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Chapter 3
Value Co-Creation in AI-Driven Services: Hyper-Personalization, Distributed Agency, and Consumer Experience

Aysun Sahin
http://orcid.org/0000-0003-3285-1232
Duzce University, Turkey

Azize Şahin
http://orcid.org/0000-0002-3115-6812
İstanbul University, Turkey

ABSTRACT

This conceptual chapter examines how AI-driven hyper-personalization reshapes value co-creation in service consumer experiences. Integrating S-D Logic, ANT, and post-phenomenology, the chapter explains how AI systems redistribute agency, mediate lived experience, reconfigure resources, and generate relational tensions around privacy, opacity, trust, and vulnerability. It develops an integrative framework linking AI personalization capabilities to four mechanisms: distributed agency, experiential mediation, resource reconfiguration, and relational tension. The chapter proposes a typology of hyper-personalization design logics, from efficiency-centered to intrusive or extractive personalization, and illustrates the framework across retail, hospitality, healthcare, and financial services. It contributes to service marketing by reframing hyper-personalization as an ethically governed service ecosystem phenomenon that can produce value co-creation and co-destruction. Managerial implications emphasize transparency, consumer control, human oversight, and responsible AI service design.

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1. INTRODUCTION

Artificial intelligence is reshaping consumer experience in services by moving personalization from a segment-level practice to a continuously adaptive interactional process. Earlier systems matched customers to predefined offers, content categories, or recommendation rules. AI-driven hyper-personalization is more consequential because it uses real-time behavioral, contextual, and relational data to anticipate needs, generate responses, and adjust service encounters as they unfold (Davenport et al., 2020; Huang & Rust, 2021). This raises a central theoretical question for service marketing: when an AI system interprets consumer data, recommends actions, speaks through conversational interfaces, and modifies the service journey, who is actually co-creating value?

The question cannot be answered by treating AI as a neutral tool. Recommendation engines, conversational agents, and adaptive interfaces influence the options consumers see and how alternatives are framed, and such encounters carry experiential costs as well as benefits (Puntoni et al., 2021). Service-Dominant Logic argues that value emerges through resource integration among actors rather than through firm delivery alone (Vargo & Lusch, 2008, 2016); AI-driven hyper-personalization extends this logic by introducing intelligent non-human systems into that process. These systems are not autonomous moral agents in the human sense, yet they can materially shape action possibilities, interpretations, and value outcomes (Chandra & Rahman, 2024; Kaartemo & Helkkula, 2018).

This chapter conceptualizes AI-driven hyper-personalized services as relational, experiential, and ethically governed value co-creation systems. Its central claim is that hyper-personalization does not merely improve efficiency or recommendation accuracy; it reconfigures value co-creation itself, through four mechanisms — distributed agency, experiential mediation, resource reconfiguration, and relational tension — defined and examined against recent evidence in Section 5. Because no single theory accounts for all four, the chapter draws on three complementary lenses: Service-Dominant Logic for value emergence through resource integration, Actor-Network Theory for the distribution of agency across human and non-human actors, and post-phenomenology for the mediation of lived experience (Ihde, 1990; Latour, 2005; Vargo & Lusch, 2016; Verbeek, 2005).

The framework responds to three limitations in current discussions of AI-enabled services. The first is technological reductionism: accounts emphasizing prediction and conversion devote less attention to the relational conditions under which consumers experience personalization as empowering or intrusive, even though technical capability does not by itself resolve acceptance, data governance, or relationship quality (De Bruyn et al., 2020). The second is an overly positive reading of value creation, since resource integration can also produce value co-destruction (Echeverri

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& Skålén, 2011; Plé & Cáceres, 2010), a possibility service research has examined far less systematically, as Section 2.4 documents. The third concerns consumer experience, which is a lived and interpreted encounter rather than only an evaluation of outcomes; this framing explains why the same intervention may be received as convenient, intelligent, manipulative, or intrusive.

2. CONCEPTUAL FOUNDATIONS

2.1. Service-Dominant Logic and Value Co-Creation

Service-Dominant Logic reframes marketing from the exchange of goods to the application of competencies for the benefit of another actor: service is the fundamental basis of exchange, and value is co-created through resource integration among multiple actors (Vargo & Lusch, 2008). Its later extension emphasizes service ecosystems, institutions, and institutional arrangements, moving the theory from dyadic exchange toward broader networks of actors, rules, norms, and resources that enable or constrain value formation (Vargo & Lusch, 2016). This ecosystemic view is relevant because personalization does not occur inside a single firm–consumer dyad; it is produced through platforms, data infrastructures, algorithms, interfaces, employees, regulatory norms, and consumer practices.

In AI-driven hyper-personalization, value emerges when consumers, providers, and AI systems integrate resources such as data, attention, expertise, trust, contextual knowledge, and interpretive capacity. AI can support this integration by recognizing patterns, generating recommendations, and configuring journeys, but the meaning and value of these outputs depend on how consumers interpret them and how organizations govern them.

The AI context also challenges Service-Dominant Logic productively. Traditional accounts treat consumers and organizations as principal actors, whereas AI introduces systems that structure interactions and influence the timing, sequence, and meaning of encounters. Kaartemo and Helkkula (2018) highlight the importance of human-to-non-human resource integration in AI- and robotics-enabled value co-creation, and Chandra and Rahman (2024) argue that this literature requires stronger conceptual attention to actor roles, service contexts, and the mechanisms through which AI affects value outcomes. Service-Dominant Logic also provides an ethical anchor. If value is co-created, firms cannot evaluate personalization solely by firm-side efficiency or conversion; it must also be assessed from the perspective of consumers who provide data and attention, employees who work alongside AI, and institutions that shape norms of fairness and accountability. Personalization that

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generates short-term sales while reducing autonomy or trust is better understood as asymmetrical value formation than as successful co-creation.

2.2. Actor-Network Theory and Distributed Agency

Actor-Network Theory provides a second foundation by refusing to treat social action as exclusively human. It argues that agency is distributed across networks of human and non-human actors, including technologies, texts, devices, institutions, and other material arrangements (Latour, 2005). This lens is useful because AI-driven service encounters are shaped not only by consumers and employees but by recommendation systems, customer relationship management platforms, chatbots, data pipelines, interfaces, and algorithmic rules. These non-human actors do not possess intention as humans do, yet they participate in organizing action and making some choices more likely than others.

