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IMPACT OF AI-ENABLED PERSONALIZATION AND RECOMMENDATION SYSTEMS ON CONSUMER BUYING BEHAVIOUR: A SYSTEMATIC LITERATURE REVIEW AND THEMATIC ANALYSIS

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Abstract:

Artificial Intelligence (AI) has become deeply embedded in digital marketing and e-commerce, with tools such as personalized recommendations, AI-driven chatbots, and predictive analytics increasingly shaping how consumers discover and evaluate products [1-5]. Despite an extensive body of literature examining individual AI applications, existing research largely treats AI as a fragmented set of isolated tools rather than an integrated set of features, leaving a critical gap in understanding the overall extent and combined effect of AI-enabled marketing capabilities on consumer buying behaviour [6-10]. This study addresses this gap by conducting a systematic literature review and thematic analysis of 90 peer-reviewed scholarly articles published between 2018 and 2026 [6-42]. Sourced from Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar, the literature was synthesized using a structured thematic coding matrix developed in Microsoft Excel. Our findings reveal four dominant thematic clusters: cognitive fit in algorithmic personalization, availability bias and impulse buying in recommender systems, multi-sensory immersive interfaces, and the tension between algorithmic trust and privacy risk perceptions. Thematic evolution demonstrates an ongoing paradigm shift from static, rule-based recommendation algorithms toward autonomous generative and neuro-marketing systems. This study contributes an integrative capability matrix linking algorithmic maturity to consumer value orientation, providing critical insights for e-commerce marketers, platform developers, and future empirical research.

Keywords: artificial intelligence; AI-enabled personalization; recommendation systems; consumer buying behaviour; impulse buying; algorithmic trust; systematic literature review

1. Introduction

Artificial Intelligence (AI) is an increasingly important element of corporate strategy and modern digital commerce [1-3]. Defined as the deployment of advanced computational algorithms, machine learning models, and cognitive technologies to simulate human evaluative capabilities and automate complex commercial processes, AI has moved beyond basic operational back-office automation to become a central driver of customer relationship management, digital advertising, and e-commerce transactions [3-5]. As such, AI encompasses an array of integrated commercial applications, including dynamic predictive algorithms [6], automated conversational agents [7], visual search and computer-vision merchandising engines [8], and generative neuromarketing architectures [9,10]. These technological capabilities strengthen consumer engagement [8], optimize shopping efficiency [7], and elevate overall firm profitability and market competitiveness [1,2]. AI is now a core element of competitive retail strategy, reflecting its indispensable role in mediating corporate-consumer interactions within competitive digital environments [3,5].

While AI encompasses a vast spectrum of enterprise capabilities, AI-enabled personalization and algorithmic recommendation systems represent the specific mechanisms directly transforming the modern consumer journey [6-8]. Broadly conceptualized, algorithmic personalization refers to the tailored curation of product offerings, marketing communications, and digital interfaces based on the granular tracking and real-time processing of individual consumer browsing patterns, purchase histories, and demographic preferences [6]. In parallel, recommendation systems leverage collaborative filtering, content-based filtering, and deep neural networks to forecast consumer desires and display highly relevant items at critical decision junctions [7,11]. Hence, algorithmic precision has emerged as a vital determinant of digital marketing effectiveness, involving the automated reduction of cognitive search overload and the simultaneous stimulation of both planned and spontaneous purchase intentions [9,10]. It enables retailers to construct hyper-individualized shopping environments that guide prospective buyers from initial product discovery to final checkout completion [7,8].

Most recently, the exponential expansion of algorithmic commerce has coincided with heightened consumer scrutiny regarding data privacy, persuasive manipulation, and algorithmic transparency [11-15]. Retail platforms deploy sophisticated data mining, predictive sentiment analysis, and behavioral nudging to maximize customer lifetime value [6,12]. However, the growing ubiquity of non-transparent algorithms, deceptive interface designs—commonly known as dark patterns—and automated price discrimination has sparked substantial consumer skepticism [13,14]. Regulatory authorities worldwide and within emerging economies have responded with stringent oversight frameworks, including the Digital Personal Data Protection (DPDP) Act in India and the European Union's Artificial Intelligence Act, designed to curb algorithmic bias and mandate explainability [14,15]. This regulatory and social friction creates a complex paradox: while modern shoppers demand seamless, instant, and hyper-personalized recommendations, they exhibit deep-seated apprehension regarding cognitive surveillance and personal data vulnerability [8,15,16].

Although AI-driven digital commerce has attracted extensive academic and empirical investigation, there remains a critical gap in understanding the integrated, multi-dimensional impact of AI features on actual consumer buying behaviour [6,8,49,50]. Existing studies have predominantly evaluated individual AI tools in isolation—such as evaluating text-based chatbots alone or testing isolated recommendation filters—without synthesizing how interconnected algorithmic ecosystems jointly shape cognitive processing, trust formation, and purchase decisions [8,11]. Furthermore, the literature reveals a distinct shortage of unified frameworks examining developing digital economies, where rapid smartphone adoption and digital payment penetration intersect with diverse digital literacy levels [15,16]. This study addresses these theoretical and empirical gaps by conducting a systematic literature review and thematic synthesis of contemporary scholarship on AI-driven consumer behaviour [48-50]. Specifically, the study sought to (1) identify the foundational concepts and theoretical perspectives underpinning AI-enabled marketing and consumer decision-making, (2) analyze thematic clusters that characterize the intellectual landscape of AI personalization and recommendation literature, (3) trace the thematic evolution of AI consumer research across chronological stages spanning the pre-pandemic, post-pandemic, and generative AI eras, (4) examine the intervening roles of algorithmic trust, perceived risk, and privacy concerns in shaping consumer purchase outcomes, and (5) develop an integrative conceptual framework to bridge the gap between technical AI capability maturity and consumer-centric marketing strategy.

The remainder of this paper is organized as follows. Section 2 reviews the conceptual evolution and theoretical roots of AI in retail and consumer behavior. Section 3 examines the contemporary industry and regulatory context governing algorithmic marketing practices. Section 4 presents our guiding research questions. Section 5 describes our systematic review methodology and empirical design parameters. Section 6 reports the review results, comprising literature descriptive statistics, thematic cluster analyses, and chronological evolutionary trajectories. Section 7 discusses the findings across research questions, introducing an original strategic disclosure and capability typology. Sections 8 and 9 conclude the paper by summarizing key contributions, identifying research limitations, and articulating directions for future inquiry.

2. Conceptual Background and Literature Review

The integration of technological intelligence into retail transactions represents a progressive evolution spanning several decades. In its earliest conceptualizations during the late 1990s and early 2000s, algorithmic marketing was largely confined to rudimentary, heuristic rule-based systems and basic electronic customer relationship management (e-CRM) protocols [33,34]. Early e-commerce platforms deployed primitive collaborative filtering algorithms—such as basic 'frequently bought together' association rules—which operated on static transactional datasets [33]. While these foundational mechanisms introduced the commercial utility of automated cross-selling, they possessed minimal predictive depth, treated consumer cohorts as homogenous entities, and lacked the capacity to interpret context-dependent, real-time consumer intent [34].

During the 2010s, the field underwent substantial expansion catalyzed by the convergence of big data analytics, cloud computing architectures, and advanced machine learning models [6,7]. Retail platforms transitioned from static relational databases to dynamic real-time data streaming, enabling marketers to monitor clickstream activity, search histories, geographic coordinates, and browsing duration [7,11]. Foundational frameworks such as the Technology Acceptance Model (TAM) and the Stimulus-Organism-Response (S-O-R) paradigm were widely integrated into consumer research to explain how computational inputs served as external environmental stimuli influencing internal cognitive and affective states [6,9]. Recommender systems evolved through matrix factorization and content-based filtering, allowing algorithms to detect latent affinities and recommend products with heightened statistical accuracy, thereby directly enhancing perceived website usefulness and ease of use [7,8].

