E-Commerce Behavioral Patterns and Consumer Insights: A Data-Driven Behavioral Economics and HCI Analysis

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***Abstract*—This study bridges machine learning, behavioral economics, and human-computer interaction (HCI) to enhance the understanding of consumer behavior in e-commerce environments. Leveraging a large-scale dataset of over 26 million user events from a multi-category online store, we apply data mining and pattern recognition techniques to uncover behavioral trends within the digital purchase funnel. Specifically, we use sequential pattern mining to model user interactions and transitions between browsing, consideration, and conversion stages. User decision-making processes are interpreted through behavioral economics lenses, such as bounded rationality, decision fatigue, and regret theory lenses. We also discuss how interface design and time-of-day effects impact user behavior. Our findings provide actionable insights into consumer patterns and propose interventions that can guide more informed decision-making and reduce cognitive biases. This interdisciplinary approach advances academic research at the intersection of economics and HCI. It offers practical guidance for businesses aiming to optimize user experience, improve conversion rates, and understand user behavior patterns in digital commerce.**

***Index Terms*—E-commerce, Human-Computer Interaction, Behavioral Economics, Consumer Behavior, Machine Learning, Sequential Pattern Mining, User Experience Design**

I. Introduction

The convergence of economics and human-computer interaction (HCI) remains an underexplored area, offering significant potential to enhance our understanding of user behavior in digital environments. Economics provides valuable frameworks for analyzing decision-making processes under constraints, such as bounded rationality, decision-fatigue, and regret theory, while HCI focuses on optimizing user interactions with technology. Integrating these disciplines enables a holistic understanding of how users engage with e-commerce platforms, offering opportunities to inform the design of systems that align with both user needs and business goals.

In today's competitive environment, the success of digital businesses depends not only on acquiring data but on translating that data into meaningful insights. Behavioral data, when properly structured and interpreted, becomes a powerful lens through which companies can understand their users and make informed product and design decisions [Tiwari, 2024]. This study leverages a real-world e-commerce dataset to uncover and analyze patterns in user interactions across the purchase funnel, from product views to cart actions and purchases. Rather than predicting individual behavior, the focus here is on identifying behavioral signals and bottlenecks that may inform improvements in user experience design.

The original dataset includes over 285 million events across seven months of interaction with a large multi-category online store. Due to hardware limitations, the analysis focuses on a representative subset, of October 2019, generating 26.5 million rows. This reduced yet substantial dataset still offers a rich source of behavioral insights while maintaining computational feasibility for in-depth session-level analysis.

Through this interdisciplinary lens, the study bridges economics, behavioral data mining, and HCI design to demonstrate how large-scale interaction data can be used not only to understand what users do, but also to infer why. The results serve as a foundation for companies and researchers interested in uncovering friction points, behavioral biases, and design opportunities within digital commerce environments. Not only does it contribute to academic discourse, but also it offers practical solutions for businesses seeking to optimize customer engagement and drive informed digital strategies.

This paper makes three main contributions:

- We present a large-scale sequential behavioral analysis of over 6.4 million e-commerce user sessions.
- We uncover how observed behavior aligns with behavioral economics principles, particularly bounded rationality, decision fatigue, and regret aversion.
- We propose actionable human-computer interaction (HCI) design recommendations based on real-world behavioral signals, emphasizing adaptive and cognitively aware interface design.

II. Study Goals

The goals of this study are threefold, integrating exploratory data mining, behavioral theory, and human-computer interaction (HCI) design:

1. Exploratory Data Analysis (EDA): Perform a comprehensive analysis of a large-scale e-commerce behavioral dataset to uncover patterns and trends in user activity. This includes identifying dominant event sequences, interaction frequency, session duration, and product diversity across millions of sessions.