Hyper-personalized services are particularly suited to this analysis because personalization engines translate consumer traces into action possibilities. A recommender system does not simply display options; it orders visibility and creates relevance hierarchies. A conversational agent does not merely answer questions; it frames problems, performs affective cues, and contains or escalates complaints. A predictive model does not simply forecast demand; it allocates resources and may classify consumers according to risk, value, vulnerability, or propensity.

Actor-Network Theory also avoids a simplistic contrast between human autonomy and machine control. Consumers still interpret, resist, or modify AI outputs; employees still intervene and contextualize; organizations still design, train, and govern. The result is not the disappearance of human agency but its redistribution across sociotechnical arrangements. This lens further supports a precise account of responsibility: responsibility cannot be assigned to the technical model alone but lies in the network of design choices, data practices, governance routines, incentives, and interfaces that allow AI to shape encounters. A firm cannot treat a recommendation as though the algorithm were outside the service system.

2.3. Post-Phenomenology and Technological Mediation

Post-phenomenology provides the third foundation by examining how technologies mediate human experience, shaping perception, interpretation, action, and relations between humans and the world rather than acting as deterministic or neutral instruments (Ihde, 1990; Verbeek, 2005). This lens is valuable for service consumer experience because hyper-personalization is not only a decision-support process; it changes how consumers perceive relevance, control, convenience, authenticity, and trust in service encounters. Ihde (1990) distinguishes four mediation

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relations — embodiment, hermeneutic, alterity, and background — which Section 5.2 develops for AI-driven service encounters together with the empirical evidence bearing on each.

These relations matter because value co-creation depends on how consumers experience AI-mediated interaction. A recommendation may be accurate yet undermine trust if experienced as opaque, and a chatbot may be efficient yet create detachment if it performs empathy without understanding; evidence that consumers resist medical AI when they perceive insufficient attention to their uniqueness illustrates why technical performance and lived value diverge (Longoni et al., 2019). If technologies mediate experience, then decisions about transparency, explanation, oversight, defaults, and personalization intensity are experiential and moral choices rather than merely functional ones.

2.4. Hyper-Personalization, Privacy, Trust, and Value Co-Destruction

Hyper-personalization deepens service relevance by using real-time and contextual data to configure offers, interactions, and journeys for individual consumers, but it also intensifies privacy tensions because richer personalization requires more granular data and more powerful inference. The personalization paradox captures this duality: consumers may value relevance while feeling vulnerable when data collection is hidden, unexpected, or difficult to control (Aguirre et al., 2015), and privacy decisions are further shaped by bounded rationality, information asymmetry, institutional trust, and perceptions of fairness in data use (Acquisti et al., 2016; Bleier et al., 2020).

Trust matters because AI-driven services often operate under opacity: consumers may not know what data were used, how a recommendation was produced, or whether the provider is accountable. Trust in AI depends on perceived competence, reliability, transparency, explainability, and deployment context (Glikson & Woolley, 2020), and explainable AI supports warranted trust only when explanations are usable and meaningful for the relevant stakeholder rather than technical descriptions of model operation (Langer et al., 2021).

Value co-destruction is not simply dissatisfaction; it refers to interactions in which value formation is impaired or negative value is created for one or more actors (Echeverri & Skålén, 2011; Plé & Cáceres, 2010). Recent work on human–AI service systems treats co-creation and co-destruction as intertwined outcomes shaped by agency distribution and recurring tensions between augmentation and automation, transparency and opacity, and autonomy and control (Colurcio & Caridà, 2026). In hyper-personalized services, co-destruction can occur through privacy intrusion, misclassification, loss of agency, discriminatory recommendations, manipulation,

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and reduced trust — risks structurally linked to the data intensity that makes hyper-personalization possible, and therefore requiring organizational rather than merely technical governance (Ashok et al., 2022; Hermann, 2022).

The literature has not treated these possibilities symmetrically, and this asymmetry is a limitation of the field rather than a feature of the phenomenon. Lumivalo et al. (2024) find in a systematic review that co-destruction has been examined largely as an aftermath of failed co-creation rather than as a theoretically equivalent counterpart, leaving its antecedents underdeveloped. Echeverri and Skålén (2021) argue that the two outcomes emerge from the same interactive practices rather than as opposed states, which implies that a design optimized for co-creation does not thereby reduce co-destruction risk. A second critique questions who bears the cost of co-creation: the attention, data, and corrective effort consumers contribute are often framed as engagement while their distribution goes unexamined, suggesting that apparently frictionless personalization may relocate effort instead of removing it. Empirical findings support this contested reading, since AI-personalized messages can raise purchase intentions while simultaneously provoking intrusiveness and reactance (Osman et al., 2026).

This chapter therefore treats co-creation and co-destruction as twin possibilities within the same service system, and the three limitations identified in Section 1 are drawn from these documented asymmetries rather than asserted. The three lenses operate at complementary levels: Service-Dominant Logic specifies how resources and value are integrated, Actor-Network Theory explains how action is distributed, and post-phenomenology explains how those arrangements are lived, while privacy, trust, and co-destruction research add the evaluative conditions under which distributed and mediated interaction becomes beneficial or harmful.

3. METHODOLOGICAL POSITIONING: A STRUCTURED CONCEPTUAL REVIEW

This chapter presents a structured conceptual review rather than a systematic review, meta-analysis, or bibliometric study. The purpose is theory building: integrating service marketing and interdisciplinary technology theories into an explanatory framework for AI-driven hyper-personalized service experiences. This is appropriate because the phenomenon is emerging, theoretically fragmented, and not sufficiently mature for stable cumulative synthesis. The review was nevertheless combined with a targeted empirical screening procedure so that the proposed mechanisms are examined against recent evidence rather than asserted on theoretical grounds alone.

The review was organized around five literature domains: Service-Dominant Logic and service ecosystems; AI in services and human-to-non-human resource

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integration; Actor-Network Theory and distributed agency; post-phenomenology and technological mediation; and personalization, privacy, trust in AI, explainability, and value co-destruction. Search logic combined terms corresponding to these domains across major databases and publisher platforms used in marketing, service, and information systems scholarship, including Scopus, Web of Science, ScienceDirect, Emerald, Sage, and Wiley. Priority was given to peer-reviewed work published from 2020 onward, while foundational sources required by the theoretical lenses were retained regardless of date.

