The AI-Conditioned Buyer: Conceptualising the Pre-Purchase Cognitive State Shaped by Algorithms

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Author Note:

The term AI-conditioned buyer was first introduced, defined, and conceptualised by the author in this paper. It is presented as a new theoretical construct for understanding the cognitive state of buyers shaped by algorithmic influence prior to purchase. This manuscript constitutes the formal scholarly claim to the authorship and origination of the term.

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This conceptual paper introduces the term AI-conditioned buyer to describe a distinct and increasingly common customer state in contemporary sales interactions. As digital transformation and artificial intelligence (AI) reshape the modern customer journey, consumers now arrive at human-to-human (H2H) sales encounters with pre-loaded cognitive biases, decision heuristics, and expectations shaped by algorithmically curated content. This conditioning is driven by AI-based recommendation engines, personalised advertising, predictive search algorithms, and digital social proof, mechanisms that systematically influence consumer perceptions before any direct salesperson contact.

Despite growing scholarly attention to digital and empowered buyers, existing terminology fails to capture the cognitive and behavioural specificity of this algorithmically shaped state. This paper defines and delineates the AI-conditioned buyer as a foundational concept, outlining its core attributes, underlying mechanisms, and applicable boundary conditions. A typology is developed to categorise buyers based on the intensity of AI-conditioning, ranging from low to high levels of algorithmic exposure and influence.

The paper contributes to theoretical advancement in consumer behaviour, sales management, and marketing literature by offering a concept that bridges the gap between digital content exposure and H2H sales interaction. Practical implications are discussed in detail, highlighting how this concept can inform sales training, marketing strategy, customer experience design, and curriculum development. Furthermore, the conceptualisation serves as the basis for a broader research program investigating behavioural adaptation and interactional dynamics in short-cycle, AI-influenced sales.

By naming and defining the AI-conditioned buyer, this paper offers scholars and practitioners a necessary analytic lens to better understand, anticipate, and respond to the

algorithmically shaped expectations that increasingly define customer behaviour in digitally mediated commerce.

Keywords

AI-conditioned buyer, algorithmic influence, pre-purchase cognition, short-cycle sales, consumer psychology, sales strategy.

Introduction

The nature of buyer–seller interactions has undergone substantial disruption over the past two decades, driven by accelerated technological advancements and fundamental shifts in consumer behaviour. Traditionally, the salesperson played a central role as the primary conduit of product knowledge, comparative options, pricing information, and post-purchase assurance (Singh, Marinova, & Brown, 2019). In both consumer (B2C) and business (B2B) contexts, customers relied heavily on the expertise of salespeople to inform purchase decisions, particularly during the early stages of the buyer journey. However, successive waves of industrial development, most notably the digital and now algorithmic revolutions, have transformed these dynamics. Customers have become progressively more self-informed, digitally autonomous, and less reliant on salespeople for decision support (Chaker, Trainor, & Arnold, 2022).

The rise of the internet ushered in the “zero moment of truth” paradigm, where customers engage in extensive online research before ever contacting a brand or salesperson (Lemon & Verhoef, 2016). In this context, the sales function began to shift from a role of education and guidance to one of validation and transactional execution. More recently, artificial intelligence (AI) has intensified this shift. Consumers are now exposed to highly personalised recommendations, predictive product rankings, algorithmically curated content streams, and social proof engines. These systems systematically condition customer preferences and expectations before they encounter a human salesperson (Hartmann, Chaker, Lussier, Larocque, & Habel, 2023; Puntoni, Reczek, Giesler, & Botti, 2021).

Despite growing attention to digital transformation in marketing, sales, and consumer psychology, there remains a critical gap in how contemporary scholarship accounts for the algorithmically shaped mental state of the buyer at the point of human contact. Existing constructs such as the "digitally empowered customer," "omnichannel buyer," or "self-directed consumer" offer useful framing for channel behaviours or information access (Rapp, Bachrach, Panagopoulos, & Ogilvie, 2017), but they fall short of capturing the cognitive and behavioural consequences of sustained AI exposure. These terms focus on the autonomy of the buyer rather than the conditioned mindset that precedes salesperson interaction. As algorithmic systems increasingly serve as the first and most frequent point of contact in the customer journey, a new lexicon is required to adequately conceptualise the psychological and behavioural profile of such customers.

This paper introduces and defines the concept of the AI-conditioned buyer to fill this conceptual gap. An AI-conditioned buyer is defined as a customer whose perceptions, preferences, and decision-making heuristics are significantly shaped by algorithmic systems prior to their first human-to-human (H2H) sales interaction. These systems may include AI-powered recommendation engines, predictive search tools, personalised content algorithms, and digital social proof mechanisms. The defining feature of the AI-conditioned buyer is not merely access to digital information, but the systematic preloading of product perceptions that shape and often narrow their engagement with salespeople.

