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When the Algorithm Becomes the Brand: How Consumer-Facing Artificial Intelligence Builds Platform Brand Equity Through Customer Experience, and Why AI Literacy Weakens the Effect

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Abstract

Digital platforms increasingly deliver brand encounters through algorithms, making artificial intelligence (AI) part of the brand experience itself. Integrating the stimulus–organism–response paradigm with customer-based brand equity theory, this study examines how personalization, recommendation systems and conversational agents shape brand equity through customer experience and engagement, with privacy concerns and AI literacy as boundary conditions. Survey data from 240 users of Iranian platforms were analyzed with confirmatory factor analysis and bootstrapped path analysis. The effect of AI on brand equity was entirely indirect (total effect = 0.55), with 60% carried by customer experience; engagement was the strongest driver of loyalty but did not affect awareness. Privacy concerns did not moderate the AI effect, whereas AI literacy weakened it, supporting algorithm aversion. The capabilities worked through distinct routes: recommendation through experience, personalization through engagement and loyalty. The findings guide platform investment in AI for brand value.

Keywords: Artificial intelligence; Digital platforms; Consumer-based brand equity; Customer experience; AI literacy; Personalization–privacy paradox

1. Introduction

1.1 Background and motivation

Over the past decade, the locus of interaction between brands and consumers has shifted decisively from firm-controlled channels to digital platforms. Marketplaces, ride-hailing services, classified-advertising networks and streaming services now mediate a substantial share of everyday commercial encounters, and they do so as algorithmically governed environments in which visibility, relevance and salience are allocated by computational systems rather than by editorial or media-buying decisions alone [1]. The implication for brand management is fundamental. The classical premise that brand meaning is built principally through communication controlled by the firm must be revisited when the consumer's encounter with the brand is assembled, ranked and personalized in real time by a learning system.

This development bears directly on the theoretical foundations of branding. In the customer-based brand equity (CBBE) tradition, brand equity is the differential effect of brand knowledge on consumer response to the marketing of the brand, and brand knowledge accumulates from the totality of brand-related encounters an individual experiences [2, 3]. If those encounters are increasingly authored by algorithms, then the antecedents of brand knowledge have themselves changed. Recommendations that consistently anticipate a consumer's needs may be read as evidence of competence and attentiveness; interfaces that appear to know too much may be read as surveillance. AI therefore ceases to be merely an instrument in the service of branding and becomes a constitutive element of the brand experience itself [4]. For technology and innovation management, this raises a strategic question of considerable practical weight: when a platform invests in AI, what kind of brand value does it create, by which route, and for whom?

1.2 Research gaps and research problem

The managerial relevance of this question stems from a measurement asymmetry in how platform firms evaluate their AI investments. Investments in recommendation infrastructure, personalization engines and conversational agents are typically justified and assessed with short-horizon transactional indicators—click-through, conversion, average order value and cost-to-serve—that are immediate and readily attributed. Brand-level consequences, by contrast, accumulate slowly, are diffuse in attribution and are rarely instrumented at all. A platform may therefore observe a lift in conversion while remaining unaware of a concurrent erosion of trust among users who experience the same personalization as intrusive. Because

the two effects are recorded on different instruments and time horizons, the trade-off is invisible to decision-makers. Establishing how AI capabilities relate to brand outcomes is consequently a precondition for rational technology investment rather than a theoretical refinement.

The academic literature does not yet supply this evidence. Systematic reviews of AI in marketing and consumer research observe that the field has expanded rapidly in volume while remaining uneven in theoretical integration, dominated by conceptual contributions, single-technology studies and adoption-oriented models, with comparatively few studies that trace the pathway from concrete AI capabilities through consumer psychological states to brand-level outcomes [5–7]. Four interrelated gaps can be identified.

The first is a *dimensional gap*. A considerable body of work treats AI as an undifferentiated construct—perceived AI use, AI adoption or AI service quality—so that the relative contribution of distinct consumer-facing capabilities cannot be established. This aggregation is analytically convenient but conceptually costly, because personalization, algorithmic recommendation and conversational agents engage the consumer through different psychological mechanisms: inference about the individual, curation of the choice set and service interaction, respectively [8–10]. The second is a *mechanistic gap*. Many published models test direct effects of AI on satisfaction, loyalty or purchase intention, although stimulus–organism–response reasoning and the customer experience literature suggest that technology stimuli act on brand judgements through the experiential and behavioral states they evoke [11–13]. Where mediators are modelled, they are usually single constructs such as trust or satisfaction; the sequence from AI capability through customer experience and customer engagement to a complete brand hierarchy terminating in brand equity has rarely been specified and tested [14].

The third is a *contingency gap*. Consumer responses to AI are heterogeneous. The personalization–privacy paradox suggests that privacy concerns attenuate the benefits of AI-driven personalization [15–17], yet recent findings are inconsistent [18, 19], and AI literacy—the competence to recognize, interpret and critically evaluate AI systems [20]—has scarcely been examined as a boundary condition on brand outcomes [21, 22]. The fourth is a *contextual gap*. Almost the entire body of quantitative evidence relating AI to brand outcomes derives from North American, Western European, Chinese and, more recently, Indian samples. Iran has developed a large domestic platform ecosystem—including Digikala in e-commerce, Snapp in mobility and Divar in classified advertising—that has adopted AI-enabled

personalization, recommendation and conversational service at speed, under infrastructural and data-governance conditions that differ materially from those in which the dominant evidence was generated. Whether the mechanisms and boundary conditions identified elsewhere hold in such a setting is an open question of both scholarly and managerial consequence.

Taken together, these gaps define the research problem addressed in this article: it is not established whether consumer-facing AI capabilities on digital platforms create brand-level value, through which psychological mechanisms any such effect is transmitted, or under which individual-level conditions it is strengthened or weakened.

1.3 Research questions and objectives

The principal objective of the study is to develop and empirically test an integrated model in which consumer-facing AI capabilities influence consumer-based brand equity through customer experience and customer engagement, under boundary conditions set by consumers' privacy concerns and AI literacy. Four research questions guide the inquiry:

> **RQ1.** Do consumer-facing AI capabilities influence customer experience and customer engagement, and do these states in turn shape brand trust, brand awareness, brand loyalty and consumer-based brand equity?
>
> **RQ2.** To what extent is the effect of AI capabilities on brand equity transmitted through the serial pathway of customer experience and customer engagement?
>
> **RQ3.** Do privacy concerns and AI literacy moderate the effect of AI capabilities on the experiential mechanisms, and in which direction?
>
> **RQ4.** How do personalization, recommendation systems and conversational agents differ in their contribution to experiential and brand outcomes?

