

EVALUATING SOCIO-TECHNICAL INTEROPERABILITY, CLINICIAN TRUST, AND DIGITAL EQUITY IN AI INTAKE DEPLOYMENTS: A MULTI-SITE QUALITATIVE STUDY OF US COMMUNITY HEALTH PROVIDERS

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Abstract

Artificial intelligence (AI) driven patient intake systems, ranging from automated history-taking algorithms to conversational intake chatbots are increasingly deployed across United States healthcare settings to streamline clinical documentation, reduce administrative burden, and optimize patient triage. However, their implementation within Federally Qualified Health Centers (FQHCs) and community health providers introduces complex socio-technical challenges surrounding electronic health record (EHR) interoperability, clinician trust, and digital health equity. This multi-site qualitative study evaluated the socio-technical factors influencing the integration of AI patient intake technology, examine how technical interoperability, clinician trust dynamics, and digital determinants of health intersect to impact workflow efficiency and care equity in safety net settings.

Following the Consolidated Criteria for Reporting Qualitative Research (COREQ), we conducted a multi-site qualitative investigation across three diverse US community health organizations deploying commercial AI intake platforms. Data collection comprised 42 semi-structured interviews with primary care physicians (n = 14), nurse practitioners and physician assistants (n = 10), medical assistants (n = 10), health information technology (HIT) directors (n = 4), and patient navigators (n = 4), alongside 30 hours of direct clinical workflow observations. Transcripts were analyzed using reflexive thematic analysis guided by the Systems Engineering Initiative for Patient Safety (SEIPS 2.0) model, the Digital Health Equity Framework (DHEF), and the Nonadoption, Abandonment, Scale-up, Spread, and Sustainability (NASSS) framework. Four important themes emerged: (1) *Socio-Technical Interoperability and EHR Integration Friction*, highlighting data siloing, manual workaround burden, and fragile Fast Healthcare Interoperability Resources (FHIR) API integrations; (2) *Clinician Trust Dynamics, Automation Bias, and Legal/Administrative Burden*, reveals dual anxieties over automation bias versus missing clinical nuance and liability concerns; (3) *Digital Equity, Determinants of Digital Access, and Marginalization*, illustrating how limited broadband access, low digital literacy, and linguistic non-adaptation systematically exclude vulnerable patient populations; and (4) *Adaptive Workarounds and Unintended Workflow Consequences*, documenting shadow workflows created by clinical support staff to bridge digital access gaps. AI intake platforms cannot be evaluated as isolated software interventions; rather, they operate within fragile socio-technical systems. Without intentional design for health equity, robust bidirectional EHR integration, and transparent algorithmic explanation mechanisms, AI intake tools risk amplifying administrative burden and increase existing health disparities among low-income and minoritized patient cohorts.

Keywords:

Artificial Intelligence, Digital Health Equity, EHR Interoperability, Clinician Trust, Community Health Centers.

INTRODUCTION

1.1 Background

The delivery of primary care in the United States faces unprecedented structural pressure, driven by accelerating clinician burnout, acute staffing shortages, and mounting administrative documentation demands (Lin et al., 2019). Primary care physicians currently spend upwards of two hours on electronic health record (EHR) documentation and administrative tasks for every hour of direct patient care, which lead to substantial professional dissatisfaction and cognitive fatigue (Lin et al., 2019). In response to these operational bottlenecks, healthcare systems have rapidly turned toward artificial intelligence (AI) and automated natural language processing (NLP) applications to optimize pre-visit workflows. Among these emerging technological innovations, AI-driven patient intake systems which comprises digital intake portals, adaptive pre-visit health questionnaires, and natural

language conversational agents have gained significant commercial and clinical traction. These technologies aim to engage patients prior to or upon arrival at the clinical facility, capturing past medical history, history of present illness (HPI), review of systems (ROS), and social determinants of health (SDOH) (Benda et al., 2022). Translating patient-reported narrative inputs into structured clinical summaries or draft HPI notes within the EHR, AI intake tools promise to reduce clinician clerical burden, standardize clinical documentation, and liberate valuable clinical encounter time for therapeutic engagement.

However, while initial evaluations of AI intake technologies in affluent, well resourced academic medical centers demonstrate promising efficiency gains, their deployment across safety-net healthcare settings specifically Federally Qualified Health Centers (FQHCs) and community health centers presents a radically different set of socio-technical, organizational, and ethical challenges (Veinot et al., 2018). FQHCs serve populations characterized by high rates of poverty, limited English proficiency (LEP), low digital health literacy, and unstable housing or broadband access (Sieck et al., 2021). Consequently, introducing automated digital intake solutions into safety-net primary care environments tests the boundary limits of clinical usability, technical interoperability, and health equity (Crawford & Serhal, 2020; Veinot et al., 2018).

1.2 Problem Statement

Despite the enthusiastic projection of AI as an equalizer in healthcare delivery, real-world implementations frequently encounter severe friction across three primary dimensions: technical interoperability, clinician trust calibration, and digital health equity.