This conceptual paper makes several contributions. First, it introduces the AI-conditioned buyer as a foundational construct for understanding digitally mediated sales interactions. Second, it develops a typology that classifies buyers along a continuum of AI-conditioning intensity, from low to high, based on the depth, frequency, and influence of algorithmic exposure. Third, it outlines the theoretical boundary conditions of the construct and differentiates it from existing consumer typologies. Finally, it explores the implications of AI-conditioned buyer behaviour for sales strategy, customer experience design, sales education, and ethical governance of algorithmic systems.

The emergence of AI-conditioned buyers has particular relevance in short-cycle sales environments, where customers arrive late in the decision process and expect rapid confirmation of pre-existing assumptions (Hartmann et al., 2023). In such compressed interactions, traditional sales frameworks that emphasise discovery and relationship-building become less effective. Understanding the AI-conditioned buyer provides a more accurate foundation for theorising and managing these high-velocity exchanges.

The introduction of this concept also serves as the basis for a broader research agenda. This includes empirical studies examining salesperson adaptability in the presence of AI-conditioned buyers, as well as theoretical extensions addressing how this conditioning interacts with trust formation, value co-creation, and commercial outcomes in H2H settings. Moreover, recognising AI-conditioning as a distinct buyer state has implications for how we educate future sales professionals and define competency standards for an AI-disrupted commercial landscape (Grewal, Roggeveen, & Nordfält, 2023).

In positioning the AI-conditioned buyer as a foundational construct, this paper does not seek to explain all aspects of digital buyer behaviour, nor does it advance a normative judgement about AI's role in commerce. Rather, it offers a conceptual tool for scholars, educators, and practitioners to more precisely analyse, describe, and respond to the behavioural reality of algorithmically influenced consumers. The sections that follow elaborate the theoretical background, formal definition, conceptual boundaries, and practical implications of this emerging phenomenon.

Review of the Current Discourse

The evolving dynamics between buyers and salespeople have undergone significant transformation across successive industrial revolutions, most notably due to the advent of digital technologies and, more recently, artificial intelligence (AI). In both business-to-consumer (B2C) and business-to-business (B2B) contexts, the traditional buyer journey positioned the salesperson as the primary source of information and influence. Today, however, this role has been redefined. The proliferation of digital touchpoints and AI-enhanced recommendation systems has led to a fundamental shift in the nature of buyer preparation, decisional autonomy, and the point at which they engage in human-to-human (H2H) sales interactions. This section reviews the conceptual terrain around these transformations and critically evaluates the absence of adequate terminology to describe the contemporary buyer state, culminating in the introduction of the AI-conditioned buyer.

The Historical Role of the Salesperson: An Information-Led Dynamic

Historically, the buyer-seller relationship in both B2C and B2B contexts was grounded in an information asymmetry, where the salesperson acted as the primary gatekeeper to product knowledge, pricing, and competitive differentiation (Singh, Marinova, & Brown, 2019). Particularly in B2C contexts such as automotive retail, appliances, or real estate, buyers relied heavily on the interpersonal expertise of salespeople to make informed decisions (Itani, Goad, & Jaramillo, 2019).

In B2B settings, especially during business development or pre-procurement phases, salespeople played an even more consultative role, often guiding prospective clients through complex solution architectures or regulatory requirements (Guenzi, Georges, & Pardo, 2009).

These engagements were typically relational and temporal, with decision-making contingent on long-term rapport, trust, and iterative negotiation. Sales theory during this period emphasised consultative selling (Rackham, 1988), adaptive selling (Spiro & Weitz, 1990), and relationship marketing (Morgan & Hunt, 1994).

From Industrial Revolution to the Algorithmic Age: Shifting Buyer Power

The industrial revolutions, mechanisation, electrification, digitalisation, and now the age of algorithmic augmentation, have systematically shifted the locus of power in buyer-seller interactions. Digital platforms, search engines, and third-party review aggregators have incrementally reduced buyer dependence on the salesperson, replacing information scarcity with an abundance of self-service tools (Chaker, Trainor, & Arnold, 2022).

The internet era, often framed as the fourth industrial revolution, introduced the notion of digitally empowered buyers, individuals with access to comparison tools, product reviews, pricing transparency, and social proof prior to engagement (Hartmann, Wieland, & Vargo, 2018). These capabilities challenged traditional selling scripts, prompting practitioners to shift from persuasion to validation, with the salesperson now positioned later in the buyer journey (Rapp, Bachrach, Panagopoulos, & Ogilvie, 2017).

However, while this shift is well-documented, most frameworks fail to delineate the qualitative shift in buyer cognition introduced by AI-mediated exposure. The rise of AI has not simply informed buyers, it has conditioned them through systematic exposure to curated, ranked, and personalised digital content. Buyers now arrive at sales interactions not only empowered, but pre-disposed, with cognitive heuristics and decision-making scripts shaped algorithmically (Hartmann, Chaker, Lussier, Larocque, & Habel, 2023).