1.4 Contributions and structure of the article

The study makes four contributions. First, it moves beyond aggregate treatments of AI by modelling three consumer-observable capabilities both as manifestations of a higher-order platform capability and as separate predictors, showing that their contributions are outcome- and route-specific. It also demonstrates empirically that back-end capabilities commonly included in AI inventories—customer data analytics and predictive analytics—are not distinguishable from interface capabilities in consumer perception. Second, it tests a mechanism linking AI to a full CBBE hierarchy and shows that the AI effect on brand equity is entirely indirect and carried mainly by customer experience, while engagement acts on

loyalty rather than on awareness. Third, it tests privacy concerns and AI literacy jointly as competing boundary conditions, finding that the former is inert and the latter negative—a result that adjudicates between algorithm-appreciation and algorithm-aversion accounts. Fourth, it provides systematic quantitative evidence on AI-enabled branding from the Iranian platform market, identifying a setting in which the personalization–privacy paradox does not appear to activate. For technology managers, these findings translate into guidance on how to evaluate and allocate AI investment in terms of brand value rather than transactional metrics alone.

2. Literature Review and Theoretical Framework

2.1 Theoretical foundations: stimulus–organism–response and customer-based brand equity

The model is organized by the stimulus–organism–response (S–O–R) paradigm, which holds that environmental stimuli act upon internal organismic states that in turn produce approach or avoidance responses [23]. Originally developed in environmental psychology, the paradigm has been widely applied to digital environments, in which interface characteristics function as the environment. Three properties make it suitable for the present problem. It is explicitly mediated, which is the structural feature the AI–branding literature most conspicuously lacks. It accommodates individual differences as moderators of the stimulus–organism link, which is where the boundary conditions examined here belong. And it is agnostic about the valence of a stimulus, allowing the same environmental feature to produce approach in one consumer and avoidance in another—a property essential for modelling a technology whose documented effects run in both directions.

The S–O–R paradigm specifies the shape of the model but not the internal structure of the response. That structure is supplied by CBBE theory [2, 3, 24]. Keller located brand equity in consumer memory, defining it as the differential effect of brand knowledge on consumer response [2, 25], while Aaker organized brand equity into awareness, associations, perceived quality, loyalty and other proprietary assets [3, 26]. Yoo and Donthu operationalized the theory by developing a multidimensional CBBE scale alongside a separate global measure of overall brand equity, demonstrating that the dimensions function as drivers of that global evaluation [24]. Adopting this specification carries a methodological advantage: because overall brand equity is measured as a distinct global judgement, it can be regressed on its antecedents without tautology, and the relations among the brand constructs can be modelled as directed paths rather than as correlated parallel outcomes.

2.2 AI as a brand-constitutive capability of digital platforms

Following Kaplan and Haenlein, AI is defined as a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals through flexible adaptation [27]. Because brand knowledge is formed from what consumers perceive rather than from what is technically true, the construct of interest is *perceived* AI-enabled capability: the degree to which a user experiences the platform as adaptive, anticipatory and responsive. This imposes a discipline on construct definition—only capabilities observable at the interface can be validly measured from consumer responses. Huang and Rust's distinction between mechanical, thinking and feeling intelligence [8, 28] and Davenport et al.'s framework [29] establish that AI is a family of capabilities that engage consumers in different ways. Three capabilities satisfy the joint criteria of interface observability, distinct psychological mechanism and measurement precedent.

AI-enabled personalization adapts content, offers and interface to the inferred preferences of the individual on the basis of behavioral data [9]. Its mechanism is inferential: consumers observe that the platform has drawn conclusions about them and evaluate the brand partly on the accuracy and appropriateness of those conclusions. Personalization has been linked to brand loyalty and perceived quality [30], and in an S–O–R test it affected trust and perceived usefulness, which in turn drove engagement, while its direct effect on engagement was not significant [18]. It also carries the clearest countervailing risk: overt personalization based on covertly collected data reduces advertising effectiveness by activating feelings of vulnerability [16], and disclosing information to an AI agent rather than a human can impair brand trust [31].

Algorithmic recommendation systems filter and rank alternatives to present the user with a curated choice set. Their mechanism is curatorial: consumers experience reduced search effort and the discovery of relevant options. Recommendation is regarded as a principal locus of AI value creation in retailing [32] and as the operational core of AI-driven personalization in e-commerce [17, 18], yet its brand consequences are less well documented, and privacy concerns can provoke active resistance to recommender systems [33].

Conversational AI agents—chatbots and virtual assistants—handle service interactions in natural language. Their mechanism is interactional, and consumers evaluate them against service-quality expectations of responsiveness, competence and problem resolution [34]. The evidence is substantial and largely positive: information and service quality drive satisfaction with and continuance of AI agents [35]; chatbot e-service quality affects satisfaction with

luxury brands [36]; chatbots shape user experience, satisfaction and loyalty [37] and strengthen the customer–brand relationship [38]; dialogic interaction raises satisfaction and engagement [39]; and verbal embodiment shapes consumer–brand relationships [40]. The qualifications are equally instructive: the benefits depend on task complexity and perceived problem-solving ability [41], and failures beyond the agent's competence boundary can co-destroy rather than co-create value [42].

Two capabilities frequently included in AI inventories are excluded on principled grounds. *Customer data analytics* is an internal organizational capability that is not observable at the interface; asking users to rate it elicits an inference about the firm rather than an observation of an encounter. It is, moreover, the infrastructure that enables the three retained capabilities rather than a parallel phenomenon, so modelling it alongside its own consequences introduces redundancy. *Predictive analytics* has no independent phenomenology for the consumer, who experiences it precisely as the personalized content and recommended items already captured; its items can therefore be expected to fail tests of discriminant validity [43, 44]. Both exclusions are examined empirically in Section 4.2.

The three retained capabilities are specified as first-order reflective dimensions of a second-order construct, *AI-enabled platform capability*. They are treated as alternative manifestations of a single underlying property—the degree to which the platform's consumer interface is governed by adaptive, learning systems—that typically co-occur because they are outputs of the same data infrastructure and investment. The higher-order specification preserves the multidimensional character of the construct while keeping the structural model parsimonious; the separate contribution of each capability is examined with a complementary disaggregated specification (Section 3.3).

2.3 Customer experience and customer engagement as serial mechanisms

Customer experience is the consumer's cognitive, affective, sensory, social and behavioral response to the totality of encounters with a firm across the customer journey [12, 45]. Brakus et al. established brand experience as distinct from brand attitude and involvement and as an antecedent of satisfaction and loyalty [46], and Bleier et al. showed that effective online experiences require the joint management of informativeness, entertainment, social presence and sensory appeal [47]. In the present model, experience is the evaluative state in which the encounter with AI capabilities is converted into an assessment of encounter quality—the point at which a technically sophisticated recommender becomes either helpful curation or unwanted

intrusion. Evidence that AI shapes customer experience is strong and recent: new technologies transform experience across the customer journey [13]; the effects of personalization, convenience and AI-enabled service quality on AI-enabled customer experience are transmitted through psychological states rather than directly [11]; and AI quality affects customer experience and, through it, the brand relationship [48], a pattern also observed in mobile banking platforms [49] and AI-powered luxury retail [50].

