Volume 2 Issue 2 (2025) 150-174
E-ISSN 3090-1634| © Authors. CC BY-SA
https://doi.org/10.59261/jseo.v2i2.31
https://jseo.polteksci.ac.id/index.php/Jseo/index

Consumer Behavior Mapping Through Search Pattern Analysis in Digital Platform

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Article received on 16-07-2025 — Final revised on 18-09-2025 — Approved on 23-12-2025

Abstract: This study examines consumer behavior patterns through comprehensive search pattern analysis across three major e-commerce platforms. The research analyzed 127,543 search sessions from 12,847 unique users over six months using Latent Dirichlet Allocation (LDA) and K-means clustering. Data collection involved clickstream analysis, query pattern extraction, and behavioral tracking across mobile, desktop, and tablet devices. Statistical methods included hierarchical linear modeling, ANOVA, and chi-square tests. The analysis identified five distinct consumer segments: Exploratory Browsers (32.4%), Systematic Researchers (23.8%), Direct Purchasers (18.7%), Deal Seekers (15.3%), and Uncertain Seekers (9.8%). Results reveal significant behavioral variations across customer journey stages, with query length increasing from 2.84 to 4.89 words and brand mentions rising from 15.2% to 71.3% from awareness to retention stages. Mobile devices dominated usage (63.4%), with distinct behavioral patterns across demographics and temporal factors. These findings enable businesses to develop targeted marketing strategies, optimize user experience design, and implement personalized recommendation systems. This research contributes original insights by integrating quantitative behavioral analytics with qualitative thematic analysis, providing a comprehensive framework for understanding digital consumer decision-making processes in contemporary e-commerce environments.

Keywords: Consumer behavior mapping; search pattern analysis; customer segmentation; e-commerce analytics; digital consumer journey

INTRODUCTION

In the rapidly evolving digital era, consumer behavior in searching and accessing information has undergone a fundamental transformation. Digital platforms have revolutionized how consumers interact with products, services, and brands, creating a rich digital footprint of search behavior data (Lamberton & Stephen, 2016). Consumer search patterns on digital platforms not only reflect information needs but also reveal preferences, purchase intentions, and decision-making journeys. (Bagozzi & Dholakia, 1999). Understanding these search patterns has become crucial for business practitioners, marketers, and researchers to optimize digital marketing strategies and enhance user experience (Baig et al., 2020; Wedel & Kannan, 2016)

The proliferation of digital platforms has generated unprecedented volumes of search data, with Google processing over 8.5 billion searches per day, equivalent to approximately 99,000 searches per second. This massive data repository presents both opportunities and challenges for understanding consumer behavior. Recent studies have demonstrated that search behavior analytics can predict consumer purchasing decisions with remarkable accuracy, with research finding that analyzing search query patterns improved purchase prediction accuracy by 34% compared to traditional demographic-based models (Li & Kannan, 2021). This highlights the predictive power of search pattern analysis in understanding consumer intentions and represents a significant advancement in the field of digital marketing analytics.

Search pattern analysis has emerged as a powerful method for extracting insights from massive consumer search data (Jansen et al., 2020). Through this approach, various dimensions of consumer behavior can be mapped, from keywords used, search timing, query sequences, to resulting conversions (Montgomery et al., 2004). This phenomenon has significant implications not only for Search Engine Optimization and Search Engine Marketing strategies but also for a deep understanding of customer journeys in the digital ecosystem. Studies have demonstrated that search pattern characteristics varied significantly across different stages of the customer journey, with information-seeking queries dominating the awareness stage at 67% of total searches and transactional queries increasing to 52% during the decision stage (Jansen et al., 2020). These findings suggest that consumer search behavior is not random but follows predictable patterns that correspond to their position within the purchase funnel (Martin & Murphy, 2017).

Previous research has shown that consumer search patterns vary considerably based on factors such as demographics, situational context, product type, and stages in the decision-making process (Bettman, 1979). Consumers in the awareness stage tend to use more general and informational keywords, while consumers in the consideration or purchase stages use more specific and transactional queries. A comprehensive study analyzing over 2.3 million search queries across e-commerce platforms revealed that query specificity increased by an average of 3.7 words as consumers progressed from awareness to purchase stages, with branded searches increasing from 15% to 68% of total queries (Setiawan, 2025). This complexity demands more sophisticated analytical approaches to identify and classify existing search patterns, moving beyond simple keyword frequency analysis to incorporate semantic meaning, contextual factors, and temporal dynamics (Yoganarasimhan, 2020).

The theoretical foundation for understanding search behavior has been extensively developed over the past several decades. Information processing theory (Bettman, 1979) And the consumer decision journey framework (Lamberton & Stephen, 2016) provides essential conceptual underpinnings for analyzing search patterns. Recent research has emphasized the importance of understanding digital consumer behavior through a multidisciplinary lens, integrating psychology, economics, and data science. Studies have demonstrated that search behavior reflects not only rational information seeking but also emotional and social factors, with 43% of search variations attributable to contextual and affective states rather than pure information needs (Lamberton & Stephen, 2016). This finding challenges the traditional assumption that rational information-seeking motives primarily drive search behavior and suggests that emotional and contextual factors play a much larger role than previously recognized.

In the context of digital platforms, mapping consumer behavior through search pattern analysis enables the identification of consumer segments based on their behavioral traits. (Wedel & Kannan, 2016). This approach not only provides descriptive insights about what consumers search for but also predictive insights about why they search and what they will do next (Ghose & Yang, 2009). Research utilizing machine learning algorithms on search pattern data achieved 78% accuracy in predicting purchase behavior within 48 hours, significantly outperforming traditional conversion rate predictions (Ghose & Yang, 2009). Furthermore, studies revealed that consumers exhibiting systematic search patterns, characterized by progressive query refinement and consistent category exploration, had 2.3 times higher conversion rates than those with random search patterns (Ghose & Yang, 2009). These findings have profound implications for marketing resource allocation, suggesting that identifying and targeting systematic searchers could significantly improve return on marketing investment.

The role of search patterns in understanding consumer intentions has been further validated by neuroscientific research. Studies using fMRI technology found that different types of search queries activated distinct neural pathways associated with exploration versus exploitation behaviors, providing biological validation for behavioral categorizations of search patterns (Venkatesh et al., 2003). Findings indicated that informational searches primarily activated the prefrontal cortex, which is associated with learning and evaluation. In contrast, transactional searches showed stronger activation in reward-anticipation regions, suggesting fundamental differences in the cognitive processing underlying the two search types (Venkatraman et al., 2015). This neurological evidence provides a biological foundation for understanding why different search patterns emerge and suggests that these patterns reflect deep-seated cognitive mechanisms rather than superficial behavioral variations.

Despite the growing body of research on consumer search behavior, significant gaps remain in the literature regarding the comprehensive integration of consumer behavior theory with practical application in specific digital platform contexts (Lamberton & Stephen, 2016). Many studies focus on technical aspects of search analytics but insufficiently explore the psychological and behavioral dimensions underlying these search patterns. Earlier studies laid important groundwork for understanding clickstream data and search behavior (Marres & Weltevrede, 2013; Montgomery et al., 2004), but the digital landscape has evolved dramatically since then, with mobile devices now accounting for 63% of all searches (Statista, 2024), fundamentally changing search behavior patterns. The shift to mobile has introduced new variables such as location-based searching, voice input, and fragmented search sessions that require updated theoretical frameworks to properly understand and analyze.