2. Behavioral Economics Analysis: Apply sequential pattern mining (PrefixSpan) to extract common interaction pathways across user sessions. These patterns are then interpreted through the lens of behavioral economics, with a focus on:

- *Bounded Rationality:* Evaluate how users limit their decision-making scope and make satisficing choices rather than optimizing.
- *Decision Fatigue:* Analyze how cognitive depletion over time contributes to higher cart abandonment, particularly in the evening.
- *Regret Theory:* Examine behavioral hesitation associated with delayed purchases and cart removal loops.
- *Time-of-Day Effects:* Assess how temporal context influences decision quality, browsing intensity, and conversion likelihood.

3. Human-Computer Interaction (HCI) Insights: Translate behavioral patterns into actionable HCI recommendations for interface and UX design. This includes identifying cognitive bottlenecks and proposing design interventions—such as adaptive nudges, trust cues, and progressive disclosure—to support informed and confident user decisions.

This study aims to serve as a data-driven foundation for building more effective, behavior-aware, and user-centered e-commerce platforms that align with human decision-making capabilities.

III. Related Work

The intersection of economics and human-computer interaction (HCI) is an emerging field that seeks to understand how economic principles influence digital decision-making and user behavior. Existing research explores consumer biases, decision-making processes, and predictive modeling in e-commerce, providing a foundation for integrating these three topics: behavioral economics, machine learning, and HCI to improve online shopping experiences. This section reviews key contributions in these areas and highlights gaps that this study aims to address.

The relationship between economics and HCI has been gaining attention as researchers seek to understand how economic behavior influences interactions with digital systems. Sun emphasizes the need for an interdisciplinary approach, arguing that integrating economic theories with HCI can provide deeper insights into how users make decisions in resource-constrained environments [Sun, 2010]. Similarly, Quinn explores how psychological biases, such as loss aversion and overconfidence, affect user interactions with digital platforms, suggesting that interface design can either amplify or mitigate these biases [Quinn, 2016]. More recently, Vetrivel et al. discuss the role of HCI in shaping the digital economy, emphasizing how effective user interfaces and system designs can guide users toward more informed decision-making [Vetrivel et al., 2024].

Understanding consumer behavior in e-commerce is crucial for designing better digital experiences. Sismeiro and Bucklin propose a task-completion approach to model consumer behavior, analyzing factors that influence a user's likelihood of making a purchase after engaging with an e-commerce website [Sismeiro and Bucklin, 2004]. Petcharat and Leelasantitham build on this work by introducing a retentive consumer behavior assessment model, which highlights key decision-making stages and the role of customer engagement in increasing purchase likelihood [Petcharat and Leelasantitham, 2021]. These studies suggest that behavioral insights and data-driven approaches can significantly enhance e-commerce strategies.

Recent work by Ed-Daakouri et al. further explores the application of smart data analytics in mapping online consumer behavior, emphasizing the role of big data and machine learning in understanding how users navigate digital marketplaces [Ed-Daakouri et al., 2025]. This study aligns with the findings of Kim et al., who integrate customer characteristics and browsing patterns to predict online purchases, demonstrating the effectiveness of data-driven methods in modeling consumer behavior [Kim et al., 2024]. Predicting consumer behavior using machine learning has been a growing focus in e-commerce research. The dataset provided by Kechinov offers a large-scale representation of e-commerce user interactions, making it an ideal resource for training predictive models [Kechinov, 2020].

The PrefixSpan algorithm [Pei et al., 2001] offers a computationally efficient method for discovering frequent sequential patterns, which has seen application in domains like e-commerce for understanding the order of user interactions. Trivonanda et al. [Trivonanda et al., 2020] apply this method to improve recommendation systems by extracting sequential behavior patterns from real-world shopping datasets, showcasing the value of temporal patterns in personalizing user experiences. These works support the foundation of our approach by validating sequential pattern mining as a scalable and insightful analytical tool.

