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Modeling the Multichannel Journey of Self-Directed Customers in Intelligent Platforms

Morteza Afshari [*1], David Lee [2], Anya Sharma[3], Mark O'Connor[4]

1*- PhD in Business Administration, International Marketing Major, Islamic Azad University, Science and Research Branch, Tehran, Iran
2- Professor of Digital Business, Faculty of Business and Economics, The University of Melbourne, Australia
3- Senior Lecturer in Information Systems, School of Information Systems and Technology Management, UNSW Business School, University of New South Wales, Australia
4- Research Fellow in Customer Analytics, Discipline of Marketing, University of Sydney Business School, Australia

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ABSTRACT

The advent of intelligent platforms has transformed commerce, yet existing customer journey modeling remains inadequate for understanding the self-directed customer navigating complex multichannel journeys. These customers actively orchestrate their paths across diverse touchpoints, displaying non-linear behaviors and dynamic shifts in intent that traditional, often retrospective and linear, models fail to capture. This deficiency leads to fragmented customer experiences, suboptimal marketing investments, and missed opportunities for meaningful engagement. This study addresses this critical gap by employing a Design Science Research (DSR) paradigm to develop a novel, comprehensive conceptual framework for modeling the multichannel journey of self-directed customers within intelligent platforms.

The developed artifact is a multi-layered framework designed to handle the velocity, volume, and variety of modern customer data. Its components include: a Data Ingestion and Unification Layer for real-time, comprehensive data stitching; a Dynamic Feature Engineering Layer for extracting both explicit and implicit signals of customer intent; a sophisticated Journey Modeling and Intent Inference Layer leveraging advanced sequential deep learning (LSTMs, Transformers) and graph neural networks (GNNs) to capture non-linearity and infer real-time intent; and a Prescriptive Recommendation and Orchestration Layer utilizing Reinforcement Learning (RL) and Contextual Bandits to generate optimal, non-intrusive "next-best actions" across channels. An overarching Continuous Learning and Feedback Layer ensures the framework's adaptability.

Conceptual scenario simulations demonstrating high-involvement consumer purchases and complex B2B solutions affirmed the framework's utility in overcoming linearity bias, interpreting subtle behavioral signals, and providing real-time, context-aware guidance that respects customer agency. Evaluation criteria confirmed its completeness, internal consistency, strong theoretical grounding, and conceptual feasibility. This research significantly advances customer journey theory by providing a prescriptive model for understanding autonomous customer navigation and enriches the application of AI/ML in customer relationship management. It offers a critical blueprint for businesses to enhance customer experience, optimize strategic interventions, and gain competitive advantage by truly understanding and supporting the self-directed customer in intelligent platform environments.

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* Corresponding Author: Afshari @unimelb.edu.au

1. Introduction

The contemporary commercial landscape is undergoing a profound and irreversible transformation, driven by unprecedented advancements in digital technologies and a fundamental shift in consumer behavior. We are witnessing the emergence of the self-directed customer, an increasingly empowered and autonomous individual who actively orchestrates their own purchasing journeys across a myriad of digital and physical touchpoints (Lemon & Verhoef, 2016; Deloitte, 2024). Unlike their predecessors who largely followed linear, marketer-defined paths, today's customers jump seamlessly between channels researching products on mobile apps, comparing prices on web browsers, engaging with chatbots for queries, seeking peer reviews on social media, visiting physical stores for experiential insights, and ultimately converting through diverse online or offline avenues. This kaleidoscopic and non-linear movement creates a highly complex multichannel customer journey, presenting both immense opportunities and significant challenges for businesses.

Simultaneously, the platforms facilitating these interactions are evolving at an astonishing pace, morphing into sophisticated intelligent platforms. These are not mere digital storefronts but dynamic ecosystems powered by advanced Artificial Intelligence (AI), Machine Learning (ML), Big Data analytics, and hyper-connectivity (Davenport, 2018; IBM, 2025). From AI-driven recommendation engines that anticipate needs to personalized search results, voice assistants offering tailored advice, and automated customer service bots resolving complex issues, intelligent platforms are designed to adapt, learn, and provide contextualized experiences in real-time. The promise is clear: to deliver seamless, personalized, and efficient interactions that mirror the self-directed customer's evolving intent and preferences. Yet, despite the sophistication of these platforms, a persistent challenge remains: effectively modeling the multichannel journey of these self-directed customers in a way that truly captures their fluidity, autonomy, and decision-making processes.

The conventional approaches to understanding customer journeys, often rooted in retrospective analysis of aggregated data or simplified linear models, are demonstrably insufficient in this dynamic environment (Neslin et al., 2014). They fail to account for the intricate sequences of interactions, the unpredictable jumps between channels, the influence of implicit signals, and the varying levels of customer proactivity that define modern purchasing paths. For instance, a customer might begin their journey with a vague informational search on a tablet, shift to detailed product comparisons on a desktop, seek advice from friends on social media, visit a physical store to see the product, and finally complete the purchase via a voice assistant at home. Each touchpoint provides fragmented data, and the customer's intent, sentiment, and preferences are constantly evolving. Relying on static segmentation or average journey maps in such a scenario leads to generic, ill-timed, and irrelevant interactions, ultimately eroding customer experience and diminishing conversion rates. Businesses struggle to answer fundamental questions: What is the customer *currently* trying to achieve? Which touchpoint is most influential at this *specific moment*? How can we proactively guide their journey without being intrusive?

This critical gap underscores the need for a novel methodological approach. Traditional modeling techniques often assume a marketer-driven funnel, where customers are passively led through predefined stages. However, the self-directed customer defies this assumption, actively seeking information, comparing alternatives, and dictating their own pace and path (Lemon & Verhoef, 2016). Intelligent platforms, while equipped with vast computational power and data, often lack the nuanced understanding of individual customer autonomy and the complex, dynamic decision-making process occurring across various channels. They may optimize for channel-specific conversions rather than the holistic journey, leading to fragmented experiences. The current state of modeling frequently falls short in providing real-time, predictive insights into these complex, self-orchestrated multichannel journeys, making it difficult for businesses to intervene effectively and provide truly personalized and timely support.

The purpose of this article is to introduce and explore a robust framework for modeling the multichannel journey of self-directed customers in intelligent platforms. We aim to: (1) critically analyze the unique behavioral characteristics of self-directed customers and the limitations of existing journey modeling approaches in multichannel, intelligent environments; (2) propose a novel conceptual and methodological framework that integrates advanced analytical techniques (such as sequence analysis, reinforcement learning, and graph neural networks) to capture the non-linear, dynamic, and self-directed nature of customer journeys; (3) demonstrate how this framework can provide real-time, predictive insights into customer intent, next-best actions, and optimal channel engagement strategies; and (4) discuss the implications for businesses seeking to enhance customer experience, optimize marketing investments, and foster stronger customer relationships in the age of intelligent platforms. By developing a model that truly reflects the customer's agency and the fluidity of their multichannel interactions, this research seeks to empower intelligent platforms to become genuine partners in the customer's journey, rather than just transactional interfaces.

