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Reflexive Digital Twin Marketing Theory (RDTMT)

Digital Reflexivity, Ethical Feedback Elasticity, and Value Coherence in Algorithmic Marketing

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Abstract

Algorithmic personalization has changed how marketing works, yet marketing theory still largely assumes a stable consumer who is acted upon by firms. This paper develops Reflexive Digital Twin Marketing Theory (RDTMT), a conceptual framework that treats marketing as a recursive sociotechnical system in which consumers and algorithmic systems continuously adjust to one another. Building on a scoping review of 55 studies and on sociological debates about reflexivity, habit, and platform power, the framework develops three constructs. Digital Reflexivity describes the recursive relationship through which consumer data shape algorithmic representations and those representations, in turn, shape the conditions of consumer choice; it is conceived as structurally conditioned rather than as an individual consumer competence. Ethical Feedback Elasticity captures whether ethical feedback is strong enough to change data practices, optimization objectives, and system constraints, not merely whether it is received. The Value Coherence Index assesses how competing consumer, organisational, regulatory, and societal values are reflected in algorithmic objectives. Transparency and ethical feedback channels are positioned as the governance conditions through which the three constructs operate. The paper offers nine propositions, operational indicators for each construct, and implications for managers and regulators. It argues that responsibility for ethical algorithmic marketing rests mainly with firms, platforms, and regulators, and that unequal capacity for reflexivity makes the question of whose feedback counts central to the theory.

Keywords: Algorithmic personalization, Digital reflexivity, Digital twins, Ethical AI, Platform power, Value coherence

1. Introduction

Marketing practice has changed fundamentally. Brands no longer simply design messages and send them out to audiences. They run algorithmic systems that observe consumers in real time, build predictive models of individual behaviour, and keep adjusting the content, prices, and offers each person sees. Recommendation engines suggest what we might want before we've even formed the wish, dynamic pricing reacts to demand within milliseconds, and social media

feeds decide what information reaches us each day. These systems are more than efficient tools for running conventional campaigns. They change what marketing is.

Marketing has become largely reflexive, with targeting systems shaping consumer behaviour. Algorithmic identity models create feedback loops, making it difficult to distinguish measurement from reality. For example, a shopper shown a premium product after several high-value purchases might begin to relate to brands in a specific way. Similarly, someone exposed to anxiety-provoking content may develop habits driven more by algorithmic design than by personal choice. Essentially, marketing systems not only respond to consumer actions but also actively shape them.

Marketing theory has lagged behind this development. Its main frameworks, including persuasion hierarchies, relationship marketing (Palmatier et al., 2006), service-dominant logic (Vargo & Lusch, 2004), and consumer culture theory (Arnould & Thompson, 2005), were formed when technology mainly supported human decision-making. Even models that acknowledge consumer agency usually treat exchanges as bounded episodes rather than as ongoing co-evolution.

The gap, however, is more specific than a general lag, and three problems stand out. First, when reflexivity is discussed, it is often treated as an individual capacity, the consumer's ability to notice and adapt to algorithmic environments, which shifts the burden of navigating algorithmic marketing onto consumers. It overlooks the sociological point that agency is always exercised within structural conditions (Giddens, 1984), and that in algorithmic markets those conditions are set by data infrastructures, platform architectures, and commercial incentives (van Dijck et al., 2018). It also assumes more conscious deliberation than most digital behaviour involves (Archer, 2010; Bourdieu, 1977). Second, research on algorithmic ethics has said a great deal about what firms should value, but much less about whether ethical feedback, once voiced, has enough force to change data practices, optimization objectives, or system constraints. Third, calls to align algorithmic systems with "societal values" often assume a single, settled value set, even though consumer, organisational, regulatory, and broader social values frequently conflict (Gabriel, 2020).

This paper responds with four research objectives. RO1 conceptualizes Digital Reflexivity as a recursive, structurally conditioned relationship between consumers and algorithmic systems, rather than as individual consumer competence. RO2 is to specify the conditions under which

ethical feedback produces substantive change in algorithmic marketing systems. RO3 is to theorize how competing stakeholder values are incorporated into, or excluded from, the optimization objectives of those systems. RO4 translates these ideas into testable propositions and operational indicators.

To pursue these objectives, I develop Reflexive Digital Twin Marketing Theory (RDTMT). The digital twin serves here as a heuristic lens, not as a literal claim. Digital twins were first built in aerospace and manufacturing as virtual replicas of physical systems, kept synchronized with real-world data, and they are now used in healthcare to build personalized patient models. Marketing systems do not create faithful copies of consumers. They share a structure with digital twins: they continuously model people, forecast their responses, learn from feedback, and act on the people they represent. The twin lens helps make that recursive structure visible. The theory's substantive claims, however, rest on its three constructs rather than on the metaphor.

The paper makes three contributions: a PRISMA-ScR scoping review of 55 studies that identifies four convergent patterns; three constructs (Digital Reflexivity, Ethical Feedback Elasticity, and the Value Coherence Index) together with the governance logic that connects them; and nine propositions with operational indicators. Figure 1 summarizes the framework. Section 2 reviews the literature and derives the research gaps, Section 3 describes the methodology, Section 4 reports the empirical patterns, Section 5 develops the constructs, Section 6 discusses implications, and Section 7 concludes.