A second, targeted screening stage identified recent empirical evidence bearing on the four proposed mechanisms, applying explicit criteria: publication between 2023 and 2026; an empirical design; a consumer-facing or service context; and a verifiable DOI. Conceptual papers, reviews, and bibliometric studies were excluded at this stage. Screening proceeded across four evidence domains: sector-specific outcomes of AI personalization in retail, hospitality, healthcare, and financial services; explainability effects on trust and reliance; privacy calculus and disclosure in AI settings; and regulatory and cross-cultural boundary conditions. Within each sector, at least one study reporting an adverse or mixed outcome was deliberately retained, so that the framework is examined against disconfirming as well as confirming evidence. Bibliographic records were verified against publisher and Crossref metadata.

Sources were included when they supported the framework's core mechanisms and excluded when weakly connected to the conceptual problem, primarily promotional, or bibliographically unverifiable. Synthesis proceeded through theoretical mapping rather than frequency counting: each lens was assigned a distinct explanatory function, and retained evidence was mapped onto the mechanisms in Section 5 to establish where evidence converges, diverges, or remains absent. The review has limitations: it does not test causal relationships, estimate effect sizes, or audit specific technologies; its selection is theoretically guided rather than exhaustive; and screening decisions were made by the authors without independent double-coding.

4. DEFINING AI-DRIVEN HYPER-PERSONALIZED SERVICE EXPERIENCE

AI-driven hyper-personalized service experience refers to a dynamically adapted service encounter in which AI systems use real-time, contextual, behavioral, and relational data to anticipate, configure, and mediate service offerings, interactions, and meanings for individual consumers in a service ecosystem. This definition em-

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phasizes four elements: dynamic adaptation, data intensity, experiential mediation, and ecosystem embeddedness.

Personalization adapts service content, recommendations, or interactions to individual or segment-level characteristics. Hyper-personalization uses richer data streams and real-time adaptation to tailor journeys more granularly, and AI-driven hyper-personalization adds predictive analytics, recommender systems, conversational agents, generative interfaces, contextual sensing, and algorithmic decision support (Davenport et al., 2020; Grewal et al., 2025; Huang & Rust, 2021). These systems personalize output but also shape the structure and meaning of the encounter, which consumers may experience as empowering when effort is reduced and self-endorsed goals supported, and as intrusive when the system appears to know too much or leaves little room for contestation (Puntoni et al., 2021).

Two further terms are used in a specific sense. AI agency does not imply consciousness, intention, or moral responsibility; it refers to the capacity of AI systems to shape service interactions by selecting, ordering, generating, recommending, prioritizing, or withholding options within sociotechnical service networks. Responsible AI service design refers to governance that preserves transparency, consent, explainability, fairness, human oversight, contestability, and consumer autonomy — interdependent principles that must be translated into organizational routines and stakeholder-specific explanations rather than treated as abstract compliance statements (Ashok et al., 2022; Hermann, 2022; Langer et al., 2021).

5. INTEGRATIVE FRAMEWORK AND CORE MECHANISMS

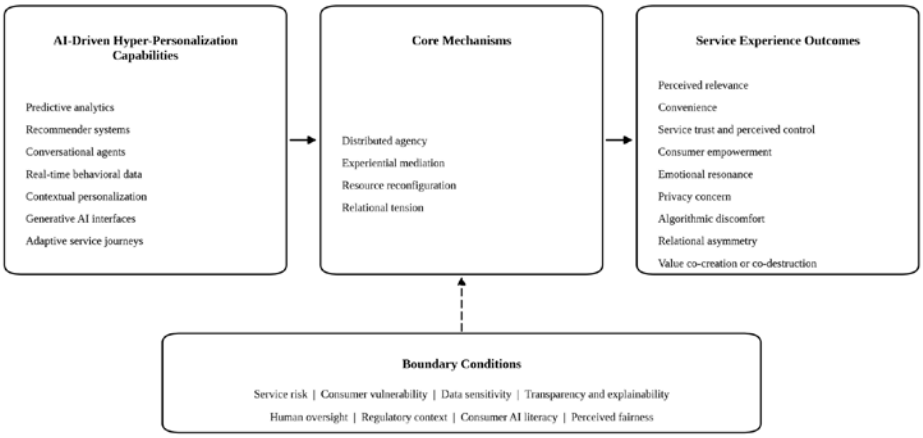
The framework begins with AI-driven hyper-personalization capabilities: predictive analytics, recommender systems, conversational agents, real-time behavioral data, contextual and ambient personalization, generative interfaces, adaptive journeys, and algorithmic decision support (Davenport et al., 2020; Grewal et al., 2025; Huang & Rust, 2021). These capabilities do not automatically create value; their effect depends on four mechanisms that translate them into service outcomes — distributed agency, experiential mediation, resource reconfiguration, and relational tension — each defined and examined against recent evidence in the subsections below.

Framework outcomes include perceived relevance, convenience, service trust, perceived control, empowerment, emotional resonance, privacy concern, algorithmic discomfort, relational asymmetry, and the twin possibilities of co-creation and co-destruction. Boundary conditions include service risk, consumer vulnerability, data sensitivity, perceived transparency, explainability, human oversight, cultural privacy norms, regulatory context, AI literacy, trust in the provider, and perceived fairness, since responses vary by service stakes, perceived uniqueness, data context, and the

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fit between explanations and stakeholder needs (Bleier et al., 2020; Langer et al., 2021; Longoni et al., 2019). The framework therefore treats hyper-personalization as neither solution nor threat, but as a capability whose value depends on relational and governance conditions. Figure 1 presents the framework and Table 1 summarizes the lenses.

Figure 1. Integrative Framework of AI-Driven Hyper-Personalized Service Experience



AI-driven hyper-personalization capabilities shape service consumer experience through four mechanisms — distributed agency, experiential mediation, resource reconfiguration, and relational tension — which influence both value co-creation and value co-destruction outcomes under the boundary conditions specified above. Source: Developed by the authors.

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Table 1. Theoretical Lenses for AI-Driven Hyper-Personalized Service Experience

Theoretical Lens	Core Concept	Role in the Framework	Main Limitation if Used Alone
Service-Dominant Logic	Resource integration and service ecosystems	Explains how value emerges among consumers, firms, employees, data, and AI systems	May understate material agency and lived experience of technology
Actor-Network Theory	Distributed agency among human and non-human actors	Explains how algorithms, platforms, interfaces, and data infrastructures structure service action	May understate consumer interpretation and normative evaluation
Post-Phenomenology	Technological mediation of experience	Explains how personalization is lived as convenience, control, opacity, or intrusion	May understate ecosystem and institutional structures
Privacy and Trust Research	Vulnerability, transparency, and explainability	Identifies why relevance can coexist with discomfort and distrust	May focus on individual perception without broader ecosystem logic
Value Co-Destruction Research	Negative outcomes of resource integration	Identifies how AI personalization may reduce autonomy, fairness, or trust	May underdevelop the technological mechanisms creating harm

Note. Developed by the authors.

