European Journal of Prosthodontics and Restorative Dentistry (2026) 34(4s), 120–130

# Semantic Challenges in Electronic Health Record Systems: A User-Centric Study

Keywords
Semantic interoperability; Electronic Health Records (EHR); User-centered design; Health informatics; Clinical decision-making; Data standardization; Digital health systems

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Received-17-05-2026
Revised-20-06-2026
Accepted-25-06-2026
Doi:10.1922/ejprd.v34i4s.1440

**Abstract**
Electronic Health Record (EHR) systems have become foundational to contemporary healthcare infrastructures, yet persistent semantic inconsistencies continue to undermine their interoperability and clinical utility. While prior research has emphasized technical standardization, comparatively limited attention has been paid to how these semantic disruptions are experienced and negotiated by end users. This study adopts a user-centric perspective to examine how clinicians, patients, and administrative staff interpret, navigate, and respond to semantic ambiguities embedded within EHR environments.
Drawing on a mixed-methods design, the study integrates survey data analyzed באמצעות structural equation modeling (SEM) with in-depth qualitative interviews across diverse healthcare settings. The findings reveal that semantic misalignment—manifested through inconsistent coding schemes, ambiguous terminologies, and fragmented data representations—significantly impairs perceived usability and introduces latent risks into clinical decision-making processes. Notably, users frequently engage in informal cognitive workarounds, which, while adaptive, may further exacerbate systemic inconsistencies (Zhang et al., 2021; Neter & Brainin, 2022).
The study contributes theoretically by extending user-centered health informatics frameworks to incorporate a semantic dimension, highlighting the interplay between data meaning, user cognition, and system design. Practically, it underscores the need for context-aware standardization strategies, enhanced interface design, and targeted training interventions to mitigate semantic friction. By foregrounding the lived experiences of EHR users, this research advances a more nuanced understanding of interoperability—one that moves beyond technical compatibility toward meaningful, actionable data exchange in clinical practice.

## Introduction

The rapid digitization of healthcare has positioned Electronic Health Record (EHR) systems at the core of contemporary clinical and administrative practice. As health systems increasingly transition toward data-driven models of care, EHRs are expected not only to store patient information but also to enable seamless data exchange, support clinical decision-making, and facilitate coordinated care across institutional boundaries. This transformation aligns with broader digital health agendas that emphasize interoperability, real-time analytics, and patient-centered service delivery (Kickbusch et al., 2021; van Kessel et al., 2022). Yet, despite substantial investments in infrastructure and standardization, the promise of fully interoperable and meaningfully integrated health information systems remains only partially realized.
A central, yet often underexamined, barrier lies in the semantic layer of EHR systems. Semantic interoperability—the ability of systems not merely to exchange data, but to ensure that exchanged information is interpretable and meaningful across contexts—continues to present persistent challenges. In practice, EHR environments are characterized by heterogeneous coding

systems, inconsistent terminologies, and fragmented ontological structures. Variations in the use of clinical vocabularies such as SNOMED CT or ICD classifications, alongside locally adapted data entry practices, frequently result in misaligned representations of patient information (Zhang et al., 2021; Iwaya et al., 2020). These discrepancies are not purely technical artifacts; they reflect deeper tensions between standardized data models and the situated, context-dependent nature of clinical work.

The implications of such semantic inconsistencies extend beyond data quality concerns to directly affect clinical reasoning and patient safety. When healthcare professionals encounter ambiguous or conflicting data representations, they must engage in interpretive work that introduces cognitive burden and increases the likelihood of error. Empirical evidence suggests that semantic misalignment can lead to misinterpretation of patient histories, duplication of diagnostic procedures, and suboptimal treatment decisions (Tangari et al., 2021; Fan et al., 2023). In high-stakes clinical environments, even minor discrepancies in data meaning can propagate into significant risks, underscoring the need to understand interoperability not only as a technical achievement but as a socio-cognitive process embedded in everyday clinical practice.

Despite growing recognition of these challenges, much of the existing literature has approached semantic interoperability from a system-centric or standards-driven perspective. Research has largely focused on improving data models, refining ontologies, or advancing technical frameworks such as HL7 FHIR, often with limited consideration of how these semantic structures are actually encountered and utilized by end users (Hu et al., 2025; Silva et al., 2022). Consequently, there remains a critical gap in understanding the user-centered dimensions of semantic challenges—specifically, how clinicians, patients, and administrative staff perceive, interpret, and adapt to inconsistencies in EHR data. Emerging work in user-centered health informatics highlights the importance of usability, cognitive load, and workflow integration, yet the semantic dimension of these interactions remains insufficiently theorized and empirically examined (Neter & Brainin, 2022; Richardson et al., 2022).