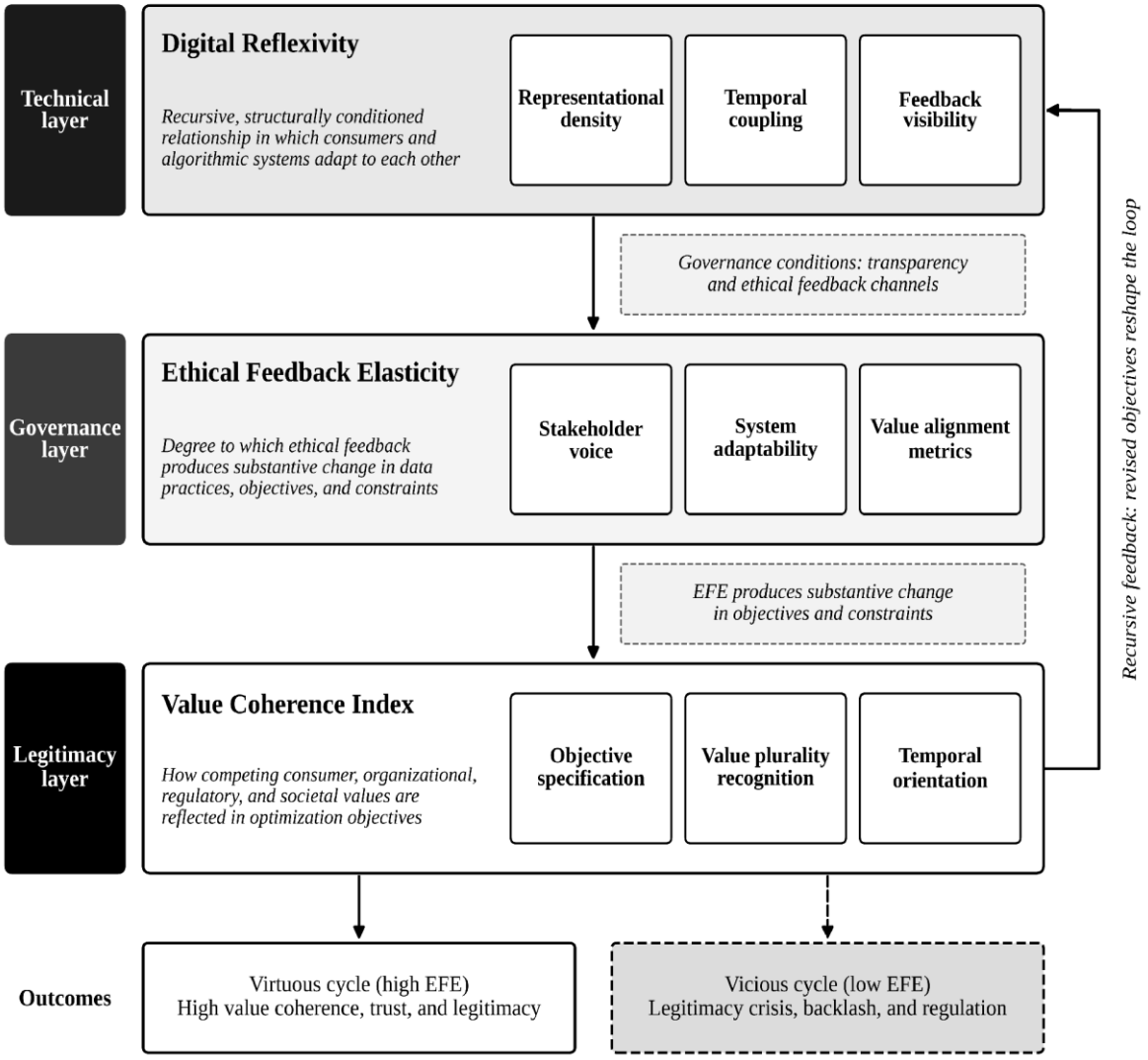

Figure 1. *The RDTMT Conceptual Framework: Constructs, Governance Conditions, and Dynamic Interactions*

Source: Author's own elaboration.

2. Literature Review

This review is organized as an argument rather than a catalog. It begins with the digital twin and its changing meaning, turns to the parallel between healthcare twins and marketing systems, and then sets out the debates about reflexivity, habit, and platform power that the RDTMT constructs need to resolve.

2.1 The Digital Twin: From Engineering Replica to Sociotechnical Steering Device

The digital twin concept originated in aerospace engineering, where organisations such as NASA built virtual replicas of spacecraft to simulate performance and support remote diagnostics (Grieves & Vickers, 2017). In its engineering sense, a digital twin is a virtual representation of a physical entity that stays synchronized with real-world data, allowing simulation, prediction, and optimization across the entity's life cycle (Attaran & Celik, 2023). Its defining features are continuous synchronization, simulation of future states, transparency to operators, and co-evolutionary adaptation as the model learns from outcomes.

As the concept has traveled from machines to people, its meaning has shifted. The engineering ideal of a high-fidelity copy assumes that the twin is a neutral mirror. Social and philosophical critics question that assumption. Korenhof et al. (2021) argue that a digital twin is better understood as a steering technique than a copy: it represents only what is selected, shaped by normative choices about what counts, and oriented toward optimization goals set by whoever builds it. Studies of health twins make a similar point, noting that personalization benefits come with risks to privacy, solidarity, and people's control over how they are defined (Bruynseels et al., 2018; Popa et al., 2021). The literature thus contains a real tension. One strand treats the twin as a technical instrument whose main problems are accuracy and security. The other treats it as a sociotechnical device that embeds values and redistributes power. RDTMT takes the second view because it explains why twin-like systems in marketing raise questions of agency and governance, not just accuracy.

2.2 Digital Twins in Healthcare: The Personalized Patient

Healthcare is the most instructive application of digital twin thinking for marketing theory. Medical twins combine genomic information, wearable sensor readings, electronic health records, and environmental exposures into patient models that update continuously, supporting precision medicine, predictive diagnostics, and participatory care (Bruynseels et al., 2018).

Health twins also recast the patient as an algorithmic entity, produced jointly by biological data, computational models, and clinical interpretation (Ruckenstein & Schüll, 2017), and the representation increasingly guides what is done to the body. This raises questions that map closely onto algorithmic marketing: who owns the model, what happens when its predictions conflict with how people understand themselves, and whose welfare it serves.

2.3 Marketing Systems as Twin-Like Assemblages

Contemporary marketing systems resemble healthcare twins in structure, though not in fidelity. They are data-driven assemblages that continuously model consumers, predict their responses, adjust to feedback, and reshape consumer subjectivities through the interventions they produce. Table 1 sets out the parallels.

Table 1. *Structural Homologies Between Healthcare Digital Twins and Marketing Systems*

Healthcare Digital Twin	Marketing System Analog
Patient as data source	Consumer as continuous data generator
Continuous physiological monitoring	Real-time behavioural tracking across touchpoints
Predictive diagnostics	Propensity and churn modeling
Personalized treatment plans	Individualized content and pricing recommendations
Clinical outcome optimization	Engagement and conversion optimization
Care team coordination	Cross-channel marketing orchestration
Patient consent and governance frameworks	Privacy policies, consent architectures, and data rights

Source: Author's own elaboration.

Both kinds of systems rely on continuous data collection, prediction, and adaptive feedback, and both create tensions between individual benefit and system efficiency, between personalization and privacy, and between optimization and autonomy. The key difference lies in governance. Health twins operate within long-established ethical frameworks grounded in autonomy, beneficence, non-maleficence, and justice, supported by research ethics review and clinical regulation (Beauchamp & Childress, 2019). Marketing has no comparable institutional structure. Data privacy in marketing is governed by a patchwork of firm policies and uneven regulation, and firms face strong commercial incentives to collect and use more data than consumers would knowingly agree to (Martin & Murphy, 2017; Zuboff, 2019). This asymmetry makes marketing the field in which the ethical stakes of twin-like systems are arguably most pressing and least theorized.

2.4 Contested Perspectives on Reflexivity, Agency, and Power

Reflexivity means different things in different traditions, and the differences matter for RDTMT. This section sets four debates side by side and draws out what each implies.

2.4.1 Reflexivity Between Structure, Deliberation, and Habit

Giddens (1991) and Beck (1992) describe late-modern life as reflexive: people continually monitor their actions and revise their sense of self. Read narrowly, this suggests that consumers simply need to become more reflexive about the systems that target them. That reading misses Giddens's broader argument. In structuration theory, agency is always exercised through structures that both enable and constrain it (Giddens, 1984). In algorithmic marketing, those structures are unusually concentrated. Data infrastructures, platform architectures, AI models, organisational incentives, and commercial objectives decide which options are visible, in what order, and at what price. A consumer's reflexivity operates inside conditions that the consumer did not design and often cannot see.