5.1. Distributed Agency

The distributed agency mechanism explains how AI-enabled systems participate in structuring service interactions. Agency is traditionally attributed to consumers, employees, and firms, but recommender systems, predictive tools, conversational agents, and adaptive platforms complicate this assumption, influencing what consumers see, which options are salient, how information is ordered, and how responses are delivered, even when they remain invisible. From a Service-Dominant Logic perspective, AI becomes part of the infrastructure through which consumer data, firm knowledge, employee expertise, and contextual signals are integrated; from an Actor-Network Theory perspective, AI systems are actors because they assemble action possibilities and stabilize relationships, participating in producing outcomes they do not intend (Latour, 2005).

Recent evidence indicates that this redistribution operates below the level of consumers' stated evaluations. In four preregistered experiments, Böhm et al. (2023) found that people rated generative AI as less competent once they learned advice was machine-generated, yet followed it at rates comparable to human-authored advice. Reliance persisted where trust was explicitly discounted, suggesting that agency shifts toward the system without a corresponding shift in attributions of authority. This shift is not uniform: Han and Ko (2025) report that design elements actively

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involving consumers in decision-making preserved perceived autonomy, whereas passive transparency features alone did little to prevent consumers from ceding agency to AI recommendations.

Distributed agency can support co-creation by increasing responsiveness and allowing services to adapt to individual contexts, but it also blurs responsibility: consumers may not know which actor produced a recommendation, employees may over-rely on automated suggestions, and firms may attribute problematic outcomes to technical systems rather than governance failures. Human oversight therefore should not be symbolic: employees need the authority to correct AI outputs, consumers need meaningful ways to contest recommendations, and managers need audit trails that reveal how automated decisions affect service outcomes (Ashok et al., 2022; Hermann, 2022). The evidence above suggests why such safeguards cannot rely on consumer skepticism alone, since discounted trust did not translate into reduced reliance.

5.2. Experiential Mediation

The experiential mediation mechanism explains how AI changes consumers' lived experience of service interactions. Consumer–AI encounters involve data capture, classification, delegation, and social interaction, producing feelings of care, convenience, surveillance, pressure, or uncanny intimacy depending on how the encounter is designed and interpreted (Puntoni et al., 2021). Ihde's four mediation relations organize these effects.

In embodiment relations, AI becomes an extension through which the consumer acts, as when a wearable triggers personalized health support; the co-creation potential rests on timely support and reduced effort, the risk on dependency and bodily surveillance. In hermeneutic relations, consumers read AI outputs as interpretations of the service world through rankings, risk scores, and dashboards. Value comes from improved comprehension and decision support, the risk from over-trust, opacity, and narrowed choice sets when consumers treat AI outputs as neutral truth. Technical transparency alone is therefore insufficient; explanations must fit the user, decision context, and consequences of error (Langer et al., 2021). In alterity relations, AI appears as a quasi-other through conversational agents, offering accessibility and continuous availability while risking false empathy, detachment, and confusion about whether the counterpart is human, machine, or hybrid. In background relations, AI shapes the environment without being focal, as when a hotel adjusts room settings or a retailer reorganizes a digital storefront; the gain is frictionlessness, the risk invisible influence and weak consent.

Empirical work qualifies the hermeneutic case in particular. Ostinelli et al. (2024) show that merely believing an explanation is available can produce an illusory

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sense of understanding an algorithm and unfounded reliance on its output, even when it is never read, and de Brito Duarte et al. (2023) report that explanations increased trust only under specific conditions and, where system performance was unreliable, induced overreliance rather than warranted trust. Anthropomorphic design cues operate along a similar dual path: human-like chatbot language increases engagement through perceived competence and authenticity (Nguyen et al., 2023), while perceived anthropomorphism simultaneously raises privacy concerns and perceived benefits, increasing disclosure intention through both routes (Zhou & Tang, 2025). Mediation therefore does not simply improve or degrade the service encounter; it reshapes what consumers believe they understand about it.

5.3. Resource Reconfiguration

The resource reconfiguration mechanism explains how hyper-personalization changes the resources integrated in service ecosystems. Service-Dominant Logic distinguishes between operand resources, such as physical objects, and operant resources, such as knowledge, skills, competencies, and relationships (Vargo & Lusch, 2008). AI-driven services expand the range of operant resources by making data, attention, contextual knowledge, trust, time, service literacy, and emotional signals central to value formation.

Where traditional personalization adapts offers to prior purchases or stated preferences, hyper-personalized resource integration is continuous: consumers supply data through browsing, location, usage, wearables, conversations, and inferred preferences; firms supply service knowledge, content, channels, and decision rules; and AI systems supply pattern recognition, prediction, generation, and adaptation. This changes co-creation from static matching to dynamic orchestration: a banking application may adapt alerts, explain spending patterns, and personalize risk communication rather than simply recommending a product, and a hospitality platform may infer trip purpose, timing, and ancillary needs rather than only storing room preferences.

Resource reconfiguration has ethical consequences, because consumers may not understand which resources they contribute or how these are transformed, and co-creation becomes questionable when one actor captures disproportionate value from resources provided by another. This asymmetry is documented rather than asserted. Zhou and Tang (2025) found that perceived anonymity and privacy statements reduced privacy concerns while raising perceived benefits, with AI literacy strengthening both pathways, indicating that the terms of exchange are understood unevenly across consumers; de Matos et al. (2026) report from the opposite side that higher financial literacy was associated with lower willingness to disclose, suggesting that consumers who best understand the exchange are least willing to enter it.

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Responsible design should therefore make resource contributions transparent and ensure that consumers receive meaningful value in return.

5.4. Relational Tension

The relational tension mechanism explains why hyper-personalization is inherently ambivalent. Personalization can increase relevance, convenience, and emotional resonance while simultaneously increasing privacy concern, algorithmic discomfort, and loss of control, because it uses consumer intimacy as a resource: the more the system knows and adapts, the more it can both help consumers and threaten their autonomy.