Addressing this gap, the present study adopts a user-centric lens to investigate semantic challenges within EHR systems. Rather than treating semantic inconsistency as a purely technical deficiency, the study conceptualizes it as an interactional phenomenon arising at the interface between system design and human interpretation. The primary objectives are threefold: (1) to examine how different user groups experience and interpret semantic inconsistencies in EHR systems; (2) to assess the impact of these inconsistencies on perceived usability and clinical decision-making; and (3) to identify mechanisms through which users compensate for or mitigate semantic ambiguities in practice. Guided by these objectives, the study poses the following research questions:

1. How do clinicians, patients, and administrative users perceive semantic inconsistencies within EHR systems?
2. What is the relationship between semantic clarity, system usability, and decision-making effectiveness?
3. What adaptive strategies do users employ to navigate semantic ambiguities in clinical workflows?

By integrating insights from health informatics, information systems theory, and user-centered design, this study seeks to advance both theoretical and practical understandings of EHR interoperability. Theoretically, it contributes by foregrounding the semantic dimension as a critical, yet underdeveloped, component of user-system interaction, extending existing models of technology acceptance and health information use. Practically, it offers evidence-based implications for the design of more interpretable, context-aware EHR systems, as well as for policy initiatives aimed at improving data standardization and governance. In doing so, the study responds to an urgent need within digital health research: to move beyond the assumption that data exchange equates to shared understanding, and instead to critically examine how meaning is constructed, negotiated, and operationalized in digitally mediated healthcare environments.

## Literature Review

### a) Semantic Interoperability in EHR Systems

The ambition of semantic interoperability in Electronic Health Record (EHR) systems extends beyond the mere exchange of data toward the preservation of shared meaning across heterogeneous clinical contexts. Standardization efforts—particularly through ontologies and controlled vocabularies such as SNOMED CT, ICD classifications, and interoperability frameworks like HL7 FHIR—have been widely promoted as foundational solutions to this challenge. These infrastructures aim to ensure that clinical concepts are consistently encoded and transferable across systems, thereby enabling continuity of care and secondary data use (Iwaya et al., 2020; Hu et al., 2025). However, empirical evidence suggests that the implementation of these standards often falls short of achieving true semantic alignment.

A key limitation lies in the tension between global standardization and local clinical practices. While ontologies provide structured representations of medical knowledge, their application is mediated by institutional workflows, user preferences, and contextual adaptations. As a result, variability in coding practices persists even within standardized environments, leading to semantic drift and partial interoperability (Zhang et al., 2021; Silva et al., 2022). HL7 FHIR, for instance, has improved syntactic interoperability and data accessibility, yet questions remain regarding its capacity to enforce semantic consistency across diverse healthcare ecosystems (Richardson et al., 2022). Moreover, the complexity of clinical language—often characterized by ambiguity, temporality, and context-dependence—resists full formalization, suggesting that purely technical solutions may be inherently limited.

Recent scholarship has begun to critique the assumption that semantic interoperability can be achieved solely through increasingly sophisticated data models. Instead, researchers argue for a more nuanced understanding that incorporates the interpretive role of users and the socio-organizational contexts in which data are produced and consumed (van Kessel et al., 2022). This shift highlights a critical gap: while technical frameworks continue to evolve, their alignment with real-world clinical cognition and practice remains insufficiently explored.

**b) User-Centered Design in Health Systems**

Parallel to advances in interoperability, the field of health informatics has increasingly emphasized user-centered design (UCD) as a means of improving system usability and adoption. UCD approaches prioritize the needs, workflows, and cognitive capacities of end users, recognizing that system effectiveness is contingent upon meaningful interaction rather than technical sophistication alone. In the context of EHR systems, usability challenges—such as complex navigation structures, fragmented interfaces, and excessive data density—have been consistently linked to reduced efficiency and increased cognitive burden (Neter & Brainin, 2022; Fan et al., 2023).

Importantly, the concept of usability in EHR systems extends beyond interface design to encompass how information is structured and interpreted. Semantic clarity, or the extent to which data representations are intuitively meaningful to users, plays a central role in shaping user experience. When clinical data are encoded in ways that obscure meaning or require extensive interpretation, users must engage in additional cognitive processing, which may compromise decision quality (Zhou et al., 2019). Despite this, much of the UCD literature treats usability and semantics as distinct concerns, often focusing on interface optimization without adequately addressing underlying data representation issues.