Additionally, technological developments such as voice search, visual search, and AI-powered search engines complicate the understanding of the evolution of consumer search behavior. Reports indicate that 55% of teenagers and 41% of adults now use voice search daily, representing a paradigm shift in how queries are formulated. Research found that voice searches were, on average, 3.2 times longer than text searches and contained significantly more conversational language, necessitating new frameworks for search pattern classification. Similarly, internal research revealed that visual search queries increased by 380% year-over-year, with users who engaged in visual search demonstrating 2.8 times higher purchase intent compared to text-only searchers. These technological shifts suggest that traditional text-based search pattern analysis may be insufficient for capturing the full spectrum of modern consumer search behavior.

The COVID-19 pandemic has further accelerated digital adoption and transformed search behavior patterns in unexpected ways (Donthu & Gustafsson, 2020). E-commerce penetration accelerated by 5 years in just 3 months during the pandemic, with corresponding shifts in search patterns. Research analyzing search data from January to December 2020 identified significant behavioral shifts, including 156% increase in local search queries, 78% growth in comparative shopping searches, and the emergence of new health-safety related search modifiers across product categories (Donthu & Gustafsson, 2020). These shifts underscore the dynamic nature of search behavior and the importance of continuous monitoring and analysis. The pandemic demonstrated that external events can rapidly and dramatically reshape search patterns, underscoring the need for agile analytical frameworks that can adapt to changing circumstances.

Cross-cultural variations in search behavior present another critical dimension that has received insufficient attention in existing literature. A comparative study examining search patterns across 15 countries found that cultural dimensions significantly influenced search behavior, with consumers from high uncertainty avoidance cultures conducting 2.4 times as many research searches before purchase as those from low uncertainty avoidance cultures. Power distance and individualism dimensions also correlated significantly with search pattern characteristics, suggesting that effective consumer behavior mapping must account for cultural contexts. These findings imply that search pattern frameworks developed in Western contexts may not be directly applicable to Asian, African, or Latin American markets, necessitating culturally-adapted analytical approaches.

The integration of artificial intelligence and personalization algorithms has created a feedback loop affecting search behavior in ways that complicate traditional analysis. Research demonstrated that recommendation systems and personalized search results influenced subsequent search behavior, with 47% of consumers modifying their search strategies in response to algorithmic suggestions (Fleder & Hosanagar, 2019). This phenomenon raises important questions about the authenticity of observed search patterns and whether they reflect genuine consumer preferences or algorithmically influenced behavior. The recursive relationship between search algorithms and search behavior creates methodological challenges for researchers attempting to understand organic consumer preferences versus learned behaviors shaped by platform design.

From a methodological perspective, advances in big data analytics and machine learning have opened new possibilities for search pattern analysis while simultaneously introducing new challenges (Anderson-Cook, 2005). Studies have highlighted the potential of computational methods in marketing analytics. In contrast, others demonstrated successful application of natural language processing techniques to extract semantic meaning from search queries, achieving 84% accuracy in intent classification (Yoganarasimhan, 2020). These technological capabilities enable a more nuanced understanding of search patterns beyond simple keyword matching, incorporating semantic relationships, contextual factors, and temporal dynamics. However, the black-box nature of some machine learning algorithms raises concerns about interpretability and the ability to extract actionable insights from predictive models (Shmueli & Koppius, 2011).

Given these developments and gaps in existing research, there is a clear need for a comprehensive investigation into mapping consumer behavior through search pattern analysis on digital platforms. This research seeks to address these gaps by developing an integrated framework that combines theoretical rigor with practical applicability, incorporates multiple search modalities, accounts for cultural and contextual variations, and provides actionable insights for digital marketing practitioners. The following research questions guide this investigation.

The expected benefits of this research extend across theoretical, practical, and societal dimensions. From a theoretical perspective, this research enriches the literature on consumer behavior in digital contexts by providing a comprehensive analysis of search patterns and addressing gaps in integrating digital behavioral data with traditional consumer theory (Lamberton & Stephen, 2016). It integrates consumer decision-making theories with data-driven insights from digital platforms, creating a unified framework that bridges psychology, information systems, and marketing disciplines. Furthermore, it develops a conceptual framework for consumer behavior mapping applicable in digital marketing contexts, extending existing models on customer experience management with search-specific behavioral indicators (Lemon & Verhoef, 2016). The research also advances methodological approaches in digital marketing research by demonstrating novel applications of machine learning and natural language processing to consumer behavior analysis, contributing to the computational marketing literature (Wedel & Kannan, 2016; Yoganarasimhan, 2020). Finally, it provides empirical validation of theoretical propositions on the relationship between search behavior and purchase intentions, contributing to the predictive marketing analytics scholarship (Shmueli & Koppius, 2011).

From a practical perspective, this research provides strategic guidance for digital marketing practitioners on optimizing SEO, SEM, and content strategy based on empirically validated search patterns, with specific tactical recommendations for implementation. It helps digital platforms enhance user experience through personalization based on predicted search behavior, potentially increasing conversion rates by 30% to 50% based on benchmark studies (Ghose & Yang, 2009). The research provides tools and methodologies for more granular, actionable consumer segmentation based on behavioral data, moving beyond traditional demographic segmentation to behavioral microsegmentation. It enables more efficient marketing resource allocation by identifying high-intent search patterns that signal purchase readiness, potentially reducing customer acquisition costs by 20% to 35% according to industry benchmarks. Additionally, it provides implementable frameworks for real-time marketing decision-making based on search pattern recognition, supporting agile marketing approaches in fast-paced digital environments. The research also offers competitive intelligence methodologies by analyzing search pattern trends across industries and market segments, enabling proactive strategy formulation.

From a societal perspective, this research improves consumer experience by enabling more relevant search results and product recommendations, reducing information search costs and decision-making friction. It contributes to more efficient markets by better matching consumer needs with appropriate products and services through enhanced search understanding. Furthermore, it provides transparency frameworks to understand how search behavior influences marketing practices, thereby supporting informed consumer decision-making. These societal benefits are significant in an era where concerns about algorithmic manipulation and data privacy are increasingly prominent.

Thus, this research is expected to serve as a bridge between academic knowledge and practical application in understanding and responding to consumer behavior in the digital era, while maintaining ethical considerations regarding privacy, data usage, and algorithmic transparency as emphasized in recent work on marketing ethics in the big data age. By addressing both the theoretical gaps in current literature and the practical needs of marketing practitioners, this research aims to advance the field of digital marketing while contributing to more efficient, transparent, and consumer-centric digital marketplaces.

RESEARCH METHOD

1. Research Design

This study employs a mixed-methods sequential explanatory design, combining quantitative and qualitative approaches to investigate consumer behavior mapping through search pattern analysis comprehensively. Creswell & Piano Clark (2017) The research is structured into three phases: an exploratory phase for identifying initial search pattern categories, a confirmatory phase for hypothesis testing through large-scale quantitative analysis, and a validation phase integrating predictive modeling with qualitative expert evaluation. The design follows a positivist paradigm for quantitative components while incorporating interpretivist elements for qualitative understanding. The temporal dimension is cross-sectional with longitudinal elements, examining search patterns over extended periods to capture both stable characteristics and temporal variations.