Archer (2010) adds a qualification that cuts in a different direction. In her account, reflexivity is the internal conversation through which people consider themselves in relation to their circumstances, but it is not continuous, and much of life runs on routine. Bourdieu's (1977) concept of habitus goes further, describing durable dispositions that guide action below the level of conscious choice. Digital behaviour shows both patterns. Endless scrolling, reacting to a notification, copying a trend, or checking for likes are mostly habitual and affective acts, whereas adjusting privacy settings or deliberately curating a feed are more reflective. The tension among these positions is productive. A construct built on Giddens alone would overstate deliberation; one built on Bourdieu alone would leave little room for consumers to notice and resist. Digital reflexivity must account for both reflective and habitual engagement rather than assuming a tidy sequence of reflection, evaluation, decision, and action.

2.4.2 Reflexive Adaptation Versus Critical Consciousness

A second debate concerns what consumers do once they become aware of algorithms. Bucher (2017) shows that people form an algorithmic imaginary: everyday beliefs about how algorithms work that shape how they behave online. An Instagram user who learns which posts gain visibility may change what and when they post. That is reflexive adaptation, but it is not necessarily critical. The user adjusts to the platform's rules without questioning the platform's power to set them. Freire's (1970) notion of critical consciousness, which involves recognizing and challenging the structures that shape one's situation, marks the difference. Survey evidence supports the distinction: Gran et al. (2021) found that algorithm awareness ranges from

unaware and uncertain through affirmative and neutral to skeptical and critical, and that these types differ systematically across demographic groups. For RDTMT, the implication is that making algorithms more visible will not, by itself, produce contestation. It may simply produce better-adapted users.

2.4.3 Who Adapts to Whom?

A third debate concerns the direction of adaptation. Much marketing writing treats personalization as a service: algorithms learn consumer preferences and respond to them. Platform scholarship challenges this view. Van Dijck et al. (2018) show that platforms do not simply mirror users; through datafication, selection, and commodification, they organize visibility, ranking, and access, and in doing so shape public values as well as private choices. Recommendations, advertising exposure, segmentation, ranking, and pricing all arrange the conditions under which choices are made. Personalization serves consumers, but it also lets firms and platforms organize the setting in which consumers choose. The relationship runs both ways: behaviour becomes data, data become a model of the person, the model drives what the person is shown, and the person's reaction becomes fresh data. The useful question is less whether consumers adapt to algorithms than how consumers and systems adapt to each other, and who has more power to set the terms.

2.4.4 Unequal Capacity, Power, and Responsibility

The final debate concerns inequality and responsibility. The capacity for reflexivity is not evenly distributed. Digital skills, privacy knowledge, time, and algorithmic literacy vary across social groups, and algorithmic systems often build on existing inequalities instead of neutralizing them (Eubanks, 2018; Gran et al., 2021). This matters for any theory that relies on feedback, because the ability to produce feedback that is heard may itself be unequally distributed. Stakeholder theory has long recognized that firms attend to stakeholders according to their power, legitimacy, and urgency (Mitchell et al., 1997), so some voices carry much further than others.

Responsibility follows the same logic. If ethical outcomes depend on consumers becoming more reflexive, responsibility shifts to those least able to bear it. Recent management scholarship argues instead that platform power has to be matched by accountability on the part

of platforms and the firms that use them (Rahman et al., 2024), and legal scholarship shows that this power operates over markets, over individuals, and over society as a whole (Graef & Bostoen, 2026). These accounts also suggest that reflexivity is relational, culturally situated, and temporally unstable. It depends on social relationships and cultural expectations, and it has to be renewed each time platforms change their rules. A theory of reflexive marketing systems should not treat it as a fixed individual competence.

2.5 Theoretical Gaps and Research Objectives

Read together, these debates expose three gaps in marketing theory, each of which corresponds to one RDTMT construct.

The first gap is reflexivity without structure. Dominant marketing frameworks describe processes that act on relatively stable consumers, and interactive models still treat participation as a series of bounded exchanges (Grönroos, 2017; Vargo & Lusch, 2004). Where reflexivity is considered, it is usually located in the individual consumer. Neither view captures a relationship in which consumers and algorithmic systems recursively constitute one another under conditions set mainly by firms and platforms (A. Mackenzie & Vurdubakis, 2011; van Dijck et al., 2018). RO1 and the construct of Digital Reflexivity address this gap.

The second gap is feedback without force. Research on surveillance capitalism (Zuboff, 2019), algorithmic discrimination (Lambrecht & Tucker, 2019), and manipulative personalization (Susser et al., 2019) shows what can go wrong, but it tends to treat ethics as an external constraint imposed through regulation or public pressure. Hirschman (1970) drew the relevant distinction more than fifty years ago: an organisation can hear complaints without changing course. Marketing theory lacks a construct for how much ethical feedback actually alters data practices, objectives, and constraints. RO2 and Ethical Feedback Elasticity address this gap.

The third gap is alignment without plurality. Calls to align algorithms with societal values often assume that those values are settled. Philosophers of AI argue that alignment is really a question of whose values are chosen, and through what process, because reasonable people disagree (Gabriel, 2020). Marketing frameworks have not yet examined how competing stakeholder values enter, or fail to enter, the optimization objectives of algorithmic systems. RO3 and the Value Coherence Index address this gap, and RO4 makes all three constructs testable.

3. Methodology: Empirics-First Scoping Review

3.1 Research Design and Rationale

The theory development follows the empirics-first approach described by Golder et al. (2023), in which patterns identified through systematic review guide conceptual abstraction, so that no predetermined framework is imposed on the literature. The review follows the scoping review framework of Arksey and O'Malley (2005) and is reported in line with the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) guidelines (Tricco et al., 2018). It synthesizes literature from three domains: digital twin applications, marketing analytics, and AI governance. These domains correspond to the technical architecture of twin-like systems, their marketing applications, and the governance challenges they raise. Digital twins in manufacturing and smart cities were left out of the main synthesis because their governance and behavioural implications differ substantially from those of consumer-facing marketing.

3.2 Search Protocol and Eligibility

I searched four databases (Web of Science, Scopus, PubMed, and Google Scholar) using structured search strings that combined terms for digital twins, algorithmic marketing, and governance. The search covered January 2010 to January 2025. Eligible sources were peer-reviewed articles, conference proceedings, and authoritative technical reports published in English that addressed digital twins, marketing analytics, algorithmic personalization, or AI governance and had behavioural or governance implications. I excluded purely technical engineering papers with no bearing on consumer behaviour or governance, as well as opinion pieces that had not been peer-reviewed.

3.3 Selection Process and Analytic Sample

The database search returned 742 records, and backward snowballing of the reference lists of relevant studies identified a further 18. After 312 duplicates were removed from the database records, 430 titles and abstracts were screened against the eligibility criteria, and 302 were excluded. The remaining 128 full texts, together with the 18 records from snowballing, were then assessed for eligibility (n = 146). Of these, 91 were excluded, mainly because they lacked

a governance or behavioural focus or were purely technical engineering papers. The final analytic sample comprised 55 studies: 22 on digital twin applications, 19 on marketing analytics, and 14 on AI governance. Figure 2 presents the selection process as a PRISMA flow diagram.