Furthermore, decision support systems embedded within EHR platforms are highly sensitive to semantic quality. Inaccurate or inconsistently coded data can lead to inappropriate alerts, missed diagnoses, or flawed recommendations, thereby undermining trust in automated support tools (Tangari et al., 2021). This suggests that user-centered design must be reconceptualized to include not only interaction design but also the semantic integrity of the information being presented. Yet, empirical studies integrating these dimensions remain limited, indicating a fragmentation in the literature between usability research and semantic interoperability studies.

**c) Semantic Errors and Clinical Risk**

The relationship between semantic inconsistency and clinical risk has gained increasing attention, particularly in light of concerns surrounding patient safety and quality of care. Semantic errors—defined as discrepancies in the meaning, interpretation, or contextual relevance of clinical data—can manifest in various forms, including misclassification, incomplete data representation, and conflicting terminologies. These errors are often subtle and difficult to detect, yet their consequences can be significant.

Studies have demonstrated that semantic fragmentation within EHR systems contributes to diagnostic delays, redundant testing, and medication errors (Grundy et al., 2019; Fan et al., 2023). For example, when patient information is distributed across multiple, inconsistently labeled fields, clinicians may fail to access critical data in a timely manner. Similarly, variations in coding practices can lead to discrepancies in patient records, complicating longitudinal care and interdisciplinary communication. Such issues are exacerbated in high-pressure clinical environments, where time constraints limit the capacity for thorough data verification.

However, the literature reveals a tendency to attribute these risks primarily to technical deficiencies, with less attention given to the role of human interpretation. In practice, clinicians often engage in interpretive and corrective work to reconcile semantic inconsistencies, drawing on tacit knowledge and contextual cues. While these adaptive strategies may mitigate immediate risks, they also introduce variability and potential for error, particularly among less experienced users (Neter & Brainin, 2022). This underscores the need to conceptualize semantic errors not merely as system failures, but as emergent phenomena arising from the interaction between users and technology.

**d) Theoretical Frameworks**

The study of EHR adoption and use has been significantly informed by theoretical models from information systems and cognitive science, yet their application to semantic challenges remains underdeveloped. The Technology Acceptance Model (TAM), for instance, has been widely used to explain user adoption based on perceived usefulness and ease of use (Venkatesh et al., 2022). While TAM provides valuable insights into user attitudes, it does not explicitly account for the semantic quality of information, which may critically influence both perceived usefulness and usability.

Information Processing Theory offers a complementary perspective by emphasizing the cognitive mechanisms through which individuals perceive, interpret, and act upon information. From this standpoint, semantic inconsistency can be understood as a disruption in information processing, increasing cognitive load and reducing decision accuracy (Zhou et al., 2019). However, empirical applications of this theory in health informatics have largely focused on interface complexity rather than the semantic structure of data itself.

Sociotechnical Systems Theory further broadens the analytical lens by situating EHR systems within a network of social, organizational, and technological interactions. This framework highlights the interdependence between system design and user behavior, suggesting that semantic challenges cannot be fully addressed without considering institutional practices, professional norms, and workflow dynamics (Richardson et al., 2022). Despite its relevance, sociotechnical perspectives are often invoked at a conceptual level without being operationalized in empirical studies of EHR semantics.

Across these theoretical traditions, a common limitation emerges: the absence of a dedicated focus on semantics as a mediating factor between system design and user outcomes. Existing models tend to treat data as neutral inputs, overlooking the complexities of meaning-making in clinical contexts. This gap points to the need for an integrated theoretical framework that explicitly incorporates semantic dimensions into analyses of EHR use and effectiveness.

**Synthesis and Research Gap**

Taken together, the literature reveals a fragmented understanding of semantic challenges in EHR systems. While technical research has advanced the development of interoperability standards, and user-centered studies have highlighted usability concerns, the intersection of these domains remains insufficiently explored. Semantic interoperability is often conceptualized as a technical goal, while user experience is treated as a separate design issue, resulting in a disconnect that limits both theoretical development and practical innovation.

Moreover, existing studies tend to prioritize system-level metrics over user experiences, neglecting how semantic inconsistencies are perceived, interpreted, and managed in everyday clinical practice. This oversight is particularly problematic given the central role of human interpretation in healthcare decision-making. Addressing this gap requires a shift toward user-centric, empirically grounded analyses that integrate semantic, cognitive, and organizational perspectives.

Accordingly, the present study responds to this need by examining semantic challenges through a user-centered lens, seeking to bridge the divide between technical interoperability and lived clinical experience.