The ambivalence is directly observable in field evidence. Osman et al. (2026) report a dual-pathway pattern in a retail field experiment, in which AI-personalized messages increased purchase behavior through perceived helpfulness while simultaneously activating an intrusiveness–reactance pathway, with the adverse route strongest among consumers holding weak brand relationships. Related evidence shows that the source attributed to a recommendation matters independently of its content, and that shoppers can welcome AI-enabled discounts while resisting location tracking within a single encounter (Canhoto et al., 2024; Weidig & Kuehnl, 2023). Relational tension is therefore not a residual risk attached to poor implementation; it is a structural property of personalization that intensifies as systems become more capable. Privacy tension is its most visible form: consumers accept data use when benefits are clear and controls meaningful, and resist covert collection or cross-context inference, particularly given the information asymmetry that prevents them from anticipating future data uses (Acquisti et al., 2016; Aguirre et al., 2015).

Algorithmic opacity creates a second tension whose remedy is conditional rather than general. Chen et al. (2024) found that post hoc explanations increased interpretability perceptions and trust, with attribute-based explanations more effective in utilitarian domains and user-based explanations more effective in hedonic ones. Mourali et al. (2025), by contrast, report that explanations can improve or damage consumer responses depending on the method used, and Ning et al. (2024) find that process transparency loses its effect when purpose transparency is already high. Transparency is therefore a design variable with conditional effects rather than a general remedy: complex disclosures may increase confusion, shallow ones may appear performative, and the design problem is intelligible and actionable transparency.

Consumer vulnerability compounds these tensions. Vulnerable consumers may have lower AI literacy, higher dependence on providers, or limited ability to contest automated decisions; hyper-personalization can support them by reducing friction and harm them by exploiting dependence or hiding choices. Relational tension is

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thus not a defect that can be eliminated permanently but a condition that must be continuously governed. Table 2 summarizes the mechanisms.

Table 2. Core Mechanisms of AI-Driven Value Co-Creation

Mechanism	Definition	Theoretical Anchor	Service Experience Effect	Value Co-Destruction Risk
Distributed Agency	AI systems participate in structuring service action and interaction	Service-Dominant Logic and Actor-Network Theory	Consumers experience more adaptive and responsive encounters	Blurred responsibility, over-reliance, and algorithmic control
Experiential Mediation	AI shapes how consumers perceive, interpret, and feel personalized encounters	Post-Phenomenology	Personalization is experienced as convenient, supportive, opaque, or intrusive	Uncanny interaction, false empathy, hidden influence, loss of control
Resource Reconfiguration	AI reorganizes data, attention, trust, time, knowledge, and service literacy	Service-Dominant Logic and service innovation	Service propositions become dynamic and context-sensitive	Asymmetric extraction of consumer data and attention
Relational Tension	Personalization creates both relevance and discomfort	Privacy, trust, and value co-destruction research	Consumers evaluate service through trust, autonomy, fairness, and vulnerability	Privacy intrusion, manipulation, distrust, and co-destruction

Note. Developed by the authors from the synthesis in Sections 2 and 5.

6. TYPOLOGY OF HYPER-PERSONALIZATION DESIGN LOGICS

This chapter identifies four hyper-personalization design logics as an original conceptual typology. A design logic is not a specific technology but the dominant orientation shaping how organizations use AI to personalize interactions; the typology integrates distinctions among automation, analytical personalization, relational AI, human augmentation, and ethical governance in prior research (Grewal et al., 2025; Hermann, 2022; Huang & Rust, 2021; Puntoni et al., 2021). The four logics are distinguished by three observable criteria rather than by intent: the locus of interpretive authority, meaning whether the system, the employee, or the consumer determines what a recommendation means; the reversibility of adaptation, meaning whether consumers can inspect, modify, or reverse the personalization applied to them; and the disclosure of resource contribution, meaning whether consumers are informed which of their resources are integrated. Because these criteria can be

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coded independently of the provider's stated orientation, the typology is usable as a classification instrument rather than only a descriptive scheme.

Efficiency-centered personalization prioritizes speed, convenience, and friction reduction, and suits low-risk, utilitarian, or repetitive contexts such as routine reordering or delivery status. Its co-destruction risk is that the encounter is reduced to operational optimization, with consumers pushed through journeys designed for conversion rather than supported as participants.

Relationally balanced personalization combines AI efficiency with human oversight and contextual responsiveness, recognizing that hospitality, healthcare, financial advice, and complaint handling involve relational dimensions that prediction accuracy cannot capture: AI provides recommendations while humans remain visible in moments requiring empathy, judgment, or reassurance. Its risk is inconsistency where firms promise oversight but do not provide it meaningfully.

Transparency-oriented personalization emphasizes consumer understanding and meaningful control through explanations, preference controls, data visibility, and opportunities to contest recommendations. It is appropriate where opacity would undermine perceived fairness or trust, as in finance, healthcare, insurance, and high-involvement retail. Its risk is transparency overload when explanations are too technical, too frequent, or not actionable, because explanation quality depends on stakeholder needs and decision context (Langer et al., 2021).

Intrusive or extractive personalization maximizes data-driven adaptation without sufficient regard for consumer boundaries, consent, or control. It may generate short-term conversion gains but creates high co-destruction risk, as consumers may feel monitored or classified in ways they cannot contest. It is particularly dangerous where data involve health, finance, identity, location, children, or vulnerable consumers, and requires explicit governance because privacy, fairness, autonomy, and accountability can conflict (Ashok et al., 2022; Hermann, 2022). The managerial implication is that personalization intensity is not an unqualified good: the appropriate level is the one consumers can experience as useful, fair, understandable, and controllable. Table 3 summarizes the logics.

6.1. Propositions

The typology yields testable expectations, each specifying a relationship that could be falsified empirically.

P1. Efficiency-centered personalization increases perceived convenience but does not increase relational outcomes such as trust or attachment; where service risk is high, its effect on trust becomes negative. This follows from evidence that helpfulness and intrusiveness operate as parallel rather than sequential pathways,

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with adverse responses concentrated among consumers with weak relational ties (Osman et al., 2026).

P2. Relationally balanced personalization outperforms efficiency-centered personalization on trust outcomes only when human oversight is consequential rather than nominal; where oversight exists but cannot alter system output, the two logics converge. Healthcare evidence in Section 7 supports the first clause (Zhu et al., 2026); the second remains untested.

P3. Transparency-oriented personalization improves trust conditionally rather than monotonically, depending on explanation type, system performance, and prior consumer expertise; where system performance is unreliable, explanation increases reliance without increasing warranted trust. This is consistent with the divergent findings of Chen et al. (2024), Ostinelli et al. (2024), de Brito Duarte et al. (2023), and Ning et al. (2024), and it predicts that transparency interventions evaluated only on self-reported trust will overstate their benefit relative to behavioral measures.