The Emergence of Short-Cycle Sales and Compressed Interactions

Simultaneous to the rise of algorithmic influence is the compression of the buyer–seller interaction timeline. "Short-cycle sales" refers to scenarios where purchase decisions are made within a single or limited interaction, common in sectors like luxury goods, automotive sales, SaaS onboarding, and real estate inspections (Itani et al., 2019). These interactions contrast sharply with traditional long-cycle engagements, where trust, exploration, and negotiation unfold over time.

In these compressed contexts, customers enter with a fully-formed problem definition, vendor preference, and often a preferred solution, shaped by pre-engagement AI conditioning (Chaker et al., 2022). This shifts the salesperson's role from relationship architect to cognitive confirmer, validating the customer's preloaded decision path.

Moreover, AI-conditioned buyers exhibit reduced openness to persuasion, demanding hyper-alignment to their expectations within compressed timeframes. Their attention spans are shorter, and their decision confidence, though potentially inflated, is reinforced by algorithmic echo chambers (Singh et al., 2019).

Existing Buyer Terminologies: Conceptual Overlap, Inadequate Precision

Despite the growing literature on digital transformation in marketing and consumer behaviour, there remains a notable conceptual gap regarding language explicitly addressing the state of buyers entering human-to-human interactions after algorithmic conditioning. Current buyer-related terminology fails to adequately capture this transformation. Terms such as: "Digitally empowered buyer" describe autonomy but neglect systematic biasing via AI (Hartmann et al., 2018), "Self-directed buyer" implies independence but omits cognitive conditioning (Chaker et al., 2022) and "Omnichannel consumer" focuses on channel integration, not decision pre-loading (Singh et al., 2019), capture aspects of consumer autonomy and multi-channel exposure. However, they fail to describe the unique cognitive and behavioural states buyers inhabit immediately prior to salesperson contact, shaped fundamentally by AI-driven content personalisation, recommendation systems, and behavioural nudging (Hartmann et al., 2023).

These descriptors are sufficient for traditional digital buyers but insufficient for understanding the buyer's altered state when shaped by recommendation engines, predictive targeting, and algorithmic personalisation. No existing construct adequately describes the cognitive frameworks or decision certainty with which modern customers arrive in short-cycle, H2H interactions.

Conceptual Gap: Absence of Language for Pre-Biased Buyer States

Despite growing scholarly attention to AI in marketing, there remains a conceptual vacuum when it comes to explicitly naming the psychological and behavioural effects of AI on buyers prior to human engagement. The literature often assumes a rational or neutral buyer entry point—an assumption that no longer holds in AI-saturated marketplaces (Itani et al., 2019).

The AI-conditioned buyer fills this gap, offering a linguistically and analytically precise term to capture:

- Preloaded expectations and decision frameworks,
- Algorithmic bias reinforcement,
- Compressed interactional receptivity,
- Diminished exploratory dialogue.

In doing so, the concept reframes the buyer not just as empowered, but as shaped, and in some cases, overdetermined, by the digital and algorithmic architecture that precedes the salesperson.

This clarity is essential as sales practices evolve from information gatekeeping and persuasion towards real-time responsiveness, credibility establishment, and behavioural alignment with rapidly formed buyer perceptions. By explicitly naming and defining this condition, future research can empirically explore the implications and behavioural outcomes of these digitally mediated buyer states, further enriching our understanding of contemporary sales phenomena.

Concept Definition: The AI-Conditioned Buyer

The rise of artificial intelligence (AI) in commercial environments has introduced a new kind of consumer, one shaped not merely by access to information but by its algorithmic curation. This section introduces the concept of the AI-conditioned buyer, a term developed to explain the specific psychological and behavioural state in which customers arrive at a human-to-human (H2H) sales interaction. Unlike prior models that describe the buyer as informed or empowered, the AI-conditioned buyer is characterised by algorithmically shaped expectations, narrowed preferences, and reduced openness to salesperson influence. This section defines the construct, outlines its core attributes, delineates its conceptual boundaries, and distinguishes it from related buyer typologies.

Formal Definition

An AI-conditioned buyer is a customer whose cognitive state, defined by pre-formed expectations, preferences, evaluative frameworks, and decision heuristics, has been systematically shaped through sustained exposure to algorithmically curated digital environments (Puntoni, Reczek, Giesler, & Botti, 2021; Hartmann, Chaker, Lussier, Larocque, & Habel, 2023). This psychological conditioning occurs prior to the point of purchase or interpersonal engagement and applies regardless of whether the eventual transaction occurs through a human-to-human interaction, a digital interface, or a hybrid pathway (Lemon & Verhoef, 2016).