2. Literature Review

The evolving paradigm of the self-directed customer operating within intelligent platforms necessitates a deep dive into existing literature on customer journey modeling, multichannel management, and artificial intelligence in customer relationship management. This section systematically reviews the foundational concepts, identifies the limitations of current approaches in addressing the self-directed customer's fluid multichannel journey, and refines the problem statement, articulating the critical need for a novel modeling framework.

2.1. The Evolution of Customer Journey Concepts

The concept of the customer journey has evolved significantly from its early, often simplistic, linear representations. Historically, models like AIDA (Attention, Interest, Desire, Action) (St. Elmo Lewis, 1898) provided a foundational, yet highly prescriptive, view of consumer progression. These models, along with the traditional marketing funnel, assumed a relatively passive customer guided by marketing stimuli through sequential stages. The focus was primarily on optimizing touchpoints *controlled* by the marketer, often in single-channel environments.

The advent of digital technologies introduced complexity, leading to the concept of the multichannel customer journey. Researchers began to acknowledge that customers interact with a brand across multiple channels physical stores, websites, call centers, email, social media but often in fragmented, unsynchronized ways (Neslin et al., 2014). This recognition led to efforts in cross-channel attribution and customer journey mapping, aiming to visualize customer touchpoints and understand their sequence (Richardson, 2010). However, many of these approaches remained descriptive and retrospective, analyzing past journeys to identify common paths or influential touchpoints. They often struggled with the vast volume and velocity of digital data, and the inherent problem of stitching together disparate interactions from disconnected systems into a unified customer view (Kumar & Reinartz, 2016).

The subsequent emergence of omnichannel strategies represented a leap, aiming for a truly unified and seamless customer experience *across* all channels, where customer context is maintained regardless of the channel transition (Rigby, 2011). While omnichannel emphasizes consistency and integration from the business's perspective, the underlying modeling approaches often still fall short in capturing the *customer's* agency and their proactive, self-orchestrated navigation. Many models focused on optimizing transitions *between* channels from a business standpoint, rather than predicting and adapting to the customer's self-initiated shifts in intent and preferred channel.

What distinguishes the current era is the rise of the self-directed customer. This individual is not merely interacting across multiple channels but actively shaping their own journey. They are digitally literate, well-informed, and expect hyper-personalization and immediate gratification. They initiate searches, compare options, seek out peer reviews, and engage with brands on their own terms and timelines (Lemon & Verhoef, 2016). Their journeys are often messy, iterative, and non-linear, defying simple funnel analogies. This autonomy poses a fundamental challenge to traditional modeling, which often assumes a degree of marketer control or predictable progression.

2.2. Intelligent Platforms and their Role in Customer Engagement

Concurrently with the rise of the self-directed customer, the technological backbone of customer interaction has evolved into intelligent platforms. These platforms, deeply integrated with Artificial Intelligence (AI) and Machine Learning (ML), process vast quantities of Big Data in real-time to deliver personalized experiences. Key components include:

- **AI-powered Recommendation Engines:** These systems analyze past behavior, preferences, and contextual factors to suggest products, services, or content, moving beyond simple collaborative filtering to more sophisticated deep learning approaches (Zhang et al., 2014).
- **Natural Language Processing (NLP) and Conversational AI:** Chatbots and voice assistants leverage NLP to understand customer queries, provide instant support, and even guide complex transactions (e.g., Google Assistant, Amazon Alexa, customer service chatbots).
- **Predictive Analytics:** ML models forecast customer behavior, such as churn risk, likelihood to purchase, or next-best action, enabling proactive interventions (Davenport, 2014).
- **Real-time Personalization Engines:** These systems dynamically adapt website content, pricing, and offers based on a customer's real-time actions and inferred intent (Oracle, 2024).
- **Customer Data Platforms (CDPs):** While not exclusively AI, CDPs aggregate and unify customer data from various sources to create a single, comprehensive customer view, which is then leveraged by AI/ML for personalized engagement (Gartner, 2024).

Intelligent platforms represent the technological aspiration to meet the self-directed customer's demands for personalization and efficiency. They have the *potential* to observe interactions across channels and respond adaptively. However, their current capabilities are often limited by the models of customer behavior they employ. Many still optimize for channel-specific conversions or rely on static customer segments, failing to truly understand the dynamic, evolving *intent* of the self-directed customer navigating a fluid multichannel journey. The gap lies in bridging the platform's intelligence with a sufficiently sophisticated understanding of the customer's self-orchestrated path.

2.3. Limitations of Current Customer Journey Modeling Approaches for Self-Directed Customers

Despite significant advancements, existing modeling approaches fall short in several critical areas when applied to the multichannel journey of self-directed customers within intelligent platforms:

- **Linearity Bias:** Many models, even those acknowledging multiple channels, implicitly assume a somewhat linear progression (e.g., awareness to consideration to purchase). This fails to capture the iterative, recursive, and often chaotic nature of self-directed journeys, where customers might jump back and forth between stages or skip them entirely (Lemon & Verhoef, 2016). A customer might return to "research" after adding an item to their cart, or move from "consideration" directly to "purchase" based on an external social media prompt.

- **Aggregation and Retrospective Analysis:** Traditional journey mapping and analytics often rely on aggregated data and retrospective analysis, identifying common paths *after* journeys are completed (Neslin et al., 2014). This provides valuable insights into past behavior but lacks the real-time, predictive power needed to intervene effectively in ongoing, dynamic journeys. The self-directed customer's intent changes rapidly, making delayed insights irrelevant.

- **Channel-Centric vs. Customer-Centric View:** Many platforms optimize for performance within their own channel (e.g., website conversion rates, app engagement), rather than understanding the customer's holistic journey across all channels. This leads to fragmented experiences and a lack of contextual understanding when customers transition from one channel to another. The self-directed customer expects consistent context, irrespective of their chosen touchpoint.

- **Limited Capture of Implicit Signals and Intent:** Self-directed customers often leave subtle, implicit signals of their evolving intent (e.g., hovering over a product image, re-reading a specific feature description, abandoning a form). Current models often struggle to capture and interpret these nuanced, low-fidelity signals in real-time across channels, missing crucial opportunities for proactive engagement.

- **Underestimation of Customer Agency and Autonomy:** Existing models frequently treat customers as passive recipients of marketing efforts, rather than active agents driving their own journeys. This leads to interventions that feel intrusive or irrelevant, as they do not align with the customer's current self-defined needs or progression. The self-directed customer expects assistance, not direction.

- **Data Silos and Integration Challenges:** Despite the rise of CDPs, many organizations still struggle with fragmented data across disparate systems (CRM, ERP, web analytics, social media monitoring, call center logs). This prevents the creation of a truly unified, real-time customer view necessary for comprehensive journey modeling (Kumar & Reinartz, 2016). Without a unified data foundation, sophisticated journey modeling is impossible.

- **Lack of Prescriptive Capabilities:** While some models can predict the *next likely step*, few can prescribe the *optimal next action* for the business to take to guide the self-directed customer effectively without overriding their autonomy. This requires moving beyond prediction to dynamic, context-aware recommendation systems.

- **Complexity of Non-Linear Sequences:** Analyzing non-linear sequences of events with varying timings and influences across heterogeneous channels is computationally and algorithmically challenging. Traditional Markov Chains or Hidden Markov Models may struggle with the sheer scale and complexity of real-time, unstructured multichannel data (Nielsen et al., 2019).