First, technical interoperability remains a persistent bottleneck in ambulatory primary care. Although regulatory mandates such as the 21st Century Cures Act have driven the adoption of Application Programming Interfaces (APIs) based on Fast Healthcare Interoperability Resources (FHIR) standards (Office of the National Coordinator for Health Information Technology [ONC], 2020), legacy EHR systems in community health centers often lack seamless bidirectional interoperability (Holmgren et al., 2017). When AI intake applications operate as isolated "walled gardens," patient-generated intake data are frequently stored in secondary PDF repositories or unformatted text blocks rather than populating native EHR discrete data fields (Holmgren et al., 2017). This technical disconnect forces clinicians and medical assistants to manually re-enter, copy-paste, or reconcile intake data, transforming a theoretical time-saving technology into a source of administrative cognitive load (Holden et al., 2013).

Second, the clinical efficacy of AI intake solutions is mediated by clinician trust and cognitive calibration (Asan et al., 2020). Clinicians face a fundamental tension between *automation bias* the tendency to uncritically accept automated algorithmic outputs and *automation disuse/skepticism*, wherein clinicians completely disregard AI summaries due to fears of hallucinated information, missed diagnostic nuances, or legal liability (Goddard et al., 2012; Parasuraman & Riley, 1997). When AI intake platforms condense complex patient narratives into algorithmic HPI summaries, clinicians express anxiety over hidden clinical errors, missing contextual history, and the erosion of the therapeutic narrative (Asan et al., 2020). Establishing an optimal level of calibrated trust requires transparent, explainable data provenance, that allows clinicians to trace how an AI algorithm synthesized patient inputs into clinical documentation (Asan et al., 2020).

Third, and most critically, AI intake deployments risk reinforcing the "social gradient of health" if digital health equity is not explicitly prioritized (Crawford & Serhal, 2020). The digital divide is no longer merely a question of physical hardware access; it encompasses digital health literacy, language access, interface usability, and structural trust in healthcare institutions (Sieck et al., 2021). When community health providers shift pre-visit history taking to smartphone-based digital platforms, patients with limited digital literacy, unstable internet connectivity, cognitive impairments, or non-English language preferences are systematically excluded (Sieck et al., 2021; Veinot et al., 2018). This exclusion creates a bifurcated care model: tech-savvy patients complete pre-visit AI intake seamlessly, arriving at clinical encounters with rich digital histories, while marginalized patients arrive without completed intake, forcing clinic staff to complete manual intake under severe time constraints or truncating the clinical visit itself (Benda et al., 2022; Veinot et al., 2018). While quantitative metrics (e.g., portal completion rates, time-to-chart completion) offer surface level snapshots of technology adoption, they fail to capture the important, qualitative lived experiences of clinicians, health IT teams, and frontline clinic staff navigating these systems. A deep qualitative examination of the socio-technical interactions occurring at the point of care is essential to explain *why* and *how* AI intake implementations succeed or fail in safety-net environments.

1.3 Theoretical Framework

To systematically investigate these intersecting challenges, this study synthesizes three established theoretical frameworks: the Systems Engineering Initiative for Patient Safety (SEIPS 2.0) model (Holden et al., 2013), the Digital Health Equity Framework (DHEF) (Crawford & Serhal, 2020), and the Nonadoption, Abandonment, Scale-up, Spread, and Sustainability (NASSS) framework (Greenhalgh et al., 2017).

1. **SEIPS 2.0 (Holden et al., 2013):** Provides a human factor engineering lens to analyze how the *Work System* (person, tools/technology, tasks, organization, physical environment) influences *Processes* (care interactions, cognitive work, adaptive workarounds) and ultimate *Outcomes* (patient safety, clinician burnout, operational efficiency). In this study, SEIPS 2.0 guides the examination of how clinicians interact with AI intake tools within their daily organizational and technical environments.
2. **Digital Health Equity Framework (DHEF) (Crawford & Serhal, 2020):** Offers an equity-centered lens to evaluate how social determinants of health (SDOH) interact with digital determinants of health (DDOH) including digital literacy, device access, connectivity, and language equity across individual, interpersonal, institutional, and societal levels.
3. **NASSS Framework (Greenhalgh et al., 2017):** Frames the complexity of technology implementation across seven domains (the condition, the technology, the value proposition, the adopters, the organization, the wider system, and continuous adaptation over time), allowing us to categorize why AI intake solutions encounter non-adoption or implementation failure in resource constrained safety net environments.

Table 1 conceptualizes the integration of these three frameworks into a cohesive analytical model for AI intake evaluation in community health settings.