Rather than arriving at the purchase moment as an autonomous, rational agent, the AI-conditioned buyer enters with a pre-structured mental model, shaped by artificial intelligence systems such as recommendation engines, predictive search algorithms, personalised content streams, and socially reinforced ranking mechanisms (Chaker, Trainor, & Arnold, 2022). These systems subtly but powerfully influence what the customer values, how they compare alternatives, and which options they consider valid, often without conscious awareness (Grewal, Roggeveen, & Nordfält, 2023).

The defining feature of the AI-conditioned buyer is not the channel through which they transact, but the pre-loaded interpretive frame they carry into that transaction, one that compresses cognitive openness, reinforces decision confidence, and reduces the receptivity to new information (Itani, Goad, & Jaramillo, 2019). This buyer does not merely use AI-enabled tools; they are cognitively shaped by them, often exhibiting behaviours and beliefs that reflect algorithmic influence more than deliberate analysis. These systems do not merely inform buyers, they pre-structure their interpretation of value, risk, and fit, leading to preloaded cognitive scripts that guide subsequent salesperson engagement.

Core Characteristics

The AI-conditioned buyer possesses several distinct features:

- Preloaded Cognitive Biases: Preferences are shaped not by salesperson dialogue, but by algorithmic priming that pre-establishes what the customer expects to find, believe, and consider acceptable (Hartmann, Chaker, Lussier, Larocque, & Habel, 2023).

- Inflated Decision Certainty: Conditioning by AI often leads buyers to overestimate the accuracy and completeness of their knowledge, even when it may be incomplete, biased, or manipulated (Puntoni, Reczek, Giesler, & Botti, 2021).
- Reduced Exploratory Openness: Having already "made up their minds," AI-conditioned buyers often exhibit minimal receptivity to salesperson-suggested alternatives or needs discovery frameworks (Itani, Goad, & Jaramillo, 2019).
- Compressed Engagement Window: Sales interactions are shortened as buyers seek validation more than exploration. The perceived role of the salesperson becomes confirmatory rather than consultative (Chaker, Trainor, & Arnold, 2022).

These characteristics together distinguish the AI-conditioned buyer from other digital-era consumer profiles by highlighting not autonomy per se, but cognitive pre-commitment shaped by algorithms. Although explainability is often promoted as a tool to enhance trust in AI systems, recent meta-analytic research shows that while explainability correlates moderately with trust, it is not sufficient to mitigate the deeper psychological influence AI has on user cognition (Atf & Lewis, 2025). This finding emphasises that AI-conditioning does not always operate at the level of rational persuasion, but instead subtly primes buyer assumptions, often below the threshold of awareness.

Mechanisms of Conditioning

AI conditioning in buyers occurs primarily through several distinct digital mechanisms:

- Algorithmic Recommendation Engines: Platforms like Amazon, Netflix, and various digital marketplaces employ advanced AI algorithms to recommend products or services tailored to user behaviour, previous purchases, and browsing histories

(Chaker et al., 2022). Such personalised recommendations shape consumer preferences and expectations before salesperson interaction.

- Personalised Advertising and Targeted Content: AI-driven personalisation of advertisements and online content significantly influences consumer perceptions by consistently exposing individuals to highly targeted messages aligned closely with their predicted interests and preferences (Hartmann et al., 2023).
- Search Engine Biases and Ranking Algorithms: Search engines employ complex ranking algorithms that prioritise results based on relevance, past user behaviour, and commercial considerations, influencing what consumers see first and reinforcing certain purchasing patterns or brand biases (Singh et al., 2019).
- Social Proof and Digital Community Influences: AI-enabled platforms heavily leverage social proof mechanisms, prominently featuring user reviews, rankings, influencer endorsements, and community feedback to condition buyers' perceptions of product value and desirability (Rapp et al., 2017).

These mechanisms create an algorithmically mediated consumer landscape where preferences, biases, and purchasing intentions become systematically curated by AI, long before human-to-human sales interaction occurs. Recent experimental evidence has demonstrated that conversational AI systems can subtly steer consumer choices without user awareness, reinforcing concerns about the invisible cognitive influence of algorithmic systems (Werner, Soraperra, Calvano, Parkes, & Rahwan, 2024). This supports the core premise of the AI-conditioned buyer: that cognitive preferences may be shaped unconsciously, well before a conscious purchase decision or human engagement occurs.

Boundary Conditions and Scope of AI-Conditioned Buyers

To ensure analytical precision and conceptual clarity, the definition of the AI-conditioned buyer is bounded by cognitive state, not transactional format. The construct is grounded in the mental schema the customer brings to the point of purchase, defined by pre-configured preferences, narrowed attention, and algorithmically reinforced decision frameworks. It applies regardless of whether the purchase occurs through a salesperson, a digital channel, or a hybrid path, and it is independent of the product or service category.