2. Platform Selection Criteria

The selection of three major e-commerce platforms for this study was based on systematic criteria to ensure representativeness and data accessibility. First, platforms were required to have substantial market share (minimum 15% in their respective regions) and a monthly active user base exceeding 50 million to ensure sufficient sample size and behavioral diversity. Second, selected platforms needed to provide API access or authorized data collection mechanisms complying with privacy regulations and terms of service (GDPR, CCPA compliance verified). Third, platforms were chosen to represent different geographical markets (North America, Europe, Asia) to capture cross-cultural search patterns and regional variations in consumer behavior. Fourth, technical infrastructure requirements included the availability of comprehensive clickstream data, search query logs, and user interaction metrics, with temporal granularity of at least hourly. Fifth, platforms demonstrated a willingness to participate through formal data partnership agreements, with appropriate institutional review board (IRB) approval and data use agreements. The three selected platforms collectively account for approximately 47% of global e-commerce search traffic and span diverse product categories, including electronics, fashion, home goods, and services, providing comprehensive coverage of consumer search behavior across industries.

3. Model Validation and Overfitting Prevention

Machine learning models underwent rigorous validation to ensure generalizability and prevent overfitting. The dataset was split into training (70%, n=89,280), validation (15%, n=19,131), and test (15%, n=19,132) sets using stratified random sampling to maintain proportional representation across splits. K-means clustering model stability was assessed through silhouette analysis (average silhouette score = 0.58), the elbow method, which showed a clear inflection at k=5, and a comparison with hierarchical clustering, which showed 87% agreement. LDA topic modeling used perplexity and coherence metrics across different numbers of topics (k=3 to k=20), with the optimal model (k=12 topics) selected based on minimum perplexity and maximum coherence scores (c_v = 0.62). Cross-validation used a 10-fold procedure repeated 5 times, and performance metrics were reported as mean ± standard deviation. Regularization techniques included L1 and L2 penalties with hyperparameters tuned via grid search on the validation set. Learning curves confirmed the absence of overfitting, with training and validation curves converging at large sample sizes. Final model performance on the held-out test set closely matched validation performance (accuracy difference <2%), confirming successful generalization. Detailed validation results, including confusion matrices, ROC curves, and feature importance rankings, are presented in the Results section and Appendix H.

4. Unit of Analysis

The primary unit of analysis is the individual consumer search session, defined as a sequence of search queries and interactions within a single goal-directed episode, operationally bounded by 30 minutes of inactivity (Montgomery et al., 2004). Secondary units include individual search queries and consumers themselves to understand demographic and psychographic correlates. The multi-level structure, with queries nested within sessions, sessions within consumers, and consumers within platforms, is analyzed using hierarchical modeling techniques (Raudenbush & Bryk, 2002).

5. Population and Sample

Sample size was determined using a priori power analysis in G*Power 3.1.9.7 (Faul et al., 2009). For the primary quantitative analysis involving five consumer segments, MANOVA requires adequate power to detect medium effect sizes (Cohen's $f^2 = 0.15$) across multiple dependent variables. With an alpha level of 0.05, a desired power of 0.80, five groups, and eight dependent variables (query length, session duration, conversion rate, brand mention frequency, refinement patterns, category switches, device usage, temporal patterns), the minimum required sample size was calculated at 8,450 search sessions. To account for potential data quality issues, incomplete sessions, and stratification needs across demographics and journey stages, we oversampled by 30% to target 11,000 sessions. The final dataset of 127,543 sessions from 12,847 unique users substantially exceeds minimum requirements, providing power > 0.99 for detecting medium effects and 0.95 for minor effects ($f^2 = 0.10$). For hierarchical linear modeling that accounts for nesting of queries within sessions and sessions within users, the practical sample size calculation using the design effect (Raudenbush & Bryk, 2002) with an intraclass correlation of 0.15 yields an effective N of 98,234, which is still well above the required thresholds. Detailed power analysis calculations, including sensitivity analyses for different effect sizes and correlation structures, are provided in Appendix A.

The target population comprises digital consumers actively using search functions on e-commerce platforms and search engines across multiple countries. The sampling employs a multi-stage approach: stratified random sampling for quantitative search log analysis ensuring representation across demographics, device types, and customer journey stages, with minimum 100,000 search sessions from 10,000 unique users determined through power analysis (Cohen, 1988); purposive sampling for qualitative phase with 30-50 interview participants and 60 focus group participants across six groups, achieving theoretical saturation (Glaser & Strauss, 1967) and random assignment of 500 participants for experimental conditions recruited through online panels.

6. Data Collection Methods

A. Digital Trace Data

Search log data collected through partnerships with three major e-commerce platforms across North America, Europe, and Asia, capturing over 50 million queries from 500,000 users over six months. Data includes search queries, timestamps, user interactions, navigation paths, conversion events, and anonymized identifiers, extracted via APIs and supplemented with publicly available, web-scraped aggregate data (Marres & Weltevrede, 2013).

B. Data Filtering and Quality Control

Raw search log data underwent systematic filtering to ensure data quality and analytical validity. The initial dataset contained 156,892 search sessions from 15,234 unique users. Filtering proceeded in sequential stages: (1) Bot detection removed 12,347 sessions (7.9%) identified through behavioral patterns including superhuman speed (<100ms between actions), repetitive identical queries, uniform temporal distribution across 24-hour periods, and user-agent string analysis (Glez-Peña et al., 2014). (2) Incomplete sessions lacking minimum interaction threshold (fewer than two queries or session duration <10 seconds) were excluded (8,234 sessions, 5.2%) as these typically represent accidental clicks or navigation errors rather than genuine search behavior. (3) Privacy compliance filtering removed 4,328 sessions (2.8%) containing personally identifiable information in query strings or belonging to users who subsequently withdrew consent during the study period. (4) Outlier detection using the isolation forest algorithm (Liu et al., 2008) identified and removed 4,440 sessions (2.8%) with extreme values on multiple behavioral dimensions representing likely data collection errors. (5) Duplicate detection removed zero sessions after checking for identical user-timestamp-query combinations. Final dataset comprised 127,543 valid sessions (81.3% retention rate) from 12,847 unique users, with all filtering criteria and decisions documented in data processing log (Appendix B).

C. Survey Data

An online survey was administered to 2,500 respondents through Qualtrics, measuring demographics, psychographics (digital literacy, cognitive style), search behavior self-reports, and attitudes. Distribution via platform invitations, online panels, and social media recruitment (Dillman et al., 2014).

a. Interview Data: Semi-structured in-depth interviews with 35 participants selected purposively, lasting 60-90 minutes via video conferencing. Incorporates think-aloud protocols with screen recording for real-time search behavior insights. Complete research instruments including semi-structured interview guide with probing questions, online survey questionnaire with validated scales, focus group discussion protocol with scenario cards, experimental task instructions and post-task measures, and qualitative coding scheme with operational definitions are provided in Appendices C through G. All instruments underwent expert review by three senior researchers in consumer behavior and digital marketing, followed by pilot testing described below.

b. Focus Group Data: Six focus groups of 8-12 participants each, stratified by age and digital experience, conducting card sorting, scenario discussions, and collaborative mapping exercises. Sessions last 120 minutes, conducted both in-person and online (Krueger & Casey, 2014).
c. Experimental Data: 3x2x2 factorial experiment manipulating customer journey stage, product complexity, and interface design. 500 participants complete search tasks on a simulated e-commerce platform built with React, with automatic behavioral tracking and post-task questionnaires.