Table 1: Cohesive Analytical Model for AI Intake Evaluation

Framework Layer	Core Analytical Focus	Key Evaluation Metrics / Indicators
Framework 1: Technical & Usability	System performance, NLP accuracy, and user interface responsiveness	Diagnostic accuracy, triage precision, error rates, patient completion time
Framework 2: Clinical & Workflow	Integration into electronic health records (EHR) and clinical decision-making	Clinician workload, referral accuracy, intake-to-care latency, staff adoption
Framework 3: Socio-Technical & Equity	Community acceptability, digital literacy, accessibility, and algorithmic bias	Health equity impact, language access, patient trust, privacy/data governance

1.4 Research Questions and Study Objectives

Guided by this integrated framework, this study addresses three central research questions:

1. How do EHR integration architectures and technical data-flow characteristics of commercial AI intake tools shape frontline clinical workflows and administrative burden in FQHCs?
2. How do clinicians calibrate trust in AI-generated intake summaries, and what strategies do they employ to manage cognitive load, automation bias, and clinical risk during patient encounters?
3. In what ways do digital determinants of health (e.g., digital literacy, English proficiency, device access) mediate patient engagement with AI intake platforms, and how do clinic staff mitigate resultant digital disparities?

METHODS

2.1 Research Design and Qualitative Paradigm

We employed a qualitative multi-site case study design (Creswell & Creswell, 2018), situated within a contextualist epistemological paradigm. Contextualism acknowledges that participants' knowledge and experiences are grounded in their specific operational, cultural, and socio-economic environments, making it particularly well-suited for evaluating complex health IT implementations in community health settings (Braun & Clarke, 2006, 2019). The reporting of this study adheres strictly to the Consolidated Criteria for Reporting Qualitative Research (COREQ) 32-item checklist (Tong et al., 2007).

2.2 Study Setting and Site Selection

The study was conducted across three federally qualified health center (FQHC) networks located in the United States, selected through purposive maximum variation sampling to capture diversity in geography, patient

demographics, EHR infrastructure, and AI intake platform configurations. To preserve organizational anonymity, sites are designated as Site A, Site B, and Site C.

- **Site A (Urban Safety-Net Network):** A large multi-clinic FQHC operating in an urban metropolitan area in the Northeastern US, that serves a predominantly racial and ethnic minoritized patient population (65% Hispanic/Latino, 25% Black/African American) with a high proportion of Medicaid beneficiaries (72%) and uninsurance (18%). Site A deployed a smartphone-based conversational AI intake chatbot integrated with a commercial enterprise EHR.
- **Site B (Rural Community Health Alliance):** A rural health center network operating five primary care clinics in the Midwestern US, serving an agricultural, geographically isolated population characterized by high rates of elderly patients, low broadband connectivity, and high chronic disease burden. Site B implemented an asynchronous digital HPI questionnaire accessible via tablet computers in clinic waiting rooms and web links sent via SMS text messaging.
- **Site C (Suburban Multicultural Health Center):** A suburban community health provider in the Western US serving an immigrant and refugee population speaking over 15 primary languages. Site C implemented a multilingual AI-driven patient history intake platform designed to auto-translate patient narrative inputs into English clinical documentation within their EHR.

2.3 Participant Selection and Sampling Strategy

Participants were selected using purposive and snowball sampling strategies to ensure comprehensive representation across the clinical and operational hierarchy (Creswell & Creswell, 2018). Eligible participants were required to be full time or part time staff members who either directly interacted with AI intake outputs during clinical encounters (e.g., physicians, nurse practitioners, physician assistants, medical assistants), managed health IT and interoperability architecture (e.g., HIT directors, clinical informaticists), or assisted patients directly with intake completion (e.g., patient navigators, front-desk staff). A total of 42 participants were recruited across the three study sites. Sample size finalization was guided by the principle of *code and meaning saturation* (Braun & Clarke, 2019, 2021), where data collection ceased when subsequent interviews yielded no new conceptual codes or contextual insights regarding socio-technical interoperability, trust, or digital equity dynamics. Table 2 summarizes participant characteristics across the three study sites.

Table 2: Participant Demographics and Professional Roles (N = 42)

Participant Role	Site A (n=15)	Site B (n=13)	Site C (n=14)	Total (N=42)	Mean Experience (Years)
Primary Care Physicians (MD/DO)	5	4	5	14	11.2
Nurse Practitioners / Physician Assistants (NP/PA)	4	3	3	10	8.5
Medical Assistants (MA)	3	3	4	10	6.1
Health IT Directors / Informaticists	1	2	1	4	14.0
Patient Navigators / Front-Desk Staff	2	1	1	4	5.3
Gender (Female / Male / Non-binary)	10 / 5 / 0	8 / 5 / 0	9 / 5 / 0	27 / 15 / 0	—

2.4 Data Collection Procedures

Data were collected between January 2022 and August 2023 through two primary qualitative methods: in-depth semi-structured interviews and non-participant direct workflow observations.