The AI-conditioned buyer is not defined by what they do, but by how they think before making a purchase. This cognitive state is the result of sustained exposure to artificial intelligence systems that influence how the buyer perceives value, risk, relevance, and choice. As such, the construct cuts across B2C and B2B domains, applies to both high- and low-involvement products, and is observable in both short-cycle and longer deliberative buying journeys.

To distinguish this concept from broader consumer typologies or digital usage models, three specific boundary conditions are articulated:

- Cognition Over Channel: The construct is applicable across all purchase pathways. Whether the buyer transacts online, offline, or through a salesperson, the AI-conditioning refers to the mental conditioning that precedes the moment of decision. It does not require human contact to be valid, though such contact may reveal the conditioned state more clearly.
- Conditioning, Not Choice Autonomy: The buyer’s state is shaped by AI, even when they believe their decisions are autonomous. This construct is not about consumer capability or access to information, it is about systemically shaped perception. Unlike digitally empowered or self-directed buyer models, this construct emphasises cognitive pre-bias, not capability or intent.

- Algorithmic Exposure as a Precondition: The buyer must have experienced meaningful interaction with AI-based systems (e.g., product ranking algorithms, predictive search, personalised advertising) that influenced their evaluative mindset. General online browsing or uncurated information access does not qualify unless it involved systems with algorithmic logic designed to guide or influence outcomes.

By defining the AI-conditioned buyer in terms of pre-transactional cognitive framing, this construct maintains conceptual precision while retaining broad theoretical and practical applicability. It is positioned to support diverse applications, from empirical behavioural analysis to strategic sales enablement and policy discourse on algorithmic influence.

Differentiation from Related Constructs

The AI-conditioned buyer is often confused with similar constructs in contemporary literature. However, it is distinct in the following ways:

- Digitally Empowered Buyer: Focuses on information access and autonomy (Hartmann, Wieland, & Vargo, 2018), not cognitive bias or decision preloading.
- Omnichannel Buyer: Centres on channel integration and touchpoint variety (Rapp, Bachrach, Panagopoulos, & Ogilvie, 2017), not algorithmic influence on cognition.
- Self-Directed Buyer: Emphasises decision independence, but lacks acknowledgement of external, system-driven influence over the content and structure of decisions (Singh, Marinova, & Brown, 2019).

Only the AI-conditioned buyer captures the algorithmically determined nature of perception and judgement, making it a more precise tool for analysing behaviour in modern H2H sales environments.

Analytical Utility and Theoretical Contributions

Defining and delineating the AI-conditioned buyer yields significant analytical and theoretical utility:

- Enhanced Understanding of Buyer Behaviour: Clarifying the AI-conditioned buyer provides scholars and practitioners a clearer framework for understanding emerging customer dynamics shaped explicitly by algorithmic personalisation and digital content delivery (Hartmann et al., 2023).
- Foundation for Future Research: Clearly defining this concept enables rigorous empirical investigation into the impacts and management strategies associated with algorithmically-conditioned buyers, contributing significantly to the advancement of sales theory and consumer behaviour literature.
- Strategic Implications for Sales Practice: Recognition of the AI-conditioned buyer facilitates more strategic, targeted, and responsive sales approaches, adapting sales training, engagement strategies, and relationship management to account explicitly for the cognitive and behavioural biases of digitally pre-conditioned consumers (Rapp et al., 2017).
- Educational and Professional Standardisation: Explicit identification of the AI-conditioned buyer as a distinct and significant phenomenon supports the integration of contemporary sales knowledge into educational curricula and professional standards, enhancing the relevance and efficacy of salesperson training and professional development programmes (Chaker et al., 2022).

Ultimately, explicitly naming and defining the AI-conditioned buyer significantly enriches theoretical frameworks, analytical models, and practical approaches to contemporary buyer engagement and sales effectiveness.

Conceptual Illustration and Typology

To operationalise the concept of the AI-conditioned buyer and facilitate its use in research and practice, this section introduces a conceptual typology. The typology does not categorise buyers by demographic profile, channel behaviour, or transaction modality, but rather by the intensity of cognitive conditioning resulting from sustained interaction with algorithmic systems. It positions the AI-conditioned buyer as a continuum of psychological influence, characterised by varying levels of preloaded expectations, confidence, and openness to external input at the point of decision. This typology offers theoretical utility for segmentation, empirical measurement, and strategic adaptation across both consumer and organisational contexts.

Typology Structure: Conditioning Intensity as Cognitive Gradient

The core dimension of the typology is conditioning intensity, the degree to which the buyer's evaluative mindset has been shaped by AI-based systems. Conditioning intensity is conceptualised as a gradient of psychological influence, not a fixed category. It captures the extent to which a buyer's mental schema has been pre-shaped by algorithmic exposure, including but not limited to recommendation systems, predictive targeting, personalised content feeds, and automated filtering tools (Puntoni, Reczek, Giesler, & Botti, 2021; Grewal, Roggeveen, & Nordfält, 2023).