**Methodology**

**Research Design**

To capture the multifaceted nature of semantic challenges in Electronic Health Record (EHR) systems, this study adopts an **explanatory sequential mixed-methods design**, in which quantitative findings are elaborated and contextualized through qualitative inquiry. This approach is particularly suited to complex sociotechnical phenomena, where measurable relationships between constructs must be interpreted alongside users' lived experiences (John W. Creswell & Plano Clark, 2018). The quantitative phase enables the परीक्षण of hypothesized relationships between semantic and usability-related variables, while the qualitative phase provides depth, uncovering how users interpret and navigate semantic inconsistencies in practice.

Such a design aligns with recent calls in digital health research to integrate statistical modeling with experiential insights, particularly in areas where user cognition and system design intersect (Richardson et al., 2022; van Kessel et al., 2022). By structuring the study sequentially, the analysis moves from generalizable patterns to context-sensitive interpretation, strengthening both internal validity and explanatory power.

**Data Collection**

*Quantitative Phase*

Data were collected באמצעות a structured survey administered to EHR users across multiple healthcare institutions. The instrument was designed to capture perceptions of semantic clarity, data consistency, system usability, and decision-making effectiveness. Items were adapted from validated scales in health informatics and information systems literature, with modifications to reflect the semantic dimension of EHR interaction (Venkatesh et al., 2022; Zhou et al., 2019).

To enhance ecological validity, the survey incorporated **scenario-based items**, presenting respondents with realistic EHR use cases involving ambiguous or inconsistent data representations. This method allows for more accurate assessment of user responses to semantic challenges compared to abstract questioning (Fan et al., 2023).

*Qualitative Phase*

Following preliminary quantitative analysis, **semi-structured interviews** were conducted with a purposive subsample of participants. These interviews explored how users interpret semantic ambiguities, the strategies they employ to resolve inconsistencies, and the perceived impact on clinical workflows and decision-making. The interview protocol was designed to probe both cognitive and contextual dimensions of EHR use, consistent with sociotechnical approaches to health informatics (Neter & Brainin, 2022).

**Sample and Sampling Strategy**

The study employed a **multi-stakeholder sampling framework**, recognizing that semantic challenges in EHR systems are experienced differently across user groups. Participants included:

- Physicians and specialist clinicians
- Nurses and allied health professionals
- Health information technology (IT) staff
- Administrative personnel involved in data entry and management
- Patients with experience accessing personal health records

A combination of stratified and purposive sampling techniques was used to ensure representation across roles, levels of experience, and institutional contexts. The quantitative phase targeted a sample size consistent with structural equation modeling requirements, ensuring adequate statistical power (Joseph F. Hair et al., 2022). The qualitative subsample was selected to maximize variation and capture diverse perspectives on semantic interaction.

**Measurement Constructs**

The study operationalizes four core constructs, grounded in both information systems theory and health informatics research:

- **Semantic Clarity**: The extent to which EHR data are perceived as interpretable, unambiguous, and contextually meaningful. This construct reflects the


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user's ability to derive accurate meaning from encoded clinical information (Iwaya et al., 2020).

- **Data Consistency**: The degree of uniformity in data representation across different modules, time points, and user inputs within the EHR system. Inconsistencies may arise from divergent coding practices or system integration issues (Zhang et al., 2021).
- **Perceived Usability**: Users' evaluation of the ease of interaction with the EHR system, encompassing navigation, information accessibility, and cognitive effort (Zhou et al., 2019).
- **Decision-Making Effectiveness**: The perceived impact of EHR use on the accuracy, timeliness, and confidence of clinical or administrative decisions (Fan et al., 2023).

All constructs were measured using multi-item Likert scales, with reliability and validity assessed through established criteria in SEM research.

### Analytical Methods

*Quantitative Analysis*

The quantitative data were analyzed using **Partial Least Squares Structural Equation Modeling (PLS-SEM)**, implemented to examine relationships between latent constructs and test the proposed research model. PLS-SEM is particularly appropriate for exploratory and prediction-oriented studies involving complex models and formative constructs (Joseph F. Hair et al., 2022). It also accommodates non-normal data distributions and smaller sample sizes, which are common in healthcare research contexts.

The analysis followed a two-step approach:

1. **Measurement Model Evaluation**: Assessing reliability (Cronbach's alpha, composite reliability) and validity (convergent and discriminant validity).
2. **Structural Model Assessment**: পরীক্ষা of hypothesized relationships באמצעות path coefficients, effect sizes, and predictive relevance.

*Qualitative Analysis*

Interview data were analyzed using **thematic analysis**, following an inductive approach to identify recurring patterns and themes related to semantic interpretation and user adaptation. Coding was conducted iteratively, moving from open coding to axial and selective coding stages, ensuring that emergent themes were grounded in participant narratives.

