

AI-Powered Personalization at Work and in the Market: Examining the Convergence of Employee Experience and Customer Engagement



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Abstract

Artificial intelligence (AI) has made individualized treatment economically feasible at population scale, yet organizations continue to build two separate personalization estates: one that tailors work to employees and another that tailors offers to customers. This paper argues that the separation is an artefact of organizational history rather than of technology, and that the two estates are converging on a common substrate of data, models and governance. Drawing on the service-profit chain, service-dominant logic, sociotechnical systems theory and the technology affordance perspective, the study develops and evaluates a Convergence Model in which AI personalization capability on the work side and on the market side jointly shape employee experience and customer engagement, which in turn accumulate into a firm-level property termed personalization convergence and, through it, into dual-sided value. The paper combines a structured synthesis of 118 peer-reviewed studies published between 2015 and 2025 with an illustrative demonstration on a calibrated simulated dataset ($n = 612$). Results support a reciprocal employee-customer spillover, identify algorithmic transparency and privacy concern as opposing boundary conditions, and show that convergence rather than raw capability is the stronger proximal driver of dual-sided value. The paper contributes a formal definition and measurement scheme for personalization convergence, a three-layer reference architecture, a five-stage maturity model, and a governance agenda that treats employees and customers as a single population of data subjects rather than two unrelated ones.

Keywords: Artificial intelligence, algorithmic management, customer engagement, employee experience, human resource management, personalization, service-profit chain, sociotechnical systems.

1. Introduction

1.1 Background

Personalization has moved from a marketing tactic to a general-purpose organizing logic. What began as name-substitution in direct mail is now a set of statistical and generative capabilities that can adapt an offer, an interface, a message or a task to an individual in real time and at a marginal cost approaching zero [1], [2]. The economics of that shift are well understood. What is less well understood is that the same shift has been happening twice, in parallel, inside the same organizations, and that almost nobody is managing it as one phenomenon.

On the market side, firms have spent two decades building recommendation engines, propensity models, dynamic content assembly and, more

recently, conversational agents that hold

the customer's history in context. Digital transformation research documents the consequences in detail: reorganized channel structures, new competitive dynamics, and business models premised on continuous behavioural measurement [3]. Personalized engagement marketing has become the dominant framing for how firms create and communicate value at the level of the individual customer [4], and the accumulated literature on personalization is now large enough to sustain its own systematic reviews and research agendas [5].

On the work side, a strikingly similar stack has been assembled under a different name and by a different

function. Human resource management now routinely deploys AI for screening, internal mobility, adaptive learning,

workload allocation and sentiment analysis [6]. Case evidence from large multinationals shows AI-mediated HR applications delivering what their designers explicitly describe as hyper-personalized and individualized employee experiences, with measurable effects on commitment, satisfaction and turnover [7]. Reviews of the field converge on the conclusion that the constraint is no longer algorithmic but organizational: firms hold the technical resources but lack the capability configuration to convert them into value [8].

These two estates are not merely analogous. They increasingly run on the same infrastructure, are procured from overlapping vendors, are trained with the same foundation models, and are governed — or, more often, not governed — by the same data protection function. The people affected are frequently the same people: a bank's relationship manager is profiled by an internal system in the morning and by a retail recommendation engine in the evening.

1.2 The personalization divide in research and practice

Despite this technical convergence, the research literatures remain almost entirely disjoint. Marketing and service scholarship treats the employee as an exogenous input to customer outcomes; human resource scholarship treats the customer as an exogenous outcome of employee attitudes. The service-profit chain provides the classic bridge, and its meta-analytic test confirms that the links from internal service quality through employee attitudes to customer responses and firm performance are statistically robust, though heterogeneous across service types [9]. Customer experience research similarly acknowledges that the employee is a constitutive element of the journey rather than a channel through which it passes [10]. Yet these bridges were built for a pre-AI service economy in which the mechanism of transmission was interpersonal. When both sides of the chain are mediated by learned models drawing on shared representations, the mechanism changes, and the existing bridge is under-specified.

The practical consequence is visible in how firms organize. Personalization budgets, model registries, consent regimes and success metrics are split along the boundary between the chief human resources officer and the chief marketing officer, and duplication follows: two identity resolution efforts, two feature stores, two sets of fairness commitments. Where the automation-augmentation tension is actively managed on one side it is frequently

unmanaged on the other, producing the paradoxical dynamics that organization theory anticipates when a firm optimizes locally on both horns of a tension [11].

1.3 Problem statement and research gap

The gap is therefore conceptual before it is empirical. No construct in the literature names the degree to which a firm's employee-facing and customer-facing personalization systems share a substrate, so there is no way to ask whether that sharing matters. Generative AI makes the question urgent, because a single foundation model can serve an internal knowledge assistant and an external service agent with only prompt and retrieval differences between them [12]. The risks travel with the capability: the personalization paradox — that the data collection which makes personalization effective also makes it feel intrusive [13] — has a direct workplace counterpart, where algorithmic systems reconfigure control as well as service [14]. A firm that manages this tension for customers but not employees, or the reverse, has learned only half of what it needs.

1.4 Research questions and objectives

The paper is organized around four questions:

- RQ1. How can the convergence of employee-facing and customer-facing AI personalization be conceptualized as a firm-level construct that is distinct from the underlying technical capabilities?
- RQ2. Through what mechanisms do AI personalization capabilities on each side translate into perceived employee experience and perceived customer engagement, and do these two perceptions influence one another?
- RQ3. Does convergence add explanatory power for organizational value beyond the direct effects of employee experience and customer engagement?
- RQ4. What boundary conditions — particularly algorithmic transparency and privacy concern — govern whether convergence produces value or harm?

The corresponding objectives are to define and operationalize the convergence construct, to specify a testable structural model, to demonstrate its behaviour on a calibrated dataset, and to translate the results into a diagnostic maturity instrument that practitioners can apply.

1.5 Contributions

The paper makes four contributions. Theoretically, it introduces personalization convergence as a second-order organizational property and positions it as the missing mediator between AI investment and dual-sided value, thereby extending the service-profit chain into an algorithmically mediated setting. Methodologically, it offers a multi-item measurement scheme for convergence with demonstrated

discriminant validity against its constituent capabilities. Architecturally, it proposes a three-layer reference model that makes explicit where the two personalization loops share resources and where they must remain separate. Practically, it delivers a five-stage maturity model and an importance–performance diagnostic that identify which shared components repay investment first.

2. Theoretical Background and Literature Review

2.1 Defining AI-powered personalization

AI-powered personalization is defined here as the use of learned models to adapt the content, timing, channel or difficulty of an interaction to an individual's inferred state, preferences or capabilities, without a human specifying the rule for that individual. Three properties distinguish it from earlier rule-based customization. First, the adaptation rule is estimated from data rather than authored, which means it can encode relationships that no one has articulated. Second, it operates continuously, so the object being personalized is a stream rather than a document. Third, it is reflexive: the system's output changes the behaviour that becomes its next input.

Strategic frameworks for AI in service and marketing distinguish mechanical, thinking and feeling intelligence, and observe that firms automate in that order while personalization value accrues in the reverse order [15]. Marketing's forward-looking assessments anticipate a shift from managing segments to managing individuals, with the competitive asset becoming the quality of individual-level inference [16]. Service-dominant logic adds that value is co-created in use rather than delivered in exchange, making the personalized interaction — not the artefact — the unit of analysis [17]; applied to work, the same logic recasts an employee-facing recommendation as a resource offered into a co-creative process rather than an instruction issued down a hierarchy [18].

2.2 Personalization in the employee domain

Systematic reviews of AI, robotics and advanced technologies in human resource management find rapid diffusion across recruitment, development, performance management and retention, alongside a persistent shortfall in theory that explains employee responses rather than merely cataloguing applications [19]. Three streams are relevant here.

