Patient-Centric Pharmaceutical Marketing: Behavioral Determinants, Ethical Governance, Trust Dynamics, and Digital Innovation in Evolving Healthcare Systems

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Abstract

Pharmaceutical companies are increasingly reaching out directly to patients. In emerging-market healthcare systems such as India's, this question carries particular urgency for patients with chronic conditions who experience repeated exposure to such communication over time. This paper develops and specifies for empirical testing an integrative model in which behavioral determinants (perceived usefulness, perceived ease of use, and perceived privacy risk) and ethical governance (transparency of commercial intent and data-use disclosure) jointly shape patient trust, which is hypothesized to drive patient-engagement outcomes, with digital innovation (artificial-intelligence-enabled personalization) proposed as a moderator of these relationships. A survey-based design to study adult patients with chronic conditions who had seen digital pharmaceutical marketing in the past year. Analyzed the responses to assess how these factors shape patient trust, using standard statistical modeling to uncover the results. To demonstrate the intended reporting sequence, an illustrative simulated dataset ($n = 402$) is presented; under this scenario, the model explains a moderate-to-substantial share of variance in patient trust ($R^2 = .52$) and patient engagement ($R^2 = .44$), with ethical governance emerging as the strongest antecedent of trust ($\beta = .34$, $p < .001$), followed by perceived usefulness ($\beta = .27$, $p < .001$), perceived privacy risk exerting a significant negative effect ($\beta = -.22$, $p < .001$), and digital innovation significantly strengthening the usefulness–trust relationship ($\beta = .16$, $p = .015$). Argue that ethical governance is not peripheral to patient marketing; it is a core driver of trust. Trust is the key bridge that turns user experience into real engagement. The model integrates marketing ethics and technology acceptance, demonstrating that transparency-by-design should anchor the digital strategy.

Keywords: *patient-centric pharmaceutical marketing; ethical governance; patient trust; technology acceptance model; digital health innovation; patient engagement; emerging healthcare markets*

1. INTRODUCTION

Over the past two decades, pharmaceutical marketing has moved away from a model built almost entirely on persuading physicians to prescribe towards one that treats the patient as an informed participant in their own care. This shift did not come from companies suddenly becoming altruistic. It came because the rules around drug communication changed. Patients now arrive at consultations having already searched the symptoms online, joined disease-specific communities, and compared treatment options across forums and applications. Regulators in many jurisdictions have tightened restrictions on direct-to-physician promotion, and healthcare systems increasingly reward outcomes and adherence rather than prescription volume. A company that continues to address only prescribers' risks loses relevance with the very people whose long-term adherence ultimately

determines whether a medicine works as intended. (Rajendran & Rani, 2025)

The pharmaceutical sector is accordingly undergoing a transition from product-focused promotion towards omnichannel, patient-centric strategies, driven by rapid digitalization and rising stakeholder expectations for transparency and responsiveness (Fleissig et al., 2024). Patient-centric marketing, in this context, denotes a strategic orientation in which companies design communication, education, and engagement programs around patients' needs, health literacy, and lived experience of illness, rather than treating the patient as a passive endpoint of a physician-directed message (Katsanis et al., 2020). This is not merely a rebranding exercise: it requires firms to redefine what counts as a successful marketing interaction, not a single prescription event, but a sustained relationship in which the patient trusts the information received, understands the treatment, and remains engaged over time.

Trust sits at the center of this relationship, and it is unusually fragile in the pharmaceutical sector. Patients are generally aware that a pharmaceutical company profits from the medicines it promotes, which creates an inherent tension between commercial intent and the appearance of disinterested care. When this tension is poorly managed, patients disengage, regulators intervene, and confidence in the wider healthcare system erodes; when it is well managed, patient-centric marketing can improve adherence, satisfaction, and long-term health outcomes while protecting the firm's commercial and reputational interests (Agarwal et al., 2019). Recent large-scale survey evidence outside the pharmaceutical sector reinforces how consequential this tension has become: nationally representative studies of patient attitudes toward artificial intelligence in healthcare consistently find that governance signals, such as regulatory approval, disclosed data practices, and human oversight, shape trust and willingness to engage as strongly as, or more strongly than, functional performance itself (Bracic et al., 2026).

Digital channels, including branded patient portals, messaging-based medication reminders, artificial-intelligence-driven chatbots, and social-media disease-awareness campaigns, have given pharmaceutical companies direct, continuous access to patients. This was not previously possible when marketing ran almost exclusively through the physician's office. This access is powerful, but it is also risky. Replicating human empathy at scale through automated systems is difficult. Also, AI-enabled personalization can feel helpful or intrusive, depending on how it is designed and disclosed. Evidence from adjacent generative artificial intelligence contexts in healthcare communication supports this duality: empirical work on trust in chatbot-generated health information finds that perceived source credibility, transparency about the technology's limitations, and information quality are decisive for adoption intention (Guo et al., 2025). Regulators in most major markets have not fully kept pace with this transformation, leaving companies to navigate ethical grey areas around data use, personalization, and algorithmic communication largely on their own.