Finally, Zaheer [Zaheer, 2020] presents a study that aligns closely with the goals of our work, highlighting how cognitive science and behavioral economics can enhance usability and reduce decision fatigue in e-commerce platforms. However, while her approach focuses on theoretical and qualitative insights to propose design improvements, our study builds upon this by grounding suggestions in evidence extracted from real data. By using behavioral data from a multi-category store, our analysis provides a contextualized and data-driven exploration of how decision fatigue, bounded rationality, and information asymmetry manifest in real consumer behavior.

While extensive research has been conducted on predictive modeling of consumer decision-making, fewer studies have focused on deriving actionable insights to inform interface and experience design. The role of HCI in shaping online shopping behavior remains underexplored, particularly when grounded in observed user patterns rather than generalized theory. Many existing works leverage data to build predictive models but stop short of translating those findings into specific design or communication improvements. This study takes a different approach. Rather than attempting to forecast individual behavior, it analyzes large-scale e-commerce data to identify common behavioral patterns and interpret them through the lens of behavioral economics. These insights are then positioned to guide interface and system design decisions that can reduce decision fatigue, mitigate cognitive biases, and promote user confidence. In doing so, this work contributes to a more interpretive and human-centered application of machine learning and behavioral analysis in e-commerce — acting not as a prediction engine, but as a diagnostic and design-support tool for more thoughtful digital commerce environments.

IV. Data

The dataset used in this study, titled *"eCommerce Behavior Data from a Multi-Category Store"*, provides comprehensive behavioral records collected from a large online retail platform over a seven-month period (October 2019 to April 2020) [Kechinov, 2020]. The full dataset contains over 285 million event-level observations, each corresponding to a unique user interaction such as product views, cart additions, cart removals, or purchases. Each entry includes attributes like user ID, session ID, product ID, product price, brand, category, and a timestamp.

Due to computational limitations, we focused our analysis on a representative subset of October 2019, which still includes over 26.5 million events. This sample preserves the overall structure and behavioral diversity of the full dataset while ensuring feasibility for deep pattern mining and sequential modeling on a personal computing environment.

Event types in the dataset include:

- view: The user viewed a product page.
- cart: The user added a product to their cart.
- remove: The user removed a product from the cart.
- purchase: The user completed a transaction.

Despite the absence of demographic data, behavioral signals allowed meaningful insights. We extracted features that reflect both the intensity of the interaction and the dynamics of the session. The inherent imbalance of the data set, where 94% of the events are product views, is typical of e-commerce platforms, where users often browse extensively before committing to a purchase. Although this skew poses challenges for traditional modeling, it is highly informative for behavioral economics analysis, as it highlights moments of intention, hesitation, and abandonment throughout the digital purchase journey.

To prepare the dataset for analysis, several preprocessing steps were taken. First, data cleaning was performed by removing rows with missing critical fields, including product price, product ID, or category information, to ensure the integrity of subsequent analyses. Next, user sessions were reconstructed by grouping events according to session ID and ordering them chronologically based on their timestamps, allowing for an accurate representation of sequential user behavior.

Several session-level features were engineered to enrich the behavioral analysis following session construction. These features included the event sequence for each session (e.g., `view` → `cart` → `view` → `purchase`), the average product price encountered within the session, and the total session duration measured in seconds. Each event was assigned a time-of-day label (Morning, Afternoon, Evening, Night) based on its timestamps, capturing temporal dynamics in user activity. Finally, behavioral segmentation was applied by categorizing sessions into price tiers (Low, Medium, High) and associating them with the dominant product category interacted with during the session. These engineered features provided a multidimensional view of user behavior, enabling more nuanced pattern discovery and subgroup analysis.

The final dataset used for analysis contained more than 6.4 million distinct user sessions with interaction sequences spanning from single-product views to complex multi-step funnels. This setup allowed for robust pattern mining and the application of behavioral lenses (e.g., bounded rationality, decision fatigue) to interpret emerging user pathways.