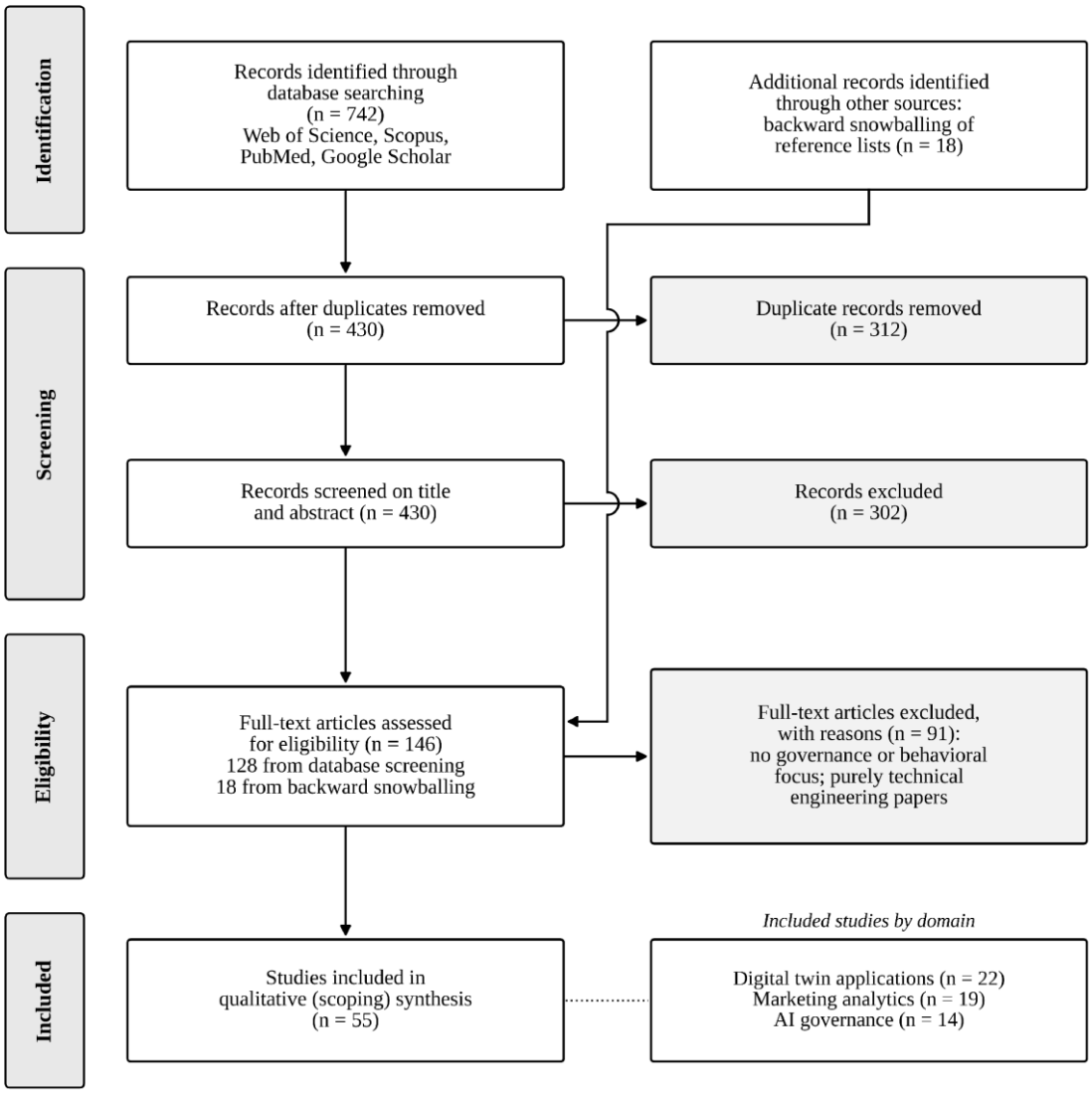

Figure 2. *PRISMA Flow Diagram of the Study Selection Process*

Source: Author's own elaboration.

3.4 Co-occurrence Network Analysis and Thematic Synthesis

To identify conceptual patterns across the literature, I carried out a co-occurrence network analysis in VOSviewer (van Eck & Waltman, 2010). The technique maps relationships between

terms that frequently appear together in titles, abstracts, and keywords, revealing conceptual clusters without imposing predefined categories. I applied a minimum term frequency of five occurrences and used association-strength normalization to correct for differences in term frequency. Modularity optimization of the resulting network produced four clusters.

To move from these descriptive patterns to theoretical constructs, I used thematic synthesis (Thomas & Harden, 2008) in four stages: (1) line-by-line inductive coding of the included studies, (2) grouping of codes into descriptive themes, (3) abstraction of descriptive themes into higher-order analytical constructs, and (4) integration of these constructs into the RDTMT framework. I kept an audit trail at each stage to support transparency and reproducibility. Co-occurrence mapping shows that concepts are connected, but it cannot by itself establish what the constructs mean; the constructs take their meaning from the thematic synthesis, and the VOSviewer output served as a structuring device. The sociological literature on reflexivity, habitus, and platform power reviewed in Section 2.4 was not part of the scoping sample. It was drawn on deliberately, after the synthesis, to interpret and sharpen the constructs that the synthesis suggested.

4. Results: Four Convergent Empirical Clusters

The thematic synthesis of the 55 included studies, supported by the co-occurrence analysis, identified four convergent patterns that run across the digital twin, marketing analytics, and AI governance literatures. The patterns are analytically distinct but closely interdependent, and together they describe how twin-like marketing systems operate. Figure 3 presents the four clusters and the links between them.

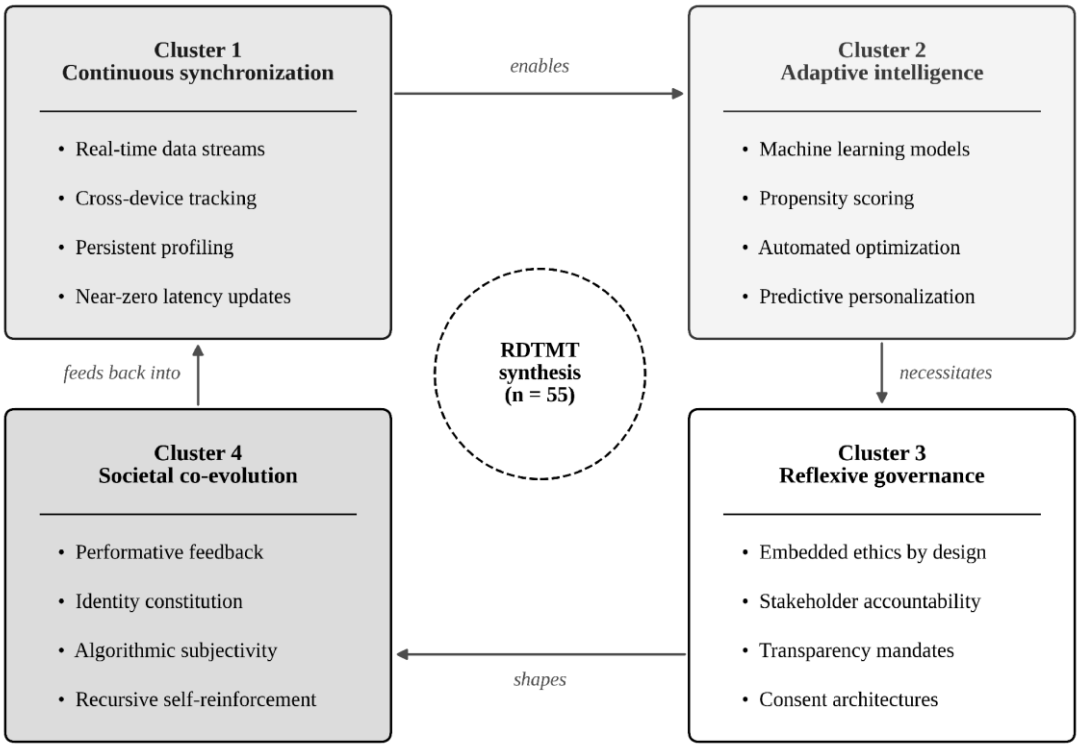

Figure 3. *Four Convergent Empirical Clusters from the Thematic Synthesis of 55 Studies*
Source: Author's own elaboration.