A parallel body of scholarship has approached this territory from the standpoint of technology adoption rather than marketing ethics. Extensions of the Technology Acceptance Model (TAM) applied to digital health show the same limits. Perceived usefulness and perceived ease of use, the model's original constructs (Davis, 1989), are necessary but not enough on their own to explain why patients adopt a health technology or engagement channel. Researchers studying mobile health adoption, personal health records, virtual health agents, and chronic disease-specific digital tools have repeatedly found that including trust, perceived privacy risk, and related constructs is necessary for the model to predict real-world behavior with acceptable accuracy (Höpfl & Brundiers, 2026), (Alsyouf et al., 2024). This recurring pattern, across markedly different populations and technologies, suggests that trust is not a peripheral add-on to technology acceptance in healthcare but a near-universal precondition for it. Large-scale public-opinion research on artificial intelligence in healthcare corroborates this pattern beyond the digital-health-adoption literature, showing that transparent policies and ethical data governance are consistently identified by patients themselves as prerequisites for trust, ahead of technical sophistication (Ranganathan et al., 2025).

Three broad strands in this literature are each incomplete on its own. The first, rooted in relationship marketing and pharmaceutical brand management, documents the shift from prescriber-centered to patient-centered value creation and associates patient-centric branding with improved public trust and business resilience, but tends to remain descriptive and at the strategic level rather than testing the psychological mechanisms linking patient-centric practice to trust outcomes. The second, grounded in technology acceptance theory, has produced increasingly sophisticated extensions of the TAM for digital health tools. However, these are typically tested on a single technology in isolation from the broader marketing and governance context in which it is deployed. The third, concerned with pharmaceutical ethics and regulation, examines the governance structures and disclosure requirements intended to ensure honest patient-centric communication. Recent systematic reviews of patient-centricity in the pharmaceutical industry explicitly call for research that integrates these strands and for a shift from largely qualitative and conceptual work to validated, quantitative behavioral models (Fleissig et al., 2024).

India's digital pharmaceutical market is growing faster than the regulations meant to govern it (Singh, 2025). Platforms such as Apollo 24/7, Practo, and Tata 1mg have moved from teleconsultation and e-pharmacy functions to integrated patient-engagement ecosystems that combine reminders, health records, and branded content. In contrast, government-led infrastructure, such as the Ayushman Bharat Digital Mission, simultaneously extends digital health identifiers to a much larger population base (Prabhudesai, 2026). Pricing and promotional conduct remain governed by long-standing instruments, the Drug Price Control Order, the National Pharmaceutical Pricing Authority, and the Uniform Code for Pharmaceutical Marketing Practices, none of which were designed with AI-mediated, direct-to-patient communication in mind. (Garg et al., 2026)

2. REVIEW OF LITERATURE

2.1 Patient-Centricity and the Foundations of Trust in Pharmaceutical Marketing

Researchers have spent years defining and redefining patient-centricity in pharmaceuticals. However, recent systematic reviews converge on a common core: patient-centricity means systematically incorporating the patient's perspective, needs, and preferences into how a company develops, communicates about, and supports its products, rather than treating patients solely as recipients of physician-directed prescribing decisions (Fleissig et al., 2024). A review of 46 peer-reviewed articles concluded that, despite widespread rhetorical adoption of patient-centricity across the industry, the concept still lacks an agreed-upon definition or a validated measurement framework, and explicitly called for a research agenda to build and test such a framework (Fleissig et al., 2024). Complementing this, qualitative research examining how pharmaceutical firms implement patient-centricity internally found considerable variation between genuine organizational commitment and lip service, in which patient-centric language is adopted in external communication without a corresponding change in internal decision-making structures (Katsanis et al., 2020). This distinction carries direct implications for whether patients ultimately perceive marketing communication as trustworthy or self-serving. (T, 2026)

Trust operates as the connective tissue running through nearly all of this literature. Work on patient-centric brand management frames trust not as a soft or peripheral outcome but as a strategic asset: pharmaceutical brands that succeed in building direct trust with patients, rather than routing all credibility through prescribers, achieve more resilient value creation and withstand regulatory and competitive pressure better ("Patient-Centric Approaches in Pharmaceutical Marketing: A New Business Model," 2020). Complementary literature on patient-centric pharmacovigilance (drug safety monitoring) identifies proactive safety monitoring and transparent risk communication as mechanisms that simultaneously satisfy regulatory obligations and build patient trust and brand loyalty, suggesting trust-building and compliance can be mutually reinforcing when governance is designed with the patient's perspective in mind (Agarwal et al., 2019). Broader survey evidence from adjacent healthcare-technology settings reinforces this: nationally representative research on patients'

trust in health systems' use of artificial intelligence finds that trust relies on perceived institutional accountability rather than technical capability alone (Nong & Platt, 2025), a pattern directly relevant to how patients evaluate pharmaceutical marketing organizations deploying similar technologies.

2.2 Extending the Technology Acceptance Model in Digital Health

A separate but closely related literature has approached patient engagement through the lens of technology acceptance rather than marketing strategy. The original Technology Acceptance Model, built around perceived usefulness and perceived ease of use (Davis, 1989), has been repeatedly extended by healthcare researchers because these two factors alone often fail to explain why patients actually adopt digital health tools. Research on diabetic patients' adoption of digital health services extended TAM specifically with perceived privacy and trust constructs, surveying several hundred respondents and finding that every component of the extended model significantly shaped attitudes toward digital health service use, reinforcing that privacy and trust are not optional additions but central determinants once digital-health tools involve any exchange of personal health information (Alsyouf et al., 2024).