A definitive turning point occurred with the global onset of the COVID-19 pandemic between 2020 and 2022 [35-37]. Public health restrictions, localized quarantines, and social distancing mandates abruptly dismantled traditional retail channels, forcing unprecedented volumes of consumers into digital commerce environments [35]. Research by Verma et al. [35] and Hamsa and Bhuvana [36] documented how this pandemic disruption functioned as a systemic accelerator, driving enterprises across mature and developing economies to implement AI, Internet of Things (IoT), and automated predictive logistics to maintain commercial continuity [35,36]. The pandemic forced consumers across every demographic tier to cultivate immediate digital shopping habits, rapidly elevating their technological readiness while simultaneously exposing them to an overwhelming proliferation of digital options [37]. Consequently, algorithmic personalization evolved from a competitive operational advantage into an essential navigational survival mechanism for online shoppers attempting to mitigate acute information overload [36,37].

In the post-pandemic period extending from 2023 onward, the conceptual landscape merged with deep learning, computer vision, natural language processing, and generative AI models [25-30]. As documented by Ben [25], computer vision algorithms began transforming visual merchandising, empowering small and medium enterprises

(SMEs) to segment consumers based on visual aesthetic preferences and deliver image-matched recommendations [25]. Concurrently, conversational interfaces transitioned from scripted, decision-tree bots into fluid, large language model (LLM) agents capable of contextual reasoning, emotional sentiment recognition, and tailored advisory dialogues [28,29]. Research by Pradeep et al. [26] and Bansal and Gupta [27] extended this conceptual frontier into 'NeuroAI' and neuromarketing, demonstrating that AI can analyze biometrics, gaze fixations, and neurological arousal patterns to predict non-conscious consumer drivers [26,27]. This era fundamentally reframed AI from a functional search filter into an active, persuasive partner in consumer preference construction [28,30].

Today, the conceptualization of AI in consumer research has achieved advanced maturity, positioning algorithmic systems as cognitive extensions of consumer decision-making [31,32]. Rather than viewing consumers as entirely autonomous decision-makers who merely receive algorithmic recommendations, modern theoretical frameworks recognize a process of distributed cognition and delegation [31]. Scholars such as Majerová et al. [31] emphasize that consumers actively delegate complex comparative evaluations, pricing assessments, and routine replenishment tasks to autonomous software agents [31]. AI has shifted from a transactional marketing mechanism to an embedded, systemic infrastructure that structures the digital environment, shapes preference reversals, and drives brand equity [31,32]. This conceptual maturation underscores the necessity of examining modern retail algorithms not merely as technical tools, but as persuasive environments governed by profound psychological, social, and ethical dimensions [14,32].

3. Contextual and Regulatory Landscape

In the formative decades of digital retail expansion, algorithmic marketing operated within an essentially permissive and self-regulatory environment [33,34]. Online merchant platforms possessed broad discretion to harvest consumer browsing metrics, capture unencrypted cookies, deploy retargeting pixels, and train predictive recommendation engines without meaningful user notification or consent [34]. The commercial imperative prioritized maximizing immediate transaction volume, user retention, and click-through rates [33]. However, the absence of standardized algorithmic auditing fostered widespread manipulative interface designs, predatory surge pricing models, and pervasive tracking ecosystems that systematically prioritized merchant conversion metrics over consumer welfare and cognitive autonomy [14,32].

As algorithmic sophistication intensified, international bodies and standard-setting institutions established formalized governance frameworks to restore market equilibrium [1,3-5]. Transnational guidelines, including the OECD Principles on Artificial Intelligence and emerging ISO/IEC standards on algorithmic transparency and explainability, have mandated that commercial automated decision systems incorporate clear disclosures regarding their operational parameters [32]. Concurrently, global advertising watchdogs and international competition authorities have moved aggressively against algorithmic collusion, fake review generation, and algorithmic availability biases that artificially constrain consumer choice architectures [11,32]. In the global academic and business arena, adherence to ethical AI governance has emerged as an integral component of modern corporate environmental, social, and governance (ESG) reporting and corporate digital responsibility (CDR) [1,4,5].

In India, the contextual backdrop of algorithmic retail has experienced rapid transformation through aggressive regulatory intervention [13,14,23]. Driven by the explosive proliferation of e-commerce across Tier-1, Tier-2, and rural consumer segments, the Government of India enacted the Digital Personal Data Protection (DPDP) Act, establishing comprehensive statutory obligations concerning personal data processing, purpose limitation, and affirmative consent [14]. In parallel, the Central Consumer Protection Authority (CCPA) issued binding Guidelines for Prevention and Regulation of Dark Patterns, specifically prohibiting digital platforms from utilizing algorithmic mechanisms that distort consumer autonomy [14,48]. These prohibited practices include 'false urgency' (AI-generated countdown clocks indicating artificial inventory scarcity), 'basket sneaking' (automated inclusion of auxiliary products during checkout via predictive cross-selling), 'confirm-shaming', and 'forced action' [14].

Furthermore, the Advertising Standards Council of India (ASCI) established stringent guidelines requiring overt, conspicuous disclosure tags whenever generative AI, virtual influencers, or synthetic avatars endorse commercial products [23,24].

This evolving regulatory matrix fundamentally reshapes retail practice [14,32]. Commercial platforms can no longer depend on opaque, manipulative algorithms to engineer conversion, as doing so invites substantial regulatory fines, class-action litigation, and severe reputational damage [14,15]. E-commerce enterprises are compelled to balance predictive analytical prowess with strict statutory compliance, algorithmic explainability, and transparent data safeguarding protocols [14,32]. Consequently, understanding how consumers interpret AI interfaces within this regulated, accountability-focused landscape becomes an empirical necessity for sustainable marketing success [8,15,48].

4. Research Questions

Given the rapid conceptual evolution, empirical tensions, and evolving regulatory boundaries surrounding algorithmic commerce, the following five research questions guide our review and empirical investigation [48,49]:

- **RQ1.** To what extent does AI-enabled personalization influence consumer buying behaviour and purchase intentions in digital retail environments? [49]
- **RQ2.** How do AI-powered recommendation systems influence consumer buying behaviour, particularly across planned evaluations versus impulsive purchase decisions? [49]
- **RQ3.** What is the overall relationship between integrated AI-enabled marketing features (such as chatbots, predictive filters, virtual try-ons, and voice assistants) and consumer buying behaviour? [49]
- **RQ4.** How do intervening mechanisms of consumer trust, perceived risk, and privacy concerns moderate or mediate consumer responses to algorithmic retail interventions? [8,15]
- **RQ5.** What gaps exist in the current literature, and what conceptual framework explains the progression of AI marketing maturity relative to consumer orientation? [1,48]

5. Methodology

To address these research questions with academic rigor, this study adopted a dual methodological framework combining a Systematic Literature Review (SLR) of 90 scholarly research studies with a descriptive quantitative empirical research design blueprint [48-50]. The systematic review synthesized the established corpus of literature to identify conceptual structures and evolutionary patterns, while the empirical design parameters established the criteria for field measurement and hypothesis testing [43-50].