TABLE I
SUBSET SUMMARY: OCTOBER, 2019

Statistic	Value
Time Period	October, 2019
Total Number of Events	26,560,620
Number of Unique Users	2.3 Million
Number of Sessions	6.4 Million
Event Type Distribution	View (94%) Cart (3%) Remove (1%) Purchase (2%)
Number of Features per Event	9 (e.g., timestamp, product ID, event type, etc.)
Key Engineered Features	Session duration, interaction sequence, average price, time of day

This cleaned and structured dataset was the foundation for all sequential analysis and pattern mining procedures, providing a solid empirical basis for uncovering how digital consumers behave across time, product categories, and price ranges. The dataset is publicly available and maintained by the REES46 Marketing Platform, with appropriate licensing for academic research.

V. Methods

This study adopts an analytical framework focused on uncovering patterns in user behavior by leveraging sequential pattern mining techniques and behavioral subgroup segmentation. Rather than building predictive models, our goal is to derive interpretable insights from real user behavior that inform how e-commerce platforms can be optimized through better interface design and behavioral economics awareness.

To discover recurring consumer behavior patterns, we used the PrefixSpan (Prefix-Projected Sequential Pattern Mining) algorithm [Pei et al., 2001]. This method efficiently identifies frequent subsequences of user actions (e.g., view → cart → purchase) by recursively projecting only relevant portions of the dataset and avoiding costly candidate generation. Each user session was modeled as a sequence of timestamp-ordered event types (view, cart, remove, purchase), allowing us to extract patterns that capture common paths and transitions through the digital purchase funnel.

To make these findings more interpretable from a behavioral economics perspective, we divided sessions into three key categorical groups:

- Price Chunk: Sessions were grouped into High, Medium, and Low price segments based on the average product price seen or interacted with in each session.
- Main Product Category: Sessions were grouped by the most frequent product category (e.g., apparel, electronics) a user interacted with, helping surface domain-specific patterns (e.g., more cart removals in apparel).
- Time of Day: Sessions were grouped by when they occurred—Morning, Afternoon, Evening, or Night—to evaluate the influence of cognitive fatigue and timing on decision behavior.

This segmentation enabled the discovery of contextualized behavioral patterns. We also computed cart conversion funnel metrics, such as abandonment rate, remove-from-cart rate, and purchase rate within each subgroup, to understand behavioral drop-offs and transitions across different user contexts.

By combining PrefixSpan with context-aware subgrouping, we establish a structured approach for linking sequential user behavior to theoretical constructs from behavioral economics. This enables actionable insights not only into what users do but also why they do it, highlighting cognitive and contextual factors behind their decisions. These findings can inform future HCI improvements, platform redesigns, and strategic business decisions aimed at enhancing user experience and conversion outcomes.

VI. Results

This section presents a data-driven behavioral economics analysis of user activity from 6.4 million sessions collected during October 2019. Using sequential pattern mining (PrefixSpan), interaction filtering, and subgroup analysis, we extract insights into consumer behavior across dimensions of time, price sensitivity, evaluation depth, and session structure. Findings are contextualized using behavioral economics theories—bounded rationality, regret aversion, and decision fatigue and linked to human-computer interaction (HCI) implications for e-commerce platforms.

A. Temporal Trends and Decision Fatigue

Morning hours saw the highest volume of cart additions and purchases, while cart abandonment peaked in the evening. This supports the theory of *decision fatigue*, where cognitive resources deplete over the day, reducing users' capacity to complete even low-effort decisions [Zaheer, 2020]. In line with prior findings [Vetrivel et al., 2024], these temporal dynamics suggest that HCI systems should dynamically adjust the complexity and volume of decision stimuli based on time-of-day, offering more simplified checkout flows or nudges during evening hours.

B. Category and Price Segment Behavior

Medium-price products exhibited the highest cart-to-purchase conversion rate (53.13%), especially in categories such as Electronics, Appliances, Automotive, and Country Yard. Conversely, low-price items had the highest cart abandonment rates (56.84%), particularly across Stationery, Apparel, Sports, and Kids categories.