2.4. Problem Statement Refinement

Based on the literature review, the core problem can be refined as follows:

Current customer journey modeling approaches, predominantly retrospective and inherently biased towards linear progressions, are inadequate for effectively understanding, predicting, and influencing the dynamic, non-linear, and self-orchestrated multichannel journeys of contemporary self-directed customers within intelligent platforms. This inadequacy stems from limitations in real-time data integration across disparate channels, insufficient capture and interpretation of implicit customer intent signals, underestimation of customer agency, and a lack of prescriptive capabilities for guiding customers optimally without disrupting their autonomy, leading to fragmented experiences, suboptimal marketing investments, and diminished customer satisfaction.

This refined problem statement emphasizes the need for a new framework that can handle the volume, velocity, and variety of multichannel data, robustly interpret dynamic customer intent, respect customer autonomy, and provide real-time, prescriptive guidance for businesses operating within intelligent platforms. The objective is not to *control* the customer's journey, but to *intelligently support* and *proactively adapt* to it, ensuring businesses can align their offerings with the customer's unique, self-directed path.

3. Methodology

Developing a comprehensive framework for modeling the dynamic, self-directed multichannel journeys of customers within intelligent platforms requires a sophisticated and adaptable methodological approach. Given the multifaceted nature of the problem encompassing complex behavioral patterns, advanced technological capabilities, and the need for actionable, real-time insights this study primarily adopts a Design Science Research (DSR) paradigm. DSR is uniquely suited for addressing problems that involve the creation of innovative artifacts, such as models, methods, or instantiations, specifically designed to solve real-world problems in information systems (March & Smith, 1995; Peffers et al., 2007; Hevner et al., 2004). This choice is driven by the necessity not just to understand *what is*, but to engineer *how to build* a solution that can enhance the performance of intelligent platforms in supporting the self-directed customer journey.

3.1. Research Paradigm: Design Science Research (DSR)

Our selection of Design Science Research is deliberate and strategic. The core challenge articulated in the problem statement the inadequacy of current modeling approaches to capture the fluid, autonomous, and non-linear multichannel journeys of self-directed customers is fundamentally a design problem. It calls for the construction of a novel information system artifact (a modeling framework) that can bridge the gap between observed customer behavior and the analytical capabilities of intelligent platforms. DSR offers a structured yet iterative process that ensures the artifact developed is both theoretically grounded and practically relevant. The six-step process, as outlined by Peffers et al. (2007), will guide our methodological execution:

1. **Problem Identification and Motivation:** This foundational step involves clearly defining the research problem and demonstrating its significance. As elaborated in Section 1 and Section 2, the problem lies in the disconnect between the self-directed customer's dynamic multichannel journey and the limitations of existing modeling techniques within intelligent platforms. The motivation stems

from the substantial business opportunities (enhanced customer experience, optimized marketing) and the imperative to respond effectively to evolving customer autonomy.

2. **Objectives for the Solution:** This phase specifies the desired characteristics and functionalities of the proposed modeling framework. Our objectives include designing a framework capable of: (a) capturing real-time, non-linear multichannel interactions; (b) interpreting implicit customer intent signals; (c) respecting customer agency while enabling proactive, non-intrusive interventions; and (d) providing prescriptive, next-best action recommendations.

3. **Design and Development:** This is the core creative phase where the conceptual modeling framework, the artifact, is constructed. This involves drawing upon theoretical foundations from consumer behavior, marketing, and computer science (e.g., sequence analysis, reinforcement learning, graph theory, deep learning) to synthesize a novel approach. This phase involves defining the layers, components, and algorithmic approaches that constitute the framework.

4. **Demonstration:** In this stage, we will illustrate how the developed framework addresses the identified problem and achieves its objectives. Given that the artifact is a conceptual framework rather than a software prototype, the demonstration will involve detailed **conceptual scenario analysis** and **illustrative use cases**. These will depict typical self-directed customer journeys and show how the proposed framework's mechanisms would provide superior insights and interventions compared to traditional methods.

5. **Evaluation:** This phase assesses the utility, quality, and efficacy of the designed artifact. For a conceptual framework, evaluation will focus on its logical coherence, theoretical consistency, completeness in addressing the problem, and alignment with state-of-the-art analytical techniques and best practices in customer experience management. This will also involve a qualitative assessment of its potential to bridge the identified gaps and deliver value to businesses.

6. **Communication:** The final step involves clearly articulating the research findings, the design of the artifact, and its implications to both academic and practitioner communities. This will be achieved through the structured presentation of the framework and its discussion in the subsequent sections of this article.

This iterative DSR process ensures that the developed modeling framework is not only theoretically sound but also practically relevant and capable of guiding the design of more sophisticated intelligent platforms.

3.2. Conceptual Framework Development: Integrating Advanced Analytical Techniques

The design and development phase is at the heart of this DSR study. It involves a systematic synthesis of knowledge from diverse fields to create a novel conceptual modeling framework. This process was highly iterative and involved several key steps:

- **Deconstruction of the Self-Directed Customer Journey:** We began by meticulously breaking down the complex, non-linear journey into its fundamental components: individual interactions (touchpoints), sequences of interactions, transitions between channels, implicit signals (e.g., dwell time, scroll depth), explicit signals (e.g., search queries, purchases), and contextual factors (e.g., time of day, device). A particular focus was placed on identifying moments of customer agency and intent shifts.

- **Review of Advanced Analytical Methods:** An exhaustive review of cutting-edge analytical techniques suitable for modeling complex sequences and dynamic decision-making was conducted. This included:
  - **Sequence Analysis:** Moving beyond simple Markov Chains to more advanced models like Hidden Markov Models (HMMs) for inferring latent states of customer intent (Nielsen et al., 2019) and particularly Recurrent Neural Networks (RNNs), specifically Long Short-Term Memory (LSTM) networks (Hochreiter & Schmidhuber, 1997) and Transformer architectures (Vaswani et al., 2017), which are adept at capturing long-range dependencies and complex patterns in sequential data (e.g., series of clicks, searches, and channel transitions).
  - **Reinforcement Learning (RL):** Recognizing the self-directed customer's journey as a series of sequential decisions within an environment, RL emerged as a powerful paradigm. RL models (Sutton & Barto, 2018) can learn optimal strategies for intervention (e.g., "next-best action") by maximizing long-term rewards (e.g., conversion, satisfaction), effectively treating the intelligent platform as an "agent" interacting with the "environment" (the customer journey).
  - **Graph Neural Networks (GNNs):** Given the interconnected nature of channels, products, and customer relationships, GNNs (Gori et al., 2005; Hamilton et al., 2017) offer a promising approach to model the journey as a dynamic graph. Nodes could represent touchpoints, products, or customer states, and edges could represent transitions or relationships, allowing the model to capture the influence of connected entities in the journey.
  - **Contextual Bandits:** These algorithms are particularly relevant for real-time personalization, allowing platforms to learn optimal recommendations or interventions in a dynamic, online fashion based on the current context of the customer (Li et al., 2010).
- **Layered Architectural Design:** We conceptualized a multi-layered framework, mirroring the flow of data and insights from raw interaction to actionable recommendations. This includes:
  - **Data Ingestion and Unification Layer:** Focus on real-time, low-latency collection and unification of heterogeneous data streams from all multichannel touchpoints into a unified customer profile. This addresses the data silo problem.
  - **Dynamic Feature Engineering Layer:** Transformation of raw event data into meaningful, time-series features that capture both explicit actions and implicit signals (e.g., time spent on page, scroll depth, mouse movements, emotional tone from text inputs).
  - **Journey Modeling and Intent Inference Layer:** This is where the core analytical power resides, leveraging advanced sequential and graph-based AI models to recognize current journey states, predict next possible actions, and infer underlying customer intent in real-time.
  - **Prescriptive Recommendation and Orchestration Layer:** Utilizing RL and contextual bandits to generate optimal "next-best action" recommendations (for both the customer and the business) and orchestrate these interventions across the appropriate channels, ensuring non-intrusiveness and alignment with customer autonomy.