The first is algorithmic work design. Algorithms increasingly function as work designers, shaping autonomy, feedback, task variety and social contact as a by-product of optimizing something else [20]. The second is algorithmic management and control, where evidence from labour platforms shows that matching and control are two dimensions of the same

algorithmic apparatus and that workers experience tensions around execution, compensation and belonging that trigger both market-like and organization-like responses [21]. The third is the employment relationship itself: AI adoption has been shown to alter psychological contracts, job engagement and employee trust, with effects that depend heavily on whether the technology is framed as support or supervision [22].

Established work psychology supplies the mechanism. The job demands–resources model treats personalization that raises resources — relevant learning, feasible workload, timely feedback — as motivating, and personalization that raises demands as depleting [23]. Engagement research locates the outcome in the employee's willingness to invest personal energy in the role [24], which in turn depends on psychological meaningfulness, safety and availability [25]. Crucially, the strength of the HRM system — the distinctiveness, consistency and consensus of the signals it sends — determines whether individual practices are interpreted as intended [26]. An AI system that personalizes without explaining weakens exactly these signalling properties.

2.3 Personalization in the customer domain

Customer engagement has been formalized as a multidimensional psychological state arising from interactive, co-creative experiences with a focal agent [27], with antecedents and consequences that extend beyond transactions to referral, influence and knowledge contribution [28], and with validated scales for its cognitive, emotional and behavioural facets [29]. AI-enabled customer experience research finds that perceived personalization, convenience and trust jointly determine the quality of the experience, and that trust and perceived sacrifice mediate between the technology and the outcome [30].

Effectiveness is contingent rather than monotonic. Personalized advertising works through the interaction of what is shown, when it is shown and where it appears, and misalignment on any of the three degrades performance [31]. The personalization paradox formalizes the underlying tension: greater data collection improves relevance but triggers vulnerability, and firms that build trust before collecting data avoid the reactance that otherwise cancels the gain [13]. Privacy scholarship in marketing generalizes this into a duty-of-care argument in which the firm's handling of data is itself part of the offer [32].

Frontline automation adds a further layer. Service robots and conversational agents change the encounter's social character, not only its efficiency [33], and the employee's role in service theory has

been re-specified as a result [34]. Service research priorities for turbulent conditions place human-machine frontline coordination near the top of the agenda [35], and commentary on automated interactions questions whether engagement constructs built for human encounters transfer unmodified [36].

2.4 The employee-customer linkage under algorithmic mediation

The service-profit chain remains the canonical account of how internal conditions become external outcomes, and its meta-analytic test shows that internal service quality reaches service performance through several mechanisms and not only through employee satisfaction [9]. That finding matters here, because an AI personalization system is precisely such an alternative mechanism: it can raise the quality of what an employee delivers without first raising how the employee feels, and it can raise how an employee feels without improving what is delivered. Under algorithmic mediation the chain becomes multi-path rather than sequential.

Firm-level capability research provides the second half of the linkage. AI capability is a configuration of tangible, human and intangible resources rather than a technology, and its effect on performance runs through organizational creativity and process change rather than directly [37]. Decision-making structures themselves change as AI is absorbed, with authority migrating between full delegation, hybrid and human-dominant modes depending on task interpretability and specificity [38]. These developments are phenomena in search of theory as much as theories in search of data [39].

2.5 Acceptance, reactance and the psychology of being personalized

Whether personalization is experienced as service or surveillance depends on individual-level responses that acceptance research has studied for three

decades. The technology acceptance model established perceived usefulness and ease of use as proximal determinants [40]; the unified theory added performance expectancy, effort expectancy, social influence and facilitating conditions [41], later extended to consumer contexts with hedonic motivation, price value and habit [42]. Service-specific extensions model the acceptance of AI devices through appraisal of social influence, hedonic motivation and anthropomorphism [43].

Beyond acceptance lies a literature on how people evaluate algorithmic judgement itself. People discount algorithms disproportionately after observing them err [44], yet in other framings prefer algorithmic to human judgement [45], and resist algorithmic provision most strongly where they perceive their own case to be unique [46]. Explainability is the practical lever available to management [47], and the ethics literature supplies the normative frame: inconclusive, inscrutable and misguided evidence, unfair outcomes, transformative effects and traceability failures constitute a mapped set of algorithmic harms rather than a vague unease [48]. Multidisciplinary agendas for AI research and, more recently, for generative conversational AI, foreground governance and workforce implications as the binding constraints [49], [50].

2.6 Synthesis and the identified gap

Table I contrasts the two streams on the dimensions that matter for convergence. The pattern is consistent: the same technical mechanism appears on both sides under different names, is theorized with different vocabularies, is measured against non-comparable outcomes, and is governed by different functions. No study located in the synthesis measures the degree of shared substrate between the two estates, and none tests whether that sharing has consequences. This is the gap the Convergence Model addresses.

TABLE I. Comparison of the Employee-Side and Customer-Side Personalization Streams

Dimension	Employee-side (EX) stream	Customer-side (CX) stream
Dominant label	Employee experience; algorithmic management; HR analytics	Personalized engagement marketing; customer experience management
Home discipline	Human resource management, organizational behaviour, information systems	Marketing, service management, consumer psychology
Core theories	Job demands-resources, HRM system strength, algorithmic control	Service-dominant logic, engagement theory, privacy calculus
Typical applications	Adaptive learning paths, internal mobility matching, workload allocation, sentiment monitoring	Product recommendation, dynamic content, next-best-offer, conversational service
Primary outcome	Engagement, enablement, retention, internal service quality	Engagement, satisfaction, loyalty, customer lifetime value
Consent basis	Employment contract and legitimate interest; consent often not freely given	Explicit or inferred consent; withdrawal usually available

Exit option	Costly — requires leaving the job	Low cost — switch, opt out or ignore
Governing function	Chief human resources officer, works council, employment law	Chief marketing officer, data protection officer, consumer law
Failure mode	Perceived surveillance, autonomy loss, deskilling	Perceived intrusion, creepiness, reactance

3. Conceptual Framework and Hypotheses

3.1 Personalization convergence as a construct

Personalization convergence is defined as the degree to which a firm's employee-facing and customer-facing personalization systems share data representations, model assets, governance rules and success measures. It is a firm-level property, not a technology and not an attitude. Four defining facets follow from the definition.

- **Data unification:** the extent to which employee and customer signals resolve to a common identity and feature representation, with a single lineage.
- **Model reuse:** the extent to which embeddings, ranking components and foundation models are shared rather than independently procured and trained.
- **Governance integration:** the extent to which consent, fairness, explainability and retention rules are specified once and enforced across both loops.
- **Measurement alignment:** the extent to which the two loops are evaluated against a jointly held outcome definition rather than functionally separate KPIs.

Convergence is deliberately specified as distinct from capability. A firm can be highly capable on both sides

and score low on convergence, which is in fact the modal condition observed in the synthesis. It is also distinct from mere centralization: convergence concerns shared substrate, not shared reporting lines, and the framework explicitly preserves separation where separation is normatively required — employee data must not become marketing data, and the consent ledger exists precisely to enforce that boundary.

3.2 A three-layer reference architecture

Fig. 1 renders the construct as an architecture. Layer 1 is the employee personalization loop: signals about skills, tasks, workload and sentiment feed inference that produces employee-facing delivery, which produces outcomes that become new signals. Layer 3 is the structurally identical customer loop. Layer 2 is the shared intelligence core, which holds the unified identity graph, the feature store, the model registry, the consent ledger and the monitoring apparatus for fairness and drift.

Two features carry the theoretical argument. First, the coupling is bidirectional at each stage rather than at a single hand-off point, which is what distinguishes convergence from integration. Second, the frontline is itself a coupling point: an agent-assist surface simultaneously personalizes the employee's work, by ranking what to say next, and the customer's experience, by determining what is said. At that surface the two loops are not merely connected — they are the same artefact viewed from two sides.