These patterns align with the model of *bounded rationality*, which acknowledges that consumers, constrained by limited cognitive resources, time, and information, do not always strive for optimal decisions but rather for satisfactory ones [Simon, 1956]. Purchases such as electronics and household appliances often represent products where consumers can more easily apply heuristics. For example, relying on brand reputation, feature lists, or social proof to reach a "good enough" decision without excessive deliberation [Gigerenzer et al., 1999].

In contrast, categories like Stationery and Apparel involve products that are either low-risk or highly substitutable. Because the perceived cost of not purchasing is minimal and the differentiation among options is often unclear, users may deprioritize or defer these purchases, resulting in higher abandonment rates. This behavior exemplifies *satisficing* under uncertainty: when the cognitive effort required to finalize a decision outweighs the perceived reward, users default to inaction [Schwartz, 2004].

From an HCI standpoint, these insights suggest differentiated design strategies. In low-price, high-abandonment categories, interfaces could introduce urgency signals (e.g., limited stock alerts) or bundling recommendations to tip users toward quick decisions. Meanwhile, for categories with naturally higher conversion rates, platforms could maximize visibility and ease of access through homepage prioritization, prominent filtering, or trust-enhancing badges during high-intent periods.

C. Browsing-Only Sessions and Behavioral Inertia

Over 89% of sessions consisted exclusively of product views without any interaction events such as cart additions or purchases. These browsing-only sessions had a surprisingly long average duration of approximately ˜17.1 minutes, substantially longer than interaction-based sessions, which averaged around ˜11.5 minutes. Despite this extended exposure, these sessions frequently led to no purchase activity.

This phenomenon reflects behavioral inertia and *cognitive overload*, where an excess of choice or lack of meaningful differentiation results in non-decision [Schwartz, 2004]. It may also reflect *satisficing* behavior, where users gather just enough information to decide not to act when a clear optimal choice is lacking [Simon, 1956]. Additionally, the prolonged nature of these sessions may contribute to or stem from *decision fatigue*, in which the accumulation of minor decisions during lengthy browsing drains users' cognitive resources, leaving them less capable of committing to a final action [Kumar and Singh, 2024].

To counteract this inertia, HCI strategies can introduce progressive disclosure, interface simplification, or adaptive nudging. For instance, prompting actions after three or more views, highlighting trending or well-reviewed products, or offering a personalized "Still interested?" message could gently encourage users toward conversion by reducing friction and supporting cognitive ease.

D. Sequential Patterns and Regret Aversion

Among sessions with interaction, the most frequently observed behavioral paths were:

- `view` → `cart` → `purchase` → `view`
- `view` → `cart` → `purchase`
- `view` → `purchase`
- `view` → `cart` → `view`

Direct conversion sequences, particularly those involving only one or two steps, were associated with shorter average durations (e.g., ˜2.3 minutes), whereas paths looping between cart and view actions were substantially longer (up to ˜6.2 minutes). These prolonged sessions suggest deliberation or second-guessing behavior.

Such patterns are consistent with *regret theory*, where users delay finalizing a decision due to fear of making the wrong choice [Quinn, 2016]. This hesitation is often amplified in contexts where product differentiation is low or post-purchase consequences are uncertain. Tsiros and Mittal (2000) further elaborate that the anticipation of regret can significantly influence consumer behavior, leading individuals to avoid making decisions that might result in unfavorable outcomes [Tsiros and Mittal, 2000]. Their research highlights that anticipated regret not only affects the decision-making process but also has implications for post-decision satisfaction and future purchasing intentions.

To reduce regret aversion, platforms could deploy reassurance cues such as money-back guarantees, customer reviews, or popularity labels near the checkout stage. These design elements reduce the perceived risk and reinforce decision confidence at critical moments.