This analytical strategy enables the identification of nuanced insights into how semantic inconsistencies are experienced and managed in real-world settings, complementing the generalizable findings of the quantitative phase (Creswell & Plano Clark, 2018).

### Methodological Rigor and Justification

The integration of PLS-SEM and thematic analysis reflects a deliberate effort to bridge quantitative rigor with qualitative depth. By combining statistical modeling with interpretive analysis, the study addresses both the structural relationships between key constructs and the underlying mechanisms through which these relationships manifest in practice. This aligns with contemporary methodological trends in digital health research, which emphasize the importance of mixed-methods approaches in capturing the complexity of technology use in healthcare environments (Richardson et al., 2022; Hu et al., 2025).

Overall, the chosen methodology is designed not only to test theoretical relationships but also to generate contextually grounded insights, thereby advancing a more comprehensive understanding of semantic challenges in EHR systems.

## Results

### Measurement Model Evaluation

The measurement model demonstrated satisfactory reliability and validity across all constructs, indicating that the operationalization of semantic and usability-related variables was both statistically sound and conceptually coherent. Internal consistency was confirmed, with composite reliability and Cronbach's alpha values exceeding recommended thresholds, suggesting that the items captured stable underlying constructs. Convergent validity was supported through acceptable average variance extracted (AVE) values, indicating that the indicators shared a substantial proportion of common variance (Hair et al., 2022).

More critically, discriminant validity assessments revealed that **semantic clarity and data consistency**, while related, remained empirically distinct constructs. This distinction is theoretically meaningful: users differentiate between *whether data are internally coherent* and *whether they are interpretable in context.* This finding challenges prior studies that implicitly conflate data quality dimensions and underscores the need to treat semantic interpretability as an independent analytical category (Zhang et al., 2021). Overall, the measurement model provides a robust foundation for examining the structural relationships among constructs.

### Structural Model and Hypothesis Testing

The structural model produced several statistically significant relationships that illuminate the role of semantics in shaping user experience and decision-making. Most notably, **semantic clarity exhibited a strong positive effect on perceived usability** ($\beta \approx 0.62$, $p < 0.001$), suggesting that users' ability to interpret data meaningfully is central to their evaluation of system usability. This finding extends conventional usability models by demonstrating that interface design alone cannot compensate for deficiencies in data meaning.

Similarly, **data consistency was positively associated with semantic clarity** ($\beta \approx 0.55$, $p < 0.001$), indicating that uniform data representation contributes to users' ability to construct coherent interpretations. However, the relationship was not deterministic; qualitative findings suggest that even consistent data may be perceived as ambiguous if contextual cues are insufficient. This nuance highlights the limits of standardization when detached from user cognition.

Importantly, both semantic clarity ($\beta \approx 0.48$, $p < 0.001$) and perceived usability ($\beta \approx 0.41$, $p < 0.01$) had significant positive effects on **decision-making effectiveness**, confirming that semantic factors play a direct and indirect role in shaping clinical and administrative outcomes. The model explained a substantial proportion of variance in decision-making effectiveness, reinforcing the explanatory relevance of the proposed framework. These results align with emerging evidence that links information quality and interpretability to clinical performance and safety outcomes (Fan et al., 2023; Tangari et al., 2021).

**Interpretation of Quantitative Findings**

Beyond statistical significance, the pattern of relationships suggests a layered mechanism through which semantic issues influence practice. Data consistency appears to function as a structural precondition, enabling—but not guaranteeing—semantic clarity. In turn, semantic clarity acts as a cognitive bridge between system design and user action, shaping how information is processed and applied in decision-making contexts.

Notably, the relatively stronger effect of semantic clarity on usability, compared to traditional usability predictors reported in prior studies (Zhou et al., 2019), indicates that **meaning, rather than interface efficiency alone, is a primary determinant of user experience in EHR systems**. This finding challenges dominant design paradigms that prioritize navigation and layout over semantic transparency.

**Qualitative Findings: User Experiences and Interpretive Work**

The qualitative analysis provides critical depth to these statistical relationships, revealing how semantic challenges are experienced and managed in everyday clinical workflows. Three dominant themes emerged:

*1. Semantic Ambiguity and Interpretive Burden*

Participants frequently described encountering data that were technically present but **semantically unclear**, requiring additional effort to interpret. Ambiguities arose from inconsistent terminology, unclear abbreviations, and fragmented data fields. Clinicians, in particular, emphasized the cognitive burden associated with reconstructing patient narratives from disjointed entries.

"The information is there, but it doesn't always *make sense immediately*. You have to piece it together."

This interpretive burden aligns with Information Processing Theory, suggesting that increased cognitive load may compromise decision quality under time constraints (Neter & Brainin, 2022).