Customer engagement is the consumer's investment of cognitive, emotional and behavioral resources in interactions with a focal brand [51], captured through cognitive processing, affection and activation [52]. Engagement differs from experience in kind rather than degree: experience is evaluative and may be passive, whereas engagement is investive and requires the allocation of the consumer's own resources [53]. AI-powered voice assistants [54, 55], AI quality performance [56], interactive AI [57] and dialogic chatbots [39] have each been linked to engagement, and engagement has in turn been linked to brand loyalty [58] and customer equity [59].

Most published models treat these constructs as parallel mediators. This study specifies them serially, on three grounds. Theoretically, engagement is a motivated investment that presupposes a favorable prior evaluation; consumers do not allocate attention and interaction to platforms whose encounters they evaluate poorly [53]. Empirically, the absence of a significant direct effect of AI-enabled personalization on engagement once evaluative states are modelled [18] is consistent with serial transmission. Analytically, a serial specification yields a specific indirect effect that a parallel specification cannot estimate, answering whether an improved experience is sufficient to generate engagement or whether engagement requires separate intervention. The direct path from AI capability to engagement is nevertheless retained, so that the serial assumption is tested rather than imposed.

2.4 Boundary conditions: privacy concerns and AI literacy

Privacy concern denotes the degree of apprehension an individual holds regarding the collection, control and use of personal information by online organizations [15]. It underlies the personalization–privacy paradox, in which consumers value tailored service while objecting to the data collection that makes it possible [16, 60]. Privacy concern moderates the effectiveness of privacy assurance and privacy policy disclosure in building trust [61, 62], and in AI-specific settings it weakened the effects of AI-driven personalization on loyalty transmitted through trust and engagement [17], weakened the effect of AI service quality on

brand loyalty among Chinese online-retail customers [19], and drove resistance to AI-based recommender systems [33]. Yet in a social-media context privacy concerns did not significantly dampen engagement [18]. This inconsistency suggests that the moderating role of privacy concern is context-dependent and that its operation under a different data-governance regime is an open empirical question.

AI literacy denotes the set of competencies that enable an individual to recognize, evaluate and interact critically with AI systems and their outputs [20], spanning knowing and understanding, applying, evaluating and ethical awareness [63]; algorithmic literacy captures a parallel competence in media contexts [22]. Whereas privacy concern represents a perceived *cost* of algorithmic mediation, AI literacy represents a *competence* in interpreting it, and the two are theoretically independent: a consumer may understand recommendation systems well and object strongly to them, or understand them poorly and accept them uncritically.

The direction of the AI-literacy effect is, however, theoretically ambiguous. An algorithm-appreciation logic suggests that literate consumers recognize algorithmic outputs as probabilistic rather than authoritative, calibrate their expectations and attribute failures to system limitations rather than to brand indifference, implying a positive moderation. An algorithm-aversion logic points the other way: aversion is task-dependent and strongest where tasks are perceived as subjective [64], persists across decision settings [65], and consumers discount machine recommendations in hedonic domains [66]; literate consumers may therefore be better equipped to recognize and discount algorithmic influence, implying a negative moderation. Empirically, AI literacy shapes how consumers process AI-generated content and convert it into purchase intention [21], and a related individual difference, AI preference, moderates the link between AI quality and engagement [56].

Both moderators are placed on the paths from AI capability to the experiential mechanisms. Privacy concern and AI literacy govern how an objectively identical algorithmic encounter is subjectively interpreted; they are less plausibly involved in how an already-formed experience translates into trust or loyalty. Restricting moderation to the stimulus–organism stage is therefore theoretically motivated and, given the sample size, analytically economical.

2.5 The base model and its extension

The published study closest in structure to the present one is Jayapal's S–O–R examination of AI-driven personalization and customer loyalty in Indian online shopping, moderated by privacy concerns [17]. Its central finding—no direct effect of personalization on loyalty, with

influence operating through trust and engagement—implies that a direct-effect specification would rest on an unsound foundation. The present model retains that architecture but modifies it at four points, each corresponding to one of the gaps identified in Section 1.2: the stimulus is extended from personalization alone to a second-order construct with three capabilities (dimensional gap); the mediators are respecified as serially ordered customer experience and customer engagement, with trust relocated to the response block (mechanistic gap); the response is extended from loyalty to a CBBE hierarchy terminating in brand equity; and AI literacy is added as a second, theoretically independent boundary condition (contingency gap), with the model tested in a new institutional setting (contextual gap).

2.6 Conceptual model and hypotheses

Figure 1 presents the conceptual model. AI-enabled platform capability constitutes the stimulus; customer experience and customer engagement constitute the organism; and brand trust, brand awareness, brand loyalty and consumer-based brand equity constitute the response, ordered according to CBBE theory. Privacy concerns and AI literacy moderate the stimulus–organism paths.

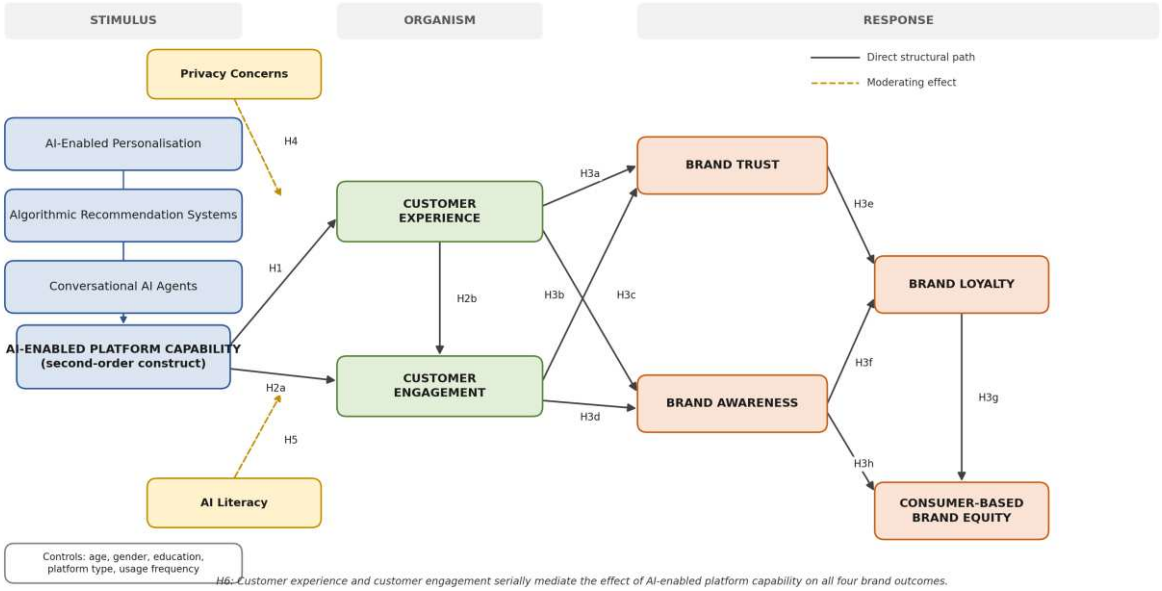


Figure 1. Conceptual model: an S–O–R specification of the effect of AI-enabled platform capability on consumer-based brand equity, with customer experience and customer engagement as serial mediators and privacy concerns and AI literacy as boundary conditions.