Three representative types are proposed for analytical clarity:

- Type I: Low AI-Conditioning (Exploratory State). Buyers in this category exhibit minimal exposure to algorithmic curation or have high resistance to its influence. Their cognitive frame is relatively open, exploratory, and receptive to new information. They exhibit low decision certainty and maintain a wide evaluative scope. These individuals are more likely to consult multiple sources, reconsider preferences mid-process, and engage critically with sales, product, or service input (Itani, Goad, & Jaramillo, 2019).

- Type II: Moderate AI-Conditioning (Anchored State). These buyers have been meaningfully exposed to personalised AI content that has shaped their expectations and preferences, but they retain partial openness to external influence. They demonstrate moderate confidence in their evaluations and display selective receptivity. Their cognitive state is characterised by anchored certainty, a belief in a preferred direction or solution, but not full cognitive closure. This is the most dynamic segment for sales and marketing intervention, as they can be influenced with effort (Chaker, Trainor, & Arnold, 2022).
- Type III: High AI-Conditioning (Committed State). Buyers in this category exhibit strong algorithmic imprinting. Their beliefs, preferences, and purchase filters have been heavily conditioned through repeated exposure to reinforcement mechanisms (e.g., retargeted ads, top-ranked search results, algorithmic social proof). They often exhibit high decision certainty, strong selective attention, and low receptivity to alternative narratives. Their cognitive state is characterised by closed-loop reinforcement, which resists interruption unless disrupted by trust-based or disconfirming signals (Hartmann et al., 2023).

This typology clarifies distinct levels of buyer conditioning, supporting precise scholarly analysis, targeted sales strategies, and effective educational frameworks tailored to these varied buyer states.

Comparative Attributes of Typology

The following table summarises and compares critical attributes across the AI-conditioning intensity spectrum, it illustrates how different levels of AI exposure affect the buyer's interpretive frame and decision posture, irrespective of product category, sales process, or transaction method:

Attribute	**Type I:** **Low Conditioning**	**Type II:** **Moderate Conditioning**	**Type III:** **High Conditioning**
Decision Certainty	Low	Moderate	High
Cognitive Openness	High	Moderate	Low
Receptivity to Input	Broad	Selective	Resistant
Evaluation Behaviour	Divergent	Anchored	Convergent
Role of AI in Mindset	Minimal	Influential	Dominant
Buyer Awareness of Bias	High	Moderate	Low

Mechanisms Influencing Conditioning Intensity (Detailed Explanation)

The varying intensity of AI-conditioning is directly shaped by several mechanisms:

- Exposure Frequency: Regular interaction with AI-curated digital content such as personalised feeds, targeted ads, and recommendation lists intensifies the level of buyer conditioning (Hartmann et al., 2023).
- Algorithmic Sophistication: Advanced AI algorithms, employing predictive analytics and behavioural nudging, significantly heighten buyer conditioning intensity by systematically reinforcing certain biases and decision-making heuristics (Chaker et al., 2022).
- Information Depth and Personalisation: Highly personalised and contextually relevant content significantly deepens cognitive biases and reduces openness to alternative salesperson suggestions (Itani et al., 2019).

Understanding these mechanisms clarifies the causal pathways through which buyers become differently conditioned, thus enabling tailored strategic responses from sales organisations.

Applications and Implications of the AI-Conditioned Buyer Typology

This typology serves as a framework for multiple academic and applied purposes:

- Empirical Segmentation: Future research can develop measurement scales to assess where individual buyers fall on the conditioning spectrum.
- Sales Strategy Design: Sales professionals can adapt message framing, timing, and engagement intensity based on the conditioning level inferred from buyer cues (Singh, Marinova, & Brown, 2019).
- Customer Experience Management: Designers of digital and physical experiences can calibrate information density, persuasion tactics, or personalisation depth based on the predicted cognitive state of the customer (Grewal et al., 2023).

Critically, the typology assumes no fixed buyer identity. A single individual may shift across types depending on product category, platform interaction, or recency of algorithmic exposure. As such, the AI-conditioned buyer is best understood as a situational cognitive state, not a static persona.

Visual Illustration: Continuum of AI-Conditioned Buyer States

This visual conveys the AI-conditioned buyer typology as a fluid continuum rather than discrete segments. It underscores the psychological nature of the construct and allows for future dimensional scaling in empirical studies.

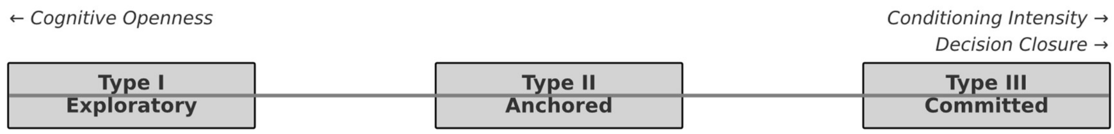

Figure 1. Continuum of AI-Conditioning Intensity

This typology illustrates the AI-conditioned buyer as a cognitive continuum comprising three states, Exploratory (Type I), Anchored (Type II), and Committed (Type III). These categories represent increasing levels of algorithmic influence on buyer expectations, decision certainty, and cognitive openness prior to the point of purchase. The model conceptualises the buyer's mental state as fluid, shaped by conditioning intensity rather than transactional context.