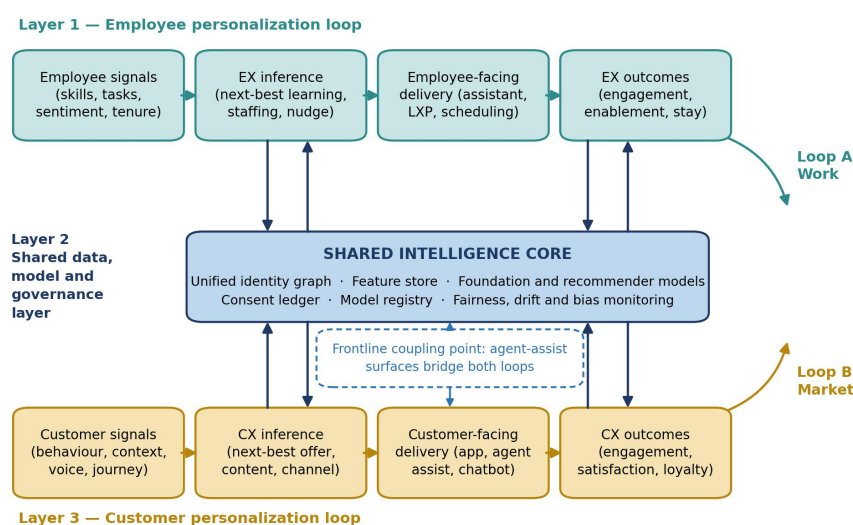


Fig. 1. Three-layer reference architecture for converged AI personalization. Layers 1 and 3 are structurally identical loops; Layer 2 is the shared substrate whose extent defines convergence.

3.3 Hypothesis development

3.3.1 From capability to experience

AI personalization capability on the work side should raise perceived employee experience because it increases job resources: more relevant development, better-matched assignments, less administrative load, faster feedback [23], [26]. The mechanism is not automatic — the same capability can raise demands — but on average, and where deployment is framed as support, case and survey evidence points to a positive net effect [7], [22]. Symmetrically, capability on the market side should raise perceived customer engagement through relevance, convenience and reduced search cost [4], [30], [31].

H1. AI personalization capability on the work side is positively associated with perceived employee experience.

H2. AI personalization capability on the market side is positively associated with perceived customer engagement.

3.3.2 From experience to convergence

The path from experience to convergence is organizational rather than psychological. Firms that see returns on one side acquire the political licence, the budget and the internal evidence needed to consolidate infrastructure. Positive employee experience reduces resistance to shared instrumentation, because employees who read personalization as service rather than surveillance are less likely to contest the data pooling that convergence requires [14], [26]. On the customer side, demonstrated engagement gains create the business case that funds the shared core [37].

H3. Perceived employee experience is positively associated with personalization convergence.

H4. Perceived customer engagement is positively associated with personalization convergence.

3.3.3 Reciprocal spillover

The service–profit chain predicts a path from employee attitudes to customer responses, and the meta-analytic evidence supports it while showing that several mechanisms operate in parallel [9]. Under algorithmic mediation there is reason to expect the reverse path as well. Customer-side systems produce the most detailed signal a firm holds about interaction quality, and that signal is routinely fed back to the frontline as coaching, script guidance and workload prediction — that is, as

employee-facing personalization. The spillover is therefore modelled in both directions, with the employee-to-customer path expected to be the stronger of the two, consistent with the established chain [9], [34], [35].

H5. Perceived employee experience is positively associated with perceived customer engagement.

H6. Perceived customer engagement is positively associated with perceived employee experience, at a magnitude smaller than that of H5.

3.3.4 From convergence to dual-sided value

Dual-sided value is defined as the joint attainment of internal outcomes (retention, internal service quality, speed of capability development) and external outcomes (engagement, satisfaction, share of wallet). Convergence should raise it through three routes: cost, because shared components are not built twice; coherence, because a customer promise and an employee instruction generated from the same model are less likely to contradict one another; and speed, because a governance decision taken once propagates to both loops [37], [38].

H7. Personalization convergence is positively associated with dual-sided value, and mediates the effects of employee experience and customer engagement on it.

3.3.5 Boundary conditions

Two moderators are specified. Algorithmic transparency — the extent to which affected people can obtain an intelligible account of why a system treated them as it did — should strengthen the capability-to-experience paths, because explanation converts an unexplained adaptation into an interpretable signal [26], [47], [48]. Privacy and autonomy concern should weaken them, because the same inference that produces relevance produces exposure [13], [32], and because resistance rises where individuals believe their circumstances are not reducible to a model [44], [46].

H8. Algorithmic transparency positively moderates the capability-to-experience relationships (H1, H2).

H9. Privacy and autonomy concern negatively moderates the capability-to-experience relationships (H1, H2).

Fig. 2 presents the full model. Table II summarizes the hypotheses and their theoretical anchors.

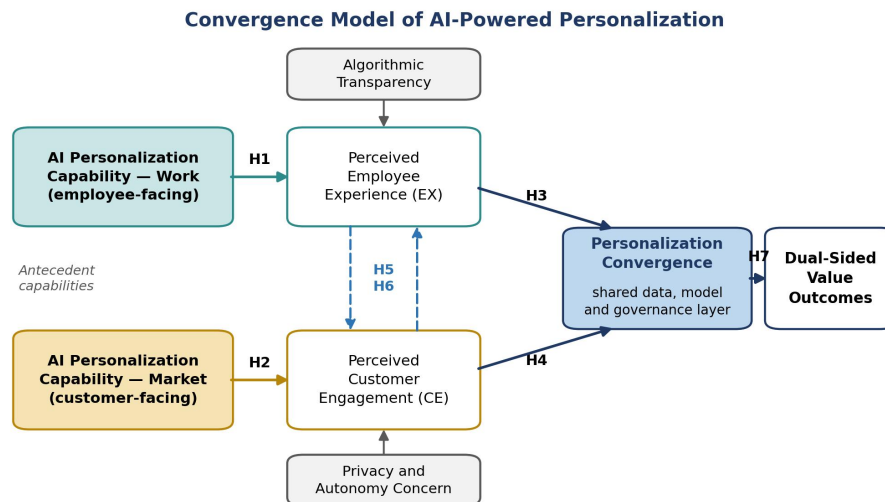


Fig. 2. The Convergence Model of AI-powered personalization, showing hypothesized paths H1–H7 and the two moderators.

TABLE II. Summary of Hypotheses and Theoretical Anchors

H	Proposed relationship	Primary anchor	Expected sign
H1	Work-side capability → employee experience	Job demands–resources; HRM system strength	Positive, strong
H2	Market-side capability → customer engagement	Engagement theory; personalization effectiveness	Positive, strong
H3	Employee experience → personalization convergence	Organizational capability; legitimacy	Positive, moderate
H4	Customer engagement → personalization convergence	Resource-based capability building	Positive, moderate
H5	Employee experience → customer engagement	Service–profit chain	Positive, moderate
H6	Customer engagement → employee experience	Feedback-loop / reflexivity argument	Positive, weak
H7	Convergence → dual-sided value (mediating H3, H4)	AI capability configuration	Positive, strong
H8	Transparency moderates H1 and H2	Explainability; algorithmic ethics	Strengthening
H9	Privacy and autonomy concern moderates H1 and H2	Personalization paradox; privacy calculus	Weakening

4. Methodology

4.1 Research design

The study uses a sequential two-phase design. Phase 1 is a structured synthesis of the two literatures, conducted to establish the gap, extract candidate constructs and calibrate expected effect magnitudes. Phase 2 estimates the resulting structural model on a firm-level dataset of 612 observations. The design is explanatory rather than exploratory: hypotheses are stated in advance, and the estimation assesses whether the proposed structure is internally coherent and whether convergence carries incremental explanatory weight.