P4. Intrusive or extractive personalization produces co-destruction that is unevenly distributed rather than uniform, with adverse effects concentrated among consumers holding greater domain knowledge, higher privacy sensitivity, or weaker relational ties. This is supported by evidence that financial literacy predicts lower disclosure (de Matos et al., 2026), that reactance is strongest among weakly attached consumers (Osman et al., 2026), and that privacy responses differ by gender in hospitality and healthcare (Hu & Min, 2023; Zondag et al., 2024).

P5. The relationship between personalization intensity and value outcomes is non-monotonic, with the inflection point determined by service risk and data sensitivity rather than by personalization capability. This follows from hospitality evidence in which stronger capability claims reduced disclosure (Shuqair et al., 2024), and predicts that studies treating intensity as a linear predictor will find weak or inconsistent effects.

6.2. Boundary Conditions of the Typology

The typology's applicability is bounded in two respects. First, the logics are not culturally invariant, since consumer responses to algorithmic services vary across national and institutional contexts in ways that do not reduce to a single dimension. Chinese respondents reported greater privacy concern regarding behavioral advertising than Dutch respondents (Zhang et al., 2023), yet Korean participants trusted an AI chatbot more than German participants in a comparable design (Kang et al., 2025), and Chinese respondents valued emotional connection with AI more, and personal control less, than European Americans (Ge et al., 2024). Across five countries, institutional trust and regulatory expectations explained privacy concern better than individualism–collectivism classifications (Viberg et al., 2024). A

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transparency-oriented logic that increases trust in one regulatory context may therefore be redundant or insufficient in another.

Second, the logics are not regulatory-neutral. Intrusive or extractive personalization intersects with the prohibitions on manipulative and deceptive techniques in Article 5 of the EU AI Act; current EU instruments protect consumer autonomy only partially against AI-driven persuasion (Fassiaux, 2023), while systems that score or triage rather than decide may fall outside GDPR Article 22 protections (Palmiotto, 2024). The typology therefore describes orientations whose legality, not only advisability, varies by jurisdiction.

Table 3. Hyper-Personalization Design Logics

Design Logic	Dominant Aim	AI Role	Co-Creation Potential	Co-Destruction Risk	Suitable Contexts
Efficiency-Centered	Reduce friction and accelerate journeys	Automate routine adaptation and recommendations	Convenience, speed, reduced effort	Over-optimization, passivity, shallow relational value	Low-risk routine retail, logistics, basic support
Relationally Balanced	Combine AI efficiency with human judgment	Support employees without replacing relational care	Trust, reassurance, contextual responsiveness	Token oversight or inconsistent escalation	Hospitality, healthcare, financial advice, service recovery
Transparency-Oriented	Make personalization understandable and controllable	Explain, justify, and expose personalization logic	Autonomy, trust, perceived fairness	Transparency fatigue or cognitive overload	High-involvement and regulated services
Intrusive or Extractive	Maximize adaptation and conversion through extensive data use	Infer, target, and optimize with limited consumer control	Short-term relevance or conversion	Privacy backlash, manipulation, co-destruction	High-risk logic to avoid or tightly restrict

Note. Original typology developed by the authors; classification criteria are specified in Section 6.

7. SECTORAL EVIDENCE

The four mechanisms operate across sectors but not identically: differences in data sensitivity, decision stakes, and consumer dependence produce distinct patterns of co-creation and co-destruction. The following discussion draws on evidence pub-

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lished between 2023 and 2026, retaining in each case at least one study reporting an adverse or mixed outcome.

In retail, the benefits of personalization lie in relevance and reduced search costs, but field evidence indicates that these benefits and their corresponding harms are produced simultaneously rather than sequentially. Combining a field experiment (N = 409) with 46 interviews, Osman et al. (2026) found that AI-personalized retail messages increased purchase behavior through perceived helpfulness while activating a parallel intrusiveness–reactance pathway strongest among consumers with weak brand relationships, indicating that relational history conditions which route dominates. Drawing on 18 interviews with UK fashion shoppers, Canhoto et al. (2024) found that participants welcomed AI-enabled discounts while resisting location tracking, producing an unresolved tension within a single encounter rather than a stable preference. Across three experiments, Weidig and Kuehnl (2023) found that recommendations attributed to data from similar customers provoked greater reactance and lower trust, particularly when inaccurate. Retailers should therefore attend to attribution and provenance, not only predictive accuracy, and recognize that evaluating personalization solely through conversion metrics understates its relational costs.

In hospitality, value can emerge from anticipatory care because guests evaluate the experience through warmth, recognition, and trust, yet the evidence is weighted toward adverse outcomes whose sources are specific rather than generic. Across two scenario-based experiments, Hu and Min (2023) found that AI devices with camera eyes and humanoid features heightened hotel guests' privacy concerns and unease, more markedly among female guests, indicating that the physical form of the device rather than its data practices alone generated the response. In a five-study investigation, Shuqair et al. (2024) found that framing an AI system as powerful increased privacy concerns, reduced perceived control, and decreased willingness to disclose the very data that personalization requires, so that capability claims undermine the conditions for their own use.

In healthcare, personalization draws on symptoms, wearable data, history, and conversational intake to support triage, reminders, and self-management. Co-creation potential is high, and so are the risks, given data sensitivity and consumer vulnerability; recent evidence indicates that harm here can be relational rather than clinical. In a vignette study of 398 Dutch hospital patients, Zondag et al. (2024) found that an AI-supported clinical decision support system significantly reduced female patients' trust in physician competence and integrity while the effect was non-significant in the full sample, so that co-destruction occurs in the patient–provider relationship rather than in the accuracy of the recommendation. What restores acceptance is equally specific: in two vignette experiments with 340 US patients, Zhu et al. (2026) found that trust in AI medical devices was driven most strongly

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by regulatory approval (average marginal effect 19.3%) and professional oversight (15.5–17.9%), whereas data privacy disclosures had minimal independent effect. Barriers also differ by professional role, since perceived risk negatively predicted adoption intention among nurses but not physicians in a survey of 2,705 Chinese medical staff (Dai et al., 2025). Oversight is therefore not only an ethical safeguard but an empirically identified precondition of patient trust.