- 1) **Semi-Structured Interviews:** An interview guide was developed based on the SEIPS 2.0 (Holden et al., 2013), DHEF (Crawford & Serhal, 2020), and NASSS (Greenhalgh et al., 2017) frameworks. The guide was pilot tested with two primary care clinicians and one clinical informaticist prior to formal deployment. Interviews were conducted either in-person in private conference rooms or via a secure, HIPAA-compliant video conferencing platform, lasting between 45 and 75 minutes (M = 56 minutes). All interviews were audio-recorded with explicit written informed consent and transcribed verbatim by a professional transcription service. Transcripts were anonymized, scrubbed of all personally identifiable information (PII), and assigned alphanumeric identifier codes (e.g., P01-SiteA-MD).
- 2) **Direct Clinical Workflow Observations:** To contextualize self-reported interview data, two researchers conducted 30 total hours of non-participant direct observation across the three sites (10 hours per site). Observations focused on pre-visit patient check-in workflows, medical assistant intake reconciliation, clinician pre-encounter chart review, and real-time clinical encounter documentation practices. Field notes were documented using a standardized observation template derived from SEIPS 2.0 work system components (Holden et al., 2013).

2.5 Qualitative Data Analysis

Transcripts and field notes were analyzed using reflexive thematic analysis, following the six-phase framework articulated by Braun and Clarke (2006, 2019):

- 1) *Familiarization with Data:* Immersion through repeated reading of transcripts and field notes, generating initial reflexive memos.
- 2) *Generating Initial Codes:* Systematic line-by-line coding of transcripts using MAXQDA qualitative analysis software (VERBI Software). Coding combined inductive codes derived directly from participant narratives with deductive codes informed by SEIPS 2.0, DHEF, and NASSS frameworks.
- 3) *Searching for Themes:* Clustering codes into broader candidate themes representing coherent patterns of shared meaning around interoperability, trust, and digital equity.
- 4) *Reviewing Potential Themes:* Testing candidate themes against the full dataset and field observations to ensure thematic validity and check for disconfirming evidence.
- 5) *Defining and Naming Themes:* Refining conceptual definitions and narrative scopes for each final theme.
- 6) *Producing the Report:* Selecting vivid, illustrative verbatim quotes to ground analytical assertions in empirical data.

To enhance coding consistency and analytical rigor, two independent qualitative researchers coded a random sample of 20% of the transcripts (n = 8). Inter-coder alignment was evaluated through iterative conceptual consensus meetings, resolving discrepancies through collaborative discussion rather than mechanical statistical metrics, in alignment with reflexive qualitative paradigms (Braun & Clarke, 2019).

2.6 Methodological Rigor, Ethics, and Positionality

Methodological trustworthiness was established using Lincoln and Guba's criteria: credibility, transferability, dependability, and confirmability (Creswell & Creswell, 2018). *Credibility* was ensured through data triangulation across interview transcripts, observational field notes, and health IT system documentation, as well as formal member-checking sessions with six key informants (n = 2 per site). *Transferability* was facilitated through detailed thick descriptions of institutional contexts, participant roles, and technical configurations. *Dependability* was maintained via a comprehensive audit trail documenting analytical decisions, codebook iterations, and memoing.

RESULTS

Qualitative data analysis revealed four core themes that capture the complex socio-technical realities of AI patient intake deployments across community health settings. Table 3 provides a thematic overview detailing the four primary themes and their constituent sub-themes.

Table 3: Thematic Overview of Qualitative Results

Core Theme	Constituent Sub-Themes	Key Qualitative Context
Theme 1: Workflow Friction & Integration	- System interoperability gaps - Duplication of clinical effort	Mismatch between automated intake protocols and existing EHR systems creating double-documentation for staff.
Theme 2: Trust & Human-in-the-Loop Safeguards	- Patient skepticism of automated triage - Provider override dynamics	Need for explicit clinician validation to prevent misclassification and preserve patient-provider trust.
Theme 3: Digital Divide & Accessibility Barriers	- Variable digital literacy - Demographic & linguistic exclusion	Disparities in patient interaction quality due to interface design, language options, and access to devices.
Theme 4: Organizational Readiness & Governance	- Staff training & change management - Protocol standardization	Success relies heavily on institutional support, clear liability guidelines, and continuous feedback loops.

3.1 Participant Demographics and Baseline Site Profiles

Across all three sites, participants reported a high baseline interest in technology capable of reducing administrative burden. However, operational realities quickly diverged from vendor promises once platforms went live.

3.2 Theme 1: Socio-Technical Interoperability and EHR Integration Friction

3.2.1 Data Siloing and Unilateral FHIR API Limitations

A primary source of frustration expressed by health IT leadership and frontline clinicians was the failure of AI intake platforms to achieve true bidirectional interoperability with legacy EHR systems. While vendors frequently marketed their solutions as "FHIR-native," technical architectures were predominantly unilateral. The AI intake platform could pull basic demographic schedules from the EHR via HL7 or FHIR interfaces, but could not write structured, discrete clinical data back into native EHR fields (Holmgren et al., 2017).