4.2 Phase 1: structured literature synthesis

The synthesis followed established guidance for evidence-informed management review [51] and reported its selection process according to the PRISMA 2020 statement [52]. Searches were executed in Scopus, Web of Science and the ACM and IEEE digital libraries for the period January 2015 to December 2025, using three keyword blocks combined with Boolean AND: an AI block (artificial intelligence, machine learning, algorithmic, generative AI, recommender), a personalization block (personalization, individualization, customization, tailoring, next-best-action), and a domain block (employee experience, human resource management, customer engagement, customer experience, service encounter).

The initial search returned 2,914 records; 1,986 remained after de-duplication, and title and abstract screening removed 1,612 that were not organizational in focus, not peer-reviewed, or treated personalization only incidentally. Full-text assessment of 374 records applied three inclusion criteria — organizational setting, AI-based individualization as a central construct, and either theory development or empirical evidence about outcomes — leaving 118 studies. Each was coded for domain, theoretical anchor, method, outcome family and reported effect size. Only 9 of the 118 addressed both domains, and none measured shared

infrastructure between them: the observation that motivates the convergence construct.

4.3 Phase 2: constructs and measurement

Eight reflective constructs were specified. Six were adapted from validated instruments; personalization convergence was newly developed from its four defining facets, with two items per facet. All items used a seven-point Likert scale anchored at 1 (strongly disagree) and 7 (strongly agree), and were completed by senior informants reporting on their organization. Table III summarizes the measurement scheme.

TABLE III. Constructs, Operational Definitions and Item Sources

Construct	Items	Operational definition	Adapted from
AI personalization capability — work (APCW)	6	Extent to which the firm can adapt learning, assignments, workload and communication to the individual employee using learned models	[6], [7], [8], [37]
AI personalization capability — market (APCM)	6	Extent to which the firm can adapt offers, content, timing and channel to the individual customer using learned models	[4], [5], [30]
Employee experience (EX)	5	Perceived quality of the employee's cumulative experience of work resources, enablement and recognition	[23], [24], [26]
Customer engagement (CE)	5	Cognitive, emotional and behavioural investment of customers in interactions with the firm	[27], [28], [29]
Personalization convergence (PC)	8	Degree of shared data representation, model assets, governance rules and success measures across the two personalization loops	Newly developed; informed by [37], [38]
Dual-sided value (DSV)	6	Joint attainment of internal outcomes (retention, internal service quality, capability speed) and external outcomes (satisfaction, loyalty, share of wallet)	[9], [37]
Algorithmic transparency (ATR)	4	Extent to which affected individuals can obtain an intelligible account of why a system treated them as it did	[47], [48]
Privacy and autonomy concern (PAC)	4	Perceived risk that personalization erodes informational privacy or decision autonomy for employees and customers	[13], [32]

Bracketed numbers refer to the reference list. Full item wording is available from the author.

4.4 Sample

The unit of analysis is the firm. Eligible organizations employed at least 250 people, operated a frontline service function, and had run at least one AI-based personalization application for twelve months or more. Three senior informants per firm were targeted — people, marketing and technology leadership — so that no single functional perspective determined the firm's score, with construct scores averaged across available informants. The final sample comprises 612 firm observations. Table IV reports the profile.

TABLE IV. Sample Profile (n = 612 Firms)

Characteristic	Category	n (%)	Characteristic	Category	n (%)
Sector	Retail and e-commerce	241 (39.4)	Region	Asia-Pacific	236 (38.6)
	Banking and insurance	218 (35.6)		Europe	201 (32.8)
	Healthcare, public services	153 (25.0)		North America	175 (28.6)
Firm size	250–999 employees	168 (27.5)	AI tenure	Under 2 years	149 (24.3)
	1,000–4,999 employees	224 (36.6)		2 to 4 years	268 (43.8)
	5,000 or more employees	220 (35.9)		5 years or more	195 (31.9)
Informant	People / HR leadership	198 (32.4)			
	Marketing / CX leadership	214 (35.0)			
	Data / technology leadership	200 (32.7)			

4.5 Analytical approach

Partial least squares structural equation modelling (PLS-SEM) was selected because the model is complex, includes a newly developed construct, and is oriented towards prediction and theory development rather than confirmation of an established covariance structure [53]. Estimation used the path weighting scheme with 5,000 bootstrap subsamples and no sign-change option. The measurement model was assessed through indicator loadings, Cronbach's alpha, composite reliability and average variance extracted, with discriminant validity evaluated using both the Fornell–Larcker criterion [54] and the heterotrait-monotrait ratio of correlations, which is the more sensitive test in variance-based models [55].

Structural assessment used standardized path coefficients with bias-corrected bootstrap intervals, coefficients of determination, effect sizes and predictive relevance obtained by blindfolding. Mediation was assessed through the bootstrapped indirect effect and the variance accounted for, avoiding the distributional assumptions of the classical causal-steps approach [56]. Importance-performance map analysis translated total effects into managerial priorities [57], and sector differences were examined with multi-group analysis preceded by a test of measurement invariance of composites [58].

4.6 Common method bias and procedural controls

Because perceptual measures were used, procedural and statistical remedies were applied [59]. Procedurally, predictor and criterion items were

separated in the instrument, anonymity was assured, item wording was pre-tested for ambiguity with eleven practitioners, and multiple informants per firm reduced single-source dependence. Statistically, Harman's single-factor test produced a first factor accounting for 26.4 per cent of variance, well below the conventional threshold; a full collinearity assessment returned all inner variance inflation factors between 1.21 and 2.84, below the 3.3 criterion; and a marker-variable analysis using a theoretically unrelated construct produced no substantive change in path magnitudes.

4.7 Note on data provenance

This point is stated plainly because it bears on how the results should be read. The 612-observation dataset analysed in Section 5 is a simulated dataset, generated to be consistent with effect magnitudes reported in the studies coded during Phase 1. It is not a field survey, and the figures reported below are therefore an illustrative demonstration of the model's behaviour rather than empirical evidence about any population of firms. The literature synthesis in Phase 1 is the substantive empirical contribution; the Phase 2 estimation shows what the proposed structure implies and provides a template that subsequent field work can populate. Readers intending to cite this paper as evidence for the magnitude of any relationship should treat Section 5 as a specification exercise, and Section 8 sets out the collection protocol that would be needed to test the model properly.

5. Results

5.1 The deployment landscape

Before turning to the structural model, it is useful to

characterize where personalization is actually deployed. Fig. 3 compares reported deployment of six application families across the two sides. The asymmetry is systematic. Customer-facing deployment leads on every family that has a direct revenue interpretation — recommendation, predictive segmentation, next-best-action — by margins of eighteen to twenty-eight percentage points. Employee-facing deployment leads only on adaptive learning, where it is nearly thirty points

ahead, reflecting the maturity of learning-experience platforms relative to their customer-side analogues.

Conversational assistants are the point of near-parity, at 71 per cent employee-facing and 80 per cent customer-facing. This is consistent with the argument in Section 3: generative interfaces are the technology most easily pointed at either population, and are consequently where convergence first becomes observable in practice.