According to the S–O–R paradigm, environmental stimuli act upon organismic states [23]. Interfaces that are adaptive, anticipatory and responsive reduce search effort, increase

relevance and resolve problems promptly, which should improve consumers' evaluations of the platform encounter [11, 13, 48]. The same capabilities also provide occasions and reasons for attention and interaction, which should stimulate engagement [54, 56, 57]. A favorable evaluation of the encounter, in turn, should motivate the investment of cognitive, emotional and behavioral resources that constitutes engagement [39, 53].

> **H1–H2.** AI-enabled platform capability positively affects customer experience (H1) and customer engagement (H2a); customer experience positively affects customer engagement (H2b).

Brand trust is the confident expectation that the brand is reliable and will act in the consumer's interest [67]; it is an inference from accumulated encounters, so that consistently positive experiences supply the evidence of reliability and benevolent intent on which it rests [11, 37, 48, 68]. Engagement deepens relational knowledge and reduces uncertainty about the brand [14, 38, 51, 52]. Brand awareness reflects the strength of the brand node in memory [2]: high-quality experiences strengthen memory encoding [47], and repeated active interaction increases salience and ease of recall [52, 54].

> **H3a–H3d.** Customer experience positively affects brand trust (H3a) and brand awareness (H3b); customer engagement positively affects brand trust (H3c) and brand awareness (H3d).

Within CBBE theory, trust is the relational antecedent of loyalty [67–69], and awareness is the entry condition of the brand knowledge hierarchy and a heuristic for risk reduction under uncertainty [2, 3]. Loyalty—a deeply held commitment to repatronize a preferred brand despite situational influences [70]—is a principal driver of overall brand equity, and awareness also enters the Yoo and Donthu structure as a direct driver of overall brand equity [24, 26]. Experiential routes to equity have been documented in brand-experience and mobile-application settings [59, 71].

> **H3e–H3h.** Brand trust (H3e) and brand awareness (H3f) positively affect brand loyalty; brand loyalty (H3g) and brand awareness (H3h) positively affect brand equity.

Following the personalization–privacy paradox [15–17, 19], consumers who are more concerned about data collection should derive less experiential value from AI-enabled features. Given the competing predictions of the algorithm-appreciation and algorithm-aversion accounts [64–66], AI literacy is expected to moderate the AI–experience relationship, but no direction is predicted; the direction obtained is itself a finding.

H4. Privacy concerns weaken the effects of AI capability on customer experience and engagement.

H5. AI literacy moderates the effects of AI capability on customer experience and engagement (no direction predicted).

H6. Customer experience mediates (H6a), and customer experience and engagement serially mediate (H6b), the effect of AI capability on the brand outcomes.

3. Research Methodology

3.1 Design, sample and data collection

A cross-sectional survey measured consumers' perceptions, the appropriate object for a study of brand knowledge [2], and matches the dominant design in comparable work [11, 17–19]. The population comprises active users of Iranian platforms such as Digikala, Snapp and Divar. Because no sampling frame exists, a quota-informed convenience procedure was used, with recruitment through multiple online channels and in person in shopping centers and universities to reach less digitally engaged users [72]. Of 242 completed questionnaires, 240 remained after screening, exceeding the minimum of 200 for maximum likelihood estimation [73, 74] and the 150–180 cases indicated by a power analysis [75]. Participation was voluntary and anonymous.

3.2 Measures

All constructs were measured with adapted, validated scales on five-point Likert scales (Table 1). The instrument was translated into Persian and back-translated [76], reviewed by three academic experts and pilot tested with 35 users [77]. Loyalty was measured attitudinally, because concentrated platform markets can make repeat use a sign of absent alternatives rather than commitment [70]. The administered instrument also measured customer data analytics, predictive analytics and brand performance; their data were retained only to test their exclusion empirically.

Table 1. Constructs and measurement sources.

Construct	Items (retained)	Source scales
Personalization	4	Kumar et al. [9]; Shanahan et al. [30]
Recommendation systems	3	Guha et al. [32]; [17, 18]
Conversational AI agents	4	Ashfaq et al. [35]; Chen et al. [10]
Customer experience	4	Brakus et al. [46]; Bleier et al. [47]
Customer engagement	4	Hollebeek et al. [52]
Brand trust	4 of 7	Delgado-Ballester and Munuera-Alemán [67]
Brand awareness	4 of 7	Keller [2]; Yoo and Donthu [24]
Brand loyalty	4 of 7	Oliver [70]; Yoo and Donthu [24]
Consumer-based brand equity	4 of 7	Yoo and Donthu [24]
Privacy concerns	4	Malhotra et al. [15]
AI literacy	4	Long and Magerko [20]; Ng et al. [63]

3.3 Analytical strategy

Following the two-step approach [78], a confirmatory factor analysis (CFA) was estimated first. Reliability and convergent validity were judged by loadings (≥ .50), alpha and composite reliability (≥ .70) and average variance extracted (AVE ≥ .50) [43, 73, 79]; discriminant validity by the Fornell–Larcker criterion [43] and the heterotrait–monotrait (HTMT) ratio (< .85, or < .90 for adjacent constructs) [44]; and common method variance by Harman's test [80, 81]. Fit was judged by $\chi^2/df < 3$, CFI and TLI ≥ .90, and RMSEA and SRMR ≤ .08 [74, 82].

Screening rules were specified before the analysis: cases with zero response variance or an invariant run longer than 40 of the 71 items were removed, univariate outliers were flagged at $|z| > 3.29$ and multivariate outliers by Mahalanobis distance ($p < .001$). The four seven-item brand scales were shortened to their four highest-loading items to improve the ratio of observations to parameters, and one recommendation item was removed for cross-construct contamination, leaving 43 indicators. Because full latent models become unstable when adjacent constructs correlate very highly, the stability of the latent structural model under bootstrapping was checked before the estimation approach was fixed.