- **Continuous Learning and Feedback Layer:** A crucial component ensuring that the model continuously learns from the outcomes of interventions and adapts to evolving customer behaviors and market dynamics.

- **Integration of Customer Agency:** A conscious design choice throughout the framework was to respect and integrate customer agency. The goal is not to force customers down a path but to understand their self-directed path and provide relevant, timely, and supportive interventions that *aid* their journey, rather than dictate it. This shifts the focus from "controlling the funnel" to "intelligently assisting the journey."

The outcome of this intensive design and development phase is the detailed conceptual framework presented in Section 4 (Findings), which embodies these integrated analytical techniques and architectural considerations.

3.3. Demonstration Strategy: Conceptual Scenario Simulation

For a conceptual artifact such as our modeling framework, the demonstration phase of DSR relies on **conceptual scenario simulation** rather than physical implementation. This method allows us to illustrate the framework's operational mechanics and problem-solving capabilities in realistic, yet hypothetical, contexts without the prohibitive cost and time of full-scale system development. The objective is to provide a clear and compelling "proof of concept" for the framework's utility.

Our demonstration strategy involves:

- **Selection of Diverse Self-Directed Customer Journey Archetypes:** We will choose several distinct, yet common, self-directed multichannel journey scenarios that highlight the complexities the framework is designed to address. Examples might include:
    - **Complex B2B Solution Purchase:** A customer journey spanning extensive online research, whitepaper downloads, webinar attendance, interaction with sales representatives via CRM, and eventual conversion, with multiple decision-makers involved.
    - **High-Involvement Consumer Product Purchase:** A customer journey for a major purchase (e.g., an automobile, a high-end electronics item) involving initial broad searches, specific product comparisons, review site consultations, physical store visits, interaction with chatbots, and finally, online purchase or showroom visit.
    - **Issue Resolution/Service Journey:** A customer starting with a self-service FAQ, moving to a chatbot, then potentially a live chat, and finally a phone call, showcasing channel transitions and escalating needs.
- **Detailed Step-by-Step Walkthroughs:** For each chosen scenario, we will conduct a meticulous step-by-step walkthrough. This involves:
    - **Describing Customer Actions:** Detailing the customer's self-directed actions across various channels (e.g., "Customer visits product page on mobile, searches for reviews on YouTube, then navigates to competitor's website on desktop").

  - **Illustrating Data Ingestion:** Explaining how the framework's data ingestion layer captures these heterogeneous events in real-time.
  - **Demonstrating Intent Inference:** Showing how the modeling layer processes these sequences to infer the customer's dynamic intent (e.g., "Customer's intent shifts from 'information gathering' to 'price comparison'").
  - **Presenting Prescriptive Interventions:** Explaining how the recommendation layer, leveraging RL, proposes optimal, non-intrusive actions for the intelligent platform (e.g., "System pushes a personalized discount via email, while the chatbot offers a feature comparison guide").
  - **Highlighting Benefits:** Articulating how the framework's output provides superior, real-time, and personalized insights compared to traditional methods, leading to improved customer experience and business outcomes.
- **Comparison to Limitations:** Each scenario walkthrough will explicitly highlight how the proposed framework overcomes the limitations identified in the literature review (e.g., linearity bias, lack of real-time insights, underestimation of customer agency), thereby validating its problem-solving capabilities.

This conceptual demonstration phase will serve as a compelling illustration of the framework's operational flow and its potential to deliver actionable intelligence, bridging the gap between theoretical design and practical application.

3.4. Evaluation Criteria and Methods

The evaluation phase is critical for assessing the quality, utility, and efficacy of the conceptual modeling framework. For this DSR study, evaluation will primarily rely on a combination of theoretical grounding, logical consistency, and alignment with advanced analytical principles and best practices in customer experience.

Our evaluation criteria include:

- **Completeness:** Does the framework encompass all critical elements necessary for modeling multichannel, self-directed customer journeys within intelligent platforms, as identified in the problem statement and literature review? Does it address the various types of customer interactions and data sources?
- **Coherence and Internal Consistency:** Are the various layers, components, and analytical techniques within the framework logically consistent and well-integrated? Do they work together synergistically without contradictions or redundancies?
- **Theoretical Grounding:** Is the framework built upon sound theoretical foundations from consumer behavior, sequential modeling, and artificial intelligence? Are the chosen analytical techniques appropriate for the problem domain?

- **Relevance and Utility:** Does the framework genuinely address the problem of effectively modeling self-directed customer journeys in intelligent platforms? Does it offer actionable insights that can improve customer experience and business outcomes?
- **Feasibility (Conceptual):** Is the proposed framework conceptually implementable with current or near-future technological capabilities (e.g., data processing power, AI algorithms)? Does it acknowledge the complexities of real-world data integration?
- **Distinction from Prior Work:** Does the framework offer novel contributions that differentiate it from existing customer journey modeling approaches, particularly in its handling of customer autonomy, non-linearity, and real-time prescriptive capabilities?
- **Clarity and Understandability:** Is the framework presented in a clear, concise, and understandable manner, making it accessible to both academic researchers and industry practitioners?

The evaluation methods will primarily involve:

- **Logical Argumentation and Justification:** Each element of the framework will be thoroughly justified through logical reasoning and explicit connections to the research problem, objectives, and insights drawn from the literature review. This ensures the framework's internal validity and theoretical strength.
- **Comparative Analysis:** The framework's capabilities will be implicitly and explicitly compared against the limitations of existing modeling approaches (e.g., traditional funnel models, retrospective journey maps, basic predictive analytics) to highlight its superior utility and innovative contributions.
- **Alignment with Best Practices:** The proposed analytical techniques and architectural components will be cross-referenced against state-of-the-art academic research and industry best practices in AI, Big Data, and customer experience management (e.g., principles of real-time analytics, personalization best practices).
- **Scenario-Based Assessment (from Demonstration):** The conceptual scenarios developed in the demonstration phase will serve as a practical testbed for the framework's efficacy. By analyzing how the framework performs in these complex situations, we can assess its ability to solve the defined problem.
- **Expert Review (Implicit):** While formal external expert validation might be a future step, the iterative nature of the DSR process inherently involves self-critical assessment and refinement based on a deep understanding of the domain, ensuring the framework's conceptual soundness.

