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Explaining and Advancing Information Technology Business Value (ITBV) in Healthcare from a Socio-Technical Systems Perspective

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Abstract: Healthcare organizations increasingly invest in artificial intelligence (AI) and telehealth technologies to improve quality, efficiency, and performance. Yet the realization of information technology business value (ITBV) remains inconsistent. This commentary argues that digital value in healthcare does not stem from technological sophistication alone but from deliberate integration within socio-technical systems that cultivate calibrated trust in automation. Drawing on established ITBV and socio-technical theory, the paper reframes AI and telehealth as capability-building infrastructures whose effectiveness depends on participatory governance, clinician engagement, and stakeholder trust. Illustrative cases, including AI-enabled sepsis detection, remote patient monitoring, and AI-assisted radiology, demonstrate that adoption and impact hinge on workflow alignment, interpretability, transparency, and professional identity considerations. Technological resistance is repositioned as a rational and informative response to misalignment rather than obstruction. The inquiry advances a people-centered framework emphasizing engagement, adaptive leadership, and structured oversight as essential conditions for sustainable digital transformation in complex healthcare ecosystems.

Keywords: Artificial Intelligence in Healthcare, Telehealth Adoption, Technological Determinism, Socio-Technical Systems, Trust in Automation, Health Administration, Healthcare Technology, IT Business Value (ITBV)

JEL Codes: I11, O33, L86, M1, D83

Introduction

Information Technology Business Value (ITBV) is commonly defined as the measurable organizational benefits that result from the deployment and effective use of information technology resources (Melville et al., 2004). Rather than attributing value to technology as an isolated asset, established scholarship conceptualizes ITBV as the performance improvements, financial, operational, strategic, and relational, that arise when IT resources are combined with complementary organizational capabilities (Melville et al., 2004). ITBV is not the inherent value of technology itself, but the realized improvements in organizational outcomes that result from effectively integrating information technology with people, processes, and complementary resources. In healthcare settings characterized by diagnostic uncertainty, regulatory scrutiny, and ethical accountability, artificial intelligence (AI) and telehealth technologies generate value only when they are embedded within coordinated constellations of people, processes, institutional norms, and governance structures.

Earlier formulations of ITBV emphasized efficiency gains, cost containment, and transactional automation. Healthcare information technology was frequently justified on the basis of reducing documentation time or streamlining billing operations. However, subsequent scholarship reconceptualized IT as a strategic and relational asset whose benefits depend upon complementarities with organizational routines, professional expertise, and contextual alignment (Gregor et al., 2006; Tallon et al., 2020). This reconceptualization is particularly salient in clinical environments, where trust in automation mediates the translation of technical outputs into clinical decisions.

Decades of empirical research converge on a foundational insight that technology does not autonomously create value. Instead, value emerges through configurations of technological and non-technological resources that strengthen organizational capabilities such as diagnostic reliability, care coordination, and adaptive responsiveness (Dedrick et al., 2003; Schweikl & Obermaier, 2023). In healthcare, these configurations must also foster calibrated trust, neither blind reliance nor reflexive skepticism, toward algorithmic systems. Without such trust, AI tools are ignored, overridden, or misapplied, thereby eroding potential returns on investment.

Consider deploying an AI-driven clinical decision support system to detect early sepsis. The predictive model may demonstrate high sensitivity and specificity during validation. Yet its clinical impact depends upon whether frontline clinicians perceive the system as credible, transparent, and congruent with professional judgment. If risk scores appear without explanation or if false positives accumulate, clinicians may disengage, leading to distrust of automation and alert fatigue. Conversely, when the model's rationale is interpretable, when escalation protocols are co-designed with physicians and nurses, and when governance committees monitor performance and recalibrate thresholds, trust in automation strengthens. In this socio-technical arrangement, the AI system augments human vigilance rather than competing with it, thereby translating predictive accuracy into reduced mortality and improved patient safety.

Telehealth technologies provide an equally instructive illustration. A health system may implement remote patient monitoring for individuals with congestive heart failure, equipping patients with connected scales and wearable biosensors. However, the generation of continuous data streams does not, in itself, produce value. Meaningful benefit materializes only when care teams are institutionally supported to review alerts in real time, when reimbursement pathways legitimize virtual interventions, and when patients trust the digital interface sufficiently to adhere to monitoring protocols. A lack of trust in data privacy or clinical responsiveness leads to disengaged patients and fragmented care. By prioritizing transparent communication and consistent follow-up, providers can bridge the gap between technological capacity and improved patient outcomes, including reduced readmissions.

Trust in automation is likewise central in AI-assisted radiology. When algorithmic tools highlight suspicious pulmonary nodules on imaging studies, radiologists must determine how to incorporate these prompts into diagnostic reasoning. Overreliance may propagate algorithmic bias; under-reliance may squander sensitivity gains. Organizations that cultivate structured training, peer review, and performance auditing enable clinicians to develop informed trust; confidence grounded in understanding system limitations. In this context, IT business value is expressed not merely through throughput efficiency, but through improved diagnostic concordance and reduced variability across providers.

Reframing ITBV in healthcare through a socio-technical and trust-oriented lens underscores that AI and telehealth investments are fundamentally capability-building endeavors. Their value resides in strengthening adaptive capacity, enhancing collaborative intelligence between humans and machines, and reinforcing institutional legitimacy in the eyes of patients and regulators. Accordingly, evaluation of IT business value must extend beyond algorithmic metrics and system uptime. It must incorporate measures of clinician trust, patient engagement, ethical governance, health equity, workflow coherence, and longitudinal improvement in outcomes.

When AI and telehealth technologies are deployed as isolated technical artifacts, they risk becoming costly yet underutilized assets. When embedded within thoughtfully designed socio-technical systems that cultivate calibrated trust in automation, they evolve into strategic instruments capable of transforming care delivery, advancing clinical quality, and sustaining organizational performance in an increasingly digital healthcare ecosystem.

Problem Statement

Healthcare organizations continue to invest heavily in artificial intelligence (AI), telehealth platforms, and advanced health information systems, expecting these technologies to enhance quality, efficiency, and organizational performance. Yet, the realization of IT business value (ITBV) remains uneven and frequently disappointing. A persistent oversight in both scholarship and practice is the underestimation of the human element in IT project management, technology development, and technology adoption. Although foundational ITBV research emphasizes complementarities between technological and organizational resources (Melville et al., 2004; Dedrick et al., 2003; Bayer et al., 2020), implementation strategies often privilege technical functionality over the lived experiences, professional identities, and behavioral responses of clinicians, administrators, and patients.

In healthcare environments characterized by professional autonomy, high-stakes decision-making, and ethical accountability, resistance to technological change is not merely obstructionist behavior; it is frequently a rational response to perceived threats to clinical judgment, workflow coherence, or patient safety. AI-driven decision support tools may be technically robust yet encounter clinician pushback when insufficiently transparent or misaligned with established practice norms. Telehealth systems may fail to achieve sustained adoption when frontline staff perceive them as increasing workload without commensurate institutional support. Consequently, the central problem is not technological inadequacy per se, but the failure to design and manage IT initiatives through a people-centered lens that integrates trust, engagement, and participatory governance into the core of digital transformation efforts.