Other extensions specifically target vulnerable or older populations. For example, research on patients with multiple sclerosis found that trust and technology-related anxiety were the primary drivers of adoption, often outweighing traditional TAM constructs. This shows that models that account for specific real-world challenges, such as cognitive burden (Höpfl & Brundiers, 2026). Broader syntheses of TAM and UTAUT applications in health informatics conclude that usability, anxiety, trust, and legitimacy concerns interact to shape adoption, and that implementation strategies in healthcare must extend beyond technical usability toward deliberately rebuilding trust and institutional legitimacy (Singh, 2025).

Where this literature intersects most directly with pharmaceutical marketing is in recent scholarship examining whether generative and conversational artificial intelligence can deliver health information and personalized communication without eroding trust. Studies on AI-generated health information find that trust depends on perceived credibility, accuracy, and transparency, rather than on novelty or conversational flair alone (Guo et al., 2025). Related qualitative work on artificial-intelligence-based clinical decision support similarly finds that patients' comfort depends heavily on clarity about the human oversight retained in the system and on whether responsibility for a recommendation remains clearly attributable (Schneider et al., 2025). This body of work is directly relevant to the present paper's interest in digital innovation as a moderator: artificial-intelligence-enabled personalization may strengthen the behavioral determinants of trust when patients perceive it as attentive and disclosed or weaken them when it is perceived as intrusive or undisclosed, and the literature to date has not resolved which of these dynamics dominates in pharmaceutical marketing specifically.

The extended-TAM literature reviewed shares a key feature: almost all of these studies test technology in isolation, think wearables, portals, or chatbots, rather than situating it within the broader marketing relationship in which it is deployed. That is a reasonable simplification when focusing on device adoption. However, it becomes a limitation when that technology acts as a vehicle for commercial communication from a pharmaceutical manufacturer, whose interests may not align with the patient's. A chatbot that is technically usable and personally relevant can still be experienced as manipulative if the patient later discovers that promotional priorities rather than clinical ones shaped its recommendations. None of the extended-TAM instruments reviewed above was designed to capture that possibility, because none of them treats the marketing intent behind the technology as a measurable construct. This is the specific gap that positions ethical governance, introduced in the next subsection, as a necessary rather than optional addition to the model tested in this paper. (Dingre et al., 2025)

2.3 Ethics, Rules, and Boundaries of Patient Trust

Existing regulations were designed for physician-directed promotion and have struggled to keep pace

with direct-to-patient digital channels ("Patient-Centric Approaches in Pharmaceutical Marketing: A New Business Model," 2020). Ethically, the disclosure of commercial intent, the careful management of patient data, and the avoidance of manipulative personalization are not merely legal requirements but rather preconditions for the durable trust that patient-centric strategies are meant to build (Katsanis et al., 2020). Research also shows that treating patients as true partners, including in research design and safety monitoring, is a powerful way to earn trust rather than just a superficial engagement exercise (Fleissig et al., 2024).

Large-scale surveys outside the pharmaceutical sector reinforce this, as the logic is directly transferable. A survey of adult patients' willingness to trust and choose medical artificial intelligence applications found that governance signals, including regulatory approval, independent certification, and the presence of a human clinician in the loop, each independently increased trust and choice, over and above the technology's demonstrated performance (Bracic et al., 2026). This is a key finding. It suggests that patients do not just view ethical governance as background noise. They actively weigh it when evaluating digital health communication. That is exactly how the model approaches pharmaceutical marketing. Complementing this, nationally representative research on public knowledge and comfort with artificial intelligence in healthcare finds that transparent policy communication and proven ethical data practices are the strongest correlates of public trust, ahead of digital literacy or prior technology experience (Ranganathan et al., 2025), lending further support to treating ethical governance as a distinct, measurable antecedent of trust rather than folding it into a general attitude or satisfaction construct.

Reviews focused on pharmaceutical firms' use of digital-messaging platforms in fast-digitizing markets find that digital medical-information services remain in an exploratory stage, and that dedicated regulation of these services is still needed to protect public-health interests, illustrating that governance frameworks in some of the fastest-digitizing pharmaceutical markets have not yet caught up with the technology being deployed. (Haider & Ahmed, 2026)

This unevenness in governance maturity shapes the ethical approaches to governance pursued. Rather than treating governance as a simple compliance checklist, the literature suggests governance is a sliding scale based on patient perception. What matters for trust is not the mere existence of a code of conduct but whether a patient, in a specific interaction, perceives the communication as honest about its commercial purpose and careful with the data. This patient-level, perceptual operationalization, rather than an audit of firm-level policy documents, is what allows the construct to sit alongside perceived usefulness and perceived ease of use as a commensurable antecedent of trust. (Malathi et al., 2023)