In financial services, hyper-personalization spans budgeting tools, risk alerts, fraud prevention, and conversational banking, but the evidence complicates the assumption that better-informed consumers are more willing participants. In a study of 408 Portuguese e-banking users, de Matos et al. (2026) found that AI personalization increased willingness to disclose personal information, that fear of AI attenuated this effect, and, more strikingly, that higher financial literacy was associated with lower disclosure. Design features also produce asymmetric returns: surveying 616 US consumers, Wang et al. (2026) found that customizability increased adoption of AI financial advisors through reduced technology vulnerability, whereas human-likeness amplified vulnerability without a corresponding adoption benefit. Anthropomorphic design in high-stakes financial contexts therefore carries costs that its relational benefits do not offset.

As Table 4 summarizes, the evidence supports a more specific conclusion than the familiar claim that personalization must be calibrated to service risk: the mechanisms do not merely intensify with risk, they change form. Co-destruction operates through reactance to perceived intrusion in retail, through embodied surveillance cues and capability framing in hospitality, through erosion of trust in the human provider in healthcare, and through vulnerability amplified by human-like design in financial services. These are not four instances of one risk but distinct failure modes, and interventions effective in one sector may be irrelevant or counterproductive in another. A further pattern cuts across sectors: in three of the four, adverse effects concentrated in identifiable subgroups — women in hospitality and healthcare, weakly attached consumers in retail, and financially literate consumers in banking — so that aggregate measures of personalization effectiveness will systematically underestimate co-destruction.

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Table 4. Sectoral Evidence on AI-Driven Hyper-Personalization

Sector	Evidenced Benefit (Co-Creation)	Evidenced Risk (Co-Destruction)	Governance Requirement
Retail	Purchase lift via perceived helpfulness (Osman et al., 2026)	Intrusiveness–reactance, strongest for weakly attached consumers; reactance to similar-customer sourcing (Osman et al., 2026; Weidig & Kuehnl, 2023)	Preference controls; provenance disclosure; relational as well as conversion metrics
Hospitality	Anticipatory care and emotional resonance	Camera-eye and humanoid cues raise privacy concern, especially among women; "powerful AI" framing lowers disclosure (Hu & Min, 2023; Shuqair et al., 2024)	Visible human care; respectful data boundaries; escalation pathways
Healthcare	Regulatory approval and professional oversight drive trust (Zhu et al., 2026)	AI decision support erodes female patients' trust in the physician; perceived risk deters nurse adoption (Zondag et al., 2024; Dai et al., 2025)	Professional oversight and regulatory assurance as trust preconditions
Financial Services	Customizability aids adoption via reduced vulnerability (Wang et al., 2026)	Human-likeness amplifies vulnerability; higher financial literacy lowers disclosure (Wang et al., 2026; de Matos et al., 2026)	Understandable logic; human support for high-stakes decisions; avoid exploiting vulnerability

Note. Developed by the authors; sources are cited in the corresponding subsections.

8. THEORETICAL CONTRIBUTIONS

The framework specifies how hyper-personalization capabilities translate into service outcomes through four mechanisms, and how the balance between co-creation and co-destruction is conditioned by governance, sector, regulation, and cultural context. Three contributions follow.

First, the chapter advances Service-Dominant Logic by extending value co-creation into AI-mediated service ecosystems, showing that hyper-personalization changes not only the efficiency of resource integration but its structure, since algorithmic actors and digital infrastructures become active components of value formation. This does not require treating AI as a human actor; it requires recognizing that value emergence is co-produced with non-human systems whose design conditions the outcome. The chapter also integrates co-destruction as an inherent possibility rather than an exceptional failure: because both outcomes arise from the same personalization practices, a service optimized for one does not thereby avoid the other, and the framework specifies the conditions that determine which dominates. This matters because AI-enabled services can be efficient and intrusive, accurate and

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opaque, convenient and manipulative at once, and such mixed outcomes cannot be captured by adoption or satisfaction measures alone.

Second, the chapter contributes to AI-driven service research by moving beyond automation and replacement logic. Huang and Rust (2021) explain how AI capabilities support mechanical, analytical, intuitive, and relational tasks; this chapter examines how AI participation changes consumer experience, resource integration, and relational governance, treating AI as a mediator of value formation rather than only a service technology. It also specifies boundary conditions that help explain why the same capability may be valued in one context and resisted in another.

Third, the chapter contributes to Actor-Network Theory-informed and post-phenomenological service research. Distributed agency provides a vocabulary for studying how algorithms, interfaces, data infrastructures, and organizational routines jointly produce service encounters, and clarifies that where agency is distributed, accountability must be designed into the network rather than asserted as ethical intention. The mediation relations explain why consumers experience the same recommendation as support, interpretation, dialogue, or invisible control. Together these contributions position governance as a condition of value co-creation: transparency, explainability, consent, fairness, oversight, and contestability are not compliance add-ons but interdependent parts of the service value architecture (Ashok et al., 2022; Hermann, 2022; Langer et al., 2021).

9. SOLUTIONS AND RECOMMENDATIONS

Service managers should avoid treating hyper-personalization as a universal performance lever, because intensity and value outcomes are not monotonically related (Osman et al., 2026; Shuqair et al., 2024). Intensity decisions therefore require an explicit ceiling, not only a target: organizations should define, for each service journey, which inferences are permitted and which are excluded, with limits reflecting data sensitivity and service risk rather than predictive capability. Personalization should also be evaluated using relational indicators alongside conversion outcomes, since dashboards focused on conversion understate co-destruction that emerges through reactance without an immediate decline in purchases: trust, perceived control, opt-out rates, and complaint content should be reported alongside efficiency metrics and disaggregated by segment.

Customer experience designers should treat personalization as an interpretable journey, although evidence cautions against treating explanation as a universal remedy (de Brito Duarte et al., 2023; Mourali et al., 2025; Ning et al., 2024; Ostinelli et al., 2024). Three criteria follow. First, the form of explanation should fit the decision domain, since attribute-based explanations are more effective in utilitarian contexts

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and user-based explanations in hedonic ones (Chen et al., 2024). Second, effectiveness should be assessed behaviorally as well as through self-reported trust, since these may diverge in high-risk settings. Third, explanations should not be provided where system performance cannot support justified reliance; there they shift risk to consumers instead of mitigating it.