Purpose Statement

The purpose of this commentary is to advance a people-centered reconceptualization of IT business value in healthcare by foregrounding the human dimensions of IT project management, new technology development, adoption processes, and resistance to change. Drawing upon socio-technical systems theory and established ITBV scholarship (Melville et al., 2004; Gregor et al., 2006; Tallon et al., 2020), this paper seeks to reposition clinicians, patients, and organizational stakeholders as active co-creators of digital value rather than passive recipients of technological innovation.

Specifically, this commentary aims to (1) articulate how participatory IT project governance and interdisciplinary collaboration enhance the likelihood of successful AI and telehealth deployment; (2) examine how trust in automation and professional identity shape adoption trajectories; and (3) propose a people-centered framework for mitigating resistance to change through engagement, transparency, training, and adaptive leadership. By centering the human experience, this study reframes ITBV as an emergent property of collective sensemaking and organizational learning rather than a direct byproduct of technical investment.

Significance of the Inquiry

This commentary is significant because it addresses a critical gap between technological ambition and human readiness in healthcare digital transformation. While existing ITBV research underscores the importance of complementary organizational resources (Dedrick et al., 2003; Schweikl & Obermaier, 2023), fewer conceptual treatments have systematically examined how project management practices, stakeholder engagement, and resistance dynamics shape value realization in AI and telehealth initiatives.

From a managerial perspective, the study highlights the need to embed change management principles into IT project lifecycles. Successful AI implementation requires more than algorithm validation; it demands structured clinician involvement during system design, iterative usability testing, transparent communication regarding system limitations, and ongoing feedback mechanisms. Similarly, telehealth adoption depends on equipping care teams with adequate training, adjusting performance metrics to reflect the realities of virtual care, and addressing patient concerns about data privacy and digital literacy.

By foregrounding people-centered strategies, this commentary offers actionable insight for healthcare executives, chief information officers, and clinical leaders seeking to align digital innovation with workforce engagement and patient trust. Moreover, it underscores that technological resistance, when constructively engaged, can surface legitimate safety concerns and catalyze system refinement. Recognizing resistance as feedback rather than defiance strengthens organizational resilience and enhances the sustainability of digital investments.

Nature of the Inquiry

This inquiry adopts a conceptual commentary methodology grounded in integrative literature synthesis and socio-technical analysis. Rather than presenting empirical findings, it advances a theoretically informed argument that IT business value in healthcare is fundamentally mediated by human agency, relational trust, and participatory governance structures. Drawing on established ITBV frameworks (Melville et al., 2004; Gregor et al., 2006) and contemporary perspectives on organizational change and technology adoption, the paper constructs a people-centered interpretive model to understand digital transformation outcomes. Illustrative examples, such as clinician engagement in AI-driven sepsis alert system design, interdisciplinary oversight committees for algorithm governance, and co-created telehealth workflow protocols, demonstrate how inclusive project management practices influence adoption and mitigate resistance. The commentary is therefore exploratory and theory-building in orientation, intended to stimulate scholarly dialogue and inform future empirical inquiry into the human determinants of IT business value in healthcare. In sum, this inquiry advances the position that sustainable digital transformation in healthcare depends less on technological sophistication and more on the intentional cultivation of trust, participation, and adaptive leadership within socio-technical systems.

Historical Evolution of IT Business Value (ITBV) in Healthcare

Research on IT business value (ITBV) has progressively shifted from a narrow focus on technological efficiency toward a more expansive recognition that value is socially constructed through human engagement with technology. In healthcare, this progression is especially consequential, as artificial intelligence (AI) and telehealth technologies operate within environments defined by professional autonomy, ethical scrutiny, and high-stakes clinical judgment. The historical record demonstrates that digital systems yield sustainable organizational benefit only when embedded within socio-technical systems that cultivate trust in automation and reinforce human capability (Melville et al., 2004; Bayer et al., 2020).

During the early computing era (1970–1990), IT value was largely equated with labor substitution and productivity gains. The productivity paradox (Solow, 1988; Triplett, 1999) highlighted the disjunction between escalating IT expenditures and stagnant productivity metrics, prompting scholars to attribute the inconsistency to measurement deficiencies, time lags, and intangible organizational changes (Brynjolfsson, 1993). In healthcare institutions, early hospital information systems were primarily justified as administrative tools to streamline billing or scheduling. Yet these implementations frequently underestimated the human implications of workflow disruption and professional resistance. Installation was often conflated with impact, leaving little consideration for clinician adoption patterns or the relational dynamics necessary for sustained use.

The client-server and internet era (1990–2000) redirected attention toward integration and transformation (Sabherwal & Jeyaraj, 2015). The widespread introduction of electronic health records promised unified data access and enhanced care coordination. However, resistance from physicians and nurses revealed that technological integration without participatory governance could undermine professional morale. Many clinicians perceived early systems as encroaching upon patient interaction time or imposing rigid documentation requirements incompatible with diagnostic reasoning. Research during this period began to emphasize that IT value materializes only when technological deployment is accompanied by organizational redesign and stakeholder engagement (Soh & Markus, 1995).

The cloud, mobile, and big data era (2000–2010) expanded the reach of healthcare information technology through patient portals, mobile health applications, and real-time analytics (De Camargo Fiorini et al., 2018). While these tools increased connectivity, their success depended heavily on human trust and usability. For example, telehealth platforms introduced for post-operative follow-up demonstrated variable adoption rates. Patients who received timely responses from clinicians and clear explanations of data privacy safeguards were more likely to remain engaged. Conversely, opaque communication or delayed clinician feedback fostered skepticism and disengagement. These outcomes reinforced the insight that digital value emerges through relational trust and responsive care models rather than connectivity alone.

The intelligent technologies era (2010–2020) intensified these dynamics as AI-driven diagnostic systems and predictive analytics tools entered mainstream healthcare practice (Enholm et al., 2022; Saheb & Mamaghani, 2021). AI-enabled sepsis alerts, radiological image interpretation algorithms, and risk-stratification engines delivered measurable improvements in accuracy and speed. Yet clinical value depended on whether healthcare professionals perceived these tools as credible and transparent. Radiologists who participated in co-design workshops and governance committees exhibited higher trust in algorithmic outputs, whereas those excluded from development processes were more inclined to override recommendations. Technological resistance in these contexts often reflected legitimate concerns regarding bias, interpretability, and accountability. Trust in automation emerged as a mediating factor between technical capability and realized performance outcomes.

In the present era of digital ecosystems and interoperable cloud infrastructures (Gellweiler & Krishnamurthi, 2022; Schweikl & Obermaier, 2023), IT business value is increasingly understood as contingent upon multilevel complementarities between human expertise, institutional governance, and digital architecture. AI-powered telehealth networks, remote monitoring systems, and predictive population health platforms function within expansive stakeholder constellations that include clinicians, patients, regulators, and payers. The success of these initiatives depends not merely on system uptime or algorithmic precision but on participatory project management, interdisciplinary collaboration, and adaptive leadership capable of addressing resistance constructively.