Structural relationships were estimated by maximum-likelihood path analysis on composite scores (Section 4.3 explains why), with AI capability as the mean of its three dimensions. Paths not hypothesized were added only when modification indices and theory both supported them, and hypothesized and respecified estimates are both reported. Significance and indirect effects were assessed with 5,000-resample bias-corrected bootstrap confidence intervals [83], and mediation was classified following Zhao et al. [84]. Moderation was tested with product terms

of standardized composites and probed with simple slopes [85]. Model B entered the three capabilities separately to estimate their total effects, supplemented by relative weights [86, 87] and an importance–performance analysis.

4. Results

4.1 Screening and sample profile

Two careless responders were removed: one with identical answers to all 71 items and one with an invariant run of 47 items. There were no missing values, and univariate skewness (maximum |1.90|) and kurtosis (maximum 5.52) were acceptable. Mardia's coefficient indicated multivariate non-normality (critical ratio 28.6), so all tests use bootstrapping; twelve multivariate outliers were retained, and excluding them changed no conclusion. Variance inflation factors were 1.24–1.95. The sample is young (78.5% under 30), educated (39.6% with a master's degree or doctorate), 59.1% male and experienced: 61.7% had used platforms for more than three years and 38.8% used them daily.

4.2 Measurement model

The model's exclusions were confirmed: the HTMT ratio was .953 between customer data analytics and personalization and .908 between predictive analytics and customer data analytics, so consumers do not perceive these back-end capabilities as distinct. The eleven-factor CFA (43 indicators) fitted acceptably (Table 3). All loadings exceeded .50 (Table 2). Alpha and composite reliability exceeded .70 except for brand awareness (.672/.683) and brand loyalty (.688/.714), and AVE was below .50 for seven constructs; these constructs are interpreted with caution [43]. The second-order AI construct was supported (loadings: personalization .88, recommendation .93, conversational agents .76).

Table 2. Descriptive statistics, reliability and convergent validity (n = 240).

Construct	Loadings	Mean	SD	α	CR	AVE
Personalization	0.64–0.74	3.39	0.78	0.764	0.772	0.459
Recommendation systems	0.65–0.78	3.57	0.75	0.751	0.765	0.522
Conversational AI agents	0.73–0.81	3.33	0.86	0.851	0.852	0.590
Customer experience	0.73–0.80	4.03	0.79	0.847	0.850	0.586
Customer engagement	0.74–0.83	2.95	1.13	0.869	0.871	0.628
Brand trust	0.61–0.71	3.50	0.75	0.748	0.747	0.425
Brand awareness	0.55–0.62	4.05	0.61	0.672	0.683	0.350
Brand loyalty	0.57–0.66	3.55	0.78	0.688	0.714	0.385
Brand equity	0.65–0.71	3.76	0.67	0.765	0.767	0.452
Privacy concerns	0.53–0.81	3.63	0.92	0.766	0.768	0.460
AI literacy	0.62–0.77	3.62	0.76	0.773	0.775	0.465

Two descriptive results matter: customer experience was rated highly (M = 4.03) but engagement was the lowest-rated construct (M = 2.95, SD = 1.13), an *experience–engagement gap* of more than one scale point; and recommendation was the highest-rated capability, conversational agents the lowest. Discriminant validity was acceptable on the HTMT criterion—most pairs were below .85, the moderators' ratios were .25–.44, and three adjacent pairs lay between .85 and .90 (recommendation–experience .86, experience–trust .86, loyalty–equity .90). The Fornell–Larcker criterion, however, was not met for these pairs because their latent correlations (up to .91) exceed the square roots of the modest AVEs. Loyalty and equity were kept distinct because loyalty is a constituent of equity in CBBE theory [3, 24]. Harman's first factor explained 32.5% of the variance.

4.3 Structural model

A full latent-variable model fitted acceptably but was unstable: in 46% of bootstrap resamples at least one standardized coefficient exceeded 1.0, reflecting the high latent correlations. The structural model was therefore estimated on composite scores, which do not correct for measurement error and so give conservative coefficients. The hypothesized model (A-H) fitted poorly (Table 3). Four theoretically grounded paths, added one at a time, removed the misfit: engagement → loyalty ($\Delta\chi^2 = 50.5$) [58], experience → equity ($\Delta\chi^2 = 29.2$) [71], and AI capability → trust ($\Delta\chi^2 = 11.3$) and → awareness ($\Delta\chi^2 = 10.7$). The respecified model (A-R) fitted well and is the final model; the added paths are findings to be confirmed in new data.

Table 3. Goodness-of-fit statistics (n = 240).

Model	χ^2	df	χ^2/df	CFI	TLI	RMSEA	SRMR
Measurement model (CFA)	1179.0	805	1.46	.919	.909	.044	.051
Second-order AI capability	50.7	41	1.24	.991	.988	.031	.035
Full latent structural model	874.2	546	1.60	.917	.909	.050	.055
A-H: hypothesized path model	113.4	10	11.34	.900	.789	.208	.109
A-R: respecified model (final)	11.8	6	1.96	.994	.980	.063	.022
B-R: capabilities entered separately	27.8	10	2.78	.986	.951	.086	.024

Ten of the eleven direct hypotheses were supported (Table 4, Figure 2). AI capability strongly affected experience (β = 0.73) and engagement (β = 0.49), and experience affected engagement (β = 0.33). Experience was the stronger antecedent of trust (β = 0.39) and awareness (β = 0.35). Engagement affected trust (β = 0.17) but not awareness: H3d, marginal in the hypothesized model, was not supported in the final model (β = 0.05, p = .527). Trust and awareness drove loyalty, and loyalty and awareness drove equity; engagement was the strongest antecedent of loyalty (β = 0.45). The model explained 54% of the variance in brand equity, and the total effects on equity were 0.55 for AI capability and 0.51 for customer experience.

The respecification changes the interpretation of the brand block. Part of the influence that the hypothesized model forced through trust and awareness is carried in fact by direct routes from engagement to loyalty and from experience to equity, so the hypothesized brand-block coefficients are smaller in the final model. Customer experience emerges as the principal channel of AI's brand effect: its total effect on equity (0.51) is close to that of AI itself and well above those of loyalty (0.35), awareness (0.25), engagement (0.18) and trust (0.07).

Table 4. Structural path coefficients (standardized; n = 240).