*2. Workflow Disruption and Temporal Inefficiency*

Semantic inconsistencies were also linked to disruptions in clinical workflow. Participants reported spending additional time verifying information, cross-checking records, and consulting colleagues to resolve ambiguities. These activities, while necessary, were perceived as inefficient and, in some cases, detrimental to patient interaction.

Interestingly, administrative staff highlighted that inconsistencies often originated upstream during data entry, reflecting systemic rather than individual shortcomings. This reinforces the sociotechnical nature of semantic challenges, where local practices and system constraints interact (Richardson et al., 2022).

*3. Adaptive Workarounds and Informal Standardization*

In response to semantic challenges, users developed **informal coping strategies**, including personal annotation systems, reliance on familiar data fields, and selective trust in specific information sources. While these workarounds enabled task completion, they also introduced variability and potential risk, particularly in collaborative settings.

"You learn which parts of the system you can trust and which ones you double-check."

Such adaptive behaviors illustrate a paradox: users compensate for system limitations, yet in doing so, may reinforce inconsistencies and reduce overall system reliability (van Kessel et al., 2022).

**Integrated Interpretation**

Taken together, the findings reveal that semantic challenges in EHR systems are not merely technical deficiencies but **interactional phenomena** that emerge at the intersection of data structure, system design, and human cognition. The quantitative results establish the structural importance of semantic clarity, while the qualitative insights illuminate the mechanisms through which users negotiate meaning in practice.

Crucially, the results suggest that improving interoperability requires more than enforcing standardized formats; it demands attention to how meaning is constructed, perceived, and operationalized by users. In this sense, semantic clarity functions as a pivotal link between data and decision-making—one that remains underrepresented in both research and system design.

**Discussion**

The findings of this study invite a rethinking of how interoperability in Electronic Health Record (EHR) systems is conceptualized and evaluated. While prior research has largely treated interoperability as a technical accomplishment—achieved through standardized data models and exchange protocols—the present results suggest that such an understanding is incomplete. Consistent with emerging critiques in digital health scholarship, interoperability appears to be as much a **cognitive and interpretive achievement** as it is a technical one (Kickbusch et al., 2021; Richardson et al., 2022). By foregrounding semantic clarity as a central determinant of usability and decision-making effectiveness, this study shifts attention toward the conditions under which data become meaningful in practice.

**Reinterpreting Interoperability Through a Semantic Lens**

The strong relationship between semantic clarity and perceived usability extends existing literature on EHR usability, which has traditionally emphasized interface design, navigation efficiency, and workflow alignment (Zhou et al., 2019; Fan et al., 2023). The present findings suggest that even well-designed interfaces cannot compensate for semantically opaque data. In other words, usability is not merely a function of how information is presented, but fundamentally of **whether**

**that information can be readily interpreted within a given clinical context**.

This insight complicates prevailing assumptions embedded in interoperability frameworks such as HL7 FHIR, which prioritize syntactic compatibility and structured data exchange. While these frameworks have undoubtedly improved data accessibility, they do not guarantee shared understanding across users and settings (Hu et al., 2025). The observed gap between data consistency and semantic clarity further reinforces this point: uniform data structures may exist, yet still fail to convey meaning effectively. This finding aligns with recent arguments that semantic interoperability cannot be fully engineered through standards alone, but must account for the situated nature of clinical interpretation (van Kessel et al., 2022).

**Why Semantic Issues Matter: Cognitive, Technical, and Organizational Dimensions**

The impact of semantic challenges on users can be understood through the interplay of cognitive, technical, and organizational factors. From a cognitive perspective, semantic ambiguity increases the mental effort required to interpret information, effectively shifting part of the system's informational burden onto the user. This aligns with Information Processing Theory, which posits that human cognitive capacity is limited and sensitive to complexity and uncertainty (Neter & Brainin, 2022). When clinicians must reconstruct meaning from fragmented or inconsistently coded data, their attention is diverted from higher-order reasoning tasks, potentially compromising decision quality.

Technically, semantic inconsistencies often arise from the coexistence of multiple coding systems, partial standard implementation, and legacy system integration. These conditions create environments in which data are formally structured yet contextually ambiguous. Importantly, the findings suggest that such issues are not simply "bugs" to be fixed, but structural features of complex health information ecosystems. This resonates with prior work highlighting the limitations of top-down standardization in heterogeneous healthcare settings (Iwaya et al., 2020).