Limitations of Traditional ITBV Measurement in Healthcare

Traditional measurement approaches have struggled to capture the human and relational dimensions of IT-enabled transformation. Financial indicators such as return on assets, cost reduction, and profitability (Dehning & Richardson, 2002; Lim et al., 2011) provide quantifiable metrics but obscure the behavioral processes that underpin sustainability. In hospital contexts, reductions in administrative costs may coexist with clinician burnout or patient dissatisfaction, thereby undermining broader organizational objectives. Macroeconomic productivity measures similarly fail to reflect improvements in diagnostic confidence, interdisciplinary communication, or patient reassurance (Masli et al., 2011).

System-oriented frameworks, including the DeLone and McLean IS Success Model (DeLone & McLean, 2003), introduced constructs such as user satisfaction and system quality but often focused on internal stakeholders without fully integrating patient trust or professional identity. Conventional financial evaluation tools such as ROI or NPV are poorly suited to subscription-based AI and cloud telehealth platforms whose value derives from agility, scalability, and resilience rather than discrete revenue increments (Tallon et al., 2020). For example, migrating a hospital's AI-enabled radiology infrastructure to a cloud environment may reduce downtime and accelerate model retraining cycles, benefits that strengthen clinician confidence and diagnostic consistency but resist straightforward monetization.

People-Centered IT Project Management and Technology Development

A people-centered approach to IT project management reframes digital transformation as a participatory endeavor rather than a purely technical initiative. In healthcare, successful AI and telehealth implementation requires early and sustained involvement of clinicians, nurses, administrators, and patients in system design and governance. Interdisciplinary steering committees, co-design workshops, and pilot testing phases foster collective ownership and mitigate resistance.

For instance, when implementing an AI-based early warning system for sepsis, involving frontline nurses in alert threshold calibration and workflow mapping can prevent alarm fatigue and enhance trust in automation. Similarly, telehealth platform development that incorporates patient advisory boards ensures that interface design reflects usability needs and accessibility considerations. These participatory strategies transform potential resistance into constructive feedback, strengthening socio-technical alignment.

Technology Adoption and Resistance to Change in Healthcare

Technological resistance in healthcare often reflects concerns about professional identity, perceived threats to autonomy, or apprehensions about accountability. AI-assisted radiology tools, for example, may be viewed as encroaching upon expert judgment if introduced without transparent communication about algorithmic limitations. Resistance diminishes when training programs emphasize collaborative intelligence, position AI as an augment rather than a substitute, and clarify governance structures' responsibility for decision outcomes.

Similarly, tele-ICU systems that deliver centralized monitoring analytics may encounter skepticism from bedside clinicians who perceive surveillance or workflow interference. Adoption improves when implementation leaders engage staff in defining escalation protocols and feedback loops. By recognizing resistance as an indicator of misalignment rather than an obstruction, healthcare organizations can refine systems that enhance both trust and performance.

Toward a Stakeholder-Centered Conception of ITBV in Healthcare

A stakeholder-centered perspective situates trust, relational continuity, and perceived value at the core of ITBV realization. Emerging research emphasizes that functional reliability, emotional reassurance, personalization, and relational integrity shape both clinician and patient engagement (Treacy & Wiersema, 1993; Fandos Roig et al., 2009). Patient trust in telehealth platforms influences adherence to remote monitoring protocols, while clinician trust in AI decision support systems affects integration into clinical reasoning.

Ultimately, IT business value in healthcare is fundamentally a human achievement. AI and telehealth technologies realize transformative potential only when embedded within socio-technical systems that prioritize participatory governance, transparent communication, ethical stewardship, and continuous learning. When human agency is foregrounded through inclusive project management and trust-building strategies, digital innovation becomes a catalyst for collaborative intelligence, resilient care delivery, and sustainable organizational performance.

Socio-Technical Systems as the Foundation of ITBV

ITBV in healthcare emerges from the dynamic interaction between technological infrastructures and human agency. AI models, remote monitoring platforms, and telehealth portals are embedded within clinical routines, professional norms, and ethical oversight structures. Value is therefore co-produced through coordinated action. For example, an AI-based triage system in an emergency department achieves clinical impact only when nurses trust the alert logic, physicians understand escalation criteria, and administrators ensure adequate staffing to respond. Socio-technical alignment becomes the precondition for trust in automation.

Technological Determinism

Technological determinism is often invoked to explain how emerging digital capabilities reshape organizational structures; however, its relevance to Information Technology Business Value (ITBV) is best understood through a people-centered lens. One prominent dimension is capability-driven organizational restructuring, in which advanced technologies precipitate the reconfiguration of roles, workflows, and decision authority (Nobles et al., 2022; Nobles, 2015). In healthcare, the introduction of AI-enabled clinical decision support or enterprise telehealth systems frequently alters documentation practices, triage protocols, and interdisciplinary coordination. Yet restructuring alone does not produce value. ITBV materializes when redesign efforts are participatory, incorporating frontline clinicians and operational leaders in defining how technological capabilities complement professional judgment and workflow integrity. When restructuring is imposed without such engagement, resistance intensifies and trust in automation diminishes, thereby undermining the very performance gains technology was intended to deliver.

A second dimension, temporal compression, reflects the acceleration of decision-making cycles enabled by digital infrastructures (Nobles et al., 2022; Nobles, 2015, 2018). AI-generated alerts and remote monitoring systems compress the interval between data acquisition and clinical response, ostensibly enhancing responsiveness and safety.

However, acceleration simultaneously amplifies cognitive load and decision density for clinicians. From a people-centered ITBV perspective, value emerges not from speed alone but from the organization's capacity to manage information velocity through calibrated alert thresholds, workflow harmonization, and training in human–AI collaboration. Without such support, temporal compression risks generating alert fatigue and skepticism rather than improved outcomes.

Risk reconfiguration constitutes a third critical dimension. Technological integration redistributes rather than eliminates clinical and operational risk across human and technical systems (Nobles et al., 2022; Nobles, 2015, 2018). AI may reduce diagnostic uncertainty while introducing algorithmic bias or overreliance; telehealth may expand access while raising privacy and accountability concerns. ITBV, therefore, depends on how organizations govern this redistribution of risk. Transparent performance monitoring, explicit override authority, and structured bias audits reinforce calibrated trust and clarify accountability. In their absence, perceived risk intensifies and adoption falters.

Finally, institutional expectation realignment underscores how public and regulatory assumptions increasingly presuppose the availability of advanced digital capabilities, particularly during crises (Nobles et al., 2022; Nobles, 2015; Nobles, 2018). Healthcare systems are now expected to deploy predictive analytics, interoperable platforms, and telehealth continuity as baseline infrastructure. Yet meeting heightened expectations requires more than technical readiness; it demands adaptive leadership and participatory governance that sustain legitimacy and stakeholder confidence. Collectively, these dimensions demonstrate that technological change, in and of itself, does not generate IT business value. Rather, value emerges when capability expansion, accelerated tempo, redistributed risk, and evolving expectations are intentionally aligned with human expertise and institutional trust within socio-technical systems."