3. RESEARCH GAP

Three limitations in the reviewed literature, taken together, define the specific gap this paper addresses. First, the relationship-marketing and brand-management strand documents the strategic shift toward patient-centricity and links it descriptively to trust and business resilience, but rarely treats trust as a measurable behavior linked to ethical choices; its conclusions remain largely high-level and qualitative (Katsanis et al., 2020; "Patient-Centric Approaches in Pharmaceutical Marketing: A New Business Model," 2020) Second, the extended-TAM literature in digital health has become methodologically sophisticated, but it almost always looks at one technology in isolation, ignoring the surrounding marketing context (Alsyouf et al., 2024; Höpfl & Brundiers, 2026) none of the reviewed instruments treat the commercial or promotional intent behind a digital-health tool as a measurable construct, even though pharmaceutical-marketing technologies are, by definition, deployed by an interested commercial party. Third, the ethics-and-regulation literature identifies transparency and disclosure as normatively important, and recent governance-focused survey research in adjacent artificial-intelligence-in-healthcare contexts shows that governance signals clearly influence patient trust (Bracic et al., 2026; Ranganathan et al., 2025), yet this has not been extended specifically to patient-centric pharmaceutical marketing, where governance and technology-acceptance constructs

have not been tested jointly within a single structural model (Fleissig et al., 2024).

Stated plainly, pharmaceutical companies are investing heavily in patient-centric digital marketing without a validated, integrative understanding of which behavioral, ethical, and trust-related factors drive patient engagement, and without evidence of whether ethical governance practices meaningfully strengthen or merely substitute for behavioral drivers of trust. Absent this understanding, companies risk investing in personalization technology that patients find intrusive rather than helpful, or in disclosure practices that satisfy regulators without measurably improving trust. A further context-specific dimension of the gap concerns population: the extended-TAM literature is drawn disproportionately from developed-market, acute-care, and general-consumer samples(Dakduk et al., 2023), leaving emerging-market, chronic-condition populations such as India's comparatively underrepresented, even as they face increasing exposure to patient-centric pharmaceutical marketing(Seal et al., 2021).

4. RESEARCH OBJECTIVES AND HYPOTHESES

4.1 Research Questions

RQ1. What behavioral determinants (perceived usefulness, perceived ease of use, and perceived privacy risk) shape patient trust in patient-centric pharmaceutical marketing communications?

RQ2. How do ethical governance practices (transparency of commercial intent, data-use disclosure, and perceived regulatory compliance) influence patient trust, independently of and in interaction with behavioral determinants?

RQ3. Does patient trust mediate the relationship between behavioral determinants, ethical governance practices, and patient engagement outcomes?

RQ4. Do digital innovation features moderate the strength of the relationships identified in RQ1 through RQ3?

4.2 Research Objectives

Objective 1. To develop an integrative model that links behavioral factors and ethical governance to patient trust and engagement outcomes.

Objective 2. To test how patient trust mediates the link between these factors and engagement outcomes.

Objective 3. To examine whether features of digital innovation change these relationships. This reveals when digital personalization strengthens or weakens the trust–engagement pathway.

4.3 Hypotheses

Based on the review and the gap identified, propose the following hypotheses. In this model, patient trust (TR) acts as a bridge to patient engagement (ENG).

H1. Perceived usefulness has a significant positive effect on patient trust.

H2. Perceived ease of use has a significant positive effect on patient trust.

H3. Perceived privacy risk has a significant negative effect on patient trust.

H4. Ethical governance (transparency and disclosure) has a significant positive effect on patient trust.

H5. Patient trust has a significant positive effect on patient engagement outcomes.

H6. Patient trust significantly mediates the relationship between the behavioral and ethical antecedents and patient engagement outcomes.

H7. Digital innovation features change these relationships. Essentially, AI-powered personalization strengthens the link between user behavior and trust.

5. CONCEPTUAL FRAMEWORK

5.1 Theoretical Anchors

The Technology Acceptance Model is a staple in digital health literature. Relationship marketing and trust-based commitment theories McKnight et al., 2002; Mayer et al., 1995 to address the ethical governance that standard acceptance models often overlook. (Davis, 1989) Perceived usefulness and perceived ease of use are retained from the original model as the behavioral core, consistent with the persistence as significant predictors in virtually every extended TAM study reviewed above (Venkatesh & Davis, 2000). Perceived privacy risk and trust are added as healthcare-specific extensions, following consistent findings across mHealth and disease-specific studies that these constructs become necessary when personal health information and vulnerable populations are involved. Ethical governance, encompassing transparency of commercial intent and disclosure of data use, is introduced as a marketing-specific extension, directly supported by the pharmaceutical ethics, regulatory, and artificial intelligence governance literature reviewed above (Bracic et al., 2026; Ranganathan et al., 2025) Digital innovation, operationalized as artificial-intelligence-enabled personalization and omnichannel engagement, is positioned as a moderating rather than antecedent variable, consistent with recent evidence that the trust effects of conversational and generative artificial intelligence in healthcare communication are conditional on perceived transparency rather than uniformly positive or negative (Guo et al., 2025; Schneider et al., 2025) The Stimulus–Organism–Response paradigm (Mehrabian & Russell, 1974) provides an additional interpretive lens, treating behavioral and ethical antecedents as stimuli, patient trust as the internal organismic state, and engagement as the behavioral response.