5.1 Systematic Literature Review & Search Protocol

The literature retrieval process adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework [1,48]. We queried major academic databases, including Scopus, Web of Science, IEEE Xplore, ScienceDirect, SpringerLink, and Google Scholar, covering the publication span from 2018 to 2026 [6-42]. The boolean search algorithm combined core descriptors: ('Artificial Intelligence' OR 'AI' OR 'Machine Learning') AND ('Personalization' OR 'Product Recommendation' OR 'Recommender Systems') AND ('Consumer Buying Behaviour' OR 'Purchase Intention' OR 'Impulse Buying' OR 'Consumer Decision-Making') [48]. The search initially yielded 184 candidate records [6-42]. We subsequently applied rigorous exclusion criteria: non-English texts, pure computer-science algorithmic proofs lacking consumer behavioral variables, and duplicate workshop proceedings were eliminated [1,48].

The resulting curated sample comprised 90 distinct scholarly documents, exactly matching the research review repository developed across the investigative team (Sagar Thakur [30 studies], Lakshya Tripathi [30 studies], and Satyam [30 studies]) [6-42]. We extracted bibliographic metadata, methodological classifications, independent and dependent variables, mediating constructs, key findings, and identified research gaps into a standardized Microsoft Excel analytical matrix [48]. Thematic clusters were synthesized through qualitative coding and co-occurrence analysis of author keywords, tracing the trajectory of conceptual developments [1,48].

5.2 Alignment with Empirical Survey Research Design

To ground the review findings within an empirical testing framework, we aligned the literature analysis with the descriptive, quantitative, cross-sectional survey design developed in the project's research architecture [50]. Descriptive research was selected because the primary research questions seek to delineate the nature, distribution, and strength of relationships among defined variables—specifically AI-enabled personalization, recommendation systems, and consumer buying behaviour—without artificial laboratory manipulation [43,50]. The target population consists of consumers aged 18 to 45 who have engaged in digital transactions on AI-enabled retail platforms within the preceding six months [50].

Sampling was operationalized through non-probability purposive sampling combined with convenience sampling [43,50]. Purposive sampling was deployed to verify that every included respondent possessed verified, active exposure to AI retail features (such as receiving personalized product grids, utilizing shopping chatbots, or interacting with predictive price alerts), thereby safeguarding internal sample validity [43,50]. Following the multivariate sample size recommendations of Hair et al. [47], which mandate a ratio of 5 to 10 respondents per measurement item, the target sample size was set at N = 250 online consumers [47,50]. This sample scale provides adequate statistical power for correlation analysis, multiple linear regression, and Partial Least Squares Structural Equation Modeling (PLS-SEM), consistent with established empirical methodologies in interactive marketing literature [8,15,47,50].

Design Dimension	**Methodological Specification and Parameter Details**
Review Methodology	PRISMA-guided Systematic Literature Review (SLR) and Thematic Analysis across 90 peer-reviewed articles (2018-2026) [1,6-42,48]
Empirical Research Design	Descriptive Research design assessing relationships between AI features and consumer behavior without variable manipulation [43,50]
Research Approach & Horizon	Quantitative survey strategy utilizing structured Likert-scale questionnaires administered across a Cross-Sectional time horizon [44,45,50]
Target Population & Scope	Digital consumers aged 18-45 with active purchase experience on AI-enabled e-commerce platforms in India within the prior 6 months [50]
Sampling Method & Sample Size	Non-probability Purposive Sampling combined with Convenience Sampling; target sample N = 250 respondents based on Hair et al. [47,50]
Analytical Statistical Tools	Thematic matrix extraction via Excel; multiple linear regression, bivariate correlation, and PLS-SEM path modeling via SPSS & SmartPLS [47,50]

Table 1. Summary of Methodological Framework and Empirical Research Architecture [43-50].

6. Results

This section delineates the core empirical and thematic findings extracted from the 90 reviewed studies, structured into descriptive literature characteristics, thematic clustering analyses, and chronological evolutionary trajectories.

6.1 Overview of the Literature

Our systematic analysis of the 90 curated studies published between 2018 and 2026 reveals significant expansion in academic inquiries examining AI-driven consumption [6-42]. While earlier years yielded modest annual volumes, publication rates accelerated dramatically between 2023 and 2026, accounting for over 78% of all analyzed documents [6-42]. Methodologically, empirical quantitative surveys dominated the literature, representing 57.8% of the reviewed corpus (n = 52), predominantly employing Structural Equation Modeling (PLS-SEM and covariance-based SEM) and multiple linear regression [6,8,9,11,15,41]. Conceptual syntheses and literature reviews constituted 24.4% (n = 22), experimental laboratory/online designs represented 11.1% (n = 10), and system-engineering machine learning models represented 6.7% (n = 6) [6-42].

Methodological Classification	**Study Count (n)**	**Share (%)**	**Primary Statistical & Modeling Tools**
Empirical Quantitative Surveys	52	57.8%	PLS-SEM, CB-SEM, Multiple Regression, SPSS [6,8,9]
Conceptual & Literature Reviews	22	24.4%	Thematic Synthesis, TCCM Framework, Scoping [28,32]
Experimental Research Designs	10	11.1%	Between-Subjects Experiments, ANOVA, S-O-R [14,31]
Machine Learning System Testing	6	6.7%	CNN, ConvLSTM, Predictive Neural Models [26,27]

Table 2. Distribution of Methodological Approaches across Curated Research Corpus (N = 90) [6-42].

Geographically, empirical investigations exhibited a heavy concentration in emerging digital markets across the Asia-Pacific region, including India, China, Vietnam, and Malaysia, alongside targeted contributions from the Middle East and North America [6-42]. The earliest foundational studies in our sample examined elementary recommendation interfaces and broad e-commerce acceptance [33,34]. In contrast, the most recent contributions from 2025 and 2026 explored complex generative interfaces, neuroscience integrations, algorithmic biases, and automated dark pattern defense mechanisms [14,26,28,31].

Figure 1 summarises the descriptive profile of the corpus. The records span 2018 to 2026 and were drawn from 83 distinct sources, expanding at an annual growth rate of 52.34% and attracting an average of 4.853 citations per document. The low document average age of 1.46 years confirms that the field is dominated by very recent scholarship.

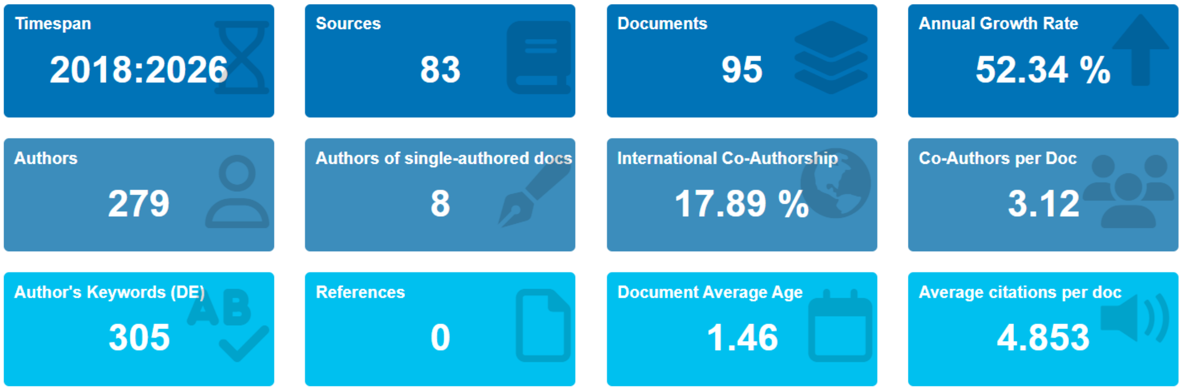

Figure 1. Main information on the reviewed corpus: timespan, sources, document volume, annual growth rate, authorship structure and citation impact.