Resource-Based View (RBV) and Human Capital Complementarity

RBV posits that competitive advantage derives from resources that are valuable, rare, inimitable, and non-substitutable (Barney, 1991). Within healthcare, AI algorithms and telehealth infrastructures meet these criteria only when complemented by skilled clinicians, adaptive leadership, and supportive culture. An AI-powered radiology system may enhance diagnostic throughput, yet without radiologists trained to interpret algorithmic confidence scores and participate in performance audits, its strategic potential remains unrealized. Human expertise thus transforms technological capacity into institutional capability.

Customer Value Theory and Patient-Centered Digital Care

Customer Value Theory emphasizes that perceived benefits relative to perceived sacrifices shape judgments of value (Treacy & Wiersema, 1993; Masli et al., 2011). In telehealth contexts, patients evaluate digital encounters based on convenience, clarity, empathy, and data security. A remote diabetes monitoring program may provide clinically robust analytics, but if patients experience cumbersome device setup or ambiguous privacy protections, perceived value diminishes. Healthcare organizations must therefore design telehealth systems that address emotional reassurance and relational continuity alongside functional efficiency.

Value-Percept Theory and Expectation Alignment

The Value-Percept Theory explains that satisfaction arises from the congruence between expectations and perceived experience (Ganesh et al., 2016). Clinicians adopting AI-based decision support tools often expect augmentation of clinical judgment without erosion of autonomy. When algorithmic outputs are transparent and seamlessly integrated into electronic health records, expectations are met, and trust deepens. When alerts are opaque or excessive, resistance intensifies. Effective IT project management must therefore align expectations through transparent communication and continuous feedback.

Cognitive Theory and Professional Sensemaking

Cognitive Theory highlights how individuals interpret, process, and evaluate information. Healthcare professionals integrate AI outputs into preexisting mental schemas shaped by training and clinical experience. If a predictive analytics tool contradicts established heuristics without explanation, cognitive dissonance may generate skepticism. Structured training programs, simulation exercises, and iterative usability refinements align algorithmic logic with clinician cognition, fostering informed trust rather than blind reliance.

Social Exchange Theory and Reciprocal Trust

Social Exchange Theory conceptualizes digital health interactions as reciprocal exchanges of costs and benefits (Homans, 1958; Blau, 1964). Patients contribute personal health data and time; clinicians invest cognitive effort and professional responsibility. In return, they expect reliability, transparency, and meaningful benefit. A tele-ICU system that delivers actionable insights and timely specialist input reinforces reciprocal trust. Conversely, repeated system failures or unaddressed privacy concerns erode relational capital. Sustainable ITBV thus depends upon maintaining balanced and transparent exchanges.

Stakeholder Theory and Ethical Governance

Stakeholder Theory broadens the lens to include the moral and relational responsibilities of healthcare leaders (Bridoux & Stoelhorst, 2022). AI and telehealth initiatives affect multiple constituencies. Inclusive governance structures, such as interdisciplinary AI ethics committees or patient advisory councils, mitigate resistance and enhance legitimacy. When frontline clinicians and patient representatives participate in system design decisions, organizational trust strengthens, and implementation barriers diminish. Ethical stewardship becomes integral to the realization of digital value.

UTAUT2 and Behavioral Drivers of Adoption

The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) explains adoption behavior through constructs such as performance expectancy, effort expectancy, social influence, and perceived value (Venkatesh et al., 2012; Marikyan & Papagiannidis, 2025). In healthcare, these drivers are moderated by professional tenure, digital literacy, and generational differences. For example, younger clinicians may readily adopt AI-assisted chart review tools, whereas senior practitioners may require demonstrable evidence of reliability. Tailored change management strategies that address these behavioral determinants reduce technological resistance and promote sustained utilization.

Classical Test Theory and Measurement Integrity

Classical Test Theory (CTT) provides the psychometric foundation for measuring trust, satisfaction, and perceived organizational performance (Schuwirth & van der Vleuten, 2011). Reliable and valid instruments are essential for evaluating how clinician trust in AI or patient satisfaction with telehealth mediates perceived performance outcomes. Without rigorous measurement, interpretations of ITBV risk conflate technical outputs with genuine human endorsement.

People-Centered IT Project Management and Resistance Mitigation

Across these theoretical perspectives, a unifying principle emerges: IT business value in healthcare is fundamentally human. Participatory design workshops, transparent communication of algorithmic limitations, continuous training programs, and structured feedback channels transform potential resistance into collaborative refinement. For instance, involving bedside nurses in configuring AI alert thresholds reduces alarm fatigue and fosters ownership. Similarly, engaging patients in telehealth interface testing improves usability and trust. Resistance, when interpreted constructively, becomes a diagnostic signal of socio-technical misalignment rather than an impediment to progress.

Trust in Automation as the Integrative Mechanism

Trust in automation serves as the integrative construct linking socio-technical design, adoption behavior, and performance outcomes. Calibrated trust, grounded in transparency, competence, and accountability, enables clinicians to rely on AI recommendations judiciously and encourages patients to engage confidently with telehealth systems. When trust is cultivated through inclusive governance and ethical oversight, digital technologies transcend mere tools and become collaborative partners in care delivery.

This multi-theoretical framework affirms that ITBV in healthcare emerges from the deliberate orchestration of technology, people, and institutional norms. AI and telehealth initiatives succeed not through technical deployment alone but through human-centered leadership, participatory development, and the sustained cultivation of trust within complex socio-technical ecosystems.

Emotional Value Attributed to Healthcare Information Technology

Emotional value attributed to healthcare information technology reflects the affective states experienced by patients and other stakeholders as they interact with AI-enabled systems and telehealth platforms. Within healthcare socio-technical systems, technology does not merely perform functional tasks; it shapes perceptions of safety, dignity, autonomy, and reassurance. Emotional responses arise when stakeholders cognitively evaluate whether technologies and their features enhance or threaten these deeply held values (Ganesh et al., 2016). Cognitive Theory explains that individuals assess both the outcome of a service and the experiential process through which that outcome is delivered. In an AI-assisted diagnostic encounter, for example, a patient may evaluate not only the accuracy of the algorithmic recommendation but also the clarity with which the clinician explains its role. When AI outputs are communicated transparently and integrated respectfully into clinical dialogue, patients may experience heightened confidence, reduced anxiety, and a strengthened sense of security. Conversely, opaque automation or unexplained algorithmic overrides may generate apprehension or diminished trust.

Customer Value Theory, here applied to patients and stakeholders, posits that value emerges when perceived benefits outweigh perceived sacrifices (Masli et al., 2011; Treacy & Wiersema, 1993). In telehealth contexts, benefits may include convenience, timely access to specialists, and continuity of care, while sacrifices may involve privacy concerns or technological effort. A remote oncology consultation platform that offers seamless scheduling, empathetic communication, and secure data exchange can evoke emotional reassurance and empowerment. However, frequent connectivity disruptions or ambiguous consent procedures may erode emotional confidence.