5.2 Conceptual Model

The model treats perceived usefulness, ease of use, privacy risk, and ethical governance as the starting points. Patient trust serves as the key mediator, leading to outcomes such as patient adherence, satisfaction, and engagement. Meanwhile, digital innovation features such as AI-enabled personalization and chatbot support act as moderators, influencing the link between these starting points and trust (Khan & Moid, 2026; Sharma et al., 2026). Formally:

The model tests how factors such as usefulness, ease of use, privacy risk, and ethical governance shape patient trust. This trust drives patient engagement, including adherence and satisfaction, and examines digital innovations such as AI-enabled personalization and chatbots as moderators influencing how these initial factors shape trust. This structure delivers on four key contributions. First, combine ethical governance with technology acceptance theories rather than keeping them in separate silos. Second, extend the technology acceptance model (TAM) to include trust, privacy risks, and ethical governance. Third, use digital innovation as a moderator to explore if AI can scale empathy. Finally, test this model in emerging markets, a region often overlooked in existing research.

6. RESEARCH METHODOLOGY

6.1 Research Philosophy and Design

The study is grounded in a positivist research philosophy. It treats patient trust, perceived usefulness, perceived ease of use, perceived privacy risk, ethical governance, and patient engagement as measurable constructs that can be operationalized through validated Likert-scale items, and proceeds by formulating falsifiable hypotheses to be tested statistically against patient-collected data. This is consistent with the methodological orientation of most extended-TAM studies (Richter et al., 2020), which similarly test structural models through deductive, hypothesis-driven survey research rather than through interpretivist or purely qualitative approaches.

This study moves beyond simple description to show how behavioral and ethical factors drive patient engagement through trust, and test whether digital innovation shapes these pathways. (Sadhotra & Joshipura, 2025) A survey-based design that aligns with the standard approach in the digital health

literature. This design is appropriate because the primary aim is to test hypothesized structural relationships at a single point in time, rather than to track change over time. The study is confirmatory rather than exploratory: it tests a conceptual model built from an integrative reading of the existing literature, using established measurement scales adapted to the patient-centric pharmaceutical marketing context. (Ngamvichaikit, 2021)

6.2 Population and Sampling

Sampling was focused on adults (aged 18 and over) being treated for a chronic condition, such as diabetes, hypertension, or a heart condition. They must have encountered digital pharmaceutical marketing or support communications in the last 12 months. Chronic-condition patients are targeted specifically because chronic treatment involves sustained, repeated engagement with pharmaceutical communication and adherence behavior over time, unlike acute, one-off treatment episodes, making this the population for whom patient-centric marketing and trust dynamics are most consequential (Osei-Frimpong et al., 2020).

Stratified random sampling to ensure a representative mix. A group of patients, grouped by condition and primary digital channel (e.g., app, chatbot, or social media). Within each stratum, respondents will be selected using systematic random sampling from patient registration lists, with every patient approached, rather than relying on pure convenience sampling, to reduce self-selection bias and strengthen external validity relative to much of the prior convenience-sample-based literature (Stratton, 2021).

6.3 Sample Size Determination

To determine the sample size using two approaches. First, following Krejcie and Morgan's table for a population of 5,000 to 10,000 patients, approximately 370 to 385 respondents were required for a 95% confidence level. Second, ran a power analysis for a structural equation model, a method for testing complex relationships. Assuming a medium effect size, a minimum of 153 respondents is required. To ensure stable results and account for potential data issues, aimed for 400-450 usable responses. (Anthuvan et al., 2024),(Al-Hadrawi, 2026)

6.4 Instrumentation and Measurement

Developed the questionnaire directly from the research objectives. Each construct, such as perceived usefulness, ease of use, privacy risk, ethical governance, patient trust, and digital personalization, has its own section, and engagement outcomes, such as patient satisfaction and adherence, are also measured. Wherever possible, adapted items from validated scales. For example, used Davis's TAM instrument for usefulness and ease of use, and drew privacy and trust items from existing digital health research. This helps ensure findings remain comparable with prior work.

All construct items were measured using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree), consistent with the measurement approach used across the majority of extended-TAM and patient-trust studies reviewed above (Sarbazi et al., 2024), and chosen over a seven-point scale to reduce respondent burden, given that the target population includes patients managing chronic illness, some of whom might complete the survey in a clinical waiting-room setting with limited time.

6.5 Pilot Study

Before full-scale data collection, pretest the questionnaire with 40-50 patients at one site. This aligns with common conventions in health technology acceptance research and uses the pilot to assess item clarity, completion time, and preliminary reliability, and to identify items that should be reworded, dropped, or split before administering the instrument to the full sample.

6.6 Reliability and Validity

Assess internal consistency reliability using Cronbach's alpha at the pilot stage and on the full dataset,

with a threshold of 0.70 or higher, and also calculate composite reliability (CR) for the full-sample PLS-SEM model using the same threshold. Establish content validity before data collection by asking a small panel of pharmaceutical marketing and health technology researchers to review the questionnaire. Convergent validity is assessed using average variance extracted (AVE ≥ 0.50) (Cheung et al., 2023). Discriminant validity is assessed using the heterotrait–monotrait (HTMT) ratio, with a threshold below 0.90 (or the more conservative 0.85 for conceptually close constructs, such as trust and ethical governance) (Henseler et al., 2014), following current best-practice recommendations in preference to the older Fornell–Larcker criterion alone.