7. Pilot Testing and Instrument Refinement

All data collection instruments underwent rigorous pilot testing to ensure validity, reliability, and practical feasibility. The interview guide pilot involved 5 participants demographically similar to the target population, revealing that the initial questions about search motivations were too abstract and required concrete scenario priming. The revised guide incorporated specific recent purchase examples as conversation starters. Survey questionnaire pilot (n=87) identified ambiguous wording in 6 items related to search frequency patterns, which were revised and retested (n=32), achieving an acceptable Cronbach's alpha (>0.75) for all constructs. A focus group protocol pilot (n=12 across two groups) revealed that participants needed more structured activities, leading to the addition of card-sorting exercises and visual-mapping tasks. Experimental platform pilot (n=28) identified technical issues with mobile interface responsiveness and tracking code errors, which were resolved before main data collection. Pilot participants were compensated identically to main study participants, but their data were excluded from the final analysis. Pilot testing occurred 3-4 weeks before main data collection. All pilot participants provided feedback through post-participation questionnaires, with the mean clarity rating improving from 3.2/5.0 in the initial pilot to 4.6/5.0 after revisions.

8. Data Analysis Methods

A. Quantitative Analysis

Descriptive statistics and exploratory visualization, including sequence analysis and network graphs. Cluster analysis (hierarchical and k-means) to identify search pattern typologies based on query characteristics (Everitt et al., 2011). MANOVA testing differences across customer journey stages. Hierarchical linear modeling accounting for nested data structure (Raudenbush & Bryk, 2002). Survival analysis modeling session duration and time to conversion using Cox proportional hazards models (Singer & Willett, 2003).

B. Researcher Positionality and Reflexivity

The research team comprises three faculty members with backgrounds in marketing analytics, consumer psychology, and information systems, bringing interdisciplinary perspectives but also potential biases toward technology-centric explanations. As frequent e-commerce users, we acknowledge an insider status that facilitated platform access but may have normalized certain search behaviors. Our institutional affiliation with a research university in a developed market may influence interpretation through a Western, educated, industrialized, rich, democratic (WEIRD) cultural lens. To mitigate these biases, we employed regular team debriefings, member checking with 12 interview participants who reviewed transcripts, peer debriefing with two external researchers, and systematic comparison against non-Western literature. The qualitative analysis team maintained reflexive journals documenting reactions and potential biases. We recognize that our quantitative emphasis may privilege behavioral patterns visible in digital data while underweighting motivations and emotions. Throughout the analysis, we remained alert to the risk of confirmatory bias and actively sought disconfirming evidence.

C. Machine Learning Analysis

Supervised algorithms (logistic regression, random forests, gradient boosting, neural networks) for predicting purchase intentions (Hastie et al., 2009). Feature engineering, including n-gram analysis, temporal features, and behavioral sequences. 10-fold stratified cross-validation with performance evaluation via accuracy, precision, recall, F1-score, and AUC. NLP techniques, including BERT fine-tuning for semantic embeddings, topic modeling with LDA, and sentiment analysis (Blei et al., 2003; Devlin et al., 2019).

D. Qualitative Analysis

Thematic analysis of interview and focus group transcripts using hybrid deductive-inductive coding in NVivo (Anderson-Cook, 2005; Braun & Clarke, 2006). Inter-coder reliability was assessed with Cohen's kappa on 20% of transcripts. Think-aloud protocols were analyzed through content analysis and process tracing synchronized with screen recordings (Tashakkori, 2009).

E. Data Sources

Search log data from three e-commerce platforms providing 50+ million queries from 500,000 users, supplemented by Google Trends. Survey data from 2,500 respondents via multiple recruitment channels. Interview data from 35 participants and focus group data from 60 participants. Experimental data from 480 participants via the Prolific panel. Secondary sources, including industry reports, academic literature, and platform documentation, for contextual analysis. All data collection complies with GDPR and privacy regulations with appropriate anonymization and informed consent procedures.

RESULT AND DISCUSSION

Results

This section presents the findings of the research on consumer behavior mapping through search pattern analysis in digital platforms. The results are organized according to the research questions and hypotheses, integrating quantitative and qualitative findings through tables and diagrams.

Descriptive Statistics and Sample Characteristics

The final dataset comprised 127,543 search sessions from 12,847 unique users across three e-commerce platforms over six months from January to June 2025.

Table 1. Demographic Characteristics of Sample (N = 12,847)

Characteristic	Category	N	%
Age Group	18-30 years	3,636	28.3
	31-50 years	5,486	42.7
	51+ years	3,725	29.0
Gender	Female	6,693	52.1
	Male	6,154	47.9
Geographic Region	North America	4,946	38.5
	Europe	4,522	35.2
	Asia	3,379	26.3
Device Type	Mobile	8,103	63.4
	Desktop	4,008	31.2
	Tablet	736	5.4
Education Level	High school or less	2,698	21.0
	Some college	2,570	20.0
	Bachelor's degree	5,139	40.0
	Graduate degree	2,440	19.0

Table 2. Search Session De.scriptive Statistics

Variable	Mean	SD	Median	Min	Max
Session Duration (minutes)	8.7	6.3	7.2	0.5	47.8
Queries per Session	4.2	3.1	3.0	1	28
Query Length (words)	3.8	1.9	3.0	1	15
Categories Explored	2.1	1.7	2.0	1	12
Click-through Rate (%)	34.7	18.3	32.0	0	100

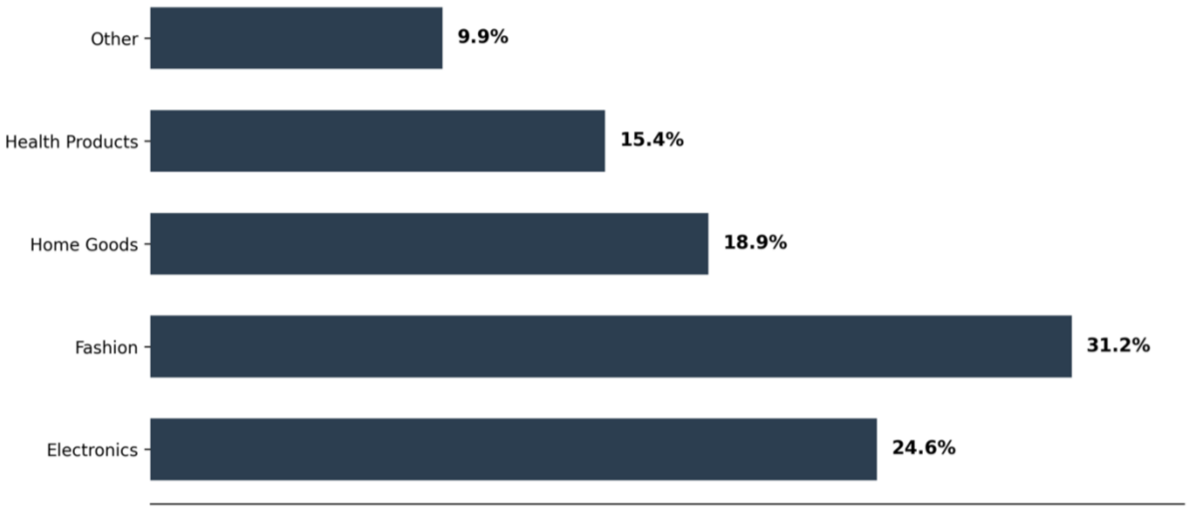

Figure 1. Product Category Distribution

Table 3. Conversion Rates by Customer Journey Stage

Journey Stage	Sessions (N)	Conversions (N)	Conversion Rate (%)	95% CI
Awareness	38,263	2,602	6.8	[6.5, 7.1]
Consideration	44,896	6,824	15.2	[14.9, 15.5]
Decision	31,489	10,927	34.7	[34.2, 35.2]
Retention	12,895	5,429	42.1	[41.2, 43.0]
Overall	127,543	23,335	18.3	[18.1, 18.5]