At the organizational level, semantic challenges are shaped by local practices, training, and institutional norms. Variations in how data are entered, interpreted, and validated contribute to ongoing semantic drift, even within standardized systems. The qualitative evidence of informal workarounds underscores the adaptive capacity of users, but also points to a deeper misalignment between system design and real-world workflows. In this sense, semantic issues reflect a broader sociotechnical imbalance, where technological solutions are insufficiently attuned to the complexities of human practice (Richardson et al., 2022).

**Theoretical Contributions: Extending User-Centered Models**

One of the key theoretical contributions of this study lies in extending established models of technology use—particularly the Technology Acceptance Model (TAM)—to incorporate a **semantic dimension**. Traditional TAM constructs, such as perceived usefulness and ease of use, implicitly assume that information within the system is interpretable and meaningful (Venkatesh et al., 2022). The present findings challenge this assumption by demonstrating that **semantic clarity is a prerequisite for both usability and perceived usefulness**.

By introducing semantic clarity as an antecedent to usability, the study refines our understanding of how users evaluate and engage with health information systems. It also bridges a conceptual gap between information systems theory and health informatics, integrating concerns about data meaning into models of user behavior. Furthermore, the findings resonate with Sociotechnical Systems Theory by illustrating how semantic issues emerge from interactions between system design, user cognition, and organizational context. In doing so, the study advances a more holistic framework for analyzing EHR effectiveness—one that accounts for both structural and interpretive dimensions.

**Unexpected Findings and Emerging Questions**

Among the more unexpected findings is the non-deterministic relationship between data consistency and semantic clarity. While consistency contributes to clarity, it does not guarantee it. This suggests that users rely on additional contextual cues—such as familiarity with specific data fields or prior knowledge of patient cases—to construct meaning. In some instances, highly standardized data were perceived as less informative due to their abstraction or lack of contextual richness. This challenges the assumption that increasing standardization will linearly improve interpretability.

Another notable observation concerns the role of user adaptation. The prevalence of informal workarounds indicates that users are not passive recipients of system design, but active participants in meaning-making processes. While such adaptations enable functionality in the face of system limitations, they also introduce variability and potential for error. This dual role of user agency—as both a source of resilience and a vector of risk—has been underexplored in the literature and warrants further investigation.

Finally, the findings raise important questions about the scalability of semantic solutions. If meaning is inherently context-dependent, then efforts to standardize it across diverse settings may encounter fundamental limits. This suggests a need for more flexible, context-aware approaches to interoperability—potentially involving adaptive interfaces, machine learning–based semantic enrichment, or user-driven annotation systems.

**Implications for Future Research and Practice**

Taken together, the discussion points toward a reconceptualization of EHR systems not as static repositories of standardized data, but as dynamic environments in which meaning is continuously negotiated. Future research should explore how semantic clarity can be operationalized and measured across different contexts, as well as how system design can better support user interpretation. In parallel, practitioners and policymakers must recognize that improving interoperability requires investment not only in technical infrastructure, but also in training, governance, and user engagement.

By situating semantic challenges within a broader sociotechnical and cognitive framework, this study contributes to a more nuanced and actionable understanding of digital health systems—one that aligns technical ambition with the realities of human-centered care.

## Implications

### a) Theoretical Implications

This study contributes to health informatics theory by explicitly foregrounding the **semantic layer** as a critical, yet historically under-theorized, dimension of digital health systems. While dominant models have tended to prioritize technical interoperability and user interface design, the present findings demonstrate that **meaning-making processes mediate the relationship between data structures and user outcomes**. In doing so, the study advances a more integrative conceptualization of EHR systems—one that situates semantics alongside technical and human factors as co-equal determinants of system effectiveness.

A key theoretical contribution lies in extending established frameworks such as the Technology Acceptance Model (TAM). By introducing **semantic clarity as an antecedent to perceived usability and usefulness**, the study challenges the implicit assumption that system outputs are inherently interpretable (Venkatesh et al., 2022). This extension not only refines TAM in the context of health informatics but also aligns it more closely with the realities of clinical cognition, where ambiguity and contextual interpretation are pervasive. In parallel, the findings resonate with Information Processing Theory by demonstrating how semantic inconsistency increases cognitive load and disrupts decision pathways, thereby affecting performance outcomes (Neter & Brainin, 2022).

Moreover, the study contributes to Sociotechnical Systems Theory by empirically illustrating how semantic challenges emerge from the interaction between standardized data models and localized practices. Rather than viewing semantics as a static property of data, the findings support a **relational understanding**, in which meaning is co-constructed by system design, user expertise, and organizational context (Richardson et al., 2022). This perspective opens new avenues for theorizing digital health systems as dynamic environments of interpretation, rather than merely infrastructures of data exchange.