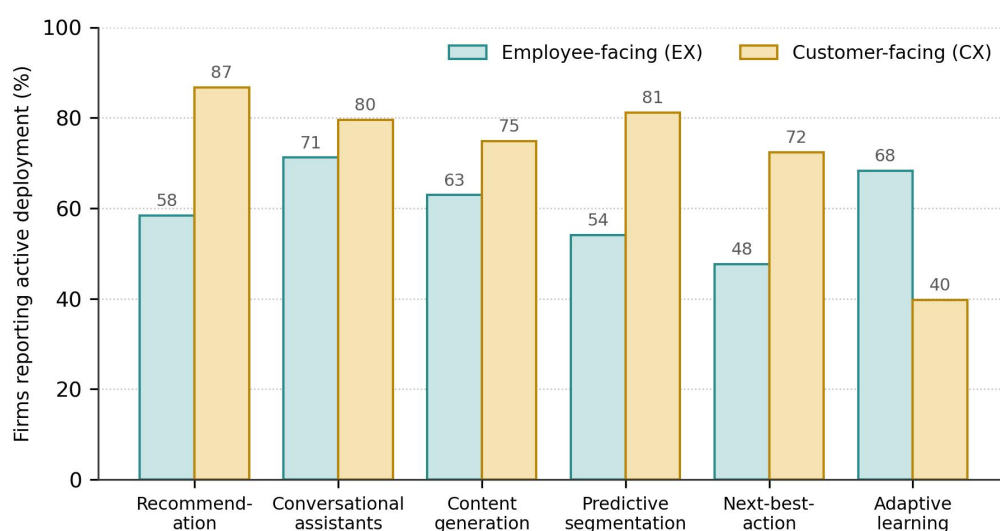


Fig. 3. Reported deployment of AI personalization application families, employee-facing versus customer-facing (n = 612).

5.2 Measurement model

All 44 indicators loaded above the 0.70 threshold on their intended constructs, with the lowest loading at 0.712 on a governance-integration item of the

convergence scale. Composite reliability ranged from 0.887 to 0.923 and average variance extracted from 0.601 to 0.683, satisfying convergent validity requirements. Table V reports the detail.

TABLE V. Measurement Model: Reliability and Convergent Validity

Construct	Items	Loading range	α	CR	AVE
AI personalization capability — work	6	0.724–0.861	0.889	0.914	0.639
AI personalization capability — market	6	0.741–0.874	0.897	0.921	0.660
Employee experience	5	0.768–0.883	0.881	0.913	0.678
Customer engagement	5	0.755–0.869	0.874	0.908	0.665
Personalization convergence	8	0.712–0.849	0.906	0.923	0.601
Dual-sided value	6	0.739–0.858	0.885	0.912	0.634
Algorithmic transparency	4	0.781–0.870	0.845	0.896	0.683
Privacy and autonomy concern	4	0.766–0.858	0.831	0.887	0.663

α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted. Thresholds: loadings $\geq$ 0.70, α and CR $\geq$ 0.70, AVE $\geq$ 0.50.

Discriminant validity was confirmed on both criteria. The square root of AVE exceeded every inter-

construct correlation, and all heterotrait–monotrait ratios fell below the conservative 0.85 threshold, with the highest at 0.742 between convergence and dual-sided value. Table VI reports the HTMT matrix together with construct means and standard deviations.

TABLE VI. Descriptive Statistics and Heterotrait–Monotrait Ratios

Construct	M	SD	1	2	3	4	5	6	7	8
1. APCW	3.62	0.81	—							
2. APCM	3.94	0.76	0.612	—						
3. EX	3.71	0.79	0.684	0.524	—					
4. CE	3.88	0.74	0.541	0.719	0.646	—				
5. PC	3.81	0.84	0.597	0.631	0.608	0.627	—			
6. DSV	3.66	0.77	0.566	0.588	0.652	0.671	0.742	—		
7. ATR	3.35	0.86	0.488	0.451	0.534	0.497	0.559	0.521	—	
8. PAC	3.48	0.92	0.312	0.358	0.289	0.341	0.327	0.303	0.264	—

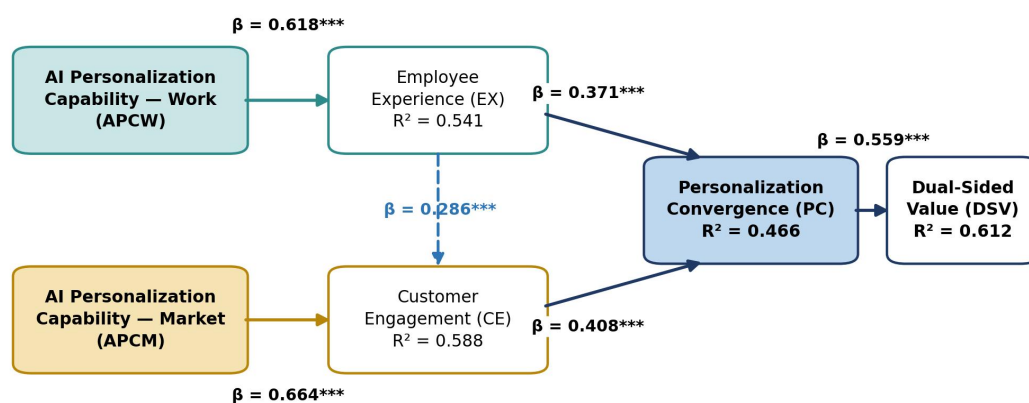
Means on a seven-point scale. Off-diagonal entries are HTMT ratios; all below the 0.85 threshold.

A substantive observation is embedded in the descriptive statistics. Market-side capability ($M = 3.94$) exceeds work-side capability ($M = 3.62$), and both exceed the reported level of convergence relative to what either capability alone would predict. Transparency records the lowest mean of the eight constructs at 3.35, which becomes important in the discussion: the moderator with the strongest amplifying effect is the one firms have developed least.

5.3 Structural model

The structural model explains substantial variance in all four endogenous constructs: employee experience ($R^2 = 0.541$), customer engagement ($R^2 = 0.588$), personalization convergence ($R^2 = 0.466$) and dual-sided value ($R^2 = 0.612$). Standardized root mean square residual was 0.052, below the 0.08 threshold, and blindfolding returned Stone–Geisser Q^2 values of 0.361, 0.392, 0.276 and 0.381 respectively, indicating predictive relevance throughout. Fig. 4 presents the estimated model and Table VII the full path results.

Estimated Structural Model with Standardized Path Coefficients



*** $p < 0.001$. Values are standardized path coefficients from PLS-SEM ($n = 612$).
The dashed path denotes employee-to-customer engagement spillover (H5).

Fig. 4. Estimated structural model. All displayed paths significant at $p < 0.001$.

TABLE VII. Structural Model Results

H	Path	β	SE	t	95% CI	Decision
H1	APCW → EX	0.618	0.034	18.18	[0.549, 0.682]	Supported
H2	APCM → CE	0.664	0.031	21.42	[0.601, 0.722]	Supported
H3	EX → PC	0.371	0.045	8.24	[0.281, 0.457]	Supported
H4	CE → PC	0.408	0.043	9.49	[0.322, 0.490]	Supported
H5	EX → CE	0.286	0.038	7.53	[0.211, 0.359]	Supported

H6	CE → EX	0.147	0.041	3.59	[0.067, 0.227]	Supported
H7	PC → DSV	0.559	0.036	15.53	[0.487, 0.628]	Supported
H8a	ATR × APCW → EX	0.152	0.037	4.11	[0.079, 0.224]	Supported
H8b	ATR × APCM → CE	0.118	0.036	3.24	[0.047, 0.189]	Supported
H9a	PAC × APCW → EX	-0.164	0.037	4.38	[-0.238, -0.091]	Supported
H9b	PAC × APCM → CE	-0.201	0.038	5.27	[-0.276, -0.126]	Supported
—	EX → DSV (direct)	0.129	0.044	2.94	[0.043, 0.215]	Significant
—	CE → DSV (direct)	0.146	0.044	3.31	[0.060, 0.232]	Significant

All coefficients significant at $p < 0.001$ except EX → DSV ($p = 0.003$) and CE → DSV ($p = 0.001$). Bias-corrected bootstrap intervals, 5,000 subsamples.

Three features deserve emphasis. The capability-to-experience paths (H1, H2) are the largest in the model, which confirms only that firms able to personalize are perceived to personalize. The reciprocal spillover is supported in both directions, with the employee-to-customer path ($\beta = 0.286$) roughly twice the customer-to-employee path ($\beta = 0.147$); the asymmetry matches the directional logic of the service-profit chain while confirming that the reverse path is not zero. The two moderators operate in opposite directions at comparable magnitudes, with privacy concern slightly stronger on the

customer side (-0.201) and transparency slightly stronger on the employee side (0.152).