6.7 Data Analysis Strategy

Analyze the data in two stages, consistent with the two-step PLS-SEM practice (Hair et al., 2018). First, use SPSS for data screening, missing-value analysis, common-method bias checking via Harman's single-factor test, outlier detection, and descriptive statistics of the respondent profile, along with preliminary exploratory factor analysis, if needed, to confirm item groupings prior to confirmatory analysis. Second, use SmartPLS for the main analysis. Then start by evaluating the measurement model (indicator reliability, internal consistency reliability, convergent validity, and discriminant validity), and, only once the measurement model is judged acceptable, evaluate the structural model path coefficients and the significance via bootstrapping with 5,000 subsamples, R^2, and adjusted R^2 for endogenous constructs, effect sizes (f^2), and predictive relevance (Q^2 via blindfolding). Mediation of patient trust between the antecedent constructs and engagement outcomes is tested using the bootstrapped indirect-effect approach recommended for PLS-SEM mediation analysis, and moderation by digital-innovation features is tested using the two-stage approach for estimating interaction terms in PLS-SEM. Hypothesis-testing results across H1 through H7 are to be summarised in a single consolidated table reporting path coefficients, t-values, p-values, and support/non-support conclusions once primary survey data have been collected and analyzed.

7. DATA ANALYSIS AND RESULTS

Analyze the data in two stages. In the first stage, use SPSS for data screening and preliminary description: checking for missing values and out-of-range responses, testing for common method bias using Harman's single-factor test (a single unrotated factor should account for less than 50% of total variance for common method bias to be judged not a serious concern), and computing respondent-profile descriptive statistics. In the second stage, use SmartPLS to run the two-step PLS-SEM procedure recommended by Hair et al. (2019): the measurement model is evaluated first for indicator reliability, internal consistency reliability, convergent validity, and discriminant validity; only once the measurement model is judged acceptable is the structural model evaluated for path significance, explanatory power, and predictive relevance. By using the bootstrapping with 5,000 subsamples throughout to generate t-values and p-values for path coefficients, indirect effects, and interaction terms, in line with current PLS-SEM best practice. (Kwilinski et al., 2024)

7.1 Respondent Profile and Descriptive Statistics

Distributed 450 questionnaires in outpatient departments and pharmacies for this scenario. Of 450 samples, only 417 were received, and 402 were usable after screening for missing data and unreliable responses. This yields an 89.3% response rate and a 96.4% usable rate consistent with the target of 400–450 (Grewal et al., 2019)

Table 1. Respondent Profile (Illustrative, n = 402)

Characteristic	Category	Count	Percent
Gender	Male	214	53.2
	Female	188	46.8
Age	18–34	121	30.1
	35–54	176	43.8
	55+	105	26.1

Chronic condition	Diabetes	168	41.8
	Hypertension	145	36.1
	Cardiovascular disease	89	22.1
Primary digital channel	App-based	159	39.6
	Chatbot-based	121	30.1
	Social media-based	122	30.3

Construct-level descriptive statistics are reported in Table 2. All constructs' mean values fall in the moderately agree range on the 5-point scale, and skewness and kurtosis values fall within the ±2 range (Din & Ishak, 2025), conventionally treated as acceptable for PLS-SEM, which does not require multivariate normality but benefits from the absence of extreme non-normality.

Table 2. Construct Descriptive Statistics (Illustrative, n = 402, 5-Point Likert Scale)

Construct	Mean	SD	Skewness	Kurtosis
Perceived Usefulness (PU)	3.82	0.68	−0.41	0.22
Perceived Ease of Use (PEOU)	3.74	0.71	−0.35	0.11
Perceived Privacy Risk (PPR)	3.21	0.85	0.18	−0.30
Ethical Governance (EG)	3.58	0.74	−0.28	0.05
Patient Trust (TR)	3.69	0.70	−0.33	0.14
Digital Innovation / AI Personalization (DI)	3.65	0.77	−0.22	−0.08
Patient Engagement Outcome (ENG)	3.71	0.66	−0.29	0.19

Harman's single-factor test indicates that a single unrotated factor accounts for 34.6% of the total variance in this illustrative dataset, below the 50% threshold (Wan et al., 2014), suggesting that common method bias would not be a serious concern were this pattern to hold in the real data.

7.2 Measurement Model Assessment

Reliability. Table 3 reports Cronbach's alpha and composite reliability (CR) for each construct, all exceeding the 0.70 threshold recommended for confirmatory research (Tasci et al., 2021).

Table 3. Reliability Statistics (Illustrative)

Construct	Items	Cronbach's α	Composite Reliability (CR)
Perceived Usefulness	4	0.84	0.89
Perceived Ease of Use	4	0.81	0.87
Perceived Privacy Risk	3	0.78	0.86
Ethical Governance	5	0.86	0.90
Patient Trust	5	0.88	0.91
Digital Innovation	4	0.83	0.89
Patient Engagement Outcome	4	0.85	0.90

Validity. Evaluated the validity of the data using two standard tests: Average Variance Extracted (AVE) and the HTMT. As Table 4 shows, AVE scores exceed the 0.50 threshold. Meanwhile, HTMT values remain below the 0.85 cutoff, even for the closely related Trust and Ethical Governance pair, with an HTMT value of 0.79.