Hyp.	Path	β (A-H)	β (A-R)	95% BC CI (A-R)	Result
H1	AI → Customer experience	0.729	0.729	[0.630, 0.805]	Supported
H2a	AI → Customer engagement	0.486	0.486	[0.324, 0.654]	Supported
H2b	Experience → Engagement	0.327	0.327	[0.137, 0.492]	Supported
H3a	Experience → Trust	0.498	0.389	[0.214, 0.541]	Supported
H3b	Experience → Awareness	0.474	0.353	[0.147, 0.566]	Supported
H3c	Engagement → Trust	0.274	0.169	[0.020, 0.330]	Supported
H3d	Engagement → Awareness	0.165	0.048	[−0.107, 0.225]	Not supported
H3e	Trust → Loyalty	0.429	0.205	[0.035, 0.361]	Supported
H3f	Awareness → Loyalty	0.287	0.181	[0.037, 0.325]	Supported
H3g	Loyalty → Equity	0.489	0.349	[0.185, 0.506]	Supported
H3h	Awareness → Equity	0.314	0.189	[0.057, 0.321]	Supported

Hyp.	Path	β (A-H)	β (A-R)	95% BC CI (A-R)	Result
—	Engagement → Loyalty	—	0.448	[0.327, 0.566]	Added
—	Experience → Equity	—	0.338	[0.161, 0.497]	Added
—	AI → Trust	—	0.247	[0.096, 0.408]	Added
—	AI → Awareness	—	0.275	[0.044, 0.502]	Added

Note. A-H = hypothesized model; A-R = final model. R^2 (A-R): experience .53; engagement .57; trust .53; awareness .39; loyalty .50; equity .54.

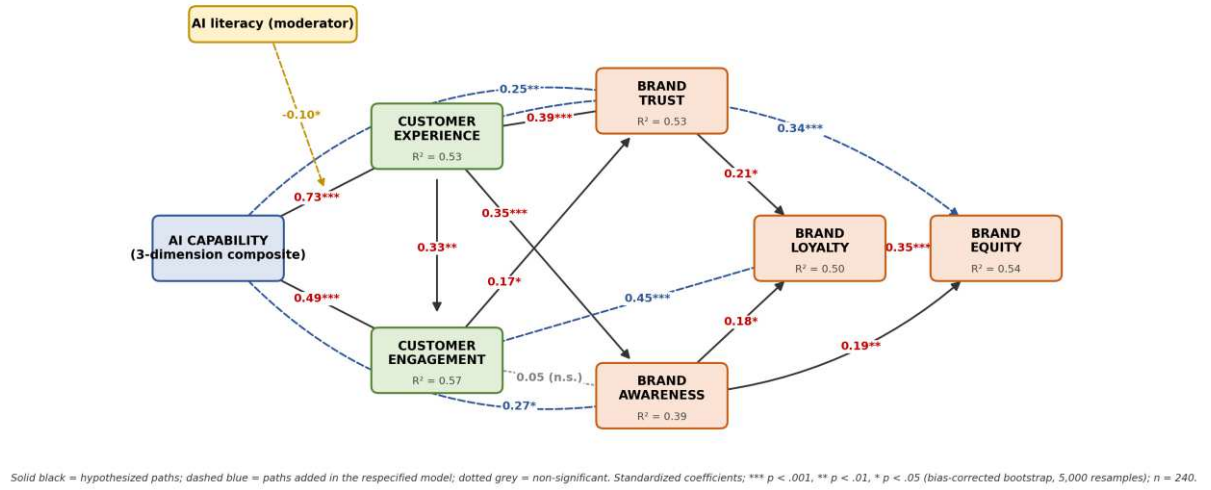


Figure 2. Final structural model (A-R), standardized coefficients. Dashed blue: added paths; dotted grey: non-significant; gold: moderation by AI literacy.

4.4 Mediation and moderation

The total indirect effect of AI capability on equity was 0.549 (95% CI [0.461, 0.631]); a direct AI → equity path added to the final model was negligible (β = 0.01, CI [−0.18, 0.20]), so mediation is indirect-only [84]. Routes through experience alone carried 60% of the effect, the serial experience–engagement route 8%, engagement alone 16%, and the direct AI effects on trust and awareness 16% (Table 5, Figure 3). H6a and H6b are supported, although the serial route is small.

Table 5. Indirect effects of AI capability on brand equity (bias-corrected bootstrap, 5,000 resamples).

Mechanism	Effect	95% CI	Share
Total indirect effect	0.549	[0.461, 0.631]	100%
Through customer experience only (H6a)	0.332	[0.227, 0.426]	60%
Serially through experience and engagement (H6b)	0.043	[0.018, 0.082]	8%
Through customer engagement only	0.088	[0.042, 0.150]	16%
Directly through trust or awareness	0.087	[0.028, 0.170]	16%

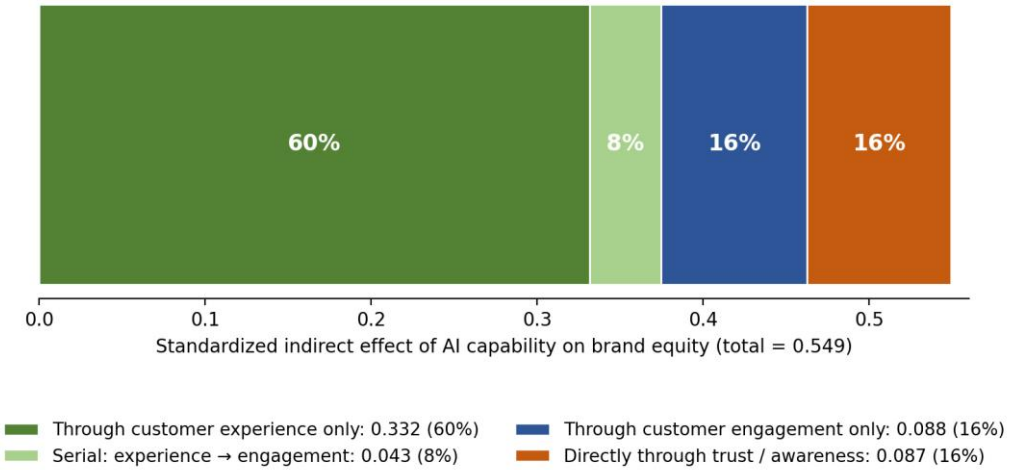


Figure 3. Decomposition of the indirect effect of AI capability on brand equity by mechanism.

Privacy concerns did not moderate the effect of AI on experience (β = −0.048, p = .198) or engagement (β = −0.012, p = .741), so H4 is not supported. AI literacy weakened the AI–experience path (β = −0.098, p = .020) but not the AI–engagement path (β = 0.074, p = .072). The slope of experience on AI fell from 0.82 at low literacy to 0.63 at high literacy (Figure 4), supporting H5 in the direction of algorithm aversion.