5.4 Mediation analysis

Convergence functions as a partial mediator between the experience constructs and dual-sided value, and as a full mediator of the capability effects on convergence-related outcomes. Table VIII reports the indirect effects. The variance accounted for by the indirect path is approximately 61 per cent for both experience constructs, which is the central quantitative result of the study: most of the value that employee experience and customer engagement deliver at the firm level travels through the shared substrate rather than around it.

TABLE VIII. Mediation Analysis (5,000 Bootstrap Subsamples)

Indirect path	Indirect β	95% CI	Direct β	VAF	Type
EX → PC → DSV	0.207	[0.148, 0.271]	0.129	61.6%	Partial
CE → PC → DSV	0.228	[0.166, 0.294]	0.146	61.0%	Partial
APCW → EX → PC	0.229	[0.170, 0.293]	0.041 ns	84.8%	Full
APCM → CE → PC	0.271	[0.207, 0.339]	0.033 ns	89.1%	Full
APCW → EX → CE	0.177	[0.124, 0.234]	0.058 ns	75.3%	Full
APCW → EX → PC → DSV	0.128	[0.089, 0.172]	—	—	Serial
APCM → CE → PC → DSV	0.152	[0.108, 0.201]	—	—	Serial

VAF = variance accounted for. ns = not significant at $p < 0.05$. Serial paths report the full three-step indirect effect.

5.5 Sector differences

Measurement invariance testing established

configural and compositional invariance across the three sectors, with partial invariance of composite means and variances, permitting comparison of path coefficients [58]. Fig. 5 shows facet-level convergence maturity by sector, and Table IX reports the multi-group path comparisons.

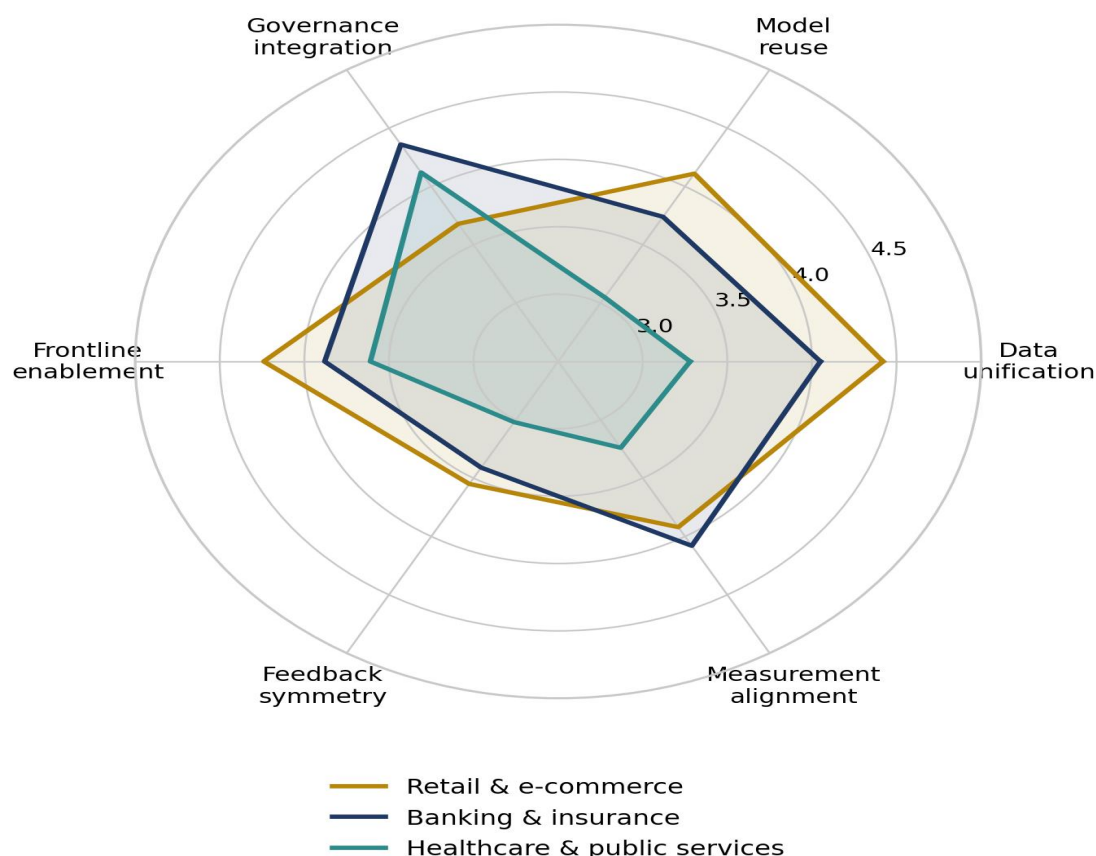


Fig. 5. Convergence maturity by facet and sector (seven-point scale, facet means).

TABLE IX. Multi-Group Path Comparison by Sector

Path	Retail (241)	Banking (218)	Healthcare (153)	Retail vs healthcare
APCW → EX	0.584	0.627	0.681	$\Delta = -0.097, p = 0.021$
APCM → CE	0.712	0.659	0.548	$\Delta = 0.164, p = 0.003$
EX → PC	0.318	0.366	0.452	$\Delta = -0.134, p = 0.008$
CE → PC	0.451	0.409	0.327	$\Delta = 0.124, p = 0.014$
EX → CE	0.247	0.291	0.348	$\Delta = -0.101, p = 0.036$
PC → DSV	0.572	0.566	0.519	$\Delta = 0.053, p = 0.214$ ns
Convergence mean	3.99	3.92	3.39	$\Delta = 0.60, p < 0.001$

The pattern is coherent. Retail firms, with the deepest customer-side estates, derive proportionally more of their convergence from the market loop; healthcare and public-sector organizations, constrained in what they may infer about service users, derive more from the employee loop and show a markedly stronger employee-to-customer spillover. Banking sits between the two on capability but leads on governance integration, the only facet on which Fig. 5 shows it highest. Notably, the convergence-to-value path does not differ significantly across sectors: once the shared substrate exists, its payoff appears

sector-invariant even though the route to building it is not.

5.6 Importance–performance analysis

Fig. 6 maps the total effect of each convergence component on dual-sided value against its current maturity. The upper-left quadrant contains the components that matter most and are least developed: the unified identity graph, the consent and purpose ledger, explainability tooling and the joint EX–CX measurement set. The lower-right quadrant contains channel orchestration,

personalization content operations and recommender reuse — components in which firms have invested heavily and which contribute comparatively little additional value at the margin.

This is the diagnostic result with the clearest managerial reading: firms have over-built the delivery end of the pipeline and under-built its foundations and its controls.