E. Evaluation Depth and Cognitive Load

Interaction-based sessions averaged 3.3 discrete events per session and typically included a wider variety of products and brands. As the number of viewed or carted items increased, so did session duration and product diversity, suggesting a higher cognitive load and more extensive decision-making process.

Across session types, behavioral complexity was also reflected in the diversity of explored content. Browsing-only sessions involved an average of 2.6 unique products and 1.63 unique brands, which is slightly higher than interaction sessions, which averaged 2.62 products and 1.53 brands. This suggests that users who explore more do not necessarily proceed further into the purchase funnel. In fact, browsing sessions may reflect a more exhaustive but ultimately indecisive evaluation process, where cognitive load and lack of differentiation hinder progression toward action.

From an HCI perspective, platforms can support evaluation depth without overwhelming users by surfacing tools such as product comparison matrices and filters. Real-time indicators such as "only 3 left" or "highest rated in category" can also assist users in reaching satisfactory decisions without extensive searching.

F. Summary of Evaluation Behavior

Taken together, these findings underscore how user evaluation depth is shaped not just by the number of products viewed, but also by session structure, product diversity, and cognitive load. Users often gather substantial information before committing—or choosing not—to act. The marginal increases in product and brand exploration between session types suggest that extended evaluation does not necessarily yield better outcomes, and that complexity may hinder rather than help decision-making.

From a behavioral economics lens, these behaviors reflect an interplay between bounded rationality, search cost thresholds, and satisficing strategies. In turn, these insights reveal clear opportunities for e-commerce platforms to design support mechanisms that reduce friction, alleviate cognitive burden, and guide users toward more confident decisions. A summary of key observations and actionable HCI recommendations is presented in Table II.

VII. Discussion

The results of this study highlight key patterns in consumer decision-making behavior across 6.4 million sessions. Using sequential pattern mining and subgroup segmentation, we observed that users exhibit repeatable behavioral structures that vary with context, especially time of day, price sensitivity, and product category.

From a behavioral economics perspective, our findings demonstrate bounded rationality in action. Users frequently engaged in extended browsing (e.g., sequences of 6–10 views), often without making a purchase, supporting theories of satisficing under cognitive constraints [Simon, 1956]. The high incidence of browsing-only sessions (89%) and their longer average duration (17 minutes) compared to interaction sessions (11.5 minutes) suggests that more time spent does not necessarily lead to better outcomes. Rather, it may reflect cognitive overload or decision avoidance [Schwartz, 2004].

Temporal segmentation further revealed that purchases and cart additions peak in the morning, while abandonment is most frequent in the evening. This aligns with *decision fatigue* literature, suggesting that users' cognitive resources decline as the day progresses, increasing the likelihood of avoidance or deferral [Kumar and Singh, 2024], [Zaheer, 2020].

Our sequential analysis of interaction sessions revealed that short patterns (e.g., `view` → `purchase`) were fast and efficient, while looping paths involving cart additions and removals were longer and more hesitant, often lasting over 6 minutes. This behavior maps closely to *regret theory*, where users fear making suboptimal choices and delay decisions under uncertainty [Tsiros and Mittal, 2000], [Quinn, 2016].

These findings have practical implications for HCI. Dynamic UI adjustments, such as simplification during cognitively depleted times (e.g., evening), adaptive nudges after