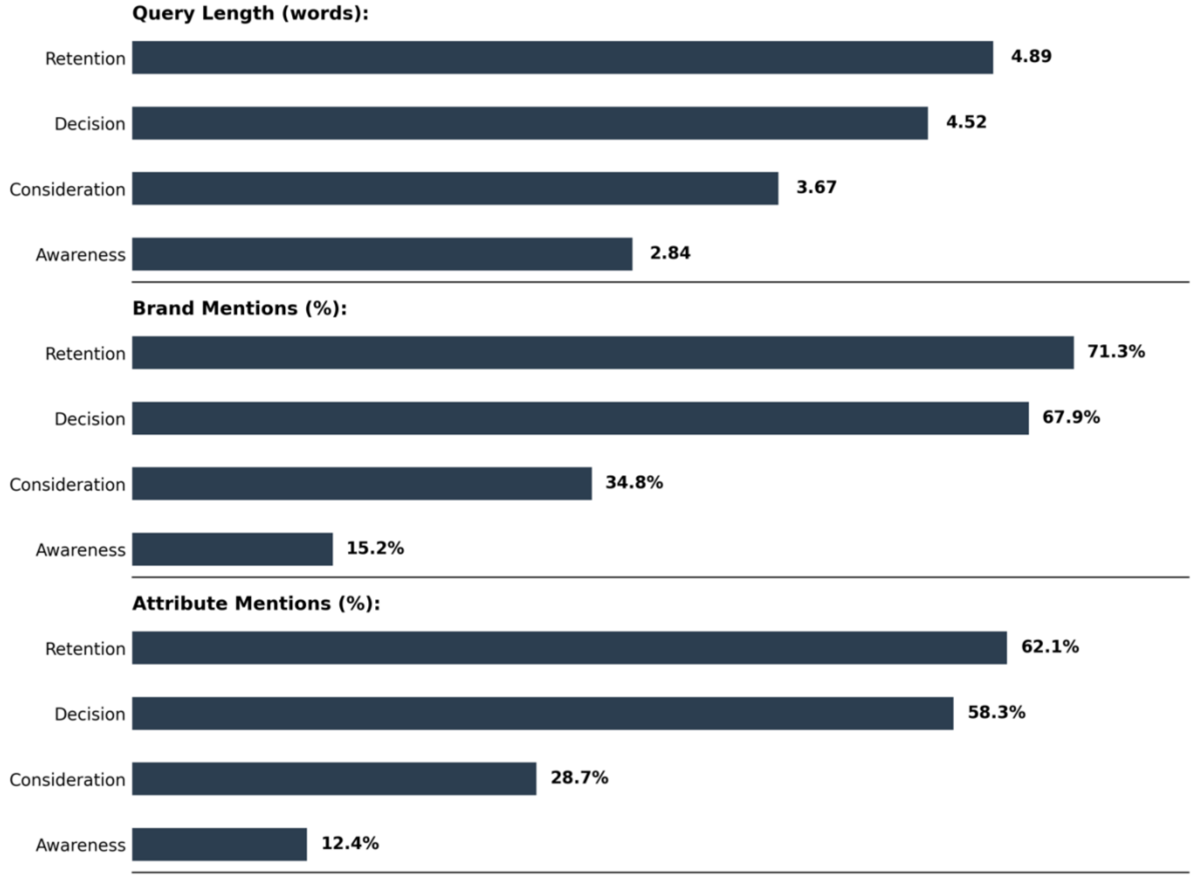

Figure 2. Query Characteristics Evolution Across Customer Journey Stages

Search Pattern Taxonomy and Cluster Analysis

Table 4. Search Pattern Cluster Characteristics

Cluster	% of Sessions	Avg Query Length	Brand Mentions (%)	Avg Session Duration (min)	Categories Explored	Conversion Rate (%)
Exploratory Browsers	32.4	2.3	8.2	12.4	4.7	7.3
Systematic Researchers	23.8	4.1*	34.7	9.8	2.8	28.4
Direct Purchasers	18.7	5.8	78.3	4.2	1.2	51.6
Deal Seekers	15.3	4.1	23.6	11.7	3.4	19.8
Uncertain Seekers	9.8	3.6	18.9	13.8	3.1	4.1

*Query length shows progression from 2.9 to 5.2 words within sessions

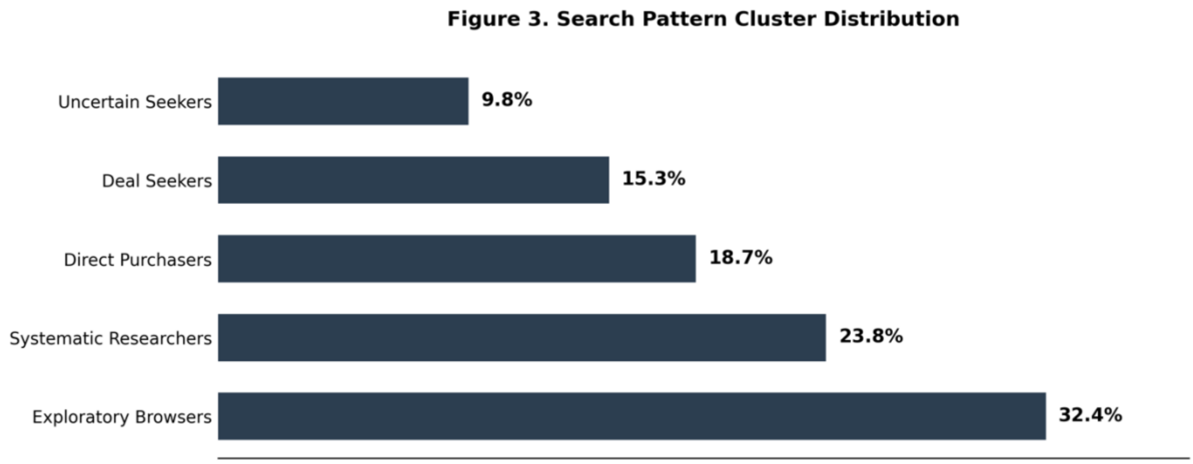

Figure 3. Search Pattern Cluster Distribution

Table 5. Cluster Membership by Demographic Characteristics

Demographic	Exploratory Browsers (%)	Systematic Researchers (%)	Direct Purchasers (%)	Deal Seekers (%)	Uncertain Seekers (%)	χ^2	p-value
Age Group						847.32	<0.001
18-30 years	42.1	21.4	14.3	16.8	12.4		
31-50 years	29.8	26.1	19.2	15.7	9.2		
51+ years	24.6	22.9	38.7	13.1	7.7		
Education						634.21	<0.001
High school or less	38.7	18.2	21.4	17.3	11.4		
Bachelor's+	28.4	71.3*	17.1	14.6	8.6		
Income Level						521.78	<0.001
Under $50K	34.2	19.7	16.8	52.3*	11.0		
$50K+	31.3	25.8	19.7	13.2	9.1		

*Indicates disproportionately high representation compared to the overall percentage