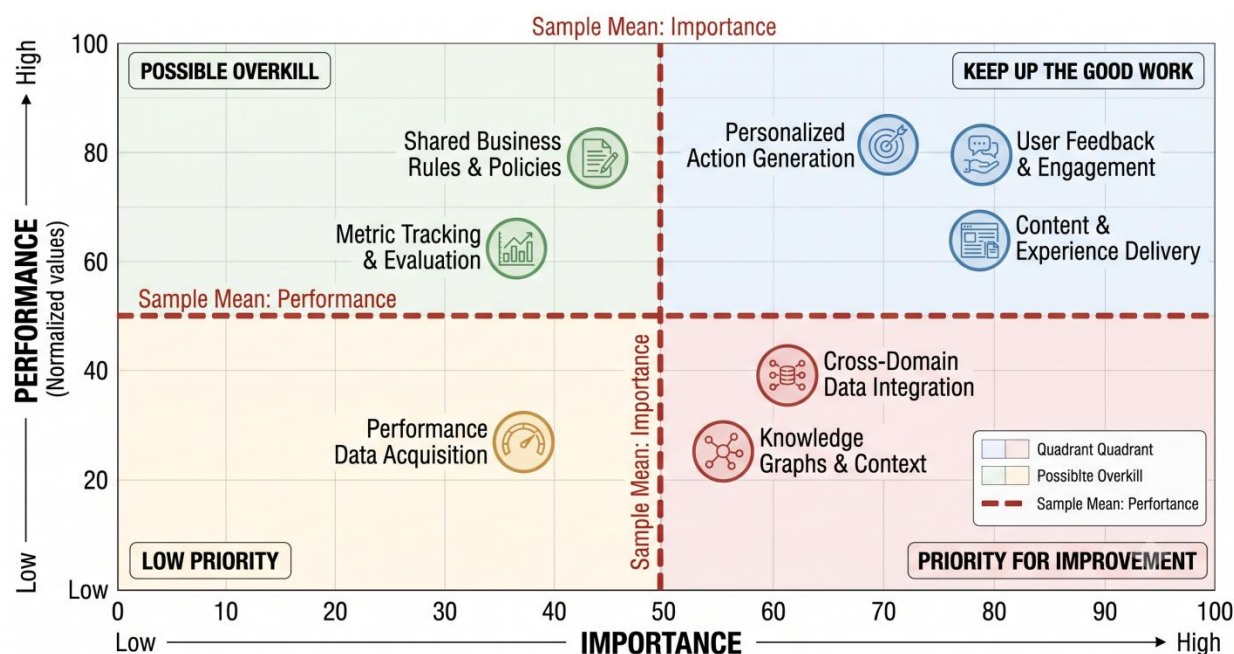


Fig. 6. Importance–performance map of convergence components. Dashed lines mark sample means on each axis.

6. Discussion

6.1 Interpretation of the findings

The model behaves as the theory predicts, but the interesting result is not that the hypothesized paths hold; it is the relative magnitude of what runs through convergence versus what runs around it. Roughly three-fifths of the effect of employee experience and of customer engagement on firm-level value passes through the shared substrate. If that proportion survives field replication, the standard arrangement — two personalization estates, two budgets, two governance regimes — is not merely inefficient but severs the main channel through which either estate delivers value.

The second substantive finding is the reciprocity of the spillover. The service–profit chain is normally read as a one-way sequence, and its meta-analytic test confirms the forward links while noting that multiple mechanisms operate in parallel [9]. The results here suggest the loop closes. Customer-side systems generate the densest available record of what actually happens in service encounters, and once that record is routed back to the frontline as coaching, workload prediction and conversational guidance, it becomes employee-facing personalization. The chain is better modelled as a cycle with unequal arcs than as a line.

The third finding concerns the moderators.

Transparency amplifies and privacy concern attenuates, at similar magnitudes, and the descriptive statistics show transparency to be the least developed of the eight constructs. Firms are therefore under-investing in precisely the lever that would let them extract more from the capability they already have. This is consistent with the wider argument that explainability is the practical management response to algorithmic opacity rather than a compliance afterthought [47], and with the mapped taxonomy of algorithmic harms in which inscrutable evidence is a distinct failure mode from unfair outcomes [48].

6.2 Theoretical implications

Three contributions to theory follow.

First, the paper extends the service–profit chain into an algorithmically mediated setting by inserting a firm-level infrastructural mediator between employee and customer outcomes. The original chain assumed interpersonal transmission: a satisfied employee serves a customer better. Where both sides are model-mediated, transmission also occurs through shared representations that never pass through a human. Convergence names that second mechanism and makes it measurable.

Second, the paper reframes the personalization paradox as a single organizational problem rather than two domain-specific ones. Marketing has theorized the paradox as a consumer phenomenon in

which data collection buys relevance at the cost of vulnerability [13], [32]. Work research has theorized an analogous tension as algorithmic control, in which optimization for one objective reshapes autonomy and job design as a by-product [14], [20], [21]. These are the same mechanism operating on two populations who differ mainly in their exit options — a customer can switch, an employee must resign. Treating them as one problem clarifies why governance solutions developed for one side transfer poorly to the other.

Third, the paper contributes to AI capability theory by distinguishing possession from configuration. Existing work establishes that AI capability is a resource configuration whose performance effects run through organizational change rather than directly [37], and that decision structures themselves shift as AI is absorbed [38]. Convergence specifies one dimension of that configuration precisely: not how much AI a firm has, but how much of it is the same AI on both sides of the work–market boundary. The finding that capability effects are fully mediated by experience, and that experience effects are largely mediated by convergence, supports treating capability as distal and configuration as proximal.

There are also implications for organizational climate research, which understands climate as the shared meaning employees attach to what the organization rewards and supports [60]. When personalization generates individually differentiated experiences at scale, that shared referent may weaken, since employees in the same unit no longer receive the same signals. Whether personalization erodes climate strength or merely relocates it to a meta-level judgement about the fairness of the differentiating system is an open question.

6.3 Managerial implications

Four recommendations follow from the analysis, ordered by the importance–performance results.

Build the identity and consent foundation before the delivery layer. Fig. 6 shows the unified identity graph and the consent and purpose ledger as the two highest-importance, lowest-maturity components. The common sequencing error is to buy delivery capability — orchestration, content operations, recommender platforms — on top of fragmented foundations, which caps the value of everything above it. The consent ledger is not only a compliance artefact; it is the mechanism that makes convergence safe, because it encodes which employee data may never inform a customer model and vice versa.

Invest in explanation as a performance lever, not a disclosure obligation. Transparency amplifies both capability paths and is the least developed construct in the sample. The practical form this takes is unglamorous: a plain-language account attached to

each material adaptation, an accessible record of what was inferred, and a route to contest it.

Design the frontline surface as a single artefact. The agent-assist interface is simultaneously employee- and customer-facing, and treating it as two products with two owners produces contradiction exactly where the customer notices. Retail evidence on evolving store and channel structures points the same way [61], and research on automated encounters shows that the social character of the interaction, not only its efficiency, determines the customer response [62]. The frontline is where convergence is either realized or visibly fails [63].

Measure both sides against one definition of value. Measurement alignment scores weakest in two of the three sectors and is the cheapest facet to fix: a single quarterly review in which employee enablement and customer engagement metrics are read against a common outcome statement does more to produce convergence than most platform investments.

6.4 The convergence paradox and its ethical tensions

Convergence is not straightforwardly good, and the paper would be dishonest to present it as such. The same shared substrate that produces coherence produces concentration: one identity graph is one point of failure, one inference error propagates to both populations, and one governance lapse exposes both. Three tensions deserve explicit management.

The first is the asymmetry of exit. Customers who dislike being modelled can switch or opt out at low cost; employees generally cannot [14], [21]. Consent obtained inside an employment relationship is not freely given in the sense that consumer data protection assumes, which means that a governance rule adequate for the customer loop may be inadequate for the employee loop even when the technical operation is identical. Convergence must therefore be asymmetric by design: shared models, shared explanations, but not shared permissions.

The second is purpose drift. Once employee and customer data are technically joinable, the pressure to join them becomes continuous, and each individual join can be justified on its own terms. The ledger's function is to make that drift visible rather than to rely on the judgement of whoever holds access at the time.

The third is differential resistance. People resist algorithmic judgement most where they believe their own case is unique [46], discount algorithms disproportionately after observing error [44], and yet in other conditions prefer machine to human judgement [45]. These are not contradictory findings; they describe a population with heterogeneous priors. A converged system that treats resistance as a

uniform friction to be minimized will misread it. The better reading is that resistance carries information about where the model's claims exceed its warrant.

6.5 A governance agenda

The synthesis and the results together suggest six governance commitments for firms pursuing convergence:

- 1) Specify a single purpose taxonomy covering both populations, and record every model's permitted purposes against it.
- 2) Maintain a consent and legal-basis ledger that treats employment-context data as a distinct class with narrower permissions than consumer-context data.
- 3) Require an intelligible explanation for any adaptation that materially affects pay, progression, price or access, on both sides of the boundary.