4.1 Cluster 1: Continuous Synchronization

Studies of healthcare digital twins (Bruynseels et al., 2018), Internet-of-Things marketing (Ng & Wakenshaw, 2017), and behavioural tracking (Nadler & McGuigan, 2018) agree on the importance of temporal density. Twin-like systems collect data continuously, not at set intervals, which allows near-real-time processing and a persistent representation of each consumer. Marketing thus moves from episodic campaigns to always-on monitoring and response, seen in cross-device tracking, real-time bidding, and recommendation engines that update with every click. The system no longer treats the consumer as a stable entity to be addressed, but as an ongoing stream of data to be modeled and remodeled.

4.2 Cluster 2: Adaptive Intelligence

Building on foundational work on recommender systems (Adomavicius & Tuzhilin, 2005), studies of predictive analytics and algorithmic marketing identify learning and adaptation as

defining capabilities of twin-like systems. Unlike rule-based automation, adaptive systems improve as they encounter new data, detect patterns human analysts might miss, and automatically tune parameters in response to performance signals. Propensity models, content recommendation algorithms, and automated A/B testing are typical examples in marketing.

The resulting asymmetry has ethical weight: systems learn faster than consumers can adapt, shifting the terms of engagement in ways consumers may not notice.

4.3 Cluster 3: Reflexive Governance

Work on algorithmic accountability (Mittelstadt et al., 2016), AI ethics guidelines (Jobin et al., 2019), and data governance (Yeung, 2017) stresses that the legitimacy of twin-like systems depends less on external compliance than on governance mechanisms built into system architecture. Privacy-by-design, consent management, algorithmic impact assessments, and ethics review shape how systems behave and how far stakeholders trust them, and this literature favors governance that is anticipatory rather than reactive.

4.4 Cluster 4: Societal Co-evolution

Studies of surveillance capitalism (Zuboff, 2019), algorithmic culture (Seaver, 2019), and data doubles (Lupton, 2014) document what may be the most consequential pattern: twin-like systems and the people they model shape each other through recursive feedback. Recommendation algorithms influence the preferences they claim to predict, social media metrics affect the identity performances they measure, and credit scores alter the financial behaviour they assess. Marketing systems are never neutral observers of consumer behaviour; they help to produce it.

This cluster describes the phenomenon well, but it leaves three questions open, and these are the questions that motivate the research objectives. The co-evolution studies are mostly critical and descriptive. They show that systems shape people, yet they rarely specify the structural conditions under which consumers can still notice and resist that shaping, or how unevenly that capacity is spread (RO1). They document harms but say little about whether, when, and why firms change course in response to ethical criticism (RO2). And they tend to describe the values at stake from a single critical standpoint, without examining how consumer, organisational, regulatory, and societal values are traded off inside the systems themselves (RO3).

4.5 From Empirical Patterns to Research Objectives

Taken together, the four patterns form a cycle: synchronization makes adaptive intelligence possible, adaptive intelligence calls for reflexive governance, governance shapes co-evolution, and co-evolution influences what data the system collects next. Table 2 links each pattern to the issue it leaves unresolved, the research objective it informs, and the RDTMT construct that responds to it.

Table 2. *Linking Empirical Clusters, Research Gaps, Objectives, and Constructs*

Empirical cluster	Issue left unresolved in the literature (gap)	Research objective	RDTMT response
1. Continuous synchronization	How data infrastructures and platform design set the conditions under which consumers act within the loop	RO1	Digital Reflexivity (representational density, temporal coupling)
2. Adaptive intelligence	Who adapts to whom, and whether awareness leads to adaptation or to contestation	RO1	Digital Reflexivity (feedback visibility); P1 to P3
3. Reflexive governance	Whether ethical feedback is strong enough to change data practices, objectives, and constraints, and whose feedback is heard	RO2	Ethical Feedback Elasticity; P4 to P6
4. Societal co-evolution	Whose values are represented in optimization objectives, and how conflicts among them are resolved	RO3	Value Coherence Index; P7 to P9
All four clusters	How the constructs can be measured and tested	RO4	Operational indicators (Tables 3 and 4)

Source: Author's own elaboration.

5. Reflexive Digital Twin Marketing Theory (RDTMT): Framework and Constructs

RDTMT views marketing as a sociotechnical learning system marked by recursive feedback between algorithmic representations and consumer behaviour. Its three constructs are theoretically distinct but dynamically related. Each responds to one of the gaps identified in Section 2.5 and is grounded in the patterns reported in Section 4.

5.1 Core Construct 1: Digital Reflexivity

5.1.1 Definition and Conceptual Basis

Digital Reflexivity is the recursive, structurally conditioned relationship between consumer data generation and algorithmic identity construction, through which consumers and marketing systems continuously adjust to one another. behavioural outputs become inputs to predictive models; those models shape the contexts in which later behaviour occurs; and that behaviour produces new data, closing the loop. Figure 4 shows the five stages of the cycle.