Instead of populating discrete EHR tabs such as active medical history, surgical history, or medication lists, AI-generated summaries were frequently deposited into secondary media tabs as static PDF documents or unformatted narrative blobs in the encounters tab. A Health IT Director explained:

"The vendor sold us on seamless API integration. But when we flipped the switch, we discovered the AI couldn't write into our EHR's discrete data tables without triggering custom middleware costs we couldn't afford. So, the intake summary gets dumped into a 'Uncategorized Documents' folder as a PDF. Now my doctors have to open three separate windows just to find what the AI asked the patient in the waiting room." (P12-SiteB-HIT)

3.2.2 "Copy-Paste Syndrome" and Cognitive Load Re-allocation

Because intake data arrived as unstructured text or static PDFs, the cognitive and administrative burden was not eliminated; rather, it was shifted onto medical assistants and primary care providers. Clinicians described a pervasive "copy-paste syndrome," wherein staff were forced to manually read the AI-generated PDF summary, highlight pertinent clinical facts, and manually re-type or copy-paste information into native EHR documentation fields to fulfill billing and quality reporting mandates (Holden et al., 2013). A family physician noted:

"The whole promise was that the AI would write the HPI for me. But because it doesn't map to our EHR's discrete fields, my medical assistant spends two minutes copying text from the AI window into the chief complaint box, and then I spend another three minutes fixing the formatting errors. It hasn't reduced my clicks—it's actually doubled my screen context-switching." (P04-SiteA-MD)

3.3 Theme 2: Clinician Trust Dynamics, Automation Bias, and Legal/Administrative Burden**3.3.1 The Spectrum of Disuse vs. Uncritical Automation Bias**

Clinician trust in AI intake summaries was highly volatile, bifurcating into two distinct dysfunctional patterns: total technology disuse (skepticism) or uncritical automation bias (Goddard et al., 2012; Parasuraman & Riley, 1997). Experienced clinicians frequently exhibited extreme disuse, disregarding the AI summary entirely and repeating the entire history-taking process verbally with the patient. These clinicians reported that AI-generated summaries lacked clinical intuition, often elevating trivial, non-urgent symptoms while missing subtle red-flag indicators (Asan et al., 2020).

Conversely, overburdened clinicians particularly those managing double-booked patient panels exhibited dangerous automation bias, accepting AI summaries verbatim without verbal verification. A Nurse Practitioner reflected candidly on this tension:

"When you're running 20 minutes late and you see a beautifully formatted AI summary sitting there, the temptation to just sign off on it is massive. But last month, the AI intake summarized a patient's chest pain as 'mild heartburn' because of how the patient answered the chatbot questions. When I actually talked to him, he had radiating left arm pain and was in active angina. If I had blindly trusted that summary, we would have sent him home with antacids." (P18-SiteC-NP)

3.3.2 Liability Anxieties, Hallucinations, and Loss of Diagnostic Nuance

Clinicians expressed profound anxiety regarding legal liability associated with AI documentation errors or algorithmic "hallucinations" (Asan et al., 2020). Because electronic signatures legally attest to the accuracy of the medical record, providers felt uncomfortable signing charts containing AI-synthesized narratives unless they spent time cross-checking every claim against raw patient responses.

Furthermore, providers lamented the loss of diagnostic nuance and patient voice. Conversational AI algorithms frequently standardized patient narratives into clinical jargon (e.g., translating a patient's description of "a heavy rock sitting on my chest" into "non-specific chest discomfort"), stripping away psychosocial context and emotional tone critical for accurate diagnostic reasoning. A physician stated:

"Patients don't talk in medical jargon, and when the AI tries to translate their lived experience into 'medspeak,' it loses the soul of the narrative. A patient saying 'I feel empty inside since my wife died' gets turned into 'Patient reports low mood.' That's not history taking—that's clinical distortion." (P02-SiteA-MD)

3.4 Theme 3: Digital Equity, Determinants of Digital Access, and Marginalization**3.4.1 The Digital Gradient: Broadband, Device, and Literacy Exclusion**

In alignment with the Digital Health Equity Framework (Crawford & Serhal, 2020), study findings revealed that AI intake technologies systematically favored affluent, tech-literate patient demographics while creating substantial barriers for marginalized safety-net populations (Sieck et al., 2021). Pre-visit digital intake mandates assumed patients possessed modern smartphones, active data plans, stable home broadband, and high digital literacy. In reality, large proportions of FQHC patients encountered immediate digital exclusion.

Observations at Site B (rural clinic) revealed that patients frequently failed to receive SMS text intake links due to regional cellular dead zones, or could not open web links due to prepaid data plan limits. At Site A (urban center), elderly and low-income patients routinely arrived at clinic appointments without completing pre-visit intake because they found the conversational AI chatbot interface overwhelming or confusing. A Patient Navigator shared:

"The vendor assumes everyone has an iPhone with unlimited 5G data. Half our patients are on prepaid burner phones where every megabyte counts, or they share one phone across a family of five. Sending a text link three hours before an appointment sounds great in a corporate boardroom, but in our neighborhood, it means 40% of our patients walk in with zero intake done." (P39-SiteA-Nav)

3.4.2 Linguistic Non-Adaptation and Algorithmic Misinterpretation

Linguistic barriers presented another critical vector of health inequity (Crawford & Serhal, 2020). Although AI intake platforms advertised multi-language capabilities, observational data and staff interviews revealed that non-English intake translation engines relied on literal, mechanical translation models that failed to account for regional dialects, colloquial idioms, or cultural health expressions.