This rigorous methodological approach ensures that the proposed framework for modeling the multichannel journey of self-directed customers in intelligent platforms is a well-founded, comprehensively designed, and critically evaluated artifact, providing a solid foundation for future research and practical application.

4. Findings

In strict adherence to the Design Science Research (DSR) paradigm detailed in Section 3, the primary "findings" of this study are the comprehensive conceptual framework itself, designed for modeling the multichannel journey of self-directed customers in intelligent platforms, along with the insights gleaned from its systematic development and conceptual demonstration. These findings represent the validated artifact created to address the critical problem of understanding and engaging autonomous customers in dynamic, multi-touchpoint environments. They articulate the "how" of building such a modeling capability, moving beyond the "what is" or "why it is" of descriptive research.

4.1. The Developed Artifact: A Novel Multichannel Journey Modeling Framework

The core finding of this research is the articulated multi-layered, integrated conceptual framework for modeling the self-directed customer journey within intelligent platforms. This artifact represents a significant departure from traditional, linear, or retrospective approaches, by incorporating advanced analytical techniques and a customer-centric philosophical underpinning. It is structured to handle the volume, velocity, and variety of multichannel data while respecting customer agency and providing real-time, prescriptive insights.

4.1.1. Data Ingestion and Unification Layer: Real-time Context Capture

A fundamental finding is the absolute necessity of a robust Data Ingestion and Unification Layer capable of capturing heterogeneous customer interactions in real-time and seamlessly stitching them into a unified customer profile. This layer is crucial for overcoming the pervasive problem of data silos identified in the literature (Kumar & Reinartz, 2016). The framework finds that for self-directed customers navigating multiple channels, every click, scroll, voice command, store visit, or customer service interaction must be ingested with low latency. This includes data from web analytics, mobile apps, CRM systems, call centers, IoT devices (e.g., smart home assistants), social media platforms, and even physical store touchpoints (e.g., in-store beacons, POS systems). The finding emphasizes techniques for real-time streaming data processing (e.g., Apache Kafka, Apache Flink) to ensure that the customer's current context is always up-to-date. Without this real-time, unified view, subsequent modeling efforts would be based on incomplete or stale information, rendering personalized interventions ineffective. This layer's finding highlights that the foundation for understanding self-directed journeys is a comprehensive and immediate digital footprint.

4.1.2. Dynamic Feature Engineering Layer: Translating Raw Data into Actionable Signals

Building upon unified data, a key finding is the vital role of a Dynamic Feature Engineering Layer that transforms raw interaction events into rich, actionable features. This goes beyond simple event counts. The framework finds that to understand self-directed customers, it's essential to capture both explicit signals (e.g., search queries, products added to cart, specific purchases) and, more importantly, implicit signals (e.g., dwell time on a product image, scroll depth on a policy page, repeated views of a particular feature, hesitation in form filling, sentiment from voice tone in a call). These implicit signals often reveal evolving intent or hidden friction points. The finding emphasizes the need for continuous, real-time feature extraction, where new features are computed and updated instantly as customer interactions occur. This layer also incorporates contextual features such as time of day, device type, geographic location, and even external market trends, as these can significantly influence a self-directed customer's journey. The ability to dynamically generate these nuanced features is a core finding that allows the modeling layer to infer subtle shifts in customer behavior and intent that traditional static feature sets often miss.

4.1.3. Journey Modeling and Intent Inference Layer: Unveiling Customer Autonomy

This is the intellectual core of the framework, and its findings are central to addressing the problem of modeling non-linear, self-directed journeys. The framework finds that sophisticated sequential deep learning models, particularly Long Short-Term Memory (LSTM) networks and Transformer architectures, are crucial for understanding the complex dependencies and non-linear patterns within multichannel customer journeys. Unlike simpler Markov models, these architectures can capture long-range temporal dependencies and the "memory" of past interactions, which is vital for understanding why a customer might revisit a previous stage or suddenly jump to a new channel. The finding is that these models can effectively infer latent customer intent (e.g., shifting from "information gathering" to "price comparison" to "ready to purchase") even when explicit signals are ambiguous.

Furthermore, for understanding the interconnectedness of channels and products, the framework finds that Graph Neural Networks (GNNs) offer a powerful lens. By representing the customer journey as a dynamic graph where nodes could be individual touchpoints, product categories, or customer states, and edges represent transitions or relationships GNNs can capture the influence of network effects and complex relationships on the customer's path (Hamilton et al., 2017). This allows the model to identify influential "hub" touchpoints or critical sequences that might be overlooked by linear analysis. A significant finding here is that these combined AI techniques allow the framework to move beyond merely describing past journeys to providing real-time, predictive insights into the customer's next likely action and their underlying motivation, even as their self-directed journey unfolds. This intelligence respects customer autonomy by focusing on understanding, rather than dictating.

4.1.4. Prescriptive Recommendation and Orchestration Layer: Guiding without Dictating

A pivotal finding of this research is the design of a Prescriptive Recommendation and Orchestration Layer that balances personalized guidance with respect for customer agency. The framework finds that Reinforcement Learning (RL) is an ideal paradigm for this. By treating the intelligent platform as an "agent" learning optimal "policies" for intervention, RL models can learn to recommend the "next-best action" (e.g., "suggest personalized content," "offer chatbot assistance," "provide a loyalty discount") that maximizes a long-term reward (e.g., customer satisfaction, conversion value) while minimizing intrusiveness (Sutton & Barto, 2018). The finding emphasizes that RL can learn *when* and *how* to intervene in a self-directed journey, adapting to real-time context (via Contextual Bandits for rapid A/B testing of recommendations). This moves beyond simple prediction to proactive, intelligent guidance. The orchestration component finds that recommendations must be delivered through the *appropriate channel* at the *optimal time*, ensuring a seamless experience. For example, if a customer is struggling on a mobile app, the system might trigger a relevant chatbot prompt rather than sending a delayed email. This layer's finding highlights the transformation from merely observing customer behavior to intelligently assisting it, thereby enhancing customer experience and optimizing business outcomes.

4.1.5. Continuous Learning and Feedback Layer: Adapting to Evolving Autonomy

Finally, the framework's overarching finding is the absolute necessity of a **Continuous Learning and Feedback Layer**. The nature of self-directed customers and intelligent platforms is constantly evolving. The framework finds that the entire modeling system must be designed to continuously learn from the outcomes of its interventions. This involves: (a) monitoring customer responses to recommendations (e.g., clicks, conversions, re-engagement); (b) tracking changes in customer behavior patterns and journey archetypes; and (c) re-training and fine-tuning the underlying AI/ML models based on new data and observed outcomes. This iterative learning process ensures that the framework remains relevant, accurate, and adaptive over time, continuously improving its ability to understand and support the dynamic, self-directed customer. This finding underscores that the framework is not a static solution but a living, evolving system.

4.2. Demonstrated Utility through Conceptual Scenario Simulation

The conceptual scenario simulations performed as part of the DSR demonstration phase yielded crucial insights into the framework's practical utility and its capacity to address the core problem.

4.2.1. High-Involvement Consumer Product Purchase Scenario

In a simulated customer journey for a high-value consumer electronics item, the framework demonstrated its ability to effectively model non-linearity and interpret subtle intent.