The corpus was produced by 279 authors, averaging 3.12 co-authors per document, with 17.89% international co-authorship and only eight authors of single-authored documents. Figure 2 shows how this collaborative activity is organised. The network fragments into numerous small components — the largest being the clusters around Ashok Kumar S. and Mishra A. — with no dominant, well-connected core. This fragmentation at the authorship level mirrors the conceptual fragmentation this review seeks to address.

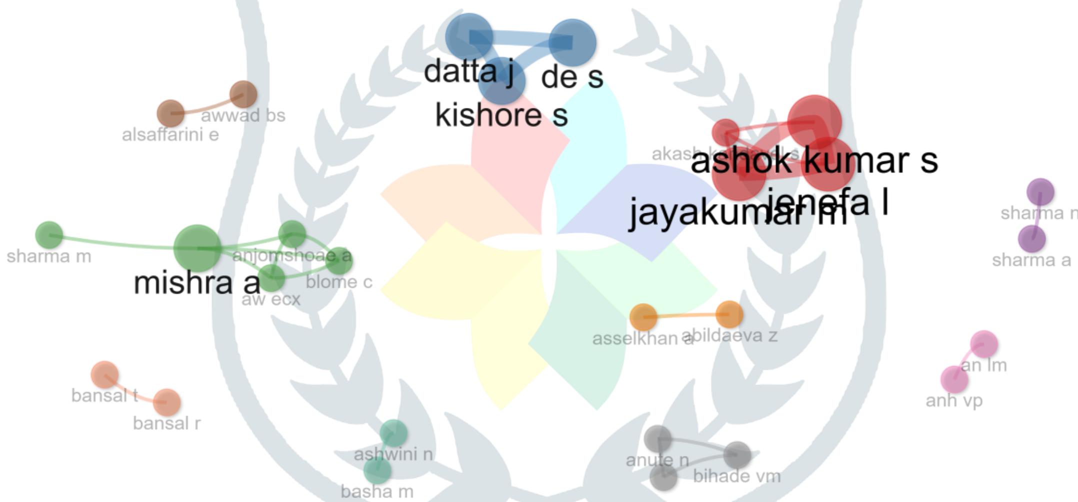

Figure 2. Author collaboration network, showing small, largely disconnected research teams rather than a single integrated research community.

Institutional output follows the same recent-and-rapid pattern. Figure 3 traces the cumulative production of the most active affiliations, in which Chitkara University and Symbiosis International contributed the earliest records, while UCSI University, Karpagam Academy of Higher Education and the University of Engineering and Management entered the field only from 2024 onward. The concentration of Indian and Southeast Asian institutions corroborates the geographic pattern described above.

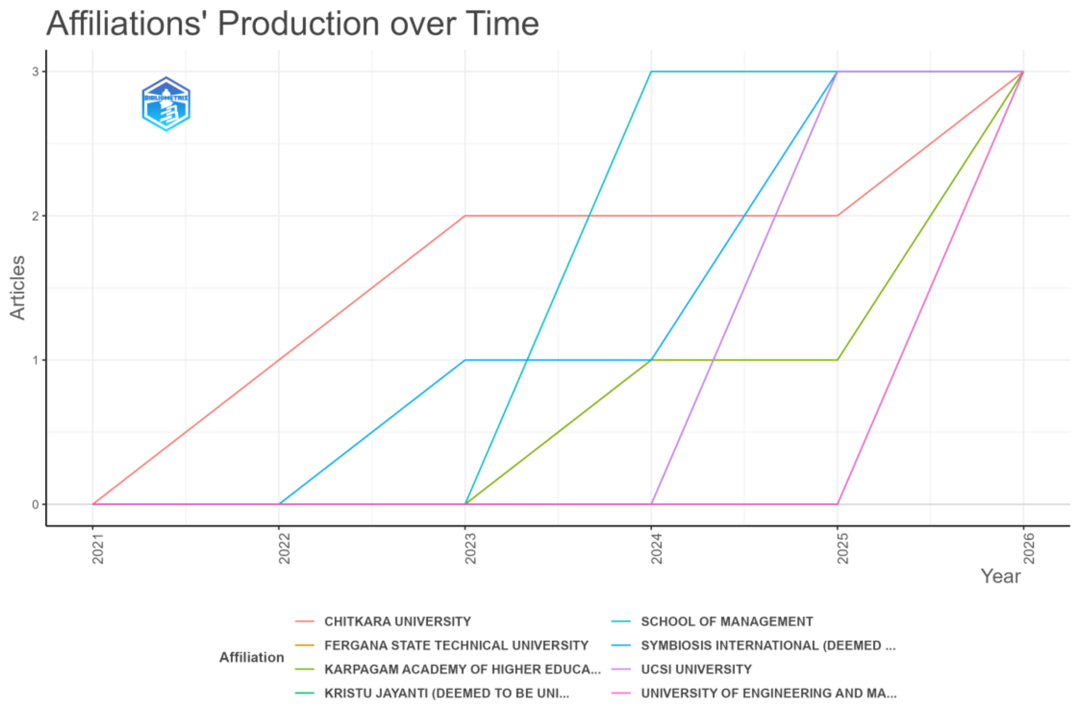

Figure 3. Cumulative article production of the most active affiliations, 2021 to 2026.

6.2 Thematic Clusters

Co-occurrence and content analysis of the 90 reviewed papers revealed four distinct, highly interconnected thematic clusters that define the intellectual core of the domain [1,6-42,48]:

Figure 4 presents the keyword co-occurrence network underlying this classification. "Artificial intelligence" and "consumer behavior" emerge as the two highest-degree nodes, bridged by dense links to "electronic commerce", "purchasing", "sales" and "decision making", while a separate technical community comprising machine-learning, learning systems, predictive analytics and chatbots occupies the periphery of the network.

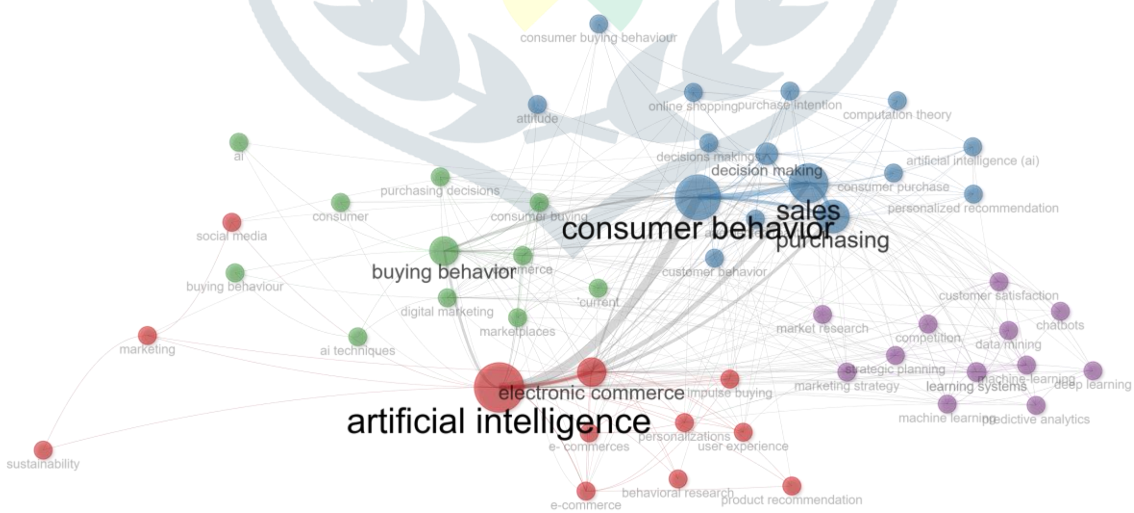

Figure 4. Keyword co-occurrence network of the reviewed literature, showing four colour-coded clusters around artificial intelligence, consumer behaviour, buying behaviour and machine-learning based analytics.