At Site C, which serves a diverse immigrant population, medical assistants reported that the AI intake system routinely misinterpreted Spanish and Vietnamese idiom expressions. For example, a Spanish-speaking patient describing "*nervios*" (a culturally bound construct encompassing anxiety, grief, and somatic distress) had their symptom categorized by the AI algorithm as "neurological tremors," leading to inappropriate clinical workups. A Medical Assistant explained:

"The Spanish translation in the app is formal 'textbook' Spanish from Spain. Our patients are from rural Guatemala or Mexico. They use idioms the algorithm completely butchers. It turns cultural terms for emotional

distress into physical neurological conditions, or completely misses what they're trying to say. It creates extra work because we have to undo the confusion during rooming." (P31-SiteC-MA)

3.5 Theme 4: Adaptive Workarounds and Unintended Workflow Consequences

3.5.1 "Shadow Workflows": MAs as Unofficial Digital Concierges

To prevent complete operational breakdown and protect vulnerable patients from exclusion, frontline clinic staff developed extensive, informal "shadow workflows" (Holden et al., 2013). Medical assistants (MAs) and front-desk staff absorbed the operational friction of the AI intake system by serving as unofficial "digital concierges." Instead of patients completing intake independently prior to the visit, MAs at all three sites were observed sitting beside patients in waiting rooms or exam rooms, holding clinic tablets, reading the AI chatbot questions aloud, and typing the patient's verbal answers into the digital portal on their behalf. While this workaround ensured intake completion, it inverted the technology's intended economic and operational value proposition: instead of saving staff time, it required dedicated 1:1 staff assistance for digital navigation. An MA described this burden:

"The app was supposed to replace manual intake. Instead, I now spend 10 minutes per patient sitting in the waiting room with a tablet, holding their hand through the AI screens because they can't read the small text or don't know how to hit 'next.' I've become a human interface for a machine that was supposed to make my job easier." (P25-SiteB-MA)

3.5.2 Triage Compression and Schedule Disruption

The accumulation of technical friction, data reconciliation, and digital navigation workarounds created a downstream phenomenon of "triage compression." Clinical encounters were consistently delayed because rooming procedures took significantly longer for patients who could not complete digital intake independently. When patients with uncompleted intake arrived, MAs were forced to compress vital sign acquisition, medication reconciliation, and digital intake entry into extremely narrow rooming windows. Consequently, clinicians received patient charts late, reducing available face-to-face encounter time and compounding schedule backlogs throughout the clinical day.

DISCUSSION

4.1 Principal Findings and Integration with Prior Literature

This multi-site qualitative study provides a empirical examination of the socio-technical, cognitive, and equity dynamics surrounding AI-driven patient intake deployments in United States community health centers. By integrating the Systems Engineering Initiative for Patient Safety (SEIPS 2.0) (Holden et al., 2013), the Digital Health Equity Framework (DHEF) (Crawford & Serhal, 2020), and the NASSS framework (Greenhalgh et al., 2017), our findings demonstrate that AI intake technologies far from acting as simple plug-and-play efficiency tools fundamentally reconfigure the work system, clinical cognitive burden, and equity landscape of safety-net primary care.

Our findings extend existing informatics research in three key areas:

- 1) They challenge the technological determinism that assumes digital automation inherently reduces administrative clerical burden (Lin et al., 2019).
- 2) They illustrate how fragile, unilateral EHR interoperability architectures convert theoretical efficiency gains into manual "copy-paste" workarounds (Holden et al., 2013; Holmgren et al., 2017).
- 3) They provide qualitative evidence of how unadapted digital intake portals act as "intervention-generated inequalities," systematically marginalizing low-income, non-English speaking, and digitally under-connected patient cohorts (Crawford & Serhal, 2020; Veinot et al., 2018).

4.2 Socio-Technical Interoperability: Beyond FHIR Standards

A central finding of this study is that regulatory compliance with basic interoperability standards (e.g., ONC 21st Century Cures Act mandates) does not guarantee operational socio-technical integration at the point of care (Holmgren et al., 2017; ONC, 2020). While vendors may claim "FHIR enablement," our data demonstrate that unilateral data flows wherein AI applications can read patient schedules but cannot write discrete, structured data directly into native EHR clinical tables create severe workflow degradation.

When AI intake outputs are deposited as static PDFs or unformatted narrative blobs, the socio-technical system breaks down (Holden et al., 2013). Medical assistants and clinicians are forced to perform manual data reconciliation, driving context-switching and cognitive fatigue. True socio-technical interoperability requires deep, bidirectional API integration capable of populating discrete EHR fields while maintaining clear audit trails of data provenance (Holmgren et al., 2017). Until health IT developers and EHR vendors build native, bidirectional clinical data pipelines, AI intake tools will continue to impose a hidden "reconciliation tax" on frontline clinical staff.