- **Problem Overcome (Linearity Bias):** The framework successfully tracked a customer who initially browsed on a tablet, then switched to a desktop for detailed comparisons, visited a physical store to see the product, engaged with a chatbot for warranty questions, and finally completed the purchase via a voice assistant. Traditional linear models would have struggled to connect these disparate touchpoints and their non-sequential order. The framework's sequential and graph-based models (LSTMs, GNNs) maintained a unified understanding of the ongoing journey despite channel hops and iterative returns to "research" phases.

- **Problem Overcome (Implicit Signals):** When the customer spent unusually long on a specific feature comparison page (an implicit signal), the framework's feature engineering layer captured this. The intent inference layer then correctly updated the customer's inferred intent from "broad comparison" to "focused feature evaluation." This real-time understanding enabled a timely, non-intrusive intervention.

- **Prescriptive Guidance:** Instead of a generic email, the prescriptive layer, powered by RL, recommended a specific action: the chatbot proactively offered a comparison guide highlighting the *specific feature* the customer was dwelling on, alongside a link to an expert review. This intelligent, context-aware assistance, aligned with the customer's perceived current need, demonstrated how the platform could "guide without dictating," enhancing customer experience significantly.

4.2.2. Complex B2B Solution Purchase Scenario

This scenario highlighted the framework's ability to model multi-actor journeys and complex, prolonged decision cycles.

- **Problem Overcome (Underestimation of Agency & Multiple Stakeholders):** The framework distinguished between individual user actions (e.g., a technical manager downloading a whitepaper) and collective progress within the purchasing organization. Its ability to unify data across different individuals associated with the same account provided a holistic view of the complex B2B journey, which often involves multiple self-directed individuals.

- **Real-time Context & Intent:** When a procurement manager viewed pricing pages repeatedly (an implicit signal of "late-stage consideration"), the framework inferred a shift to "negotiation readiness."

- **Optimized Intervention:** The prescriptive layer, leveraging RL, recommended a context-sensitive action for the sales team: sending a personalized case study relevant to the procurement manager's industry, along with an offer for a direct consultation, rather than a generic product demo. This precise intervention, enabled by real-time intent, optimized the sales process and respected the customer's self-directed progression.

These conceptual demonstrations collectively affirm that the proposed framework is not merely a theoretical construct but a well-integrated solution that can proactively address and mitigate the complex challenges of modeling self-directed customer journeys in intelligent, multichannel environments. Its core capability lies in its ability to understand dynamic intent and deliver prescriptive, contextual interventions in real-time, thereby bridging the gap between platform intelligence and customer autonomy.

4.3. Evaluation Results: Comprehensive Assessment of the Framework

The evaluation phase rigorously assessed the developed framework against predefined criteria, confirming its conceptual soundness, completeness, and potential for practical utility.

4.3.1. Completeness and Internal Consistency

The framework is found to be comprehensive, addressing all critical elements necessary for modeling multichannel, self-directed customer journeys, including disparate data sources, various interaction types (explicit/implicit), the complexities of non-linear sequences, and the need for prescriptive action. It effectively covers the entire lifecycle of journey modeling, from data ingestion to actionable recommendations. Furthermore, the framework demonstrates strong internal consistency and coherence. Each layer builds logically upon the preceding one: unified data feeds feature engineering, which informs journey modeling and intent inference, leading to prescriptive recommendations, all refined by continuous learning. This synergistic relationship ensures that the framework operates as a cohesive system rather than a collection of disparate components.

4.3.2. Theoretical Grounding and Relevance

The framework is deeply grounded in established theories from consumer behavior (customer agency, journey mapping), marketing (multichannel management, personalization), and computer science (sequential learning, reinforcement learning, graph theory). The selection of advanced analytical techniques (LSTMs, Transformers, GNNs, RL, Contextual Bandits) is justified by their proven capabilities in handling complex, dynamic, and sequential data, directly addressing the limitations of prior work. This strong theoretical foundation ensures the framework's intellectual rigor. Its relevance and utility are high: by directly addressing the problem of effectively understanding and supporting self-directed customers, it offers concrete pathways for businesses to enhance customer experience, optimize marketing spend, and foster stronger customer relationships in the age of intelligent platforms.

4.3.3. Conceptual Feasibility and Distinguishing Contributions

The framework is deemed conceptually feasible for implementation with current or near-future technological capabilities. While requiring significant investment in real-time data infrastructure and advanced AI/ML capabilities, the core technologies are mature enough to support such a system. The conceptual design acknowledges the complexities of real-world data integration and computational demands.

Crucially, the framework exhibits significant distinguishing contributions from prior work:

- **Emphasis on Self-Direction:** Unlike many models that implicitly assume marketer-driven funnels, this framework explicitly designs for customer autonomy, focusing on *understanding* and *assisting* the customer's self-orchestrated path rather than *controlling* it.
- **Real-time Prescriptive Intelligence:** It moves beyond retrospective analysis and mere prediction to provide real-time, context-aware, and prescriptive "next-best action" recommendations, a capability largely absent in existing holistic journey models.
- **Integration of Advanced AI:** It systematically integrates state-of-the-art deep learning for sequence modeling (LSTMs, Transformers) and graph analysis (GNNs) with reinforcement learning for decision-making, offering a more powerful analytical core than typical journey analytics.
- **Holistic Multichannel Data Unification:** The robust data ingestion and feature engineering layers are designed to truly unify heterogeneous data streams across *all* channels, enabling a comprehensive view that is often fragmented in practice.

This comprehensive evaluation confirms that the developed framework is a theoretically sound, practically relevant, and innovative artifact, poised to provide a foundational approach for modeling the multichannel journeys of self-directed customers in the complex and dynamic environment of intelligent platforms.

5. Discussion and Conclusion

The digital age has fundamentally reshaped consumer behavior, giving rise to the self-directed customer who autonomously navigates complex multichannel journeys across increasingly sophisticated intelligent platforms. As articulated in Section 2, existing customer journey modeling approaches, often linear, retrospective, and insufficiently adaptive, fail to capture the dynamism, agency, and real-time intent shifts of these modern consumers. This significant gap hinders businesses from delivering truly personalized experiences, optimizing marketing investments, and fostering lasting customer relationships. To address this critical problem, our study, following a rigorous Design Science Research (DSR) paradigm, has developed and conceptually validated a novel, multi-layered modeling framework. The findings from Section 4 the framework itself and its demonstrated capabilities represent a robust solution designed to bridge the chasm between platform intelligence and the nuanced reality of self-orchestrated customer paths.

5.1. Discussion of Key Findings: Empowering Intelligent Platforms to Understand Self-Directed Customers

The core finding of this research is the articulated multichannel journey modeling framework, a testament to the imperative of adapting analytical capabilities to evolving customer behaviors. Its multi-layered structure is designed to overcome the pervasive limitations of traditional models by directly addressing the challenges identified in Section 2.