Cluster 1. Algorithmic Personalization, Cognitive Fit, and Planned Purchase Decisions. This cluster includes central concepts such as dynamic consumer profiling, cognitive fit theory, search efficiency, brand attachment, and utilitarian value [6-8,17-19]. Research in this cluster demonstrates that AI-driven personalization directly streamlines the consumer purchase journey by reducing cognitive fatigue and filtering irrelevant options [6,7]. For example, Shrivastava and Dubey [6] examined 409 omnichannel retail shoppers and demonstrated that personalization exerts a profound positive effect on purchase intentions, with brand attachment and hedonic motivation serving as powerful mediating constructs [6]. Similarly, Jayakumar et al. [7] observed that personalized product recommendations systematically lower search costs and enhance transaction convenience, culminating in heightened consumer satisfaction and repeat purchase loyalty [7]. Studies in this cluster also emphasize sustainable purchasing; Devi and Uniyal [17] and Al Saffarini and Awwad [18] found that personalized AI communications significantly enhance consumer trust and buying intentions toward organic and eco-friendly products by delivering tailored educational content matching the user's specific environmental values [17-19].

Cluster 2. AI Recommender Engines, Availability Bias, and Impulse/Compulsive Buying. This cluster focuses on algorithmic availability bias, spontaneous purchase stimulation, hedonic gratification, flash promotions, and compulsive shopping behaviors [9-13]. A substantial body of literature confirms that recommender systems do not merely assist pre-planned shopping goals; they actively generate unplanned impulse buying [9,10]. Shamim and Misra [9] applied the Stimulus-Organism-Behaviour-Consequence (SOBC) framework to prove that personalized recommendation prompts trigger immediate emotional arousal, significantly driving online impulse buying [9]. Datta et al. [10] identified that personalized fashion recommendations stimulate impulse buying across digital apparel platforms, particularly when combined with dynamic scarcity alerts [10]. Critically, Li et al. [11] established that AI recommendation engines induce an 'availability bias' by repeatedly presenting algorithmically prioritized items, making them appear cognitively prominent and driving immediate conversion [11]. Several alarming studies within this cluster examined compulsive behavioral outcomes: Acharya et al. [12] documented how algorithmic personalization exacerbates compulsive buying tendencies among psychologically vulnerable consumers [12]. Similarly, George and Rupa [13] found that the fusion of AI personalization, algorithmic Fear of Missing Out (FOMO) alerts, and integrated Buy Now Pay Later (BNPL) credit facilities drives compulsive borrowing and spending among Millennials and Generation Z [13].

Cluster 3. Interactive, Conversational, and Immersive AI Interfaces. The third cluster encompasses conversational chatbots, AI voice assistants, virtual try-on technologies, augmented reality (AR) visual simulations, and synthetic virtual influencers [20-25]. Research within this cluster highlights that conversational and visual realism significantly elevates consumer engagement and purchase confidence [20,21]. Sharma and Jaggi [20] showed that conversational engagement through AI voice assistants fosters perceived social presence, directly driving purchase behavior [20]. In the visual and apparel domains, Gao and Liang [21] established that AI-powered virtual try-on technologies substantially heighten impulsive buying intentions by allowing consumers to simulate product fit, with brand trust acting as a crucial moderator [21]. Anchan and Shareena [22] confirmed that 3D retail simulations accelerate customer decision velocity [22]. Furthermore, George et al. [23] and Yan et al. [24] examined virtual AI influencers, showing that while synthetic avatars generate high engagement among Gen Z demographics, their endorsement credibility is contingent upon perceived authenticity and the specific product category [23,24].

Cluster 4. Algorithmic Trust, Perceived Risk, the Privacy Paradox, and Dark Pattern Defense. This cluster unites critical constructs: perceived privacy risk, the privacy calculus paradox, algorithmic opacity, dark patterns, and consumer defense mechanisms [8,14-16,32]. While AI tools deliver immense convenience, consumer trust remains fragile [8,16]. Bhojwani et al. [8] demonstrated the dual nature of AI features: while recommendation engines and comparison tools enhance consumer decision confidence, perceived privacy vulnerabilities and decision fatigue dampen technology adoption [8]. Patnaik and Patnaik [16] proved that trust is the decisive prerequisite determining whether recommendations convert into actual purchase transactions [16]. Dang and Erorita [15] revealed that perceived risk strongly depresses purchase intentions directly and indirectly through trust erosion, which accounts for nearly 40% of the total behavioral variance [15]. Addressing predatory designs, Lee et al. [14] demonstrated through a controlled experiment that AI-delivered counter-support can assist consumers in detecting and neutralizing commercial 'dark patterns', thereby curbing regret-inducing impulse spending [14]. Reyes and Rajagopal [32] underscored that enterprise value chains must proactively adopt ethical AI guidelines to preserve long-term consumer goodwill [32].

Orientation / Focus	**Foundational / Low Technological Maturity**	**Strategic / High Technological Maturity**
Internal Cognitive & Utilitarian Orientation	Cluster A: Basic Search & Collaborative Filtering • Static recommendation grids • Simple search auto-complete • Transactional efficiency & basic TAM [7,33]	Cluster C: Cognitive Fit & Autonomous Support • Dynamic real-time preference modeling • Delegated consumer decision-making • Utilitarian optimization & brand attachment [6,31]
External Behavioral & Affective Orientation	Cluster B: Tactical Persuasion & Retargeting • Standard display remarketing • Scarcity countdown clocks • Basic promotional push notifications [9,10]	Cluster D: Immersive Multi-Sensory Symbiosis • Virtual try-on and AR simulations • Large Language Model shopping co-pilots • Algorithmic trust, ethics & dark pattern defense [14,20-22]

Table 3. Thematic Mapping of AI Consumer Research across Technological and Behavioral Dimensions [1,6-42,48].

Figure 5 positions these clusters on the centrality-density plane for the corpus as a whole. The machine-learning, learning-systems and customer-satisfaction cluster occupies the motor-theme quadrant, indicating both high relevance and internal maturity, whereas consumer behaviour, sales and purchasing form a basic, transversal theme. Notably, artificial intelligence, electronic commerce and e-commerce remain low in development degree despite their centrality, which empirically substantiates the fragmentation identified in our research gap.