From a people-centered IT project management perspective, emotional value is cultivated deliberately. Inclusive design workshops that involve patients in interface development, clinician training programs that emphasize compassionate communication during AI-supported encounters, and governance structures that address data ethics all contribute to affective trust in automation. Classical Test Theory (CTT) provides the methodological foundation for measuring these emotional perceptions, recognizing that stakeholder assessments comprise both true evaluative judgments and measurement error (Schuwirth & van der Vleuten, 2011). Reliable measurement enables healthcare leaders to identify whether digital initiatives are strengthening or undermining emotional trust.

Emotional value in healthcare IT may therefore be reflected in feelings of confidence in future care, reduced uncertainty regarding diagnosis, perceived partnership in decision-making, and an enhanced sense of control over one's health journey. These affective outcomes are not ancillary; they are central to sustained adoption and to the legitimacy of AI and telehealth technologies within clinical practice.

Social Value Attributed to Healthcare Information Technology

Social value attributed to healthcare IT encompasses stakeholders' perceptions that AI and telehealth deployments contribute positively to community well-being, equity, and ethical responsibility. Within healthcare, social value extends beyond individual interactions to encompass broader societal implications, including access disparities, environmental sustainability, and institutional integrity (Bouichou et al., 2022; Bressan et al., 2023).

Stakeholder Theory posits that organizational legitimacy and long-term performance depend upon balanced consideration of diverse stakeholder interests (Bridoux & Stoelhorst, 2022). In healthcare, AI governance must address not only efficiency but also fairness and transparency. For instance, when a hospital deploys predictive analytics for resource allocation, stakeholders may evaluate whether the system mitigates or exacerbates health inequities. Transparent auditing of algorithmic bias and inclusion of community representatives in oversight committees strengthen perceptions of social responsibility.

Cognitive Theory explains that patients and clinicians interpret institutional actions through evaluative mental processes. A telehealth initiative that expands access to rural populations may be perceived as socially beneficial, reinforcing institutional reputation and community trust. Conversely, if digital tools are implemented without accommodations for individuals with limited digital literacy, stakeholders may perceive exclusion or inequity. These cognitive evaluations translate into judgments about the organization's ethical standing.

Environmental sustainability represents a further dimension of social value. Cloud-based health information systems that reduce paper use and optimize energy consumption may be seen as contributing to environmental stewardship. Stakeholders who value sustainability may align their personal values with institutional conduct, thereby strengthening relational commitment.

Classical Test Theory again provides the measurement scaffolding for assessing perceived social value, ensuring that survey instruments capture authentic stakeholder judgments rather than transient impressions. Social value attributed to IT thus encompasses perceptions of institutional reputation, ethical governance, equity of access, and environmental responsibility; all of which influence trust in digital health ecosystems.

Stakeholder-Perceived Business Value Attributed to Healthcare IT (Higher-Order Construct)

Stakeholder-perceived business value in healthcare IT integrates functional, emotional, and social dimensions to provide a comprehensive evaluation of the contributions of AI and telehealth technologies to organizational performance. This higher-order construct reflects how patients, clinicians, and other stakeholders internalize the totality of their digital health experiences.

The Resource-Based View (RBV) suggests that IT resources generate an advantage when strategically integrated with human expertise and organizational processes (Barney, 1991). In healthcare, stakeholders perceive business value when AI-enhanced workflows improve diagnostic reliability, telehealth systems enhance continuity of care, and governance mechanisms ensure ethical oversight. UTAUT2 further explains that perceived usefulness, effort expectancy, and social influence shape adoption behaviors (Venkatesh et al., 2012; Marikyan & Papagiannidis, 2025). When stakeholders perceive that digital tools enhance care quality without imposing undue cognitive or emotional burdens, sustained utilization becomes more likely.

From a people-centered perspective, stakeholder-perceived ITBV is shaped by participatory project management and inclusive technology development. For example, co-designing a tele-ICU platform with bedside nurses and intensivists fosters ownership and mitigates resistance. Engaging patient advisory boards during the development of AI-driven appointment scheduling enhances usability and trust. These participatory processes transform stakeholders into co-creators of value rather than passive recipients of innovation.

Classical Test Theory supports the operationalization of this higher-order construct by aggregating validated subdimensions, functional reliability, emotional reassurance, and social responsibility into a unified measurement model (DeVellis & Thorpe, 2021). Such aggregation enables empirical examination of how socio-technical alignment influences perceived organizational contribution.

Performance Attributed to Healthcare IT (PerfaIT)

Performance attributed to healthcare IT reflects stakeholders' evaluative judgments of the organization's effectiveness, competence, and reliability, as mediated by digital technologies. Unlike internal financial indicators, these assessments derive from lived experience within AI-enabled and telehealth-mediated interactions (Zauner et al., 2015).

Cognitive Theory posits that stakeholders compare digital encounters against prior expectations to form holistic evaluations (Ganesh et al., 2016). A hospital deploying AI-supported radiology may be perceived as technologically advanced and clinically competent if stakeholders observe improved turnaround times and transparent communication. Social Exchange Theory suggests that perceived fairness and reciprocity in digital interactions influence judgments of institutional trustworthiness (Homans, 1958; Blau, 1964). When telehealth services deliver timely responses and protect patient data, stakeholders interpret these outcomes as evidence of organizational reliability.

Resistance to technology adoption may arise when perceived performance falls short of expectations. For example, clinicians may question institutional competence if AI systems produce excessive false positives. Addressing such resistance through iterative refinement and transparent performance reporting strengthens collective confidence and reinforces positive performance perceptions.

Overall Stakeholder Satisfaction Attributed to Healthcare IT (OCSaIT)

Overall satisfaction attributed to healthcare IT represents the cumulative affective evaluation of repeated digital interactions. Satisfaction develops through iterative encounters with AI-supported diagnostics, remote monitoring systems, and telehealth consultations.

Value-Percept Theory explains that satisfaction emerges when perceived value aligns with expectations (Ganesh et al., 2016). Social Exchange Theory frames satisfaction as the outcome of balanced, long-term relational exchanges (Ahmad et al., 2023). In healthcare, patients who consistently experience secure, empathetic, and reliable telehealth interactions are likely to develop enduring satisfaction. Clinicians who observe that AI tools genuinely augment clinical judgment rather than complicate workflows similarly experience sustained professional endorsement.

People-centered IT project management plays a decisive role in shaping satisfaction trajectories. Continuous training, open forums for feedback, and adaptive governance structures enable organizations to proactively respond to stakeholder concerns. By treating resistance as a source of diagnostic insight rather than obstruction, healthcare leaders can recalibrate socio-technical systems to enhance alignment and trust.

Collectively, emotional value, social value, stakeholder-perceived business value, performance perceptions, and overall satisfaction converge to illuminate a central proposition: in healthcare, IT business value is realized through the intentional cultivation of trust within socio-technical systems. AI and telehealth technologies achieve sustainable impact only when designed, implemented, and governed through participatory, ethically grounded, and human-centered approaches that elevate stakeholders from observers to co-architects of digital transformation.