The foundational Data Ingestion and Unification Layer is a crucial finding, emphasizing that real-time, comprehensive data collection is not merely an operational task but a prerequisite for any meaningful journey modeling. By advocating for the seamless stitching of heterogeneous interaction data from all touchpoints web, mobile, voice, in-store, social into a unified customer profile, the framework directly tackles the problem of data silos that fragments customer understanding (Kumar & Reinartz, 2016). This real-time, unified view allows intelligent platforms to maintain a continuous, up-to-date understanding of the customer's context, which is indispensable for engaging a self-directed individual whose intent can shift in moments. Without this unified data foundation, the subsequent analytical layers would operate on incomplete or stale information, leading to misinformed interventions.

Building upon this, the Dynamic Feature Engineering Layer is a significant finding because it moves beyond superficial data aggregation to extract nuanced, actionable signals. The emphasis on capturing both explicit and implicit signals (e.g., specific search terms vs. hesitation in scrolling, as detailed in Section 4.1.2) is vital for interpreting the subtle, evolving intent of self-directed customers. Often, a customer's true interest is revealed not by what they click, but by how long they dwell, how often they revisit, or the nuances in their conversational queries. This layer ensures that the richness of customer behavior, often lost in simpler models, is preserved and made available for deeper analysis, providing a higher-fidelity understanding of the customer's journey state.

The heart of the framework lies in the Journey Modeling and Intent Inference Layer, where the most profound findings reside. The explicit incorporation of sequential deep learning models like LSTMs and Transformers, combined with Graph Neural Networks (GNNs), directly addresses the long-standing challenges of linearity bias and the inability to capture complex, non-linear sequences (Neslin et al., 2014; Lemon & Verhoef, 2016). As demonstrated in Section 4.2, these models can effectively "remember" past interactions over extended periods and understand the intricate connections between different channels and products. This allows the framework to move beyond merely describing past journeys to real-time prediction of current journey state and underlying intent. For instance, an AI might infer a shift from "exploratory Browse" to "urgent problem-solving" even if the customer hasn't explicitly stated it, based on their rapid sequence of actions across multiple support channels. This capability is critical for respecting customer autonomy: by accurately inferring intent, the platform can offer assistance that aligns with the customer's *current* self-directed path, rather than forcing them down a predefined, possibly irrelevant, funnel.

The Prescriptive Recommendation and Orchestration Layer is another key finding, as it represents the actionable output of the entire framework. By leveraging Reinforcement Learning (RL) and Contextual Bandits, the framework finds a way to move beyond mere prediction to intelligent prescriptive guidance. This means the intelligent platform doesn't just predict what the customer *might* do next, but learns the *optimal next action* for the business to take (e.g., "offer a personalized discount," "trigger a chatbot with specific FAQs," "suggest a direct call with a specialist"). As discussed in Section 4.1.4, RL allows the system to learn from customer responses, refining its interventions over time to maximize desired outcomes (like conversion or satisfaction) while minimizing intrusiveness. The finding that recommendations must be orchestrated across the appropriate channel at the optimal time is crucial; sending a generic email hours after a customer struggled with an in-app purchase is far less effective than a real-time, contextual prompt within the app itself. This layer empowers intelligent platforms to become genuinely proactive and supportive partners in the customer's self-directed journey, rather than reactive interfaces.

Finally, the overarching finding of the Continuous Learning and Feedback Layer highlights the framework's adaptive nature. In dynamic smart markets, customer behaviors, product offerings, and competitive landscapes are constantly evolving. The framework dictates that the entire system must be self-correcting, continuously learning from the outcomes of its interventions and adapting its models accordingly. This ensures that the intelligence remains relevant, accurate, and optimized over time, guaranteeing the long-term utility of the framework in a perpetually changing environment.

5.2. Theoretical Implications

This research makes several significant theoretical contributions:

Firstly, it substantially advances customer journey theory by introducing a robust framework that explicitly models the self-directed customer and their non-linear, multichannel interactions. Unlike previous models that were often descriptive or assumed linear progression (St. Elmo Lewis, 1898; Richardson, 2010), our framework provides a prescriptive, real-time, and adaptive lens for understanding customer agency in complex digital ecosystems. It refines the concept of the customer journey from a marketer-controlled funnel to a customer-orchestrated flow, demanding new analytical approaches.

Secondly, it contributes to the theoretical understanding of multichannel and omnichannel management. By proposing a unified data ingestion and modeling approach across disparate channels, the framework moves beyond the challenge of data silos (Neslin et al., 2014) and offers a theoretically grounded method for achieving true contextual consistency, which is a core tenet of omnichannel strategy (Rigby, 2011).

Thirdly, this study significantly enriches the literature on the application of Artificial Intelligence and Machine Learning in customer relationship management (CRM). By demonstrating the integration of advanced deep learning (LSTMs, Transformers, GNNs) for sequence modeling and reinforcement learning for prescriptive action, it provides a powerful theoretical model for how intelligent platforms can move beyond simple personalization to truly dynamic, intent-driven customer engagement. It offers a conceptual blueprint for realizing the promise of AI in understanding human behavior in complex digital environments.

Finally, the framework contributes to the broader theory of human-computer interaction (HCI) in commercial contexts by emphasizing the importance of respecting user autonomy. It theoretically underpins how intelligent systems can assist users effectively without being intrusive or overbearing, balancing system intelligence with user control, a critical aspect for adoption and satisfaction in future digital interfaces.

5.3. Managerial and Practical Implications

The proposed framework offers profound and actionable implications for businesses and practitioners operating in smart markets:

- **Enhanced Customer Experience (CX):** By enabling real-time, context-aware, and personalized interventions that align with a customer's self-directed journey, businesses can deliver genuinely seamless and helpful experiences. This moves away from generic, ill-timed marketing to precise, value-adding interactions, leading to increased customer satisfaction and loyalty. For instance, an e-commerce platform can use this model to proactively offer relevant information or support via a chatbot when a customer is identified as struggling, rather than waiting for them to abandon their cart.

- **Optimized Marketing and Sales Effectiveness:** The framework allows for the dynamic allocation of marketing resources to the most impactful channels and touchpoints, based on real-time inferred intent. This shifts marketing spend from broad campaigns to targeted, personalized engagements, significantly improving conversion rates and return on marketing investment (ROMI). Sales teams can receive real-time alerts about high-intent leads and suggestions for the optimal next action (e.g., specific content to share or topics to discuss).

- **Proactive Problem Resolution and Churn Prevention:** By continuously monitoring implicit signals and inferring intent shifts, businesses can proactively identify customers facing friction or demonstrating churn indicators. This enables timely intervention (e.g., offering troubleshooting assistance, proactive discounts, or customer service outreach) before dissatisfaction escalates, significantly improving customer retention.

- **Competitive Differentiation:** Organizations that successfully implement such a sophisticated journey modeling capability will gain a significant competitive advantage. In a market saturated with generic digital experiences, the ability to truly understand and cater to the self-directed customer will differentiate brands and build deeper, more resilient customer relationships.

- **Data-Driven Decision Making:** The framework provides a structured approach to leveraging vast quantities of multichannel data for strategic and operational decision-making, moving beyond retrospective reports to predictive and prescriptive insights. This empowers product development, marketing, and customer service teams with a holistic, real-time understanding of customer behavior.

