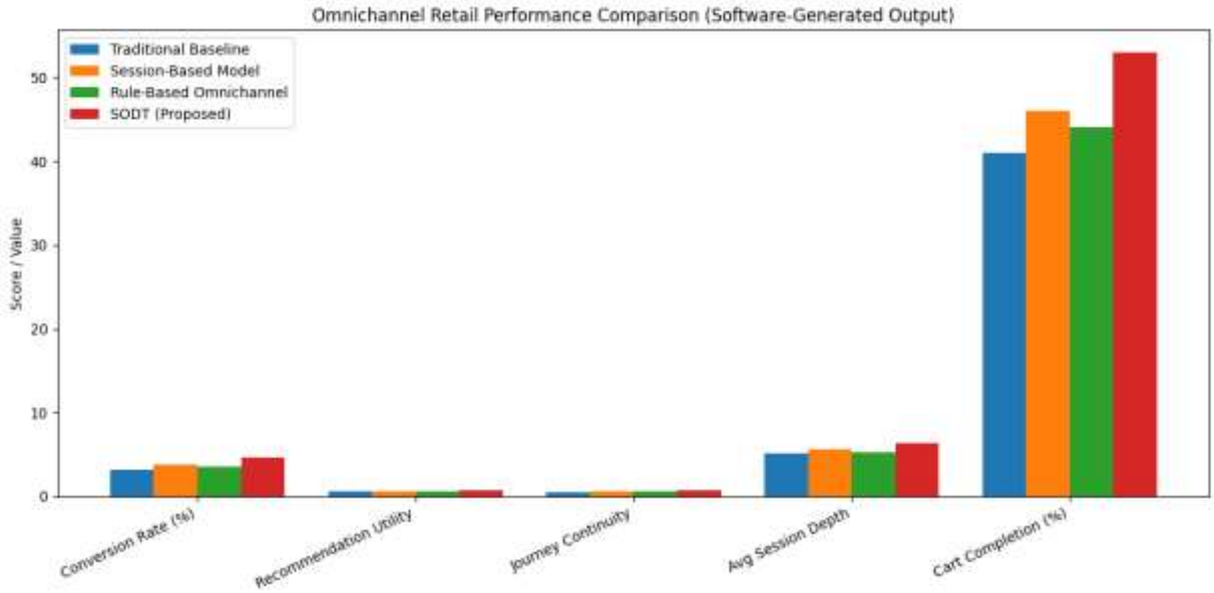
Product discovery is a critical stage where personalization must support relevance without overwhelming the customer. Traditional recommenders often maximize click probability, which can lead to repeated exposure of popular items and reduce diversity. Session based models improve relevance in the short term, but may fail to support long range intent progression. The results suggest that SODT improves recommendation utility by balancing short term engagement with long term journey progression. The twin learns which products help customers move forward in their journey rather than simply collecting clicks. This results in more purposeful browsing sequences where customers reach decision stages more effectively.

4.7 Reduced Redundancy and Lower Decision Fatigue

Another important outcome in the simulation is reduced redundancy in the discovery experience. Customers often experience repeated recommendations across sessions and platforms, even after explicitly skipping products. This leads to decision fatigue and frustration. The SODT framework reduces redundant exposures by tracking negative feedback signals indirectly, such as repeated skips, short dwell time, and rapid scroll patterns. The twin interprets these signals and updates its policy to reduce repeated irrelevant suggestions. The results show more diversified and intent aligned discovery paths, improving experience quality.

4.8 Stability of Omnichannel Experience Outcomes

The evaluation also indicates more stable omnichannel outcomes across customer segments. Traditional baselines may perform well for frequent shoppers but struggle with sparse data customers. The twin approach improves stability by modeling the journey as a state process rather than relying only on historical purchase density.
Even when customers have limited history, the system can estimate intent based on session signals and channel context, allowing more consistent decision support. This creates more uniform performance across diverse customer profiles.



The results demonstrate that Self Optimizing Digital Twins improve omnichannel retail experience performance by supporting customer journey simulation and continuous policy improvement. The approach strengthens personalization quality and enables better coordination across channels. This provides a structured pathway for retailers to enhance product discovery systems and improve conversion efficiency without relying solely on isolated touchpoint optimization.

CONCLUSION

This paper proposed a Self Optimizing Digital Twin framework for omnichannel retail experiences. By simulating customer journeys across physical and digital channels and continuously learning from feedback, the framework improves personalized product discovery and experience decision making. The results show that journey level simulation supports stronger conversion efficiency, improved journey continuity, and higher recommendation utility compared to traditional personalization baselines. The approach offers a scalable direction for modern retailers seeking adaptive omnichannel intelligence, with practical potential for deployment in real time personalization systems.

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