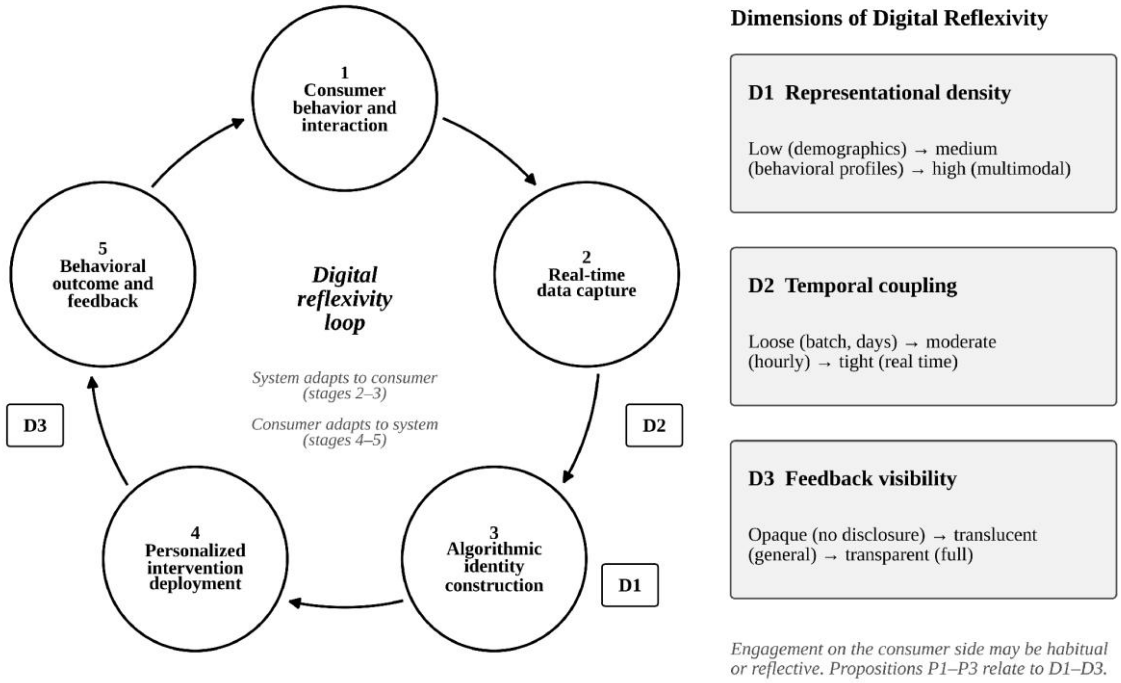

Figure 4. *Digital Reflexivity: The Five-Stage Recursive Feedback Loop*

Source: Author's own elaboration.

Three features distinguish this construct from conventional ideas of consumer reflexivity. First, it is a property of the consumer–system relationship, not of the consumer alone. Consumers do exercise agency in the loop, but, following Giddens (1984, 1991), they do so within conditions set by data infrastructures, platform architectures, and commercial objectives. Much of the monitoring and adjustment is carried out by the system, which adapts to consumers (stages 2 and 3) while consumers adapt to the system (stages 4 and 5). Second, the construct does not

assume that consumers deliberate continuously. Drawing on Archer (2010) and Bourdieu (1977), it allows that much of the consumer side of the loop runs on habit and affect, and that a system's ability to work through habit is part of what makes it powerful. Third, the construct separates reflexive adaptation from critical consciousness (Bucher, 2017; Freire, 1970). A consumer may understand the loop well enough to play it without ever questioning who designed it, or why.

Because it is relational, Digital Reflexivity is also culturally situated and temporally unstable. What consumers know about algorithms depends on their social networks and cultural expectations, varies across groups (Gran et al., 2021), and has to be relearned whenever platforms change their rules. Digital Reflexivity is also what makes algorithmic marketing systems performative in the sense used in science and technology studies (Callon, 1998; D. MacKenzie, 2006): the system does not just represent consumer preferences; it helps to form them.

5.1.2 Dimensions

Digital Reflexivity varies along three dimensions. Representational density refers to the granularity and breadth of consumer models, from coarse demographic segments to models that combine transaction histories, browsing patterns, social signals, location data, and biometric inputs. Temporal coupling refers to the delay between generating behavioural data and updating the model, from batch processing over several days to near-real-time synchronization. Feedback visibility refers to how far the workings of the loop are open to inspection, from complete opacity to transparency in which people can see, question, and correct their algorithmic profiles. Feedback visibility is defined as a property of the system, not of the consumer, which keeps responsibility for it with the firm.

5.1.3 Propositions

P1: Higher Digital Reflexivity, characterized by denser representation and tighter temporal coupling, increases personalization effectiveness but systematically reduces consumer autonomy by narrowing the behavioural options the system presents.

P2: Digital Reflexivity generates performative feedback loops in which algorithmic predictions become self-fulfilling because they structure the information environments through which consumers express their preferences.

P3: Greater feedback visibility weakens the autonomy-reducing effects of Digital Reflexivity, but the effect is moderated by consumers' algorithmic literacy and resources, so that visibility alone tends to produce strategic adaptation among the most capable consumers rather than broad-based contestation.

5.2 Core Construct 2: Ethical Feedback Elasticity

5.2.1 Definition and Conceptual Basis

Ethical Feedback Elasticity (EFE) is the degree to which ethical feedback from stakeholders produces substantive change in a marketing system's data practices, optimization objectives, system constraints, and marketing decisions, in proportion to the intensity and breadth of that feedback. Feedback may come from consumers, regulators, civil society, employees, and other affected parties.

The construct borrows the logic of elasticity from economics: just as price elasticity describes how demand responds to price, EFE describes how system behaviour responds to stakeholder value concerns, and it can be expressed as the ratio of the change in relevant system parameters to the change in the intensity of ethical feedback. A highly elastic system picks up concerns early and adjusts. An inelastic system keeps optimizing for narrow commercial goals however strong the criticism becomes, and in doing so sets the stage for a legitimacy crisis.

Ordinary responsiveness does not meet this definition. Every adaptive marketing system responds to consumers in one sense, because it learns from their clicks and purchases. EFE concerns a different kind of response. It asks whether ethical feedback has enough influence to change what the system is trying to achieve and the limits within which it operates, not merely whether the organisation receives and acknowledges complaints (Hirschman, 1970). EFE is therefore the mechanism through which a recursive system becomes able to respond to ethical concerns and not just to behavioural signals. It also raises the question of whose feedback counts. Because the capacity to produce feedback is unequal (Gran et al., 2021) and firms attend most closely to powerful stakeholders (Mitchell et al., 1997), a system can appear elastic to some groups while remaining inelastic to those with the least voice.

5.2.2 Components

Ethical Feedback Elasticity has three interacting components. Stakeholder voice mechanisms are the channels through which affected parties can raise concerns. They may be absent, narrow (standard complaint processes), or broad (ethics advisory boards, user councils, and public consultations), and they vary in how far they include groups with low digital capacity. System adaptability is the technical and organisational capacity to change algorithms, policies, and practices in response to feedback, from rigid (hard-coded rules and slow governance cycles) to fluid (adaptive systems that allow timely policy adjustment). Value alignment metrics are the means by which ethical conflicts are detected and monitored, from reactive monitoring through proactive auditing to anticipatory impact assessment.

5.2.3 Propositions

P4: Marketing systems with higher Ethical Feedback Elasticity maintain stakeholder trust more effectively during algorithmic controversies, because they show responsive adjustment rather than defensive entrenchment.

P5: Ethical Feedback Elasticity is negatively associated with the intensity of short-term commercial optimization pressure: as competitive pressure to maximize narrow performance metrics increases, the system's responsiveness to stakeholder value concerns declines.

P6: Institutionalizing diverse and inclusive stakeholder voice mechanisms, including ethics boards, user representation structures, and public consultation processes that deliberately include groups with low digital capacity, increases Ethical Feedback Elasticity by widening the range of concerns that reach governance decision-making.

5.3 Core Construct 3: The Value Coherence Index

5.3.1 Definition and Conceptual Basis

The Value Coherence Index (VCI) assesses how, and how far, the competing values of a marketing system's stakeholders are reflected in its optimization objectives. Those values include consumer autonomy and well-being, organisational goals such as growth and profitability, regulatory requirements such as fairness and data protection, and broader social concerns such as sustainability and the quality of public discourse.