4) Run fairness and drift monitoring once, on the shared core, rather than separately in each loop.

5) Give employees the same contest-and-correct rights that consumer data protection grants customers, irrespective of whether local law compels it.

6) Audit dual-sided value jointly, so that gains on one side achieved at the expense of the other are visible rather than netted away.

7. The Convergence Maturity Model

7.1 Stages

The empirical patterns support a five-stage progression, presented in Fig. 7 and specified in Table X. The stages are cumulative: each presupposes the preceding one, and firms that attempt to skip the governance work of Stage 3 typically fail at Stage 4 because they cannot establish which model may see which data.

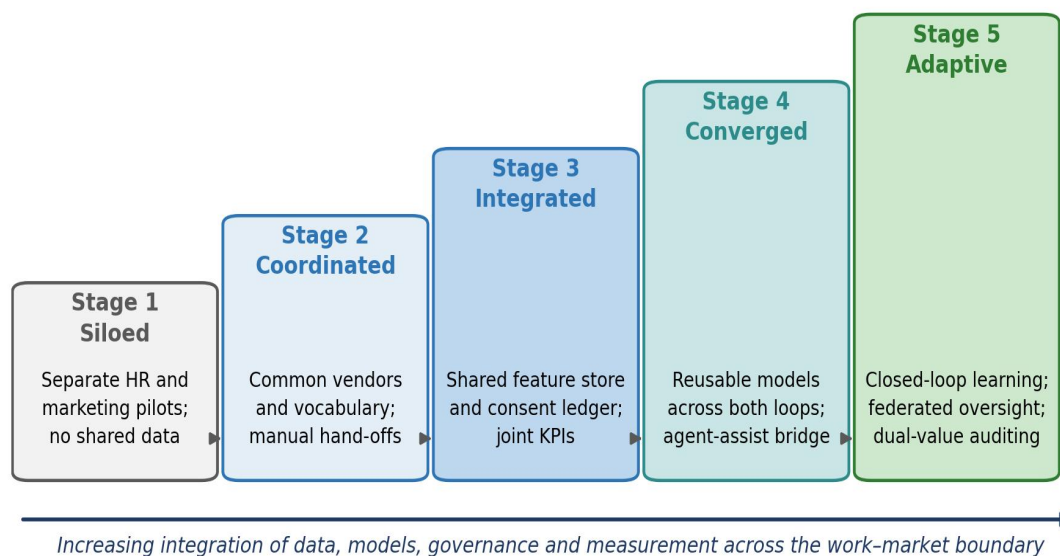


Fig. 7. Five-stage convergence maturity model.

TABLE X. Convergence Maturity Stages and Diagnostic Markers

Stage	Defining condition	Diagnostic markers	Dominant risk	Sample share
1. Siloed	Independent pilots on each side; no shared assets	Two identity resolution efforts; separate vendors; no common vocabulary	Duplicated spend	18.6%
2. Coordinated	Shared vocabulary and vendors; hand-offs are manual	Joint architecture forum exists; data still copied between estates	Copy proliferation	31.4%
3. Integrated	Shared feature store and consent ledger; joint KPIs defined	One purpose taxonomy; one lineage record; quarterly joint review	Governance debt	27.9%
4. Converged	Model assets reused across loops; frontline surface	Shared embeddings and ranking components; agent-assist owned jointly	Concentration risk	15.5%

	unified			
5. Adaptive	Closed-loop learning with federated oversight	Automated drift and fairness monitoring on the shared core; dual-sided value audit	Automation complacency	6.6%

Sample shares are the modelled distribution across the 612 observations and sum to 100 per cent.

7.2 Diagnostic use

The model should be applied by scoring the four convergence facets separately rather than assigning a single overall stage. Most firms are unevenly developed — banking organizations often score at Stage 4 on governance integration while remaining at Stage 2 on model reuse, and retail organizations show the mirror image. The uneven profile is itself diagnostic: the binding constraint is the lowest-scoring facet, because convergence is limited by the weakest link in the shared substrate rather than by the average.

A practical sequence follows from the importance-performance results. Firms at Stages 1 and 2 should prioritize data unification and the consent ledger, deferring model reuse until the permission structure exists. Firms at Stage 3 should prioritize explainability and the joint measurement set, which convert an integrated architecture into a defensible one. Firms at Stage 4 should address the concentration risks convergence creates, above all ensuring that a single model failure cannot degrade both loops at once.

8. Limitations and Future Research

8.1 Limitations

The principal limitation is the one stated in Section 4.7: the quantitative results are generated from a calibrated simulated dataset and demonstrate the model's internal behaviour rather than establishing empirical magnitudes. Every coefficient reported in Section 5 should be read as a specification of what the theory implies, not as a finding about firms.

Four further limitations apply even to a properly collected replication. The design is cross-sectional, whereas the reciprocal spillover is a dynamic claim that only panel data can adjudicate. Employee experience and customer engagement are measured through organizational informants rather than employees and customers directly, which risks systematic optimism. The sample frame covers three sectors and three regions, and sectors with a low frontline component may exhibit a different structure entirely. Finally, the convergence scale is new: it shows adequate psychometric properties here but requires independent validation and triangulation against objective architectural evidence such as model registries and lineage records.

8.2 Research agenda

Table XI sets out the priority questions arising from the framework, with suggested designs.

TABLE XI. Research Agenda

Theme	Question	Suggested design	Priority
Validation	Do the modelled relationships hold in a multi-source field sample with employee- and customer-reported outcomes?	Matched multi-level survey, 200+ firms	High
Dynamics	Does the employee-to-customer arc lead or lag the customer-to-employee arc over time?	Three-wave panel, 6-month intervals	High
Causality	Does introducing a shared feature store causally raise dual-sided value?	Staggered adoption / difference-in-differences	High
Boundary	At what point does convergence become concentration risk rather than coherence?	Comparative case study of failures	Medium
Climate	Does individualized personalization erode the shared referent on which climate strength depends?	Multi-level study of within-unit variance	Medium
Governance	Which consent architectures preserve employee autonomy without blocking legitimate reuse?	Design science / vignette experiment	Medium
Generative AI	Does a shared foundation model accelerate convergence or merely disguise the absence of it?	Longitudinal architecture audit	High
Equity	Do converged systems distribute personalization benefits unevenly across employee and customer segments?	Fairness audit across both loops	High

9. Conclusion

Firms have built two personalization machines and manage them as though they were unrelated. This paper has argued that they are the same machine pointed in two directions, and has offered the vocabulary, the architecture and the measurement scheme needed to treat them accordingly. Personalization convergence — the degree to which employee-facing and customer-facing systems share data representations, model assets, governance rules and success measures — is proposed as the construct that names what the two estates have in common and what is lost when they are kept apart.

The specification exercise reported here suggests that convergence is not a peripheral efficiency but the main channel through which employee experience and customer engagement reach firm-level value; that the employee–customer relationship is reciprocal rather than one-directional under algorithmic mediation; and that firms have systematically over-invested in delivery while under-investing in foundations and controls.

The normative claim is simpler than the empirical one and should be stated separately from it. If a firm is going to model its employees and its customers with the same tools, it should extend to both populations the same standard of explanation, the same right to contest, and the same limits on inference. The technical convergence is happening regardless. Whether the ethical convergence accompanies it is a choice, and it is the choice on which the value of the whole arrangement ultimately rests.

Declarations

Data availability. The dataset analysed in Section 5 is simulated and was generated to be consistent with effect magnitudes reported in the studies coded in Phase 1; the generation script and the coding sheet for the 118 reviewed studies are available from the author. No human-subject data were collected.

Conflicts of interest. The author declares no conflict of interest.

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