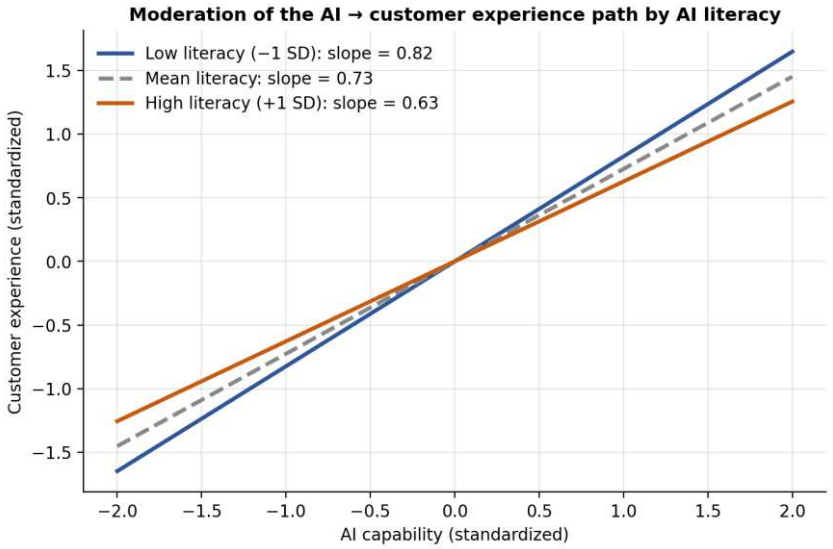


Figure 4. Simple slopes of AI capability → customer experience at low, mean and high AI literacy.

4.5 Capability-level contributions

In Model B (Table 6), recommendation systems were the strongest driver of experience (0.45) and had the largest total effects on trust and equity; personalization was the strongest driver of engagement (0.45) and loyalty (0.28); and conversational agents contributed most to awareness (0.29). The three total effects on equity were close, with overlapping confidence intervals. Relative weights (Figure 5), which partition each outcome's variance without imposing the

mediating structure, gave recommendation 46% of the explained variance in experience and personalization 46% in engagement and 52% in equity. Recommendation systems thus build equity mainly through experience, and personalization mainly through engagement and loyalty. In the importance–performance analysis, recommendation systems combined the highest importance (0.25) with the highest performance (64/100); personalization (0.20; 60/100) and conversational agents (0.20; 58/100) lay below the mean on both.

Table 6. Standardized total effects of each AI capability (Model B-R).

Capability	CX	CE	Trust	Awareness	Loyalty	Equity
Personalization	0.202	**0.446**	0.240	0.189	**0.283**	0.203
Recommendation systems	**0.451**	0.161	**0.286**	0.192	0.165	**0.247**
Conversational AI agents	0.203	0.245	0.241	**0.287**	0.211	0.196

Note. Largest effect per column in bold. CX = customer experience; CE = customer engagement.

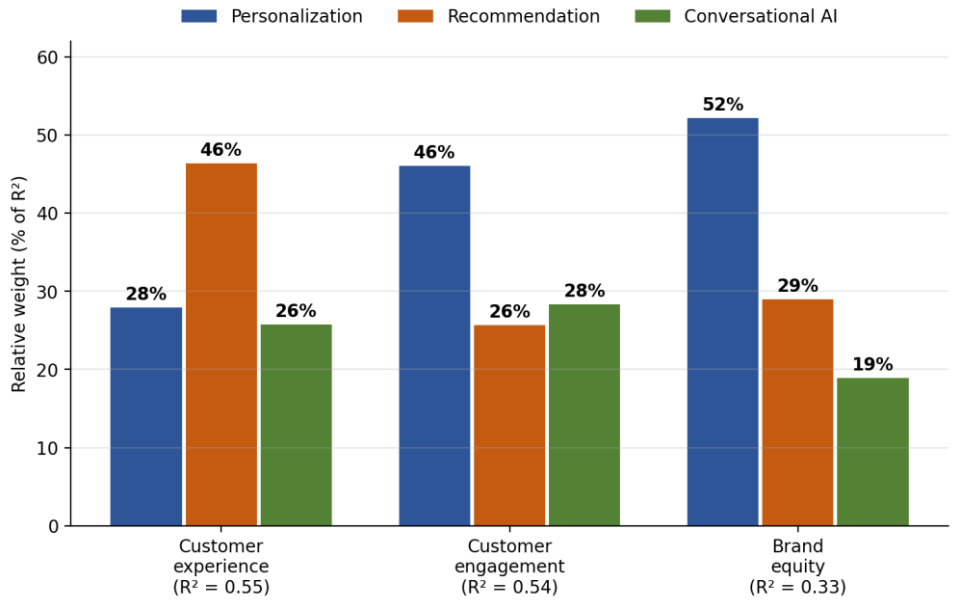


Figure 5. Relative weights of the three AI capabilities (% of explained variance).

In robustness checks, excluding the twelve outliers left the sign and significance of every path unchanged, and the latent model's point estimates agreed in direction, although it placed the experience–engagement path below significance. Overall, 13 of the 15 hypotheses were supported; H3d and H4 were not.

5. Discussion and Conclusion

5.1 Discussion of the findings

5.1.1 AI builds the brand through the experience it creates

The core architecture of the model was supported. The finding that AI acts on brand outcomes through customer experience rather than directly aligns with evidence that the effects of AI-enabled service on customer experience are transmitted through psychological states [11] and that AI quality reaches the brand relationship through experience [48]. It is also consistent with the base study, in which AI-driven personalization had no significant direct effect on loyalty [17]. The present study extends this logic in two directions—by disaggregating AI into three capabilities and by carrying the outcome chain through to brand equity—and finds that the AI effect on equity is entirely indirect, with 60% of it carried by customer experience.

5.1.2 Engagement deepens the relationship rather than the brand's salience

The data required two refinements to the hypothesized brand hierarchy. Customer engagement emerged as the strongest antecedent of brand loyalty, consistent with the engagement–loyalty link reported by Leckie et al. [58], whereas the hypothesized engagement–awareness path was not supported once that link was modelled. Engagement therefore acts on the relationship with the brand rather than on its salience in memory: engaged users are more committed, but not more aware, than less engaged users who rate their experience equally highly. Customer experience, in turn, acts on brand equity directly as well as through trust and awareness, as Pina and Dias found for brand experience [71]. Combined with the experience–engagement gap observed in the descriptive data, this indicates that the platforms convert satisfying experiences into engagement poorly, and that this conversion is the point at which loyalty—and with it brand equity—is lost.