Making oversight consequential is a distinct requirement, since oversight is meaningful only when it can change outcomes and consumers respond more strongly to its institutional reality than to assurances that it exists (Zhu et al., 2026). Employees therefore need documented authority to override system outputs without an escalation penalty, with override events logged and treated as system feedback rather than employee error, and consumers need a contestation pathway with a defined response time. Organizations that cannot demonstrate that overrides occur and influence outcomes should not communicate oversight claims. A related caution follows from evidence that consumers evaluated AI competence less favorably once advice was identified as machine-generated yet followed it at unchanged rates (Böhm et al., 2023): skepticism cannot serve as a safeguard, and disclosure of AI involvement alone does not protect against overreliance.

Anthropomorphic design should be adopted selectively by sector, since human-likeness increased technology vulnerability without improving adoption in financial services and heightened privacy concerns in hospitality, especially among female guests (Hu & Min, 2023; Wang et al., 2026; Zhou & Tang, 2025). Human-like features should be justified by the specific outcome they support and evaluated for adverse subgroup effects, not solely by the sample mean; where stakes are high or data sensitive, current evidence supports customizability and user control more strongly.

Organizations should also anticipate regulatory exposure, since intrusive or extractive design carries legal as well as reputational risk under Article 5 of the EU AI Act, and since systems that score, rank, or triage rather than decide may fall outside GDPR Article 22 protections as currently interpreted (Palmiotto, 2024). Compliance with data-protection law does not by itself establish that a practice is defensible, and because consumer expectations differ across national contexts (Ge et al., 2024; Kang et al., 2025; Viberg et al., 2024; Zhang et al., 2023), a configuration validated in one market should not be assumed transferable to another.

From an ethical perspective, reciprocity should be the governing principle: providers should treat consumer data, attention, and trust as resources whose use must generate meaningful value for consumers rather than as inputs for extraction. Empirical findings give this substance, since consumers with greater domain knowledge disclosed less in banking, so those who understood the exchange most clearly were the most guarded participants (de Matos et al., 2026). When informed consumers withdraw, the exchange is not reciprocal regardless of how providers characterize it — the distinction that separates responsible co-creation from data-driven co-extraction.

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10. FUTURE RESEARCH DIRECTIONS

Measurement is the most immediate need. Existing measures of technology acceptance, trust, personalization, and satisfaction do not capture distributed agency, technological mediation, or resource reconfiguration (Chandra & Rahman, 2024). A dedicated scale could include perceived AI participation, consumer resource contribution, interpretive transparency, autonomy support, relational fairness, and perceived co-created value.

The propositions in Section 6.1 define a second agenda. Experimental research should manipulate explanation depth, AI disclosure, oversight visibility, personalization intensity, and control features, measuring not only adoption intention and satisfaction but also warranted trust, perceived autonomy, vulnerability, and fairness, and evaluating whether explanations satisfy the needs of the intended audience (Langer et al., 2021). Because P3 predicts divergence between self-reported and behavioral trust, such designs should include behavioral reliance measures rather than attitudinal ones alone.

Value co-destruction warrants direct rather than residual study. Qualitative research could examine how consumers narrate harmful personalization experiences, while longitudinal and ethnographic designs could track whether short-term convenience erodes long-term attachment as consumers move from resistance to routinization to dependence. Q-methodology can map distinct subjective positions — personalization as care, convenience, surveillance, or manipulation — without assuming that all consumers evaluate AI services by the same criteria.

Finally, because failure modes differ by sector, general models require complementary sector theories emphasizing uniqueness and professional oversight in healthcare, explainability and fairness in finance, emotional resonance and discretion in hospitality, and contextual privacy and control in retail (Bleier et al., 2020; Longoni et al., 2019). Comparative research should examine how cultural privacy norms and regulatory regimes shape the boundary between value creation and destruction, and how organizations translate ethical principles into governance routines, audits, and accountability coordinated across vendors, platforms, managers, and employees (Ashok et al., 2022; Hermann, 2022).

11. CONCLUSION

AI-driven hyper-personalization is becoming a defining feature of consumer experience in contemporary services, but its capacity to create value does not follow automatically from technical sophistication. This chapter has argued that it transforms value co-creation through four mechanisms — distributed agency,

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experiential mediation, resource reconfiguration, and relational tension — which together explain why the same capability can generate co-creation for some consumers and co-destruction for others. Co-destruction is neither exceptional nor uniform: it emerges through distinct sectoral failure modes and concentrates in subgroups that aggregate averages obscure.

The managerial implication is that providers should not maximize personalization simply because the technology permits it: responsible implementation requires explicit limits on permissible inferences, behavioral evaluation of explanations, oversight with authority to alter outcomes, and sector-specific assessment of anthropomorphic design. The framework also has limitations that define its research agenda: it has not been empirically tested, and its evidence base remains concentrated in four sectors and predominantly Western and East Asian contexts, leaving open whether the mechanisms and typology apply across other settings and regulatory regimes. Within service ecosystems, AI can support value co-creation when governed through transparency, trust, meaningful oversight, privacy protection, and responsible institutional practice; without these safeguards, the same capabilities shift the process from co-creation to co-destruction.

Artificial Intelligence Disclosure Statement

AI-assisted tools were used solely for language polishing, structural checking, formatting consistency, and readability enhancement. The authors remain fully responsible for the chapter's conceptual framing, scholarly argumentation, selection of sources, verification of citations, and final content.

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Azize Şahin (azize.sahin@istanbul.edu.tr)
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KEY TERMS AND DEFINITIONS

AI Agency: The capacity of AI systems to shape service interactions by selecting, ordering, generating, recommending, prioritizing, or withholding options within sociotechnical systems, without implying human-like consciousness, intention, or moral responsibility.

AI-Driven Hyper-Personalization: The use of AI systems to adapt service offerings, interactions, recommendations, and meanings in real time by drawing on contextual, behavioral, and relational data.

Distributed Agency: The distribution of action-shaping capacity across consumers, employees, organizations, platforms, algorithms, interfaces, and other service network participants.

Post-Phenomenology: A philosophical approach that examines how technologies mediate human experience, perception, interpretation, and action.

Responsible AI Service Design: The design and governance of AI-enabled services through transparency, explainability, fairness, consent, contestability, and human oversight.

Service-Dominant Logic: A marketing perspective that treats service as the fundamental basis of exchange and explains value as co-created through actor-to-actor resource integration.

Value Co-Creation: The formation of value through resource integration among multiple actors, including consumers, firms, employees, platforms, and AI-enabled systems.

Value Co-Destruction: A negative outcome of interaction in which resource integration reduces trust, autonomy, fairness, well-being, or service value for one or more actors.