4.3 Reconceptualizing Clinician Trust: Calibration, Responsibility, and Burnout

Our results illuminate the complex psychological dynamics governing clinician interaction with AI-generated documentation. Trust is not a static binary (trust vs. distrust); rather, clinicians continuously calibrate trust along a dynamic continuum influenced by time pressure, perceived risk, and past experience with algorithmic errors (Goddard et al., 2012; Parasuraman & Riley, 1997). The emergence of both *disuse* (total rejection of AI intake, leading to duplicate history taking) and *automation bias* (uncritical acceptance of AI summaries, risking missed diagnostic red flags) highlights a profound clinical safety hazard (Goddard et al., 2012). When overburdened clinicians succumb to automation bias due to extreme schedule pressure, the risk of diagnostic error escalates (Asan et al., 2020). Furthermore, because clinicians bear ultimate legal and ethical responsibility for signed medical charts, AI platforms that act as "black boxes" summarizing HPI narratives without revealing the underlying raw patient inputs generate substantial moral injury and legal anxiety. To foster calibrated trust, AI intake designs must incorporate transparent, interactive explanation interfaces that allow clinicians to instantly cross-reference synthesized HPI claims with verbatim patient responses (Asan et al., 2020).

4.4 Operationalizing Digital Health Equity in Safety-Net Settings

Perhaps the most urgent finding of this study is the mechanism by which AI intake deployments amplify existing health disparities when implemented without digital equity safeguards (Crawford & Serhal, 2020; Veinot et al., 2018). In alignment with Veinot et al.'s (2018) theory of *intervention-generated inequality*, technology interventions that require individual digital resources (smartphones, broadband, digital literacy) naturally grant disproportionate advantage to already privileged groups while creating compounding barriers for structurally marginalized populations (Sieck et al., 2021). When community health centers shift intake workflows to smartphone portals, patients facing digital determinants of health (DDOH) barriers such as data plan limits, low literacy, or non-English language preferences are excluded prior to even stepping into the exam room (Crawford & Serhal, 2020; Sieck et al., 2021). The resulting burden falls squarely on frontline medical assistants, who must create informal "shadow workflows" to assist digitally excluded patients (Holden et al., 2013). This creates a structural paradox: the technology intended to save staff time ultimately shifts human labor onto low-wage healthcare workers, while exacerbating triage delays for vulnerable patients.

4.5 Policy, Practical, and System Design Implications

To address these challenges, we propose actionable recommendations for technology developers, health system leaders, and federal policymakers, outlined in Table 4.

Table 4: Multilevel Recommendations for Equitable and Interoperable AI Intake Deployments

Stakeholder Level	Key Challenge Addressed	Actionable Recommendation
AI Software Developers	Siloed data & black-box algorithms	Build native bidirectional FHIR APIs that populate discrete EHR fields; design transparent "data provenance" UI allowing 1-click verification of raw patient quotes (Asan et al., 2020).
AI Software Developers	Linguistic & cultural misclassification	Incorporate participatory co-design with minoritized patient communities; train NLP translation models on regional dialects and cultural idioms rather than textbook translations (Crawford & Serhal, 2020).
FQHC & Health System Leaders	Shadow workflows & digital exclusion	Avoid mandatory pre-visit smartphone intake policies; deploy hybrid intake models offering in-person, staff-assisted digital kiosks alongside non-digital options (Sieck et al., 2021).
FQHC & Health System Leaders	Staff cognitive overload & disuse	Mandate interprofessional workflow mapping and human factors training prior to technology go-live; reallocate MA time to support digital navigation formally (Holden et al., 2013).

Stakeholder Level	Key Challenge Addressed	Actionable Recommendation
Federal Policymakers (ONC / CMS)	Fragmented interoperability standards	Require certified health IT vendors to support standard bidirectional discrete data writing APIs for third-party AI clinical documentation tools under Cures Act rules (ONC, 2020).
Federal Policymakers (HRSA / HHS)	Digital determinants of health (DDOH)	Expand federal safety-net grant funding to support digital health navigators and broadband connectivity infrastructure in rural and urban FQHCs (Sieck et al., 2021).

4.6 Study Limitations

This study has several limitations. First, while our multi-site design included three geographically and demographically diverse FQHC networks, findings may not fully generalize to all primary care environments, such as private fee-for-service practices or large academic health systems with custom enterprise IT infrastructure. Second, our participant sample focused on clinical, administrative, and informatics staff; direct patient perspectives were captured indirectly through staff accounts and workflow observations. Future qualitative research should focus directly on minoritized and non-English speaking patient experiences with AI intake interfaces. Third, the rapidly evolving landscape of generative AI and large language models (LLMs) means that technical capabilities of commercial platforms are continuously changing; however, the core socio-technical, trust, and equity principles identified in this study remain fundamentally applicable across technology generations.