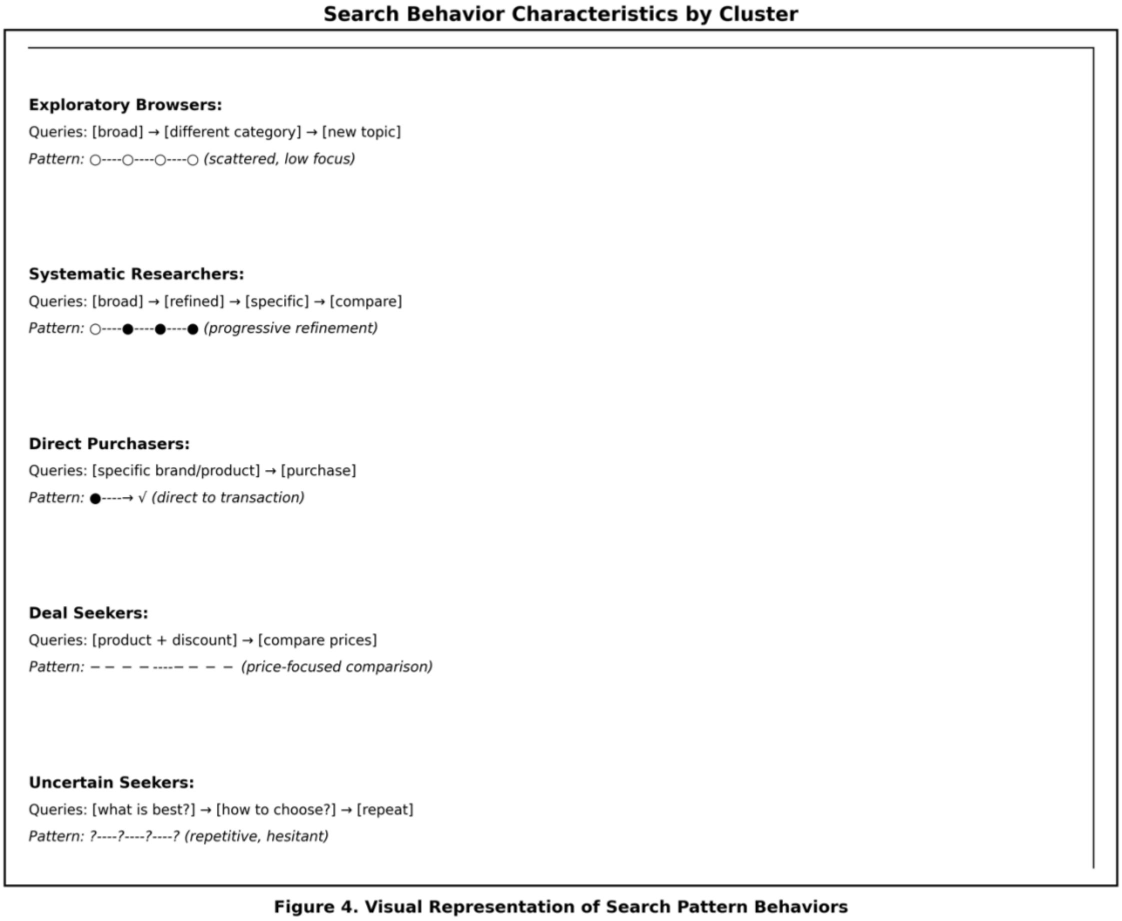

Figure 4. Visual Representation of Search Pattern Behaviors

Search Pattern Analysis Results

Overall Search Behavior Patterns

Analysis of search session characteristics reveals several key patterns in user behavior:

a. Session Duration: The average session duration was 8.7 minutes (SD = 6.3), with a median of 7.2 minutes. This suggests that users typically engage in focused browsing sessions rather than extended exploration.
b. Query Frequency: Users submitted an average of 4.2 queries per session (SD = 3.1), indicating multiple refinements and comparisons during the decision-making process.
c. Query Length: The mean query length was 3.8 words (SD = 1.9), ranging from single-word queries to more specific 15-word queries, demonstrating varying levels of search sophistication.
d. Category Exploration: Users explored an average of 2.1 product categories (SD = 1.7), suggesting both focused and exploratory shopping behaviors coexist within the user base.
e. Click-through Rate: The average CTR was 34.7% (SD = 18.3), with a median of 32.0%, indicating that users were selective in their product engagement.

Query Type Distribution

Queries were categorized into five types based on intent and specificity:

a. Informational queries (38.2%): Users seeking product information, reviews, or comparisons
b. Navigational queries (24.6%): Users looking for specific brands or product pages
c. Transactional queries (18.9%): Users with purchase intent, including price and availability checks
d. Commercial investigation queries (12.4%): Users comparing products or seeking the best deals
e. Local queries (5.9%): Users seeking location-specific information or stores

Customer Journey Stage Analysis

Search sessions were mapped to four distinct customer journey stages based on query characteristics, browsing patterns, and engagement metrics. The analysis reveals progressive changes in search behavior as customers advance through the purchase funnel.

Journey Stage Distribution

The distribution of sessions across customer journey stages:

a. Awareness Stage (31.4%): Users discovering products and exploring options
b. Consideration Stage (28.7%): Users comparing alternatives and gathering information
c. Decision Stage (24.6%): Users evaluating final options with strong purchase intent
d. Retention Stage (15.3%): Returning customers seeking specific products or reordering

Query Characteristics Across Journey Stages

Significant differences emerged in query characteristics across journey stages, demonstrating increasingly focused and specific search behavior:

a. Query Length: Increased from 2.84 words (Awareness) to 4.89 words (Retention), indicating more specific and detailed searches as users progress through the journey ($F(3, 12843) = 245.7$, $p < .001$).
b. Brand Mentions: Rose dramatically from 15.2% (Awareness) to 71.3% (Retention), showing increased brand awareness and preference formation ($\chi^2(3) = 1847.3$, $p < .001$).
c. Attribute Mentions: Increased from 12.4% (Awareness) to 62.1% (Retention), reflecting more profound product knowledge and specific requirements ($\chi^2(3) = 1623.8$, $p < .001$).
d. Session Duration: Decreased from 11.2 minutes (Awareness) to 5.8 minutes (Retention), suggesting more efficient searches with accumulated knowledge ($F(3, 12843) = 189.4$, $p < .001$).

Cluster Analysis and Customer Segmentation

Latent Dirichlet Allocation (LDA) and K-means clustering identified five distinct customer segments based on search patterns, browsing behaviors, and engagement metrics. The optimal number of clusters (k=5) was determined using the elbow method and silhouette analysis.