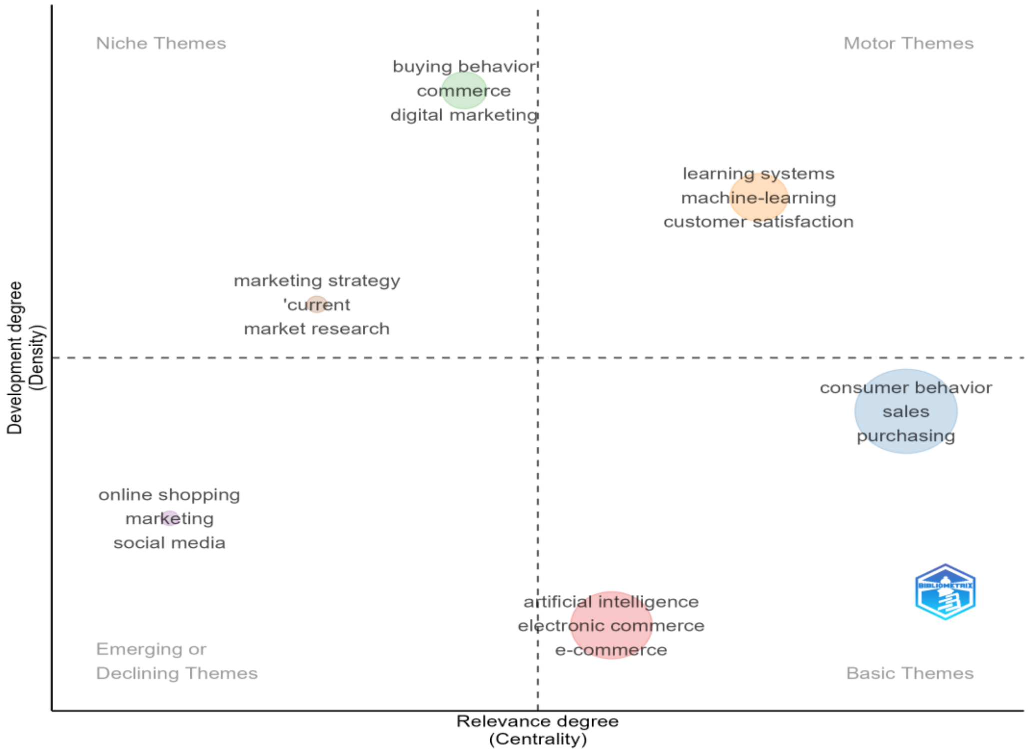

Figure 5. Thematic map of the full corpus, positioning clusters by centrality (relevance) and density (development).

6.3 Thematic Evolution Over Time

Tracing the 90 studies across chronological time frames illustrates a structural transition from functional automation to cognitive and behavioral persuasion [1,6-42,48]:

Figure 6 traces this transition as a flow of themes across three successive time slices. Broad early themes such as artificial intelligence, electronic commerce, chatbots and decision making progressively split and recombine into consumer behaviour, online shopping and competition in the intermediate slice, before converging in the most recent period on attitude, learning systems, behavioural research and digital marketing.

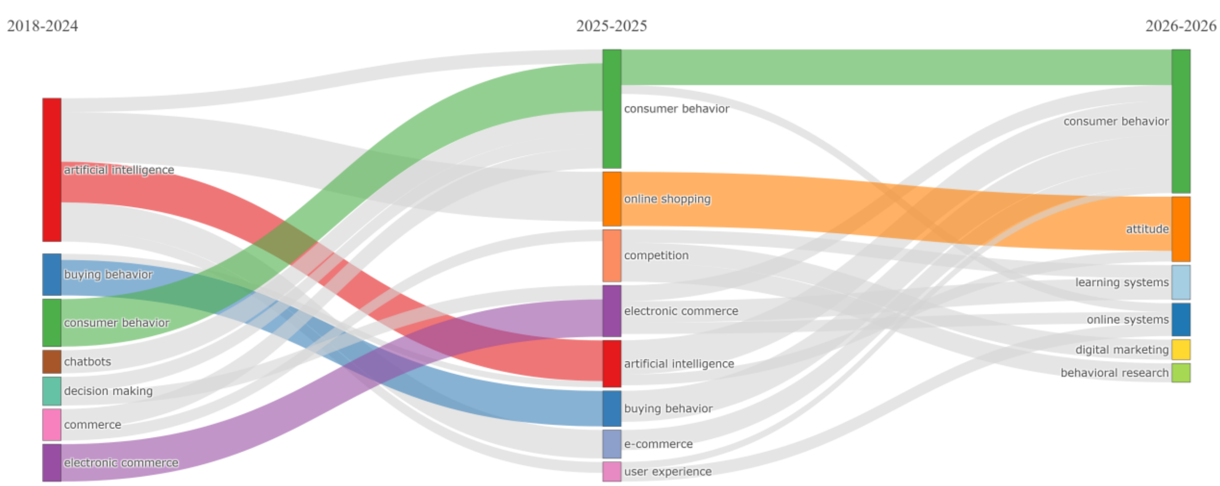

Figure 6. Thematic evolution of the corpus across three successive time slices (2018-2024, 2025 and 2026), showing the flow of themes between periods.

Period 2018 to 2021. In the earliest period of our review, research concentrated almost exclusively on functional utility, basic system usability, and baseline e-commerce adoption [33,34]. Representative studies, such as Carp [33] and Mok [34], explored how AI and technopreneurial digital technologies optimized supply networks and introduced automated product recommendations [33,34]. The primary inquiry during this period was utilitarian: determining whether automated recommendations reduced consumer search duration and improved website transaction volume [33]. Trust was evaluated primarily as system reliability rather than data ethics [34].

Period 2022 to 2024. Between 2022 and 2024, the thematic landscape experienced explosive diversification provoked by the COVID-19 pandemic [35-37]. As demonstrated by Verma et al. [35] and Boustani [37], the forced migration of populations to digital platforms prompted researchers to investigate omnichannel integration, predictive analytics, and algorithmic service delivery [35-37]. Research shifted from basic usability toward psychological constructs, including emotional satisfaction, brand attachment, and the hedonic motivations driving consumer acceptance [6,38-40]. During this window, studies by Zhu et al. [38], Sharma et al. [39], and Jangra and Jangra [39] documented how algorithmic marketing migrated from desktop portals into personalized mobile applications, establishing recommender algorithms as ubiquitous determinants of everyday retail discovery [38,39].

Period 2025 to 2026. In the most recent period, the research domain achieved advanced conceptual maturity, characterized by investigations into generative AI, real-time computer vision, neuromarketing, and behavioral exploitation [14,26,28,31]. Scholars moved beyond asking whether AI works, focusing instead on how cognitive delegation alters preference construction [31]. Research by Aw et al. [28], Zhou et al. [29], and Charan et al. [30] examined how generative AI and predictive machine learning models forecast seasonal and festive impulsive surges with unprecedented accuracy [28-30]. Concurrently, studies by Majerová et al. [31], Lee et al. [14], and George and Rupa [13] introduced critical ethical perspectives, analyzing dark patterns, preference reversals, compulsive BNPL borrowing, and the psychological mechanisms required to protect consumer autonomy [13,14,31].

The period-specific thematic maps in Figures 7 and 8 make this maturation visible. In the intermediate slice, electronic commerce, learning systems and machine learning functioned as motor themes alongside a strongly developed consumer behaviour, sales and purchasing cluster, while user experience and real-time personalisation remained niche concerns and behavioural intention sat among the emerging themes.