The construct extends the institutional concept of organisational legitimacy (Suchman, 1995) to algorithmic systems, which face a sharper version of the legitimacy challenge because their objectives are precisely specified and pursued relentlessly by design, while stakeholder values are plural, contested, and changing. For this reason, VCI does not presume one agreed list of "societal values" against which a system can be scored. Consumer, organisational, regulatory, and wider social values often conflict, and platform scholarship shows that public values are themselves negotiated through platform design (van Dijck et al., 2018). Following Gabriel (2020), the relevant question is whose values are represented in optimization, and through what process conflicts among them are resolved. A high VCI indicates that competing values have been identified, weighed through a legitimate process, and written into the system's objectives and constraints. It does not mean that every conflict has disappeared.

5.3.2 Dimensions and Ethical Risk Indicators

The VCI varies along three dimensions. Objective specification ranges from narrow single metrics to holistic, multi-stakeholder objectives. Value plurality recognition ranges from systems that assume everyone shares the same preferences to systems that provide deliberative mechanisms for working through trade-offs. Temporal orientation ranges from maximizing short-term metrics to managing long-term stakeholder relationships. Table 3 shows how common optimization objectives give rise to distinct ethical risk dimensions, and it proposes operational indicators for each so that the risks can be measured as well as named. The indicators for manipulative choice architecture draw on the audit methods developed by Mathur et al. (2019).

Table 3. *Optimization Objectives, Ethical Risk Dimensions, and Operational Indicators*

Optimization objective	Ethical risk dimension	Operational indicators	Coherence-enhancing strategies
Maximize engagement	Attention exploitation: addiction, attention manipulation, compulsive use	Share of sessions exceeding user-set limits; share of late-night use; notification-triggered re-entries; self-reported regret about time spent	Engagement-quality metrics; time-well-spent design; user-controlled limits
Maximize conversion	Manipulative choice architecture: pressure tactics, dark patterns, cognitive exploitation	Dark-pattern elements per purchase flow (audit coding); steps to cancel compared with steps to sign up; post-purchase return and regret rates	Voluntary-conversion tracking; equally easy sign-up and exit; satisfaction monitoring

Optimization objective	Ethical risk dimension	Operational indicators	Coherence-enhancing strategies
Maximize revenue	Distributive unfairness: pricing exploitation, accessibility barriers, inequality	Price dispersion for identical offers across consumer segments; accessibility compliance score; complaint rate among vulnerable consumers	Fair-pricing audits; accessibility provisions; protections for vulnerable consumers
Maximize efficiency	Loss of human agency: dehumanization, worker displacement, reduced consumer autonomy	Share of consequential decisions with human review; availability and use of appeal routes; perceived-autonomy scale scores	Human-in-the-loop requirements; appeal mechanisms; worker protection

Source: Author's own elaboration.

5.3.3 Propositions

P7: Higher Value Coherence, characterized by holistic objective specification, explicit recognition and negotiation of competing stakeholder values, and a long-term temporal orientation, is positively associated with marketing system legitimacy and long-term sustainability.

P8: Value Coherence declines as optimization objectives become narrower and more short-term, producing a gradual erosion of legitimacy that may not appear as an immediate crisis but builds into systemic vulnerability.

P9: Participatory governance mechanisms that involve diverse stakeholder groups in setting optimization objectives increase Value Coherence by bringing to light plural value commitments that narrow managerial decision-making would otherwise overlook.

5.4 Governance Logic: How the Constructs Work Together

The three constructs are analytically distinct, but a governance logic connects them. Rather than adding further constructs, RDTMT casts transparency and ethical feedback mechanisms as the enabling conditions for the existing constructs (Figure 1). Transparency opens the loop of Digital Reflexivity to inspection, letting stakeholders see how a system arrives at what it shows, prices, or recommends. Ethical feedback mechanisms give them a route to contest those outcomes. Ethical Feedback Elasticity captures how far the system changes in response to that challenge. The Value Coherence Index then assesses the result: how coherent the system's objectives are with the stakeholder values that have been articulated. Each condition is necessary but none is sufficient. Transparency without channels for challenge produces

knowledge without leverage, a limit that Ananny and Crawford (2018) identify in the transparency ideal more generally, and channels without elasticity produce voice without change (Hirschman, 1970).

These relationships produce two contrasting pathways, shown in Figure 5. In a virtuous cycle, high EFE lets the system detect value conflicts created by Digital Reflexivity, revise its objectives, and sustain high Value Coherence over time. In a vicious cycle, low EFE prevents timely adjustment, narrow objectives continue to dominate despite mounting concern, and Value Coherence erodes toward a legitimacy crisis.

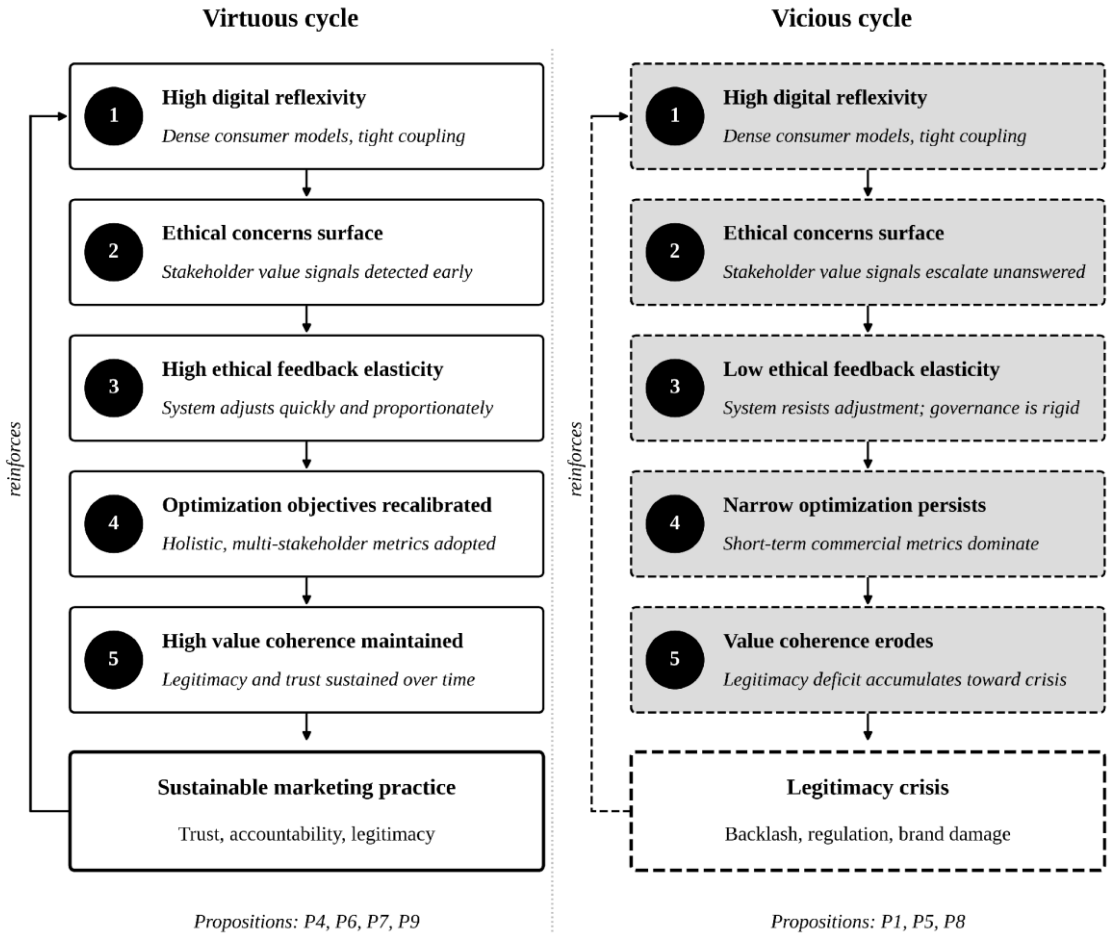

Figure 5. *RDTMT Dynamic Pathways: Virtuous and Vicious Cycles*

Source: Author's own elaboration.