TABLE II
SUMMARY OF BEHAVIORAL PATTERNS AND HCI IMPLICATIONS

Observation	Behavioral Theory	HCI Suggestion
Morning conversions peak	Decision Fatigue	Prioritize promotions and simplify checkout flows during evening hours when cognitive resources are lower
Browsing-only sessions dominate	Bounded Rationality	Trigger gentle nudges toward carting after three or more views in a session
Cart → View loops common	Regret Aversion	Add visual reassurance elements (e.g., "best rated" badges, satisfaction guarantees) near checkout
Low-price abandonment high	Satisficing Bias	Bundle low-cost items and introduce subtle urgency messages (e.g., "low stock")
Mid-price purchase peak	Cost-Benefit Reasoning	Emphasize security (returns, warranties) to make moderate-cost decisions easier
Longer browsing patterns	Cognitive Load	Provide quick comparison tools or shortlist features to reduce overload

repeated browsing, or social proof cues near the cart, can reduce friction and encourage confident decisions. Our results also indicate that category and price segmentation matter: electronics (mid-priced) were most likely to convert, while stationery and apparel (low-cost, highly substitutable) were frequently abandoned. This suggests that UX should be tailored to the user's purchase context, urgency cues and bundling for low-commitment items, and trust elements for moderate-commitment purchases.

Finally, browsing and interaction sessions both plateaued around 2.6 products per session, indicating that decision depth may be bounded more by cognitive capacity than product interest. HCI designs can accommodate this by offering side-by-side comparisons, shortlist tools, or micro-personalized recommendations to reduce search friction and mitigate cognitive load.

VIII. Limitations and Generalizability

While this study provides valuable insights into consumer behavior, several limitations must be acknowledged. First, the dataset lacked demographic or psychographic information, limiting the ability to segment users by characteristics such as age, gender, or income. Second, behavioral patterns were derived from a single multi-category retail platform during a specific period, which may constrain generalizability across other industries or regions. Third, while sequential patterns offer strong descriptive insights, they do not capture the full range of factors influencing decisions, such as promotions, external browsing behavior, or device type. Future work should aim to incorporate richer user metadata, multi-platform datasets, and hybrid models to validate and extend the behavioral patterns uncovered here.

IX. Future Work

This study opens several promising avenues for future exploration at the intersection of data science, behavioral economics, and human-computer interaction (HCI). One key direction is the integration of probabilistic and graph-based models to capture deeper behavioral dynamics and user-product relationships. While this study used sequential pattern mining (PrefixSpan) to identify dominant behavioral paths, future work could incorporate Hidden Markov Models (HMMs) to infer latent intent states (e.g., browsing vs. consideration) based on observable actions. This would allow a more nuanced understanding of user transitions within the digital funnel.

Additionally, graph-based approaches such as Graph Neural Networks (GNNs), particularly those leveraging attention mechanisms, could be used to model the complex relational structures between users, sessions, and products. This would enable the detection of influential interaction pathways, user segments, or product categories that disproportionately affect outcomes such as cart abandonment or conversion.

Another direction for future work lies in building adaptive user interfaces informed by the behavioral patterns extracted from the dataset. For example, platforms could dynamically adjust interface complexity or the timing of nudges based on time-of-day fatigue indicators or user session depth. This aligns with the goal of mitigating decision fatigue and bounded rationality through targeted HCI interventions.

Finally, applying these methods to more diverse e-commerce datasets, including those with demographic or psychographic data, would enable a richer understanding of how behavioral economics principles manifest across user types and contexts. Such generalization is essential for developing robust, ethically grounded, and context-aware design recommendations.

X. Conclusion

This study presents a large-scale, data-driven analysis of consumer behavior in e-commerce through the lens of behavioral economics and HCI. By analyzing over 6.4 million sessions from October 2019 and applying sequential pattern mining, we uncovered systematic behavioral trends, such as decision fatigue, bounded rationality, and regret aversion, that influence how users interact with digital shopping platforms.

Key insights include the predominance of non-interactive browsing sessions, the cognitive timing of cart abandonment, and the nuanced differences in purchase behavior by product category and price tier. These findings offer empirical support for classical behavioral models and provide actionable suggestions for UX designers, such as time-adaptive interfaces, reassurance cues, and search-easing mechanisms.

Rather than predicting individual outcomes, our work offers interpretive and diagnostic value, highlighting how behavior manifests across millions of interactions and how interface design might shape or mitigate those behaviors. The combination of data mining and behavioral theory opens a promising avenue for more human-centered digital commerce.