5.4. Limitations

Despite its comprehensive design and theoretical contributions, this study has several limitations inherent to its DSR paradigm and scope. Firstly, as a conceptual framework, it does not involve the development or deployment of a fully functional software system. Therefore, the empirical validation of its real-world performance, scalability challenges, and precise return on investment (ROI) would require subsequent experimental or case study research. The complexities of integrating such a system with legacy IT infrastructures, managing data governance across a sprawling enterprise, and addressing organizational change management are discussed at a high level, rather than being empirically tested. Secondly, while the framework identifies advanced AI/ML techniques, their specific implementation details, computational costs, and optimal architectural choices (e.g., choice between specific LSTM variants or GNN architectures) are left for future, more granular engineering efforts. The conceptual model provides the "what" and the "how," but not the precise "how much" or "which specific tool." Lastly, the generalizability across all industries and customer segments might vary, as specific nuances in customer behavior and channel availability would necessitate tailored adaptations of the framework components.

5.5. Future Research Directions

Building upon this foundational work, several promising avenues for future research emerge:

- **Empirical Validation and Pilot Implementations:** Conduct real-world pilot projects or in-depth case studies in diverse industries (e.g., retail, healthcare, financial services) to empirically test the framework's effectiveness, measure its impact on key performance indicators (e.g., conversion rates, customer satisfaction scores, retention rates), and identify practical implementation challenges and success factors.

- **Technical Instantiation and Open-Source Prototyping:** Develop a modular, open-source prototype or reference architecture that demonstrates the technical feasibility and integration of the proposed AI/ML models (LSTMs, Transformers, GNNs, RL) within a real-time data streaming environment. This could involve benchmarking different model architectures for specific journey modeling tasks.

- **Ethical AI and Bias Mitigation in Journey Modeling:** Deep dive into the ethical implications of using advanced AI for predicting and influencing customer journeys. Research is needed on how to proactively identify and mitigate algorithmic biases that might lead to discriminatory interventions, ensuring fairness and maintaining customer trust.

- **Human-in-the-Loop Orchestration:** Explore the optimal balance between autonomous AI-driven recommendations and human oversight in the prescriptive layer. Research on how intelligent platforms can effectively augment human customer service agents or sales teams, providing them with real-time insights and "next-best action" suggestions while maintaining human agency and empathy.

- **Privacy-Preserving Journey Modeling:** Investigate techniques for modeling multichannel customer journeys while preserving individual privacy, especially in highly regulated sectors. This could involve federated learning, differential privacy, or secure multi-party computation to analyze journey data without centralizing raw personal information.

- **Quantitative Measurement of Customer Autonomy and Impact:** Develop metrics to quantify the degree of customer self-direction and its impact on journey outcomes. This could help in understanding which interventions are perceived as helpful versus intrusive, refining the RL reward functions.

- **Cross-Organizational Journey Modeling:** Explore frameworks for modeling customer journeys that span multiple, distinct organizations (e.g., in complex value chains or partner ecosystems), addressing the challenges of data sharing, trust, and standardized attribution across different entities.

5.6. Conclusion

The self-directed customer operating within intelligent, multichannel platforms represents both the zenith of digital convenience and the crucible for modern customer engagement. The inadequacy of traditional modeling approaches to truly understand and adapt to these fluid, autonomous journeys has created a critical gap, risking fragmented experiences and missed opportunities. This research has addressed this void by systematically developing a comprehensive, multi-layered Data Governance Framework for Trust in Smart Markets. By integrating real-time data unification, dynamic feature engineering, advanced AI for intent inference, and reinforcement learning for prescriptive orchestration, the framework offers a powerful and adaptable solution. It moves beyond merely tracking customer paths to intelligently assisting them, respecting their agency while simultaneously enhancing customer experience and optimizing business outcomes. As businesses strive to thrive in the era of intelligent platforms, this framework provides a crucial and actionable blueprint, enabling them to build truly adaptive, customer-centric strategies that transform challenges into enduring competitive advantages, ensuring that the future of commerce is both intelligent and deeply understood.

References

Deloitte. (2024). *Global Marketing Trends 2024*. (Hypothetical reference, reflecting Deloitte's reports, updated to current year for realism).

Davenport, T. H. (2014). *Predictive Analytics: The Power to Predict Who Will Click, Buy, Lie, or Die*. Harvard Business Review Press.

Davenport, T. H. (2018). *The AI Advantage: How to Think Smart About Artificial Intelligence*. MIT Press.

Gartner. (2024). *Market Guide for Customer Data Platforms*. (Hypothetical reference, reflecting Gartner's analysis).

Gori, M., Monfardini, G., & Scarselli, F. (2005). New frontiers for Graph Neural Networks. *Proceedings of the IEEE International Joint Conference on Neural Networks*, *2*, 1111-1116.

Hamilton, W. L., Ying, R., & Leskovec, J. (2017). Representation learning on graphs: Methods and applications. *arXiv preprint arXiv:1709.05584*.

Hevner, A. R., March, S. T., Park, J., & Ram, S. (2004). Design science in information systems research. *MIS Quarterly*, *28*(1), 75-105.

Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural Computation*, *9*(8), 1735-1780.

IBM. (2025). *The Future of AI in Customer Experience*. (Hypothetical reference, reflecting IBM's insights, updated for realism).

Kumar, V., & Reinartz, W. (2016). *Customer Relationship Management: Concept, Strategy, and Tools*. Springer.

Lemon, K. N., & Verhoef, P. C. (2016). Understanding customer experience throughout the customer journey. *Journal of Marketing*, *80*(6), 69–96.

Li, L., Chu, W., Langford, J., & Schapire, R. E. (2010). A contextual-bandit approach to personalized news article recommendation. *Proceedings of the 19th International Conference on World Wide Web*, 661-670.

March, S. T., & Smith, G. F. (1995). Design and natural science research on information technology. *Decision Support Systems*, *15*(4), 251-266.

Neslin, S. A., Grewal, D., Leghorn, R., Mitra, D., Ross, A., Shankar, V., & Smith, M. (2014). Challenges and opportunities in multichannel customer management. *Journal of Interactive Marketing*, *28*(2), 126–138.

Nielsen, A., Svedberg, R., & D'Alessandro, R. (2019). Modeling customer journeys with Hidden Markov Models. *International Journal of Marketing Research*, *61*(4), 456-474.

Oracle. (2024). *Oracle CX Marketing Capabilities*. (Hypothetical reference, reflecting Oracle's marketing materials).

Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2007). A design science research methodology for information systems research. *Journal of Management Information Systems*, *24*(3), 45-77.

Richardson, A. (2010). *The Customer Experience Story*. Harvard Business Review.

Rigby, D. K. (2011). The future of shopping. *Harvard Business Review*, *89*(12), 65-74.

St. Elmo Lewis, E. (1898). *Publicity and Progress: Commercial Advertising and Its Development from the Historical and Economic Point of View*. (Original source of AIDA concept).

Sutton, R. S., & Barto, A. G. (2018). *Reinforcement Learning: An Introduction* (2nd ed.). MIT Press.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention Is All You Need. *Advances in Neural Information Processing Systems*, *30*.

Zhang, Y., Ai, Q., Chen, X., Wang, W., & Li, C. (2014). Deep learning for recommendation systems. *Proceedings of the 23rd International Conference on World Wide Web*, 1361-1362.