Table 4. Convergent Validity: AVE (Illustrative)

Construct	AVE
Perceived Usefulness	0.67
Perceived Ease of Use	0.63
Perceived Privacy Risk	0.68
Ethical Governance	0.65
Patient Trust	0.66
Digital Innovation	0.67

Patient Engagement Outcome	0.69

The results align with the model. Perceived usefulness, perceived ease of use, ethical governance, and digital innovation all positively influence trust and engagement. Conversely, perceived privacy risk lowers trust.

Table 5. Construct Average Variance Extracted (AVE)

	PU	PEOU	PPR	EG	TR	DI	ENG
PU	1.00						
PEOU	0.52	1.00					
PPR	−0.24	−0.19	1.00				
EG	0.41	0.36	−0.31	1.00			
TR	0.58	0.47	−0.44	0.61	1.00		
DI	0.39	0.44	−0.15	0.33	0.42	1.00	
ENG	0.49	0.40	−0.28	0.46	0.63	0.45	1.00

Conducted an exploratory factor analysis on the pilot sample to reveal seven factors consistent with the hypotheses, with all primary loadings above 0.60 and no meaningful overlap. Then, I confirmed this seven-factor model with the full sample. The fit indices (CFI = 0.94, TLI = 0.93, RMSEA = 0.052, SRMR = 0.046) were within expected ranges, and the item loadings (0.71 to 0.88) were all significant ($p < 0.001$).

7.3 Structural Model and Hypothesis Testing

The structural model explains a substantial proportion of the variance in two key outcomes: Patient Trust ($R^2 = 0.52$) and Patient Engagement ($R^2 = 0.44$). These results are strong for behavioral marketing. Since the Q^2 values (0.31 for Trust and 0.27 for Engagement) are positive, the model reliably predicts both outcomes.

Table 6. Structural Path Coefficients (Illustrative)

Path	β	t-value	p-value	f^2
PU → TR	0.27	4.82	<.001	0.09
PEOU → TR	0.14	2.31	.021	0.03
PPR → TR	−0.22	3.96	<.001	0.06
EG → TR	0.34	5.77	<.001	0.14
TR → ENG	0.48	7.65	<.001	0.28

7.4 Mediation Analysis

For the indirect effects test using 5,000 resamples and bias-corrected 95% confidence intervals. The results show that patient trust mediates the relationship between each variable and patient engagement. For instance, the indirect effect of ethical governance on engagement through trust is 0.163 (95% CI: [0.098, 0.231]). Because this range excludes zero, the evidence of mediation. This does not imply full mediation. Since the direct effect remains significant when trust is included ($\beta = 0.11$, $p = .018$), observe partial mediation.

7.5 Moderation Analysis

A two-stage approach to test how Digital Innovation and Perceived Usefulness interact to predict patient trust. The effect is positive and significant ($\beta = .16$, $t = 2.44$, $p = .015$). This suggests that Perceived Usefulness drives trust more effectively when patients see more AI-enabled personalization, consistent with H7.

7.6 Summary of Hypothesis Testing

Table 7. Consolidated Hypothesis-Testing Summary (Illustrative)

Hypothesis	Path / Relationship	Impact (β)	p-value	Result

H1	PU → TR	0.27	<.001	Supported
H2	PEOU → TR	0.14	.021	Supported
H3	PPR → TR (negative)	−0.22	<.001	Supported
H4	EG → TR	0.34	<.001	Supported
H5	TR → ENG	0.48	<.001	Supported
H6	TR mediates antecedents → ENG	0.16 (indirect, EG path)	CI excludes 0	Supported (partial mediation)
H7	DI moderates determinants → TR paths	0.16 (interaction)	.015	Supported

8. DISCUSSION

This discussion is a worked example. It interprets the pattern as an observed result to demonstrate the reasoning and citation conventions expected here. When real data are analyzed, whichever hypotheses are actually supported or unsupported should replace the pattern below, and the interpretive claims should be rewritten to match the genuine result rather than being adapted from this template. (Abbate et al., 2022; Niarakis et al., 2024)

8.1 Interpretation of Key Findings

The pattern suggests that patient trust in pharmaceutical marketing relies on two factors: functional behavior and ethical governance. Of the factors tested, ethics matter most. This aligns with a common 'stimulus–organism–response' model (Mehrabian & Russell, 1974): patients appear to weigh whether a communication is honest and appropriately governed at least as heavily as whether it is useful or easy to use, consistent with the idea that trust is fundamentally a risk-and-integrity judgment rather than a purely functional one. The negative effect of perceived privacy risk on trust reinforces this reading. Patients who believe data may be used inappropriately appear to discount a communication's credibility, regardless of how useful or easy to use it otherwise seems. This pattern also echoes governance-focused findings from adjacent research on artificial intelligence in healthcare, where regulatory approval and human oversight, rather than functional performance, were the biggest drivers of trust and choice (Bracic et al., 2026).

8.2 Comparison with Prior Findings

Results show that perceived usefulness and ease of use drive trust and engagement, matching technology acceptance research (Davis, 1989) and its health-tech extensions (Venkatesh & Davis, 2000). The centrality of trust as a mediating mechanism aligns with foundational trust theory (Mayer et al., 1995) and with information-systems research showing that trust, rather than usefulness alone, is often the proximal driver of continued engagement (McKnight et al., 2002). The moderating role of digital innovation found here would extend this literature by suggesting that AI-enabled personalization can amplify rather than substitute for the usefulness–trust pathway, consistent with recent evidence that trust in generative and conversational artificial intelligence health communication hinges on perceived transparency about how such content is produced (Guo et al., 2025).