5.1.3 Privacy concerns did not moderate the AI effect

The non-significant moderation by privacy concerns is the study's most consequential divergence from the base study, in which elevated privacy concern weakened the effects of AI-driven personalization [17], and from evidence that privacy concern attenuates the effect of AI service quality on loyalty [19] and drives resistance to recommender systems [33]. The result is not without precedent: Teepapal likewise found that privacy concerns did not dampen engagement [18]. The explanation proposed here is contextual. Privacy concern was present as an attitude—its mean of 3.63 indicates moderate concern—but did not translate into a discounting of the AI-enabled experience. Where algorithmic data use has become a

normalized and largely unavoidable condition of participating in the digital economy, the personalization–privacy paradox may not activate at the point of experience, consistent with the documented divergence between stated privacy attitudes and behavior [15, 60]. Two alternative explanations should be acknowledged: interaction effects are typically small and the sample offers limited power to detect them, and privacy concern was measured as a general disposition rather than with respect to specific data practices. The null result is therefore evidence that the paradox is not a strong boundary condition in this context, rather than proof of its absence.

5.1.4 AI literacy weakened the AI–experience link

The negative moderation by AI literacy adjudicates between two theoretical accounts that the literature had left unreconciled. The algorithm-appreciation logic holds that understanding breeds receptivity; the algorithm-aversion logic holds that understanding breeds discounting, because consumers who recognize an output as an algorithmic inference rather than an act of genuine understanding attribute less value to it [64–66]. The data support the second account, although the effect is modest ($\Delta R^2 = .011$) and confined to the experience path. This introduces a tension into a widely held assumption: to the extent that greater literacy attenuates the experiential impact of a platform's AI, the transparency that supports informed trust may also dampen part of the experiential effect. This is not an argument against transparency, which has strong independent justification, but it indicates that literate consumers must be won through substantive rather than novelty value.

5.1.5 Capability contributions are route-specific

The disaggregated analysis shows that aggregate treatments of AI conceal economically meaningful differences. Recommendation systems are the capability through which users most directly perceive the platform's usefulness: they dominate customer experience and, through it, have the largest structural effect on brand equity. Personalization dominates customer engagement and loyalty and accounts for the largest share of the variance in equity explained directly by the capabilities, consistent with evidence linking personalization to brand loyalty [30] and with its inferential mechanism, which produces a sense of being individually understood. Conversational agents, though the lowest-rated capability, contribute mainly to brand awareness, plausibly because service interactions make the brand salient; their benefits nonetheless depend on task complexity, and failures beyond their competence boundary destroy value [41, 42]. On brand equity itself the three structural contributions are close, so the

defensible conclusion is not that one capability builds the brand but that each builds it through a different route.

5.2 Theoretical contributions

The study makes four theoretical contributions. The *dimensional contribution* is to show that consumer-facing AI capabilities build the brand through different routes: recommendation chiefly through experience, personalization chiefly through engagement and loyalty, and conversational agents chiefly through awareness. The study also shows, through near-unity HTMT ratios, that back-end AI capabilities lack an independent phenomenology for consumers—a methodological point of general relevance for survey research that asks consumers to rate capabilities they cannot observe.

The *mechanistic contribution* is to specify and test a full pathway from AI capability through customer experience and customer engagement to a CBBE hierarchy terminating in brand equity, and to locate the mechanism more precisely than prior work: the AI effect on equity is entirely indirect, experience carries most of it, and engagement acts on loyalty rather than on awareness. The *contingency contribution* is to test privacy concerns and AI literacy jointly as theoretically independent boundary conditions—one a perceived cost, the other an interpretive competence—and to show that the former is inert and the latter negative in this setting. The *contextual contribution* is to extend the evidence base on AI-enabled branding into a distinct institutional setting and to identify a boundary condition—the non-activation of the personalization–privacy paradox—that the dominant research settings had obscured.

5.3 Practical and policy implications

For platform managers and technology strategists, five implications follow. First, AI investment should be justified by its effect on experience rather than by its technical sophistication or deployment metrics, and experience-quality measures should sit alongside conversion metrics in the evaluation of AI initiatives. Second, recommendation systems should be maintained and protected as the platform's experience engine: they are the best-performing capability (64/100) and the strongest driver of experience, so degradation in their relevance is likely to propagate directly to brand outcomes.

Third, personalization is the principal lever for closing the experience–engagement gap. Engagement was the lowest-rated construct yet the strongest antecedent of loyalty, and personalization is its dominant driver while its current performance is below average (60/100). Personalization that invites participation—tailored content, individualized prompts and

features that reward interaction—is therefore likely to yield loyalty returns that recommendation-centric optimization does not. Fourth, conversational agents should be resourced to a competent service standard, with clear escalation to human staff when tasks exceed their competence [42], because they contribute to brand awareness and their failures damage the brand. Fifth, because AI-literate users derive less experiential value from AI features, platforms should compete for this growing segment through substantive value—accuracy, user control and meaningful explanation—rather than through the novelty of automation.

5.4 Limitations and directions for future research

The conclusions must be read within the limits of the design. First, the cross-sectional design establishes covariation consistent with the hypothesized structure but cannot demonstrate temporal precedence; the mediation findings should be read as consistent with, rather than proof of, the proposed mechanism. Second, non-probability sampling and the young, well-educated profile of the sample limit statistical generalization. Third, all variables were self-reported at one time, so common method variance cannot be ruled out entirely. Fourth, discriminant validity among adjacent constructs was limited, which led to estimation on composite scores that do not correct for measurement error.

These limitations define an agenda for further research. The respecified structure—in particular the engagement–loyalty and experience–equity paths—should be tested confirmatorily in new samples. The non-activation of the privacy paradox should be replicated across markets with different data-governance regimes. The mechanism of the AI-literacy effect should be tested directly, for example by measuring the attributions literate consumers make about algorithmic outputs. Longitudinal and experimental designs, objective indicators of algorithmic performance, multi-group comparisons across platform categories, and extensions to generative AI and to outcomes such as advocacy and willingness to pay would each strengthen and extend the framework.

5.5 Conclusion

This study set out to determine whether, how and under what conditions the AI capabilities of digital platforms influence the brands those platforms hold in the minds of their users. Evidence from 240 Iranian platform users indicates that AI does build the brand, and does so substantially, but not on its own terms. It builds the brand entirely through the constructs it influences—above all through the experience it creates—so that its brand value is realized

chiefly to the extent that consumers feel a better experience. Its capabilities do so through different routes: recommendation through experience, personalization through engagement and loyalty, and conversational agents through awareness. And its effect is undiminished by the privacy concerns consumers profess, yet dampened by the very understanding that AI education seeks to instill. The central lesson for technology managers is that AI is not a brand asset in itself: it becomes one when it is experienced as relevance, care and understanding, and when that experience is converted into engagement.

Declarations

Ethics statement. The study involved anonymous adult respondents and was conducted in accordance with the ethical requirements of Amirkabir University of Technology; consent was given by submitting the questionnaire.

Data availability. The data and analysis script are available from the corresponding author upon reasonable request.

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