Future research should extend these methods to longitudinal datasets or diverse platforms, incorporate richer demographic features, and explore personalized real-time interventions informed by user journey patterns. Ultimately, this work contributes to building more intuitive, ethical, and decision-supportive digital shopping environments.

REFERENCES

[Ed-Daakouri et al., 2025] Ed-Daakouri, I., Alla, L., and Bouhtati, N. (2025). Smart data analytics for efficient mapping of customers' online shopping behavior: A systematic review of the literature. *Mapping Human Data and Behavior With the Internet of Behavior (IoB)*, pages 239–270.

[Gigerenzer et al., 1999] Gigerenzer, G., Todd, P. M., and the ABC Research Group (1999). Simple heuristics that make us smart. *Oxford University Press*.

[Kechinov, 2020] Kechinov, M. (2020). Ecommerce behavior data from multi-category store. Accessed: 2025-02-09.

[Kim et al., 2024] Kim, S., Shin, W., and Kim, H.-W. (2024). Predicting online customer purchase: The integration of customer characteristics and browsing patterns. *Decision Support Systems*, 177:114105.

[Kumar and Singh, 2024] Kumar, R. and Singh, A. (2024). Decision fatigue for the online/digital shoppers. *Partners Universal International Research Journal*, 3(4):20–29.

[Pei et al., 2001] Pei, J., Han, J., Mortazavi-Asl, B., Pinto, H., Chen, Q., Dayal, U., and Hsu, M.-C. (2001). Prefixspan,: mining sequential patterns efficiently by prefix-projected pattern growth. In *Proceedings 17th International Conference on Data Engineering*, pages 215–224.

[Petcharat and Leelasantitham, 2021] Petcharat, T. and Leelasantitham, A. (2021). A retentive consumer behavior assessment model of the online purchase decision-making process. *Heliyon*, 7(10).

[Quinn, 2016] Quinn, P. (2016). Economic behaviour and psychological biases in human–computer interaction.

[Schwartz, 2004] Schwartz, B. (2004). The paradox of choice: Why more is less. *Harper Perennial*.

[Simon, 1956] Simon, H. A. (1956). Rational choice and the structure of the environment. *Psychological Review*, 63(2):129–138.

[Sismeiro and Bucklin, 2004] Sismeiro, C. and Bucklin, R. E. (2004). Modeling purchase behavior at an e-commerce web site: A task-completion approach. *Journal of marketing research*, 41(3):306–323.

[Sun, 2010] Sun, H. (2010). Developing an interdisciplinary area of economics and human-computer interaction. *AIS Transactions on Human-Computer Interaction*, 2(4):151–166.

[Tiwari, 2024] Tiwari, V. (2024). Role of data analytics in business decision making. *Knowledgeable Research: A Multidisciplinary Peer-Reviewd Refereed Journal*, 3(01):18–27.

[Trivonanda et al., 2020] Trivonanda, R., Prihatmanto, A. S., and Riadi, I. (2020). Sequential pattern mining for e-commerce recommender system using prefixspan algorithm. *International Journal of Computer Applications*, 176(34):25–30.

[Tsiros and Mittal, 2000] Tsiros, M. and Mittal, V. (2000). Regret: A model of its antecedents and consequences in consumer decision making. *Journal of Consumer Research*, 26(4):401–417.

[Vetrivel et al., 2024] Vetrivel, S., Sowmiya, K., Sabareeshwari, V., and Arun, V. (2024). Navigating the digital economy: The crucial role of human-computer interaction. In *Social Reflections of Human-Computer Interaction in Education, Management, and Economics*, pages 184–216. IGI Global.

[Zaheer, 2020] Zaheer, S. (2020). The psychology of choice in e-commerce: Designing for decision-making. *International Journal of Human–Computer Interaction*, 36(21):1980–1991.