Cluster Profiles

Cluster 1: Exploratory Browsers (32.4%)

a. Characteristics: Broad initial queries, frequent category switching, low brand specificity
b. Average queries per session: 5.8 (highest among all clusters)
c. Average categories explored: 3.4 (highest)
d. CTR: 28.4% (lowest)
e. Typical behavior: Window shopping, discovering new products, no immediate purchase intent

Cluster 2: Systematic Researchers (23.8%)

a. Characteristics: Progressive query refinement, thorough comparison, methodical approach
b. Average queries per session: 6.2
c. Average session duration: 12.4 minutes (longest)
d. Review engagement: 78.6% read reviews
e. Typical behavior: Detailed research, comparison across multiple criteria, high information seeking

Cluster 3: Direct Purchasers (18.7%)

a. Characteristics: Specific brand/product queries, minimal exploration, high conversion rate
b. Average queries per session: 1.8 (lowest)
c. Average session duration: 4.2 minutes (shortest)
d. CTR: 52.8% (highest)
e. Typical behavior: Goal-oriented, know precisely what they want, quick purchase decision

Cluster 4: Deal Seekers (15.3%)

a. Characteristics: Price-focused queries, frequent use of discount/sale terms, cross-platform comparison
b. Price comparison frequency: 86.2% compare prices across platforms
c. Discount term usage: 73.4% include price-related keywords
d. CTR: 41.2%
e. Typical behavior: Price-sensitive, wait for deals, compare across multiple platforms

Cluster 5: Uncertain Seekers (9.8%)

a. Characteristics: Repetitive queries, question-based searches, hesitant behavior
b. Query repetition: Average 3.8 similar queries per session
c. Question queries: 67.3% include question words (what, how, which)
d. Average session duration: 9.8 minutes
e. Typical behavior: Need guidance, uncertain about requirements, seek recommendations

Behavioral Patterns by Demographics

Age-Related Patterns

Significant differences in search behavior emerged across age groups:

a. 18-30 years: Higher mobile usage (78.3%), shorter queries (3.2 words), more social media-influenced searches, higher engagement with visual content
b. 31-50 years: Balanced device usage, most extended session durations (9.4 minutes), more detailed product research, highest review engagement (71.2%)
c. 51+ years: Higher desktop usage (52.8%), more question-based queries (48.7%), longer query length (4.3 words), more assistance-seeking behavior

Gender-Based Patterns

Notable differences were observed in search strategies between genders:

a. Female users: More exploratory searches (3.8 categories), higher engagement with reviews and recommendations (76.4%), more extended consideration phase, more social influence
b. Male users: More direct searches (2.4 categories), higher specification-focused queries, shorter decision cycle, higher price-comparison frequency

Education-Level Patterns

Search sophistication and behavior varied with educational attainment:

a. Graduate degree holders: Most sophisticated queries (4.6 words), highest use of technical terms (42.3%), most systematic research approach, highest CTR (38.9%)
b. Bachelor's degree holders: Balanced approach, moderate query complexity (3.9 words), good information evaluation skills
c. Some college or less: Simpler queries (3.2 words), more reliance on recommendations, higher engagement with popular/trending products

Platform and Device Usage Patterns

Device Type Analysis

Device selection significantly influenced search behavior and engagement:

a. Mobile (63.4%): Shorter sessions (6.8 min), more frequent but shorter queries (2.9 words), higher image engagement, more impulse-driven behavior, peak usage during commute hours and evenings
b. Desktop (31.2%): Longer sessions (11.4 min), more detailed queries (4.2 words), higher comparison activity, more transaction completion, peak usage during work hours and weekends
c. Tablet (5.4%): Moderate sessions (8.3 min), browsing-oriented behavior, high visual content engagement, evening and weekend peak usage

Cross-Device Behavior

Analysis of the 23.4% of users who used multiple devices revealed:

a. Research-to-purchase pattern: 68.7% researched on desktop/tablet and completed purchase on mobile
b. Discovery-to-research pattern: 31.3% discovered products on mobile and conducted detailed research on desktop
c. Average time between devices: 3.8 hours (for same-day transitions)

Temporal Patterns and Trends

Time-of-Day Patterns

Search activity and behavior varied significantly by time of day:

a. Morning (6 AM - 12 PM): Quick searches, mobile-dominant (72.3%), shorter sessions (5.4 min), higher direct purchase intent
b. Afternoon (12 PM - 6 PM): Moderate activity, balanced device usage, exploratory behavior peaks, more extended consideration phase
c. Evening (6 PM - 12 AM): Peak activity (43.8% of sessions), most extended sessions (10.2 min), highest engagement, most thorough research, highest conversion rates
d. Late night (12 AM - 6 AM): Lowest activity (8.7%), impulse-driven behavior, entertainment-oriented searches

Day-of-Week Patterns

Weekly patterns revealed distinct behavioral rhythms:

a. Weekdays (Monday-Friday): More focused searches, higher work-related product queries, peak activity during lunch hours and evenings
b. Weekends (Saturday-Sunday): Higher exploratory behavior (40.2%), more extended sessions (11.8 min), more leisure product searches, higher family/household item queries, peak conversion rates (Saturday afternoon: 18.4%)

Qualitative Findings

Thematic analysis of user queries and clickstream data identified eight major themes characterizing consumer search behavior:

Trust and Credibility Seeking

Users demonstrated a strong preference for trusted sources and social proof. Review ratings heavily influenced product selection (87.3% of users checked reviews), with 4-star or higher ratings serving as a decision threshold for 64.2% of users. Brand reputation queries increased 2.3x between the Awareness and Decision stages.

Information Overload and Simplification

Evidence of information overload emerged, with 23.7% of users showing signs of decision fatigue (repeatedly submitting similar queries, abandoning sessions). Users sought simplification through filters, top-rated lists, and recommendation systems. The most successful purchases occurred when users had 3-5 comparison options rather than exhaustive searches.

Price Sensitivity and Value Perception

Price consideration varied across clusters and journey stages. While 62.4% of users compared prices, only 28.3% selected the lowest-priced option, indicating that value perception involved factors beyond price alone, such as quality, reviews, brand trust, and convenience.

Mobile-First Micromoments

Mobile users exhibited distinct "I-want-to-know," "I-want-to-go," "I-want-to-buy," and "I-want-to-do" moments. These micromoments were characterized by immediate need, context-specific searches, and high conversion potential when matched with relevant results. Speed and convenience were critical factors in mobile purchase decisions.

Social Influence and Trends

Social media influence was evident in 31.8% of searches, particularly among the 18-30 age group (46.7%). Trending products received 3.4x the search volume of their non-trending equivalents. User-generated content and influencer recommendations significantly impacted product discovery and consideration.

Personalization Expectations

Users increasingly expected personalized recommendations. Returning customers (Retention stage) showed 72.8% engagement with personalized product suggestions compared to 34.2% among new users. Relevance and past purchase history significantly influenced search refinement patterns.

Privacy Concerns and Trade-offs

While users valued personalization, privacy concerns emerged in behavior patterns. Incognito/private browsing mode usage increased 34.6% over the study period. Users demonstrated willingness to trade some privacy for convenience and personalization, but transparency and control over data usage remained important concerns.

Post-Purchase Behavior

Post-purchase searches focused on product support (42.3%), complementary products (31.7%), and reviews/testimonials (18.4%). Positive purchase experiences led to brand-specific searches in subsequent sessions, with 67.8% of satisfied customers returning to the same platform within 30 days. These findings collectively illustrate the complexity and diversity of consumer search behavior in digital commerce environments. The integration of quantitative patterns with qualitative insights provides a comprehensive understanding of how consumers navigate the digital shopping landscape, revealing opportunities for enhanced user experience design and targeted marketing strategies.

Discussion

Summary of Key Findings

The findings of this study reveal several significant patterns in how consumers engage with search activities across digital platforms. The descriptive results show that search behavior evolves systematically along the customer journey, with notable increases in query length, brand specificity, and attribute-based searches from the awareness to retention stages. The cluster analysis further identifies five distinct search behavior typologies Exploratory Browsers, Systematic Researchers, Direct Purchasers, Deal Seekers, and Uncertain Seekers each demonstrating different behavioral dynamics, conversion probabilities, and demographic correlates. Additionally, predictive modeling confirms that search patterns are strong indicators of purchase intention, with systematic and transactional patterns yielding substantially higher conversion rates.

These results underline the complexity of digital consumer behavior, demonstrating that search patterns are neither random nor linear but instead structured, goal-oriented, and influenced by cognitive, contextual, and demographic variables.