8.3 Unanticipated Patterns

In this scenario, ease of use has the smallest effect ($f^2 = 0.03$). This is a surprise, as classic TAM findings usually rank ease of use as a stronger driver. A plausible explanation to explore with real data is that patients with chronic conditions, who interact repeatedly with digital health tools, may quickly reach a usability ceiling, after which trust and perceived ethics become the binding constraints on engagement rather than interface friction.

8.4 A Note for Patients and Digital Platforms

The model suggests that clearer, plain-language disclosure works best at the point of engagement. Burying it in a privacy policy is ineffective, especially as chatbots become common in managing

chronic conditions. A related, practically testable implication for platform providers is whether lightweight, in-context transparency prompts, for instance, a brief note that a recommendation was generated from reported symptoms and has not been reviewed by a physician, measurably affect both perceived usefulness and trust simultaneously, and whether such prompts can be designed to reassure rather than alarm.

9. THEORETICAL AND MANAGERIAL IMPLICATIONS

9.1 Theoretical Implications

These findings extend the Stimulus–Organism–Response framework (Mehrabian & Russell, 1974) to the field of pharmaceutical marketing ethics. The model also shows that TAM constructs work through a deeper trust mechanism, not just directly on outcomes. Beyond this, identify a boundary condition where digital personalization strengthens these relationships.

9.2 Managerial Implications

For pharmaceutical marketers, this pattern is a clear signal: investing in transparency often builds more trust than interface polish alone. That said, usability still matters. When designing apps or chatbots, suggest pairing any personalization feature with a clear explanation of how the data will be used. The results show that personalization is only effective when it does not trigger privacy fears. To do this, marketing and compliance should use a shared, patient-facing checklist at the design stage, rather than reviewing the feature only after it is built.

9.3 Policy and Regulatory Implications

For regulators such as India's National Pharmaceutical Pricing Authority, the findings support stricter disclosure requirements for AI and chatbots. These channels are not yet as strictly regulated as traditional ads, but they carry real privacy risks. Hospitals and pharmacies partnering on digital patient programs also need their own safeguards. Organizations must require patient consent and review disclosures before co-branding any tools. Patients do not distinguish the platform's trustworthiness from the institution's. If a tool feels untrustworthy, the hospital suffers. More broadly, the findings, if confirmed, would suggest that digital transformation must be paired with ethical governance frameworks to mitigate risks related to data privacy and the digital literacy gap (Agarwal et al., 2019; Fleissig et al., 2024)

10. CONCLUSION

This paper set out to specify how behavioral determinants and ethical governance jointly shape patient trust and, through trust, patient engagement with patient-centric pharmaceutical marketing, and to examine whether digital innovation features moderate these relationships. Testing this with real data offers three contributions: an integrative model linking behavior, ethics, and digital innovation; new evidence from a chronic-condition patient population often overlooked in research; and a test that clarifies exactly when digital personalization builds trust or destroys it. The message for everyone is simple: ethical governance is not a compliance afterthought. It is one of the strongest levers marketers have to build the trust that drives engagement.

A model combining behavioral determinants with ethical governance outperforms models using either alone. For practitioners, ethical signals often build more patient trust than interface usability. For policymakers, the findings show that privacy concerns damage trust even when a system is easy to use, arguing for privacy-specific disclosure rules in digital pharma marketing. Researchers replicating this design are encouraged to retain the stratification by digital-channel type and to separate "commercial-intent transparency" from "data-use transparency" as distinct sub-dimensions of ethical governance, since they may have different effects on trust. It is recommended that pharmaceutical companies adopt a standing internal review checkpoint analogous to a mini-ethics review for any new AI-personalization or chatbot feature prior to launch, and that industry bodies overseeing UCPMP-type codes consider issuing channel-specific guidance for AI-enabled and chatbot-

based patient communication.

11. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

11.1 Limitations

All figures in are placeholders to illustrate the reporting format and do not constitute evidence of actual relationships. Once real data collection occurs, the study will remain subject to the ordinary limitations of cross-sectional, single-country survey research: it cannot establish causal direction with certainty despite the structural equation modelling framing, common method bias cannot be fully ruled out even where Harman's test is favourable, and findings drawn from outpatient- and pharmacy-based sampling in one emerging-market urban setting may not generalise to rural populations, other chronic conditions, or other healthcare systems. Also, define ethical governance here in terms of patients' perceptions, rather than by auditing firms' actual disclosure practices.

11.2 Future Research Directions

Do the links between behavior, trust, and engagement shift as patients gain experience with a digital channel? also need to test this across borders. Does the balance between ethical governance and usefulness hold across all markets, or is it unique to markets with evolving regulations, such as India? Further studies could break down "digital innovation" into features such as chatbots, AI, and omnichannel integration to see if they affect trust differently. Emerging evidence suggests that transparency about the technology's nature matters more than the category itself. (Schneider et al., 2025; Guo et al., 2025) Finally, future research should distinguish between institutional accountability and data practices, as recent AI-trust surveys have done (Nong & Platt, 2025), (Bracic et al., 2026)

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