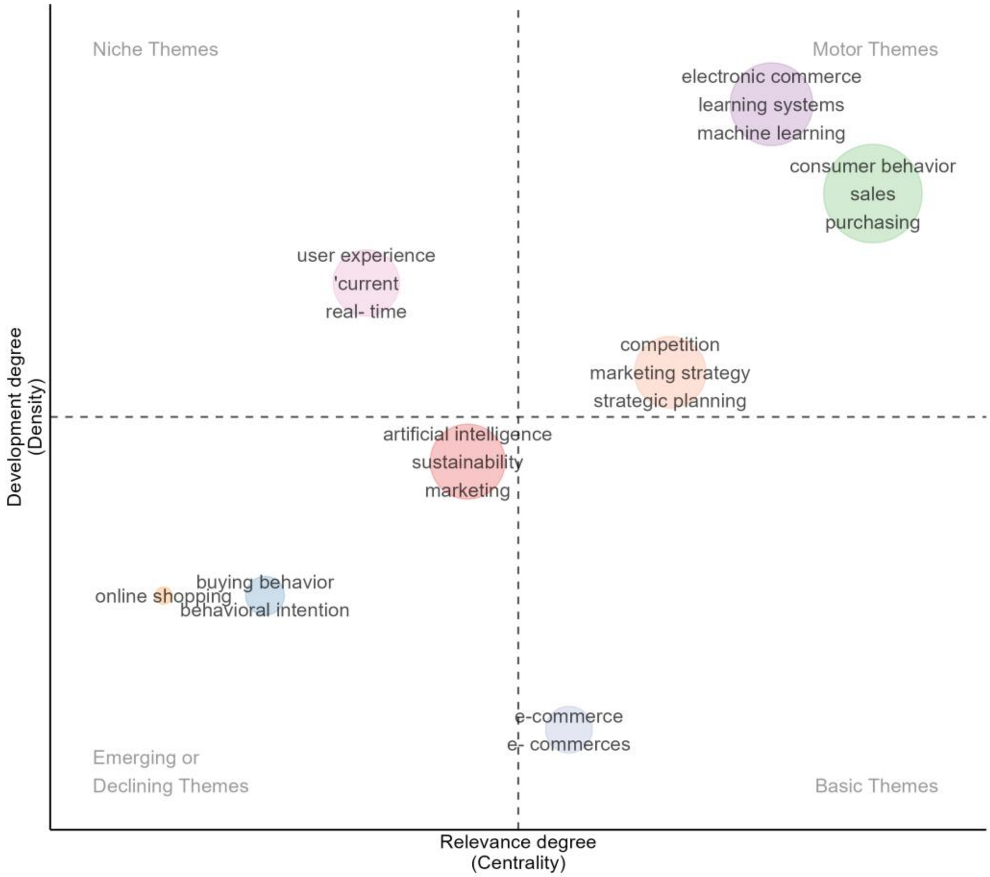

Figure 7. Thematic map for the intermediate time slice, in which electronic commerce, learning systems and machine learning operate as motor themes.

In the most recent slice, by contrast, behavioural research, ethical aspects and information systems moved toward the basic-theme quadrant, and constructs such as attitude, social influence and online shopping strengthened in density. This realignment evidences the disciplinary shift from technical performance toward consumer psychology and algorithmic accountability documented above.

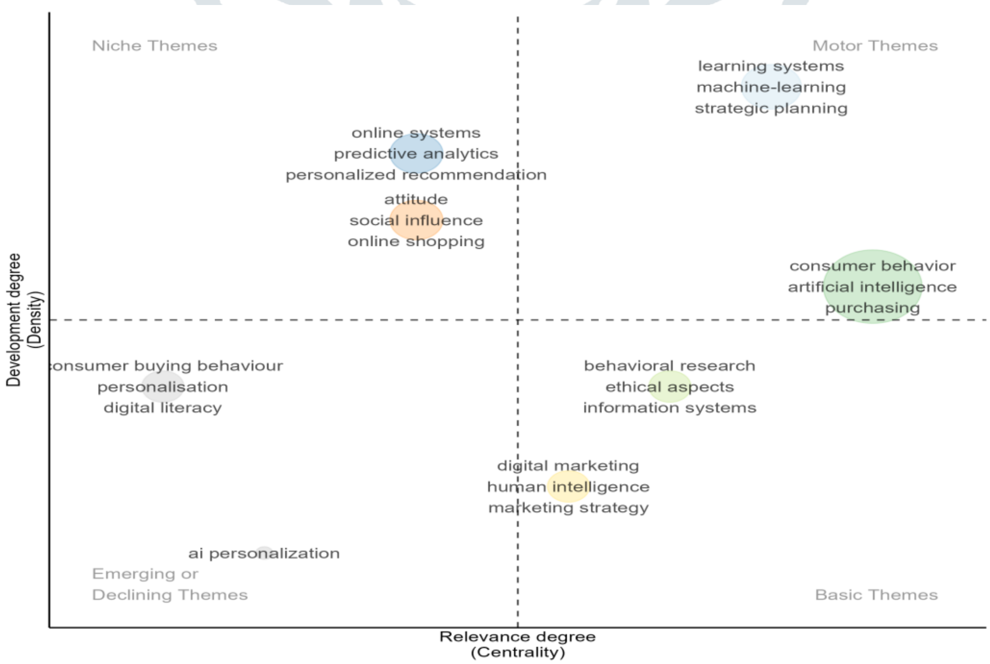

Figure 8. Thematic map for the most recent time slice, in which behavioural research, ethical aspects, attitude and social influence gain prominence.

7. Discussion

This section synthesizes our findings across the five guiding research questions, linking empirical observations to established psychological and organizational theories, and presenting an original strategic capability matrix.

RQ1. Influence of AI-Enabled Personalization on Consumer Buying Behaviour

Our systematic synthesis reveals that AI-enabled personalization exerts a statistically significant, positive influence on consumer buying behaviour and purchase intentions [6,7,49,50]. Across both empirical surveys and experimental trials, personalization operates by aligning environmental product cues with individual cognitive schema [6]. In terms of the Stimulus-Organism-Response (S-O-R) framework, personalized marketing messages act as optimized external stimuli (S) that minimize cognitive search friction, thereby inducing positive internal affective and cognitive evaluations (O) [6,19]. These internal states subsequently elicit decisive approach responses (R) manifested as elevated willingness to pay, shopping cart additions, and finalized checkout transactions [6,31]. Furthermore, as established by Shrivastava and Dubey [6] and Devi and Uniyal [17], personalization fosters brand attachment; when consumers perceive that an algorithm accurately anticipates their preferences, they attribute human-like empathy and competence to the retail platform, transforming a purely transactional interaction into a sustained psychological relationship [6,17]. For retail enterprises, these findings indicate that investing in algorithmic personalization generates superior customer retention compared to broad mass-market advertising campaigns [6,7].

RQ2. Influence of AI Recommendation Systems on Planned vs. Impulsive Purchasing

The review demonstrates that AI-powered recommendation systems operate as dual-action mechanisms, simultaneously facilitating planned product evaluations while aggressively triggering unplanned, impulsive buying behavior [9-13,49]. In planned shopping scenarios, recommendation engines function as utilitarian filters that rank options according to multi-attribute utility theory, allowing consumers to perform rapid price and feature comparisons [7,8]. However, the predominant behavioral outcome identified across contemporary studies is the stimulation of impulse buying [9,10]. Recommenders leverage cognitive availability bias, presenting algorithmically curated items alongside personalized urgency notifications (such as 'only 2 units remaining at this price') [10,11]. This algorithmic curation short-circuits deliberative System 2 cognitive processing, activating intuitive, affect-driven System 1 impulses [9,11]. As documented by Shamim and Misra [9] and Datta et al. [10], consumers frequently experience sudden, irresistible urges to purchase items they had not planned to acquire, driven by immediate hedonic gratification [9,10]. For marketing managers, recommendation systems are remarkably potent revenue multipliers, but over-optimizing for immediate impulse conversion risks driving buyer regret, elevated product return rates, and diminished lifetime satisfaction [10,14].

RQ3. Overall Relationship Between Integrated AI Marketing Features and Consumer Buying Behaviour

When examining AI-enabled marketing features as an integrated ecosystem—incorporating conversational chatbots, voice search assistants, visual try-on modules, and predictive algorithms—the findings demonstrate an amplified, synergistic relationship with consumer buying behaviour [8,20-22,49]. The holistic integration of these tools creates a seamless, immersive retail environment that engages multiple sensory modalities [20,21]. For example, when an e-commerce platform couples a computer-vision virtual try-on engine with an intelligent conversational styling chatbot, consumer hesitation regarding product fit and aesthetic compatibility is substantially reduced [21,25]. This unified architectural immersion elevates perceived self-efficacy and purchase certainty, particularly in visually sensitive retail segments like apparel, beauty, and luxury furnishings [21,22]. Consequently, retail platforms that successfully orchestrate multi-tool AI capabilities achieve significantly higher conversion rates, longer user dwell times, and lower shopping cart abandonment than platforms relying on fragmented, single-point AI solutions [8,21].