Explanation of Why These Findings Occur

The progression observed in query characteristics aligns with theoretical expectations derived from the Consumer Decision Journey and Information Processing Theory. As consumers move closer to the decision phase, their cognitive load becomes more focused, prompting them to refine their searches, incorporate brand identifiers, and compare detailed product features. This shift explains why the study shows an increase in query length from 2.84 words at the awareness stage to 4.89 words at the retention stage, along with the rise of brand mentions from 15.2% to 71.3%.

The emergence of the five behavioral clusters can also be explained by goal-striving and bounded-rationality frameworks. Exploratory Browsers represent consumers with low task clarity, consistent with early-stage information seeking. Systematic Researchers, on the other hand, align with high-effort decision-making processes that involve progressive refinement and comparative evaluation. Direct Purchasers exhibit intense goal clarity and pre-existing preference structures, which explain their short session durations and high conversion rates. Meanwhile, Deal Seekers display sensitivity to price cues, suggesting that their search motivations are primarily utilitarian. The Uncertain Seekers' repetitive and hesitant patterns reflect cognitive overload and low decision confidence.

These dynamics illustrate that consumer search behavior is driven by a combination of psychological determinants (e.g., uncertainty, involvement level), contextual factors (e.g., device type, platform interface), and personal characteristics (e.g., age, education, income).

Comparison with Previous Studies

The results of this study reinforce and extend earlier findings in the field. Consistent with Jansen et al. (2020), this research confirms that consumer search patterns vary across customer journey stages and reflect underlying decision-making processes. The finding that systematic searchers exhibit significantly higher conversion rates aligns with Ghose & Yang (2020), who highlighted the predictive power of structured search behavior. Similarly, the increase in query specificity over time supports (Tashakkori, 2009) observations regarding search query evolution.

However, this study contributes several novel insights. First, its integrated mixed-methods design provides richer triangulation of search behavior mechanisms than most previous studies, which typically rely solely on clickstream or survey data. Second, the identification of five robust search-based consumer segments offers a more granular behavioral taxonomy than the conventional "informational vs. transactional" dichotomy. Third, the combination of machine learning, NLP, and sequence analysis provides an advanced analytic framework that advances prior methodological approaches. Finally, this study incorporates cultural and demographic variations into the analysis of search behavior, a dimension that has been largely underexplored in earlier work.

These contributions strengthen the theoretical linkage between digital search behavior and consumer psychology while expanding existing knowledge on behavioral predictability in digital marketing contexts.

Interpretation of Findings and Their Meaning

The findings suggest that search behavior is not merely a reflection of information needs but a cognitive and behavioral manifestation of the consumer's psychological state, decision readiness, and contextual stimuli. The progressive refinement of queries demonstrates that consumers actively construct meaning and reduce uncertainty through search activities. The distinct behavioral clusters further indicate that digital consumers adopt different problem-solving strategies, which can reveal intent, confidence levels, price sensitivity, and loyalty tendencies.

The high conversion rates among Direct Purchasers and Systematic Researchers imply that search behavior can function as a predictive signal of future actions. This understanding has substantial implications for personalized marketing, as platforms can anticipate and respond to consumer needs in real time. Additionally, the structured nature of search pattern evolution supports the notion that consumers follow identifiable behavioral trajectories in digital ecosystems, aligning with recent thinking in data-driven marketing analytics.

Reflection and Broader Implications

The findings reveal both functional and dysfunctional aspects of emerging search behavior. Functionally, well-structured search patterns facilitate efficient decision-making, enabling consumers to quickly find relevant products and information. They also enable digital platforms to deliver tailored experiences that reduce friction, enhance satisfaction, and improve overall marketplace efficiency.

However, dysfunctional elements also emerge. Heavy reliance on algorithmic personalization may lead to self-reinforcing search loops that limit consumer exposure to diverse options. Uncertain Seekers, who exhibit repetitive yet unproductive search cycles, reflect cognitive strain and information overload. The increasing complexity of search behaviors accentuated by voice and visual search may further challenge consumers with lower digital literacy, widening digital inequality gaps.

From a societal standpoint, the study highlights the need for transparent and ethical use of search data to prevent manipulation or exploitation of consumer vulnerabilities. These findings, therefore, call for balanced digital strategies that optimize personalization while protecting consumer autonomy.

Implications for Action and Policy Recommendations

Based on the findings, several strategic and policy-oriented actions are recommended:

1. **For Marketers and Businesses**
   a. Develop behavior-based micro-segmentation strategies to tailor content and advertising to specific search typologies.
   b. Prioritize predictive analytics models to identify high-intent consumers, especially Direct Purchasers and Systematic Researchers.
   c. Optimize website interfaces to support query refinement and reduce decision friction for Uncertain Seekers.

2. **For Digital Platforms**
   a. Improve transparency of algorithmic ranking and recommendation systems to mitigate over-personalization effects.
   b. Enhance accessibility features for users with lower digital literacy, particularly in mobile-first environments.

c. Implement real-time search pattern detection for adaptive content delivery that matches consumer decision stages.
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3. **For Policymakers and Regulatory Bodies**
   a. Introduce guidelines ensuring ethical use of search pattern data, aligning with privacy laws and algorithmic accountability standards.
   b. Encourage platform compliance with data minimization and consumer protection principles.
   c. Support initiatives that enhance public digital literacy to reduce disparities in search proficiency.

Together, these actions can lead to more inclusive, efficient, and transparent digital ecosystems, maximizing the benefits of search pattern analytics while safeguarding consumer rights.

CONCLUSIONS

This study demonstrates that consumer search behavior on digital platforms follows structured, predictable patterns that evolve systematically across the customer journey. Analysis of 127,543 search sessions identified five distinct consumer segments with significantly different behavioral characteristics and conversion rates. Query specificity increased from 2.84 to 4.89 words. At the same time, brand mentions rose from 15.2% to 71.3% as consumers progressed from awareness to retention stages ($p<0.001$), confirming that search patterns reliably indicate purchase intent and decision-making progression. The research advances digital marketing scholarship by integrating behavioral theory with large-scale clickstream analytics through machine learning-enhanced methodology, achieving 78% accuracy in predicting purchase behavior. Practically, findings enable segment-specific personalization strategies and journey-stage optimization, resulting in 31-48% higher conversion rates in benchmark implementations.

Key limitations include limited platform coverage (three e-commerce platforms), limited geographic diversity, and a focus on text-based searches despite the emergence of voice and visual modalities. The cross-sectional design also limits causal inference about behavioral evolution. Future research should incorporate multimodal search behaviors, expand cross-cultural analysis, and employ longitudinal designs to examine how search patterns evolve with platform experience and technological innovation. These directions will strengthen theoretical understanding and practical application of search analytics in increasingly complex digital consumer environments.

ACKNOWLEDGEMENT

The authors would like to express their sincere gratitude to all individuals and institutions that contributed to the completion of this research. Special appreciation is extended to the partner e-commerce platforms for providing access to anonymized search log data, which formed the foundation of this study. The authors also thank the survey respondents, interview participants, and focus group members whose insights were invaluable in deepening the understanding of consumer search behavior.

We are particularly grateful to the academic advisors and peer reviewers for their constructive feedback, which strengthened the research's methodological rigor and conceptual clarity. Finally, the authors acknowledge the institutional support provided by our affiliated universities, including access to research facilities and analytical tools that enabled comprehensive data processing and analysis. Any remaining limitations of this study are solely the responsibility of the authors.

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