Implications of the Term

The conceptualisation of the AI-conditioned buyer contributes a critical new lens through which to understand customer cognition in digitally and algorithmically mediated commercial environments. While the term originates as a cognitive descriptor, its application spans multiple disciplines and sectors, carrying implications for theory building, empirical research, sales strategy, customer experience design, educational standards, and ethical governance. This section articulates these implications, demonstrating the conceptual utility and practical significance of defining this state of buyer cognition.

Theoretical Contributions

The introduction of the AI-conditioned buyer challenges and extends existing models in marketing, sales, and consumer psychology that assume decision neutrality or rationality at the moment of salesperson engagement. Most buyer frameworks assume the interactional moment begins with cognitive openness and preference elasticity (Singh, Marinova, & Brown, 2019). However, in AI-mediated environments, this is increasingly not the case.

By explicitly defining the buyer's pre-engagement mental schema, this construct shifts attention from behaviour to cognition, enabling a more accurate theorisation of buyer resistance, decision inertia, and information filtering in modern sales encounters (Puntoni, Reczek, Giesler, & Botti, 2021). It also supports reconceptualising sales influence as an act of navigating pre-structured interpretive frames rather than shaping beliefs de novo. This reframing contributes to interactional models of persuasion, customer co-creation, and the psychology of digital bias (Hartmann, Chaker, Lussier, Larocque, & Habel, 2023).

Future theory development can incorporate conditioning intensity as a moderator in models of value co-creation, salesperson effectiveness, trust formation, and customer satisfaction. The construct also opens the door to interdisciplinary synthesis, particularly with cognitive science, behavioural economics, and algorithmic ethics.

Managerial and Strategic Implications

From a business perspective, recognising and adapting to AI-conditioned buyer states is essential for competitive advantage in sales, marketing, and customer experience (CX) strategy. Organisations can no longer assume that buyers are entering a decision space with neutral expectations or a willingness to explore alternatives.

Sales professionals must adapt their techniques to account for conditioning intensity. For example, high-conditioning buyers may require immediate alignment confirmation, while low-conditioning buyers may be more responsive to consultative exploration. Training programs should explicitly address how to identify conditioning cues, verbal, behavioural, or affective, and tailor engagement accordingly (Chaker, Trainor, & Arnold, 2022).

In marketing, the concept can guide pre-engagement content strategies. By designing digital journeys that ethically influence but avoid over-conditioning, firms can enhance perceived fairness, preserve openness, and reduce downstream resistance in H2H sales interactions (Grewal, Roggeveen, & Nordfält, 2023). In omnichannel contexts, it encourages tighter alignment between digital and in-person messaging to avoid cognitive dissonance when a customer's algorithmically shaped expectations collide with real-world offerings.

Educational and Professional Standards Implications

Explicit identification of the AI-conditioned buyer provides substantial benefits for the curriculum of sales and marketing education. Organisations can leverage insights about buyer conditioning to design and manage integrated customer experiences that seamlessly align digital and human interaction points (Chaker et al., 2022). As sales environments become more compressed and cognitively front-loaded, educational institutions must update training to prepare future professionals to operate in this environment. This includes developing:

- Skills in rapid buyer profiling based on conversational cues and behavioural signals
- Awareness of algorithmic bias and customer pre-conditioning
- Methods for engaging with varying conditioning intensities across sectors and buyer types

Moreover, anticipating and actively managing the cognitive biases inherent in AI-conditioned buyers allows customer experience designers to strategically structure digital content to enhance engagement and positively influence perceptions before the buyer-salesperson interaction. This integration supports cohesive and frictionless transitions from digital research to salesperson interaction, significantly improving customer satisfaction, trust, and loyalty outcomes (Hartmann et al., 2023).

Professional bodies that accredit sales training and certification should also update competency frameworks to reflect these evolving buyer states. Doing so elevates the professionalism of the field and prepares practitioners for a more psychologically complex buyer environment.

Policy and Ethical Implications

The existence of the AI-conditioned buyer also raises concerns around consumer autonomy, transparency, and ethical design. Conditioning occurs through opaque processes that reinforce preferences based on past behaviour, potentially reducing consumer agency and reinforcing decision blind spots (Puntoni et al., 2021). As such, the term not only describes a phenomenon but also underscores the need for ethical AI design and algorithmic accountability.

Consumers increasingly report concern about fairness and privacy in retail AI applications, particularly in how personal data is used to drive recommendations and ranking systems (Adanyin, 2024). These concerns align with the conceptual framing of the AI-conditioned buyer, whose pre-engagement mental state may be shaped by data-driven systems in ways the buyer does not fully perceive or control.