The broader literature supports both pathways, though not without disagreement. Institutional theory holds that legitimacy is lost gradually as practice drifts from the normative expectations

of the environment, and that it is costly to repair once lost (Suchman, 1995). Marketing research on data privacy links privacy violations to reduced consumer trust and identifies transparency and consumer control as factors that can soften that effect (Martin & Murphy, 2017). Management scholarship argues that accountability mechanisms are what stop platform power from becoming self-reinforcing (Rahman et al., 2024), and legal scholarship shows unchecked platform power drawing regulatory intervention across markets, individuals, and society (Graef & Bostoen, 2026). Critics of surveillance capitalism are less optimistic, arguing that commercial incentives keep firms on the vicious path whatever their stated commitments (Zuboff, 2019). RDTMT treats this disagreement as an empirical question, one that measuring EFE can help to answer.

5.5 Operationalizing the Constructs

To make the framework testable (RO4), Table 4 sets out illustrative indicators for each dimension of the three constructs, together with possible data sources. The indicators are not exhaustive. They are intended to guide scale development and empirical testing, and they will need to be validated in context.

Table 4. *Operational Indicators for the RDTMT Constructs*

Construct	Dimension	Illustrative indicators	Possible data sources
Digital Reflexivity	Representational density	Number of data sources and feature categories per consumer profile	System documentation; data-access requests
	Temporal coupling	Median delay between a behavioural event and the resulting model update	System logs; vendor documentation
	Feedback visibility	Availability and depth of explanation features; ability to view, edit, or delete profile data	Interface audits; consumer surveys
Ethical Feedback Elasticity	Stakeholder voice	Number and diversity of feedback channels; share of feedback from under-represented groups	Governance records; complaint data
	System adaptability	Share of validated ethical concerns that lead to changes in data practices, objectives, or constraints; time from concern to change	Change logs; governance minutes
	Value alignment metrics	Frequency of algorithmic audits; use of anticipatory impact assessments	Audit reports; regulatory filings
	Objective specification	Number and weight of non-commercial objectives in the optimization function	Model documentation; manager interviews

Construct	Dimension	Illustrative indicators	Possible data sources
Value Coherence Index	Value plurality recognition	Range of stakeholder groups consulted when objectives are set; documented trade-off decisions	Governance records; interviews
	Temporal orientation	Share of performance metrics with horizons beyond 12 months	KPI dashboards; annual reports

Source: Author's own elaboration.

6. Discussion

6.1 Theoretical Contributions to Marketing Scholarship

RDTMT contributes to marketing theory in five ways. First, it reconceptualizes marketing as a reflexive sociotechnical system in which consumers and algorithmic systems are continuously reconstituted through data-mediated feedback, rather than as influence, exchange, or co-creation between stable parties. Second, it redefines reflexivity for algorithmic markets. By locating Digital Reflexivity in the consumer–system relationship and drawing on Giddens, Archer, and Bourdieu, it avoids treating reflexivity as a competence consumers must acquire, and by separating reflexive adaptation from critical consciousness it explains why greater algorithmic awareness does not automatically lead to resistance.

Third, it addresses the externalization problem in marketing ethics: Ethical Feedback Elasticity treats governance as part of system design and shifts attention from whether feedback is received to whether it changes anything, and for whom. Fourth, it treats value alignment as plural and contested, connecting marketing theory to wider debates about public values and AI alignment by asking whose values end up in optimization objectives. Fifth, it makes these ideas testable, since the nine propositions and the indicators in Tables 3 and 4 provide a basis for scale development and hypothesis testing.

6.2 Implications for Marketing Practice

For practitioners, Tables 3 and 4 work as a diagnostic toolkit. The most telling single indicator is probably the share of validated ethical concerns that actually lead to changes in data practices, objectives, or constraints, because it shows whether governance has force or is only a listening exercise.

The framework also changes where managers should place responsibility. Offering consumers more settings and more information is not enough, because their capacity to use such tools is

unequal and much of their behaviour is habitual. Responsible design builds ethical constraints into the system itself, and firms that do this may gain an advantage as consumers grow more aware of algorithmic manipulation.

6.3 Implications for Policy and Regulation

For regulators, transparency mandates are necessary but not sufficient. Knowing what data are collected says little about how those data shape consumer choices, and disclosure leaves the work of interpretation to consumers. Regulators could also require evidence of Ethical Feedback Elasticity: documented channels for stakeholder input, including from groups with low digital capacity, and records showing how validated concerns led to change. The Value Coherence Index offers a way to evaluate systems as a whole rather than targeting harmful practices one at a time. This systemic view fits the argument that platform power operates at market, individual, and societal levels at once, and that fragmented rules struggle to address it (Graef & Bostoen, 2026).

7. Conclusion and Recommendations

7.1 Conclusions

Marketing has entered an algorithmic era that has outrun the concepts available to scholars and practitioners. This paper developed Reflexive Digital Twin Marketing Theory in response, drawing on a scoping review of 55 studies and on sociological debates about reflexivity, habit, and platform power. Its three constructs describe a recursive, structurally conditioned relationship between consumers and algorithmic systems (Digital Reflexivity), whether ethical feedback actually changes what those systems do (Ethical Feedback Elasticity), and how competing stakeholder values are written into optimization objectives (the Value Coherence Index). Transparency and ethical feedback mechanisms connect the three.

The framework's central message is that consumers cannot be handed responsibility for ethical algorithmic marketing. It rests mainly with the firms, platforms, and regulators that design the environments in which consumers choose. My hope is that RDTMT will encourage empirical work that tests its propositions and theoretical work that extends or challenges it.

7.2 Limitations

The RDTMT constructs require operationalization and psychometric validation before their full potential can be realized, and the indicators proposed in Tables 3 and 4 are a starting point, not validated measures. The scoping review's focus on three domains favors coherence over breadth. The sociological literature used to refine the constructs was drawn on interpretively and was not part of the systematic search. Finally, because Digital Reflexivity is relational, culturally situated, and temporally unstable, findings from one platform, culture, or period may not transfer easily to another.

7.3 Directions for Future Research

Five directions seem especially promising. Experiments could manipulate feedback visibility to test whether it produces adaptation or contestation, and how this varies with algorithmic literacy (P3). Comparative case studies could examine how firms with different levels of Ethical Feedback Elasticity handle controversies, and whose feedback led to change (P4 to P6). Longitudinal studies could follow how Value Coherence changes within specific systems. Cross-cultural research could compare RDTMT dynamics across regulatory regimes and cultural settings. Finally, research on digital inequality could identify which groups are least able to recognize, contest, or give feedback on algorithmic treatment, and which governance designs make their voices count.

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