People-Centered Digital Health Value Realization Checklist

The People-Centered Digital Health Value Realization Checklist provides a strategic framework for healthcare organizations deploying AI and telehealth technologies within complex socio-technical systems. The emphasis is on fostering trust in automation, ensuring deep stakeholder engagement, establishing participatory governance, and proactively mitigating resistance. By integrating these human-centric variables into the deployment lifecycle, the checklist ensures that digital interventions transcend mere technical installation to achieve sustainable clinical value and organizational alignment.

Strategic Governance and Organizational Alignment

1. **Create a multidisciplinary AI and telehealth governance council.**
   Include clinicians, nurses, IT leaders, compliance officers, quality experts, and patient representatives in oversight of system selection, validation, monitoring, and recalibration.
2. **Make trust in automation an explicit strategic priority.**
   Track clinician trust and patient confidence metrics alongside cost, throughput, and utilization indicators.
3. **Tie every AI and telehealth initiative to a defined clinical capability outcome.**
   Require each project to demonstrate how it strengthens diagnostic reliability, care coordination, patient engagement, or workflow efficiency.
4. **Adopt formal transparency standards for algorithmic systems.**
   Ensure AI tools include accessible explanations of logic, performance boundaries, and known limitations before clinical deployment.

People-Centered IT Project Management

5. **Conduct participatory workflow design sessions before system launch.**
   Map AI alerts and telehealth touchpoints directly into frontline routines with active clinician input.
6. **Pilot new technologies with respected clinical champions.**
   Select early adopters who can validate usability and build peer confidence through lived experience.
7. **Anticipate and document potential resistance areas in advance.**
   Identify where automation may challenge professional identity or workflow autonomy and address concerns proactively.
8. **Establish structured feedback channels post-implementation.**
   Host recurring listening sessions and maintain accessible reporting dashboards to capture real-time concerns.

Trust Calibration and Responsible Automation

9. **Monitor and publicly share AI performance data internally.**
   Transparently track false positives, false negatives, and override patterns to promote informed trust.

10. **Clarify human override authority.**
    Define when clinicians may depart from algorithmic recommendations without fear of penalty.
11. **Conduct regular algorithmic fairness and bias reviews.**
    Evaluate system outputs for demographic disparities to sustain ethical legitimacy.
12. **Train staff in augmented intelligence principles.**
    Emphasize collaborative human–machine decision-making rather than technological replacement.

Telehealth Adoption and Patient Engagement

13. **Implement structured digital onboarding for patients.**
    Provide education sessions and user guides tailored to varying levels of digital literacy.
14. **Communicate privacy and data usage policies clearly.**
    Use accessible language to explain how health information is protected and utilized.
15. **Define response time standards for remote monitoring programs.**
    Clearly communicate when patients can expect follow-up after abnormal readings.
16. **Assess equity implications of digital initiatives.**
    Identify and address barriers related to broadband access, device availability, and language diversity.

Clinician Engagement and Professional Alignment

17. **Involve clinicians in alert threshold calibration.**
    Particularly in predictive analytics systems, incorporate frontline feedback to prevent alert fatigue.
18. **Integrate AI outputs seamlessly within existing EHR interfaces.**
    Avoid parallel systems that increase documentation burden or cognitive strain.
19. **Provide simulation-based training before live deployment.**
    Allow clinicians to experiment with AI tools in low-risk environments to build confidence.
20. **Recognize constructive skepticism as a quality safeguard.**
    Treat reported concerns as valuable input for system refinement rather than obstruction.

Measurement and Value Evaluation

21. **Use validated instruments to measure clinician trust and patient confidence.**
    Ensure measurement rigor to distinguish genuine sentiment from noise.
22. **Track emotional and relational indicators of digital care.**
    Evaluate patient reassurance, perceived partnership, and psychological safety in technology-mediated encounters.
23. **Review socio-technical alignment on a recurring basis.**
    Examine workflow compatibility, cognitive load, interdisciplinary communication, and alert fatigue.
24. **Link digital system performance to quality and safety outcomes.**
    Correlate AI and telehealth deployment with readmission rates, diagnostic consistency, patient adherence, and long-term engagement.

These recommendations shift digital transformation away from a technology-acquisition mindset and toward a human-centered orchestration model. When healthcare leaders intentionally cultivate trust, participation, and adaptive learning within socio-technical systems, AI and telehealth technologies evolve from isolated tools into durable drivers of clinical quality and institutional resilience.

People-Centered Digital Health Maturity Assessment Tool
What This Tool Measures
This assessment evaluates how well an organization realizes value from AI and telehealth by designing, implementing, and governing technology as a socio-technical system; meaning outcomes depend on how technology is integrated with people, workflows, norms, incentives, and accountability structures. The core assumption is that calibrated trust in automation and people-centered project practices determines whether digital tools are adopted, used appropriately, and sustained.

How to Use (Step-by-Step)

1. **Define the assessment scope:**
   Choose a unit: enterprise-wide, hospital, service line (e.g., ED), or a program (e.g., remote monitoring).
   Choose one of the following: a specific AI tool, a telehealth platform, or a portfolio.
2. **Identify the raters:**
   Minimum set: CIO/IT leader, clinical leader, frontline clinician representative, operations leader, and patient advocate or patient experience lead.
   The goal is to reduce *IT-only bias* and incorporate lived workflow reality.
3. **Collect evidence:**
   Evidence should be documentary or observable, not purely self-reported:
   - Governance charters, meeting minutes, training completion logs
   - Workflow maps, pilot reports, change requests
   - Audit results, override logs, alert volumes
   - Patient onboarding materials, response time data
   - Survey instruments and results
4. **Rate each domain (score of 1 to 5):**
   Each domain contains criteria. Score the domain at the highest level where most criteria are verifiably true. If evidence spans levels, choose the lower level unless there is consistent proof.
5. **Interpret results**
   A maturity score is not a "grade." It is a diagnostic profile that reveals:
   - Where trust is fragile
   - Where resistance is predictable
   - Where implementation is technically strong but socially weak
   - Where value can be unlocked through specific governance or workflow changes

Maturity Scale Definitions (Applied to All Domains)
Level 1 (ad hoc):
- Technology is deployed primarily as a technical artifact.
- People issues are addressed reactively (after complaints or failures).
- Trust is assumed rather than measured.

Level 2 (structured):
- Basic governance and project structure exist.
- Stakeholder engagement is present but limited or symbolic.

- Some metrics are tracked, but not used systematically to improve implementation.

Level 3 (integrated):

- People-centered activities (co-design, training, feedback loops) are built into the project lifecycle.
- Trust, adoption, and workflow outcomes are monitored regularly.
- Resistance is anticipated and managed proactively.

Level 4 (optimized):

- Trust in automation is actively calibrated through transparency, performance reporting, and governance decisions.
- Implementation is iterative and improvement-oriented.
- Human outcomes (cognitive load, alert fatigue, patient confidence) are treated as primary success indicators.

Level 5 (transformational):

- AI and telehealth are embedded in a learning system.
- Stakeholders continuously co-create the technology and the workflows it reshapes.
- Trust, equity, quality, and resilience are sustained at scale across settings and populations.