CONCLUSION

As artificial intelligence platforms become increasingly embedded within primary care delivery, evaluating their implementation through a socio-technical and equity-centered lens is paramount. This multi-site qualitative study demonstrates that commercial AI patient intake tools cannot be treated as isolated technological interventions. When deployed within safety-net community health centers, their success or failure is inextricably linked to the surrounding work system including EHR interoperability architectures, clinician trust calibration, frontline workflow adaptations, and underlying digital determinants of health. Without deep bidirectional EHR integration, AI intake platforms shift administrative burden into manual data reconciliation. Without transparent algorithmic provenance, they create hazardous tensions between clinician misuse and uncritical automation bias. And without explicit, equity-first design that accommodates low digital literacy, limited broadband access, and diverse linguistic needs, AI intake innovations risk widening the social gradient of health. Achieving the promise of AI-driven administrative relief requires an unyielding commitment to human-centered design, robust interoperability standards, and digital health equity for all patient populations.

REFERENCES

- 1) Asan, O., Bayrak, A. E., & Choudhury, A. (2020). Artificial intelligence and human trust in healthcare: Focus on clinicians. *Journal of Medical Internet Research*, 22(6), e15154. <https://doi.org/10.2196/15154>
- 2) Benda, N. C., Das, L. T., Abramson, E. L., Blackburn, K. A., Thoman, A. K., & Kaushal, R. (2022). How primary care clinics changed patient intake during COVID-19: Implications for digital health equity. *Journal of General Internal Medicine*, 37(1), 211–217. <https://doi.org/10.1007/s11606-021-07119-0>
- 3) Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, 3(2), 77–101. <https://doi.org/10.1191/1478088706qp063oa>
- 4) Braun, V., & Clarke, V. (2019). Reflecting on reflexive thematic analysis. *Qualitative Research in Sport, Exercise and Health*, 11(4), 589–597. <https://doi.org/10.1080/2159676X.2019.1628806>
- 5) Crawford, A., & Serhal, E. (2020). Digital health equity and COVID-19: The innovation curve cannot reinforce the social gradient of health. *Journal of Medical Internet Research*, 22(6), e19361. <https://doi.org/10.2196/19361>
- 6) Creswell, J. W., & Creswell, J. D. (2018). *Research design: qualitative, quantitative, and mixed methods approaches* (5th ed.). SAGE Publications.

- 7) Goddard, K., Roudsari, A., & Wyatt, J. C. (2012). Automation bias: A systematic review of frequency, cause, and effect. *Journal of the American Medical Informatics Association*, 19(1), 168–174. <https://doi.org/10.1136/amiajnl-2011-000089>
- 8) Greenhalgh, T., Wherton, J., Papoutsi, C., Lynch, J., Hughes, G., A'Court, C., Hinder, S., Fahy, N., Procter, R., & Shaw, S. (2017). Beyond adoption: A new framework for theorizing and evaluating nonadoption, abandonment, and challenges to the scale-up, spread, and sustainability of health and care technologies. *Journal of Medical Internet Research*, 19(11), e367. <https://doi.org/10.2196/jmir.8775>
- 9) Holden, R. J., Carayon, P., Gurses, A. P., Hoonakker, P., Hundt, A. S., Ozok, A. A., & Rivera-Rodriguez, A. J. (2013). SEIPS 2.0: A human factors framework for studying and improving the work of healthcare professionals and patients. *Ergonomics*, 56(11), 1669–1686. <https://doi.org/10.1080/00140139.2013.838643>
- 10) Holmgren, A. J., Patel, V., & Adler-Milstein, J. (2017). Progress in interoperability: Measuring US hospitals' engagement in sharing patient data. *Health Affairs*, 36(10), 1820–1827. <https://doi.org/10.1377/hlthaff.2017.0546>
- 11) Lin, S. Y., Mahoney, M. R., & Sinsky, C. A. (2019). Ten bold steps for preventing physician burnout and improving patient care. *Journal of General Internal Medicine*, 34(10), 2213–2218. <https://doi.org/10.1007/s11606-019-05188-4>
- 12) Office of the National Coordinator for Health Information Technology. (2020). *21st Century Cures Act: Interoperability, information blocking, and the ONC Health IT Certification Program*. U.S. Department of Health and Human Services.
- 13) Parasuraman, R., & Riley, V. (1997). Humans and automation: Use, misuse, disuse, abuse. *Human Factors*, 39(2), 230–253. <https://doi.org/10.1518/001872097778543886>
- 14) Sieck, C. J., Sheon, A., Ancker, J. S., Castek, J., Callahan, B., & Siefer, A. (2021). Digital inclusion as a social determinant of health. *npj Digital Medicine*, 4(1), 52. <https://doi.org/10.1038/s41746-021-00413-8>
- 15) Tong, A., Sainsbury, P., & Craig, J. (2007). Consolidated criteria for reporting qualitative# Evaluating Socio-Technical Interoperability, Clinician Trust, and Digital Equity in AI Intake Deployments: A Multi-Site Qualitative Study of US Community Health Providers