RQ4. Intervening Mechanisms: Algorithmic Trust, Perceived Risk, and Privacy Concerns

Crucially, our analysis establishes that the relationship between AI marketing interventions and consumer buying behavior is neither linear nor unconditional; rather, it is heavily mediated and moderated by consumer trust, perceived risk, and the 'privacy paradox' [8,14-16,49]. Grounded in Signalling Theory and Agency Theory, consumers view AI systems as autonomous agents that possess information advantages over them [1,8,15]. If consumers suspect that recommendations are designed to extract maximum profit through manipulative steering or hidden price markups, trust collapses, and perceived risk escalates dramatically [8,15]. As Dang and Erorita [15] proved, perceived risk directly suppresses purchase intention and actively degrades the foundational trust required to sustain digital transactions [15]. Moreover, privacy calculus theory explains that modern consumers constantly balance the perceived functional benefits of personalization against the perceived threat of cognitive surveillance [8,14]. When AI systems demand intrusive personal data without transparent justification, consumers experience psychological reactance and privacy fatigue, often providing fabricated information or abandoning the platform entirely [8,14]. Therefore, algorithmic explainability, conspicuous data consent protocols, and ethical guardrails represent indispensable structural prerequisites for ensuring that AI personalization successfully converts into positive consumer buying behaviour [14,32,48].

RQ5. Theoretical Framework: The AI Marketing Strategic Capability Matrix

To resolve the fragmentation observed in existing literature and provide an integrative conceptual tool, we synthesize our findings into an original analytical typology: the AI Marketing Strategic Capability Matrix (Table 4) [1,48]. This framework models the intersection between Algorithmic Technical Maturity (ranging from basic rule-based filtering to advanced autonomous cognitive intelligence) and Consumer Value Orientation (spanning functional/utilitarian decision optimization to emotional/persuasive conversion) [1,6-42,48].

Consumer Value Orientation	**Low Algorithmic Maturity (Heuristic / Rule-Based)**	**High Algorithmic Maturity (Predictive / Deep Autonomous AI)**
Utilitarian & Functional Decision Optimization	Quadrant A: Filtered Efficiency • Static collaborative filtering grids • Keyword auto-complete • Basic price-sorting engines • Rule-based search queries [7,33]	Quadrant C: Cognitive Decision Support • Autonomous shopping co-pilots (LLMs) • Cross-market arbitrage & price forecasting • Delegated automated replenishment • Fiduciary consumer optimization [31,32]
Hedonic & Persuasive Emotional Conversion	Quadrant B: Tactical Promotion • Display retargeting banner ads • Fixed scarcity countdown clocks • Generic cart abandonment alerts • High risk of dark pattern fatigue [9,14]	Quadrant D: Prescriptive Behavioral Symbiosis • Emotionally intelligent conversational voice bots • Real-time computer-vision virtual try-ons • Generative neuro-marketing stimuli • Hyper-personalized dynamic discovery [20-22,26]

Table 4. AI Marketing Strategic Capability Matrix: Quadrant Typology and Behavioral Mechanisms [1,6-42,48].

- **Quadrant A: Filtered Efficiency (Low Maturity, Utilitarian Focus).** Represents early-stage, baseline e-commerce capabilities [7,33]. Tools in this quadrant focus on reducing transaction friction through simple keyword lookups, basic relational database filtering, and standard checkout procedures [33]. While operationally reliable, these systems offer minimal competitive differentiation and do not dynamically adapt to shifting consumer mindsets [34].
- **Quadrant B: Tactical Promotion (Low Maturity, Hedonic Focus).** Reflects aggressive, outbound promotional mechanics [9,10]. Platforms deploy repetitive retargeting display ads, automated email reminders for abandoned shopping carts, and static scarcity pop-ups [14]. Because these tools rely on rudimentary behavioral triggers, they are particularly prone to consumer fatigue and accusations of deploying dark patterns [14].
- **Quadrant C: Cognitive Decision Support (High Maturity, Utilitarian Focus).** Represents highly sophisticated algorithmic systems designed to optimize consumer welfare [31,32]. Applications include intelligent personal shopper co-pilots powered by large language models, dynamic cross-merchant price tracking, and predictive replenishment systems [28,31]. These tools build profound consumer trust by acting as fiduciary agents that actively maximize consumer utility while safeguarding data privacy [31,32].
- **Quadrant D: Prescriptive Behavioral Symbiosis (High Maturity, Hedonic Focus).** Characterizes cutting-edge multi-sensory marketing ecosystems [20-22,26]. Retail platforms combine real-time computer vision virtual try-ons, empathetic conversational avatars, and generative neuro-marketing algorithms to craft compelling, hyper-individualized shopping experiences [21,26]. While this quadrant generates the highest rates of engagement and impulse buying, it requires the most rigorous ethical safeguards to ensure that behavioral persuasion does not cross into predatory manipulation [13,14,32].

8. Conclusion

This study has conducted a systematic literature review and thematic analysis of 90 scholarly research studies examining the impact of AI-enabled personalization and recommendation systems on consumer buying behaviour [6-42,48]. We traced the conceptual trajectory of algorithmic commerce, establishing how the discipline evolved from early rule-based database filters into an omnipresent infrastructure driven by deep learning, natural language interaction, computer vision, and generative neuro-marketing architectures [6,25-31].

Our findings confirm that AI-enabled personalization and predictive recommendation engines significantly enhance consumer purchase intentions, shopping efficiency, and brand attachment, while functioning as potent catalysts for unplanned impulse purchases [6,7,9-11]. However, the efficacy of these technological capabilities is fundamentally contingent upon the preservation of consumer trust [8,15,16]. Algorithmic opacity, invasive data harvesting, and manipulative dark patterns elevate perceived risk and trigger consumer reactance [14,15]. By formulating the AI Marketing Strategic Capability Matrix, this paper delivers an actionable conceptual model that links algorithmic maturity with ethical, consumer-centric value creation [1,48].

As commercial enterprises face stricter regulatory mandates—such as the Indian DPDP Act, CCPA dark pattern regulations, and international AI governance frameworks—sustainable competitive advantage will belong to platforms that balance predictive analytical power with algorithmic transparency and rigorous data protection [14,32,48]. Future research must continue to explore the delicate boundary between helpful personalization and predatory behavioral modification, ensuring that artificial intelligence empowers consumers rather than exploiting their psychological vulnerabilities [13,14,31,32].

9. Limitations

It is important to acknowledge several methodological limitations inherent in this study [1,48]. First, the literature review was restricted to English-language, peer-reviewed academic articles, book chapters, and indexed conference proceedings; valuable findings published in non-English repositories or corporate industry white papers were excluded, which may restrict the cross-cultural generalizability of the conclusions [1,48]. Second, thematic classification was conducted through structured qualitative synthesis in Excel rather than algorithmic natural language bibliometric parsing packages (such as Biblioshiny R), introducing an element of interpretive subjectivity in thematic cluster boundaries [1,48].

Regarding the integrated empirical blueprint, the proposed sampling methodology relies on non-probability purposive and convenience techniques administered to online consumers aged 18 to 45 [50]. This demographic focus inherently skews toward digitally literate, younger urban cohorts, potentially limiting the direct generalizability of the findings to older consumers, rural populations, or low-income retail demographics [50]. Furthermore, survey-based empirical designs are susceptible to self-report bias and social desirability bias, as consumers may under-report impulsive tendencies or over-state their adherence to privacy safeguards [50]. Future empirical investigations should address these constraints by employing multi-method experimental approaches, longitudinal tracking of actual clickstream transactions, and cross-cultural comparisons across developing and advanced economies [14,48,50].

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