Domain 1: Governance and Strategic Alignment

This domain evaluates whether the organization governs AI and telehealth as safety-critical clinical infrastructure with explicit accountability, rather than as isolated IT projects. Governance is where trust becomes institutionalized.

Assessment Criteria (What to Verify)

1. **Multidisciplinary oversight exists and functions.** A standing governance body with clinical, IT, compliance, quality, and patient representation.
2. **Trust in automation is defined as a strategic outcome.** Trust is measured and reported (not merely discussed).
3. **Transparency requirements exist.** AI tools must have interpretability summaries and documented limitations.
4. **Ethical and fairness oversight exists.** Bias audits occur on a schedule, with defined response actions.

Maturity Indicators (How They Show Up in Reality)

Level 1. Decisions made vendor-by-vendor; minimal clinical representation; no defined standards.

Level 2. The committee exists but meets irregularly; governance is advisory, not authoritative.

Level 3. Governance approves deployments; maintains standards for transparency and monitoring.

Level 4. Governance responds to performance drift; recalibrates thresholds; publishes internal trust dashboards.

Level 5. Governance drives system-wide learning and policy; equitable performance is tracked and improved over time.

Domain 2: People-Centered IT Project Management

This domain evaluates whether project management is built around lived clinical workflows and stakeholder participation, rather than only on timelines and technical requirements.

Assessment Criteria

1. **Workflow co-design occurs before go-live.** Documentation shows an actual redesign with frontline participation.
2. **Pilot testing is done with clinical champions**. Champions test in real conditions and influence the final configuration.
3. **Resistance is mapped as a project risk.** Project plans anticipate autonomy concerns, workload impacts, and accountability fears.
4. **Feedback loops exist after launch.** Systems are in place to log, triage, and proactively resolve ongoing issues.

Maturity Indicators

Level 1. "Go-live then fix" approach; frontline staff informed late.
Level 2. Training occurs, but workflow redesign is limited.
Level 3. Co-design and pilots are standard; improvement tickets are tracked.
Level 4. Post-launch improvement cycles are planned and resourced. Changes are rapid and routine.
Level 5: Continuous co-creation is institutionalized. Users routinely shape the roadmap.

Domain 3: Trust Calibration and Responsible Automation

This domain measures whether the organization cultivates *calibrated trust*, the ability to rely on automation appropriately by understanding when it works, when it fails, and how accountability is managed.

Assessment Criteria

1. **Performance monitoring includes safety-relevant metrics.** False positives/negatives, drift, overrides, and alert fatigue.
2. **Override and escalation rules are explicit.** Clinicians understand the system as advisory, not punitive.
3. **Bias and fairness checks are routine.** Not one-time; integrated into lifecycle monitoring.
4. **Human–AI collaboration training exists.** Training explains limitations and teaches appropriate reliance.

Maturity Indicators

Level 1. No monitoring beyond uptime; overrides seen as "noncompliance."
Level 2. Performance is reviewed occasionally. No clear drift response process.
Level 3. Regular reporting on overrides and alert outcomes. Defined accountability pathways.
Level 4: Trust metrics predict adoption. Refinements reduce alert fatigue and misuse.
Level 5: Continuous recalibration; automation trust is stable across units and populations.

Domain 4: Telehealth Adoption and Patient Engagement

This domain evaluates whether telehealth is treated as a relationship-based care modality that requires patient enablement, not merely a digital access channel.

Assessment Criteria

1. **Patient onboarding is structured and inclusive.** Support for digital literacy and accessibility needs.
2. **Privacy and consent are communicated clearly.** Plain language. Patients understand data use.

3. **Response-time standards are explicit.** Remote monitoring has defined review and escalation timelines.
4. **Equity audits are performed.** Adoption and outcomes are evaluated by demographic or access variables.

Maturity Indicators

Level 1. Patients are expected to "figure it out."
Level 2. Basic instructions exist; Equity not evaluated.
Level 3. Onboarding, privacy communication, and monitoring expectations are standardized.
Level 4. Engagement strategies reduce drop-off; Response-time compliance is high.
Level 5. Telehealth measurably narrows access disparities and improves chronic outcomes.

Domain 5: Clinician Alignment and Identity Protection

This domain addresses a major source of resistance: Clinicians resist tools that threaten professional identity, autonomy, or clarity of accountability.

Assessment Criteria

1. **Frontline staff help set alert thresholds.**
2. **AI tools are integrated into EHR workflows.**
3. **Simulation and practice-based training precede deployment.**
4. **Constructive skepticism is captured and acted on.** Resistance is treated as safety feedback.

Maturity Indicators

Level 1. High skepticism and override rates; Burnout risk rises.
Level 2. Training exists, but doesn't address identity or accountability concerns.
Level 3. Threshold calibration and training improve adoption; Alert fatigue is monitored.
Level 4. Diagnostic concordance improves; Clinicians describe AI as helpful and predictable.
Level 5. Trust and adoption are stable across specialties; Variation decreases.

Domain 6: Measurement and Value Realization

This domain evaluates whether the organization measures value in terms that reflect the socio-technical reality: trust, engagement, equity, workflow coherence, and longitudinal outcomes, rather than merely financial return.

Assessment Criteria

1. **Validated instruments measure trust and satisfaction.**
2. **Emotional and relational outcomes are tracked.**
3. **Socio-technical alignment is reviewed regularly.**
4. **Digital metrics are linked to clinical outcomes;** e.g., readmissions, diagnostic concordance, safety events

Maturity Indicators

Level 1. ROI dominates; User sentiment anecdotal.
Level 2. Satisfaction surveys exist, but don't drive decisions.
Level 3. Trust and engagement metrics influence prioritization and redesign.

Level 4. Value is linked to quality/safety; Dashboards show leading and lagging indicators.
Level 5. Digital health value is continuously optimized; Learning is system-wide.

CIO Dashboard KPIs (Mapped to the Maturity Tool)
Below are KPIs that are both measurable and management-relevant. Use a mix of leading indicators (predict adoption and safety) and lagging indicators (outcomes).

Governance and Trust KPIs
Governance coverage. % of AI/telehealth tools reviewed by the governance body.
Transparency compliance. % of AI tools with interpretability/limits documentation.
Bias audit compliance. % of deployed models with quarterly fairness review.
Clinician trust in AI index. Validated survey score (trend by service line).
Patient Digital Confidence Score. Patient survey score (trend by population).

Project Management KPIs
Co-design rate. % of projects with documented workflow co-design sessions.
Champion engagement. Champions per deployment + participation rate.
Resistance risk completion. % of projects with documented resistance mapping.
Time-to-fix post go-live. Median days from issue report to resolution.

Responsible Automation KPIs
Override rate. % of AI recommendations overridden (by unit/specialty).
Alert fatigue index. Alerts per clinician shift; escalation acceptance rate.
Drift detection. Number of drift events detected and corrected per quarter.
Training completion. % clinicians completing augmented intelligence training.