Policymakers and regulators may find this concept useful in refining definitions of algorithmic manipulation, particularly in advertising, ecommerce, and financial services. Mandating transparency in how recommendations are delivered, and ensuring users can identify when they are being nudged, will become increasingly necessary as AI-conditioning becomes the norm, not the exception.

The concept also has implications for the design of consumer protection frameworks. As conditioning intensity increases, consumers may unknowingly enter interactions with reduced ability to evaluate alternatives or critically assess offers. Ethical sales practices must therefore shift from persuasion to alignment, ensuring fairness and informed consent in decision contexts.

Authorial Intent and Research Agenda

This paper introduces and defines the term AI-conditioned buyer as a foundational contribution to the evolving discourse on consumer cognition and algorithmic influence in commerce. While terms such as “digitally empowered,” “omnichannel,” or “autonomous” consumers have provided partial insights into digital-era buyer behaviour, they lack the precision to capture the specific cognitive and psychological state shaped by AI-based systems prior to the moment of purchase. This paper offers an explicit, conceptually distinct term to describe that condition, establishing both a formal language and a definitional boundary around a rapidly emerging commercial reality.

The primary intent of this paper is to assert conceptual authorship of the term AI-conditioned buyer, providing a clear definition, boundary conditions, and typological structure that can be used, tested, and extended by researchers and practitioners. By doing so, this paper lays the groundwork for a broader stream of theoretical development focused on how AI-mediated content systems influence consumer expectations, confidence, and decision readiness across all types of purchasing contexts.

This initial conceptual contribution will support a larger body of work exploring how organisations, sales professionals, and marketing systems respond to buyers whose cognitive states are pre-configured by algorithmic environments. Future research efforts will include empirical studies examining how varying levels of AI-conditioning affect customer receptivity, salesperson adaptability, and commercial outcomes. Particular attention will be given to the role of conditioning intensity as a moderating or mediating factor in models of sales performance, trust construction, and decision satisfaction.

Additionally, the concept provides a valuable reference point for research in digital ethics and algorithmic governance, particularly in debates around autonomy, influence, and fairness. As AI systems increasingly shape what consumers believe they want, often without conscious awareness, there is a growing need for language that helps both scholars and practitioners recognise and analyse these effects. The AI-conditioned buyer offers that language.

This paper serves as the formal declaration and analytical groundwork for this construct. Its intent is to anchor the term in scholarly discourse, establish its conceptual legitimacy, and provide a durable framework for future theoretical and practical applications. Through this paper, the author stakes an intellectual claim to the term and contribute a durable conceptual artefact to the evolving conversation about AI's role in shaping sales interactions.

About the Author

Vu Hua is an independent researcher and practitioner–scholar committed to elevating the credibility, legitimacy, and professional standing of the sales function. With over two decades of executive experience across premium automotive, luxury retail, and customer-first service sectors, he brings a commercially grounded lens to academic inquiry. His research is part of a broader mission to reposition sales as a recognised and legitimate profession, equipped with its own standards, theories, and thought leadership, equal in professional status to disciplines such as law, accounting, marketing, and human resource management etc

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Conclusion

The introduction of the AI-conditioned buyer provides a timely and necessary conceptual tool for understanding a significant shift in the cognitive orientation of modern consumers. As algorithmic systems increasingly shape how individuals evaluate options, assign value, and make purchase decisions, the need for precise terminology to describe this pre-engagement mental state has become critical. This paper addresses that gap by formally defining the AI-conditioned buyer as a customer whose perceptions, preferences, and decision-making heuristics are systematically shaped by AI-mediated digital experiences prior to the point of purchase.

Unlike previous buyer typologies that focus on autonomy, channel preference, or technological proficiency, the AI-conditioned buyer concept centres on cognition, offering a framework to interpret behaviour not as self-directed, but as pre-structured through algorithmic exposure. By decoupling the concept from specific industries, channels, or product types, this paper positions the construct as broadly applicable across B2C, B2B, digital, and human-to-human contexts.

Through the development of a conditioning-intensity typology and the delineation of clear conceptual boundaries, this paper lays the foundation for both theoretical refinement and empirical investigation. The implications are wide-ranging: researchers can explore the moderating effects of conditioning on sales performance and customer satisfaction; practitioners can adapt sales strategies and customer experience design; and policy makers can draw on the concept to better understand issues of influence, autonomy, and ethical AI use.

By formally defining and naming this cognitive state, this paper establishes the AI-conditioned buyer as a durable construct for ongoing scholarly discourse and professional application. It provides a common language to describe a previously unnamed but increasingly dominant phenomenon in AI-mediated commerce, marking an important step toward more accurate theorising, responsible design, and practitioner responsiveness in an era of algorithmic influence.

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