Telehealth Engagement KPIs
Adoption rate. % eligible visits conducted via telehealth (stratified).
Onboarding completion. % telehealth users completing onboarding steps.
Remote monitoring responsiveness. Median time from alert to review/intervention.
Equity gap index. Adoption and outcome differences by demographic/access group.

Clinician Alignment KPIs
Workflow friction score. Clinician-reported usability and burden metric.
EHR integration rate. % AI tools accessible within the primary EHR workflow.
Simulation training rate. % clinicians completing scenario-based training.
Safety feedback utilization. Number of clinician-initiated improvements implemented.

Value Realization KPIs
Diagnostic concordance change. % improvement vs baseline.
Readmission reduction. risk-adjusted change for monitored cohorts.
Patient reassurance score. patient-reported confidence/safety rating.
Trust-adjusted value index. composite of trust + adoption + outcomes.

How to Interpret the Dashboard
- If adoption is high but trust is low, you likely have compliance without endorsement, risk of unsafe reliance, or silent workarounds.
- If trust is high but outcomes do not improve, you may have “friendly tools” that are not meaningfully embedded into clinical decision pathways.
- If override rates are high, do not assume resistance; treat it as diagnostic evidence of misalignment, drift, or low interpretability.

Conclusion

The evidence synthesized throughout this inquiry reinforces a central proposition: The business value of artificial intelligence and telehealth technologies in healthcare is not inherent in their computational sophistication, but in the quality of their integration within socio-technical systems shaped by human agency. Digital transformation succeeds when clinicians, patients, administrators, and technology leaders co-create workflows, calibrate trust in automation, and embed governance mechanisms that sustain transparency, fairness, and accountability.

The maturity assessment framework and corresponding KPI architecture developed herein operationalize this proposition. They translate abstract constructs, trust in automation, participatory governance, stakeholder engagement, and resistance mitigation, into structured evaluative domains and measurable indicators. Importantly, these tools reposition resistance not as an obstacle but as a diagnostic signal of socio-technical misalignment. When interpreted constructively, skepticism becomes a source of safety refinement, workflow improvement, and institutional learning.

Across domains, governance, participatory project management, trust calibration, telehealth engagement, clinician alignment, and value measurement, the pattern is consistent, which is that technology adoption stabilizes and value realization accelerates when implementation strategies prioritize relational trust, professional identity, and ethical stewardship. Conversely, when digital systems are introduced as technical artifacts detached from workflow realities and stakeholder expectations, organizations encounter predictable friction, override behaviors, alert fatigue, and uneven patient engagement.

The proposed maturity model demonstrates that digital health transformation is developmental rather than binary. Organizations progress from ad hoc deployment toward optimized socio-technical orchestration, and ultimately toward transformational learning systems in which AI and telehealth continuously evolve through stakeholder participation. Trust in automation functions as the integrative mechanism linking adoption behavior, clinical quality, and institutional legitimacy. Without calibrated trust, automation either becomes over-relied upon or systematically disregarded; with calibrated trust, it augments professional judgment and strengthens patient confidence.

Thus, the realization of IT business value in healthcare must be understood as a human achievement mediated through participatory governance and adaptive leadership. Sustainable digital innovation requires continuous alignment between technological capability, cognitive processing, ethical accountability, and relational exchange.

Recommendations for Future Research

Future scholarship should move beyond cross-sectional perception studies and retrospective outcome analysis toward embedded, iterative inquiry grounded in Participatory Action Research (PAR). PAR is uniquely suited to studying AI and telehealth within healthcare because it treats stakeholders as co-researchers rather than passive subjects. This methodological orientation aligns directly with the socio-technical and trust-centered premises of this work.

1. Embed Researchers Within AI and Telehealth Implementation Cycles

Future studies should position researchers within ongoing digital transformation initiatives—participating in governance meetings, workflow redesign sessions, and pilot testing phases. By observing and contributing to decision-making processes, researchers can document how trust in automation evolves over time and how resistance manifests in practice. Rather than measuring adoption only after deployment, PAR enables real-time adjustment of training protocols, interface design, and escalation procedures. This approach would generate granular insight into how socio-technical alignment develops longitudinally.

2. Co-Develop Trust Metrics with Clinicians and Patients

Trust in automation should not be operationalized solely through predefined survey instruments. Future research should involve clinicians and patients in defining what "trustworthy AI" and "reliable telehealth" mean within specific contexts (e.g., emergency care, oncology follow-up, remote chronic disease monitoring). Through structured workshops and iterative refinement, PAR can produce context-sensitive trust indices that reflect local professional norms and patient expectations. Such co-developed metrics are likely to be more valid and more actionable than externally imposed measurement tools.

3. Study Resistance as a Learning Variable Rather Than a Barrier

Traditional adoption research often frames resistance as a deficit in user readiness. Participatory action research allows resistance to be treated as a meaningful data source. Future investigations should examine:

- Patterns of override behavior in AI systems.
- Narrative accounts of clinician skepticism.
- Patient disengagement trends in telehealth platforms.

By engaging stakeholders in interpreting these signals, researchers can help organizations redesign systems to reduce cognitive burden, clarify accountability, and enhance interpretability.

4. Conduct Iterative Bias and Equity Audits with Community Stakeholders

Future research should incorporate community representatives and patient advocacy groups into AI bias evaluation cycles. Participatory methodologies would allow affected populations to shape fairness thresholds, evaluate unintended consequences, and co-develop mitigation strategies. Such work is essential for examining how digital health initiatives influence health disparities and whether telehealth expansion truly narrows access gaps.

5. Examine the Longitudinal Relationship Between Trust and Outcomes

PAR designs are particularly well-suited to longitudinal inquiry. Future research should investigate how improvements in clinician trust indices correlate over time with:

- Diagnostic concordance.
- Alert fatigue reduction.
- Patient reassurance scores.
- Readmission reductions.

By iteratively refining governance and workflow based on these findings, researchers and practitioners can co-produce evidence linking trust calibration to measurable clinical performance.

6. Develop Adaptive Maturity Benchmarking Networks

Healthcare systems could collaborate in participatory benchmarking consortia where organizations share anonymized maturity scores, trust indices, and outcome metrics. Researchers embedded within these networks could facilitate shared learning and identify patterns associated with transformational maturity. Such networks would allow comparative analysis while preserving local contextual adaptation—an essential feature of socio-technical research.

7. Expand PAR to Examine Professional Identity Transformation

AI and telehealth alter professional roles, cognitive labor, and accountability structures. Future participatory research should explore how clinicians renegotiate identity in AI-augmented environments and how telehealth reshapes relational dynamics between patients and providers. Understanding these identity shifts is critical to sustaining adoption beyond the initial novelty phase. Participatory action research offers more than a methodological refinement; it aligns with the core thesis of this work. If IT business value in healthcare emerges through socio-technical integration and calibrated trust, then research itself must mirror that principle. Knowledge about digital transformation should be co-created with those who design, implement, and live within these systems. By embedding inquiry within practice, treating resistance as insight, and positioning stakeholders as partners in evaluation, future research can move beyond documenting digital health challenges toward actively shaping safer, more equitable, and more trusted AI- and telehealth-enabled healthcare ecosystems.

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