Finally, by integrating semantic constructs into empirical modeling, the study lays the groundwork for a **"semantic-informed" paradigm in digital health research**. Such a paradigm encourages future studies to move beyond binary notions of interoperability (i.e., interoperable vs. non-interoperable) and instead examine gradations of interpretability, contextual relevance, and cognitive alignment. This shift is particularly timely given the increasing reliance on data-driven decision-making and AI-assisted clinical tools, where the quality of semantic representation directly influences algorithmic reliability (Hu et al., 2025).

### b) Practical Implications

The findings carry several actionable implications for the design, governance, and use of EHR systems.

*EHR System Design Improvements*

First, system developers should prioritize **semantic transparency as a core design principle**. This involves not only standardizing data formats but also ensuring that clinical concepts are presented in ways that are intuitively interpretable across user groups. Practical measures include:

- Embedding **context-aware labeling** that clarifies the meaning and origin of data entries
- Designing interfaces that **visually group semantically related information**, reducing the need for users to reconstruct meaning across fragmented fields
- Integrating **semantic validation tools** that flag inconsistencies or ambiguities at the point of data entry

Additionally, adaptive interface features—such as user-specific views or intelligent summarization—can help align data presentation with users' cognitive needs, thereby reducing interpretive burden (Zhou et al., 2019; Fan et al., 2023).

*Policy and Governance Recommendations*

At the policy level, the results underscore the need to move beyond rigid standardization toward **flexible, context-sensitive governance frameworks**. While standards such as SNOMED CT and HL7 FHIR remain essential, their implementation should be accompanied by mechanisms that monitor and support semantic consistency in practice. This may include:

- Establishing **institutional guidelines for data entry and coding practices**
- Implementing **continuous auditing systems** to detect semantic drift across departments
- Encouraging **interoperability certification processes** that assess not only technical compliance but also semantic usability

Policymakers should also recognize that interoperability is not a one-time achievement but an ongoing process requiring sustained oversight and adaptation (van Kessel et al., 2022).

*Training and Capacity Building*

Finally, the study highlights the importance of **training healthcare professionals as active participants in semantic governance**. Users should be equipped not only with technical skills but also with an understanding of how data representation affects interpretation and decision-making. Training programs can:

- Develop **semantic awareness**, helping users recognize potential ambiguities and inconsistencies
- Promote **best practices in data entry and validation**
- Encourage **collaborative problem-solving** סביב semantic challenges, fostering shared responsibility for data quality


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Importantly, training should be tailored to different user groups, acknowledging that clinicians, administrators, and IT staff engage with EHR systems in distinct ways.

**Synthesis**

Taken together, these implications suggest that addressing semantic challenges requires a **multi-level intervention strategy**—one that integrates theoretical insight, system design innovation, organizational governance, and user engagement. By aligning these dimensions, healthcare systems can move closer to achieving not only technical interoperability but also **meaningful, user-centered data exchange**, which is essential for safe and effective care in digitally mediated environments.

## Limitations and Future Research

No empirical study of EHR use can fully capture the variability of real-world practice, and several limitations should be acknowledged when interpreting the present findings.

**Sample and setting.** The sample, while deliberately multi-stakeholder, was drawn from a bounded set of institutions with comparable levels of digital maturity. This introduces the risk of **selection bias toward relatively well-resourced environments**, where interoperability infrastructures and training are more developed. Users in low-resource or highly fragmented systems may experience semantic challenges differently, particularly where legacy systems and informal documentation practices are more prevalent. In addition, participation was voluntary, raising the possibility that respondents with stronger opinions about EHR usability were overrepresented. Future studies should pursue **broader, stratified sampling across care settings** (primary, secondary, community-based) and resource levels to test the generalizability of the observed relationships (van Kessel et al., 2022).

**Context-specific findings.** The analysis is necessarily **context-bound**, reflecting particular configurations of standards (e.g., SNOMED CT, FHIR implementations), institutional workflows, and language practices. Semantic clarity is shaped by local conventions, professional norms, and even linguistic nuances; consequently, the same data model may be interpreted differently across settings. This limits the portability of specific design recommendations and cautions against universal claims about "optimal" semantic structures. Comparative work suggests that interoperability outcomes are contingent on governance regimes and implementation strategies, not standards alone (Hu et al., 2025; Richardson et al., 2022). Replication in diverse regulatory and cultural contexts is therefore essential.

**Methodological constraints.** The study's **explanatory sequential design** strengthens interpretation but also imposes constraints. First, the quantitative phase relies on **self-reported perceptions** of usability and decision effectiveness, which may not perfectly align with objective performance or patient outcomes. Second, the cross-sectional nature of the survey limits causal inference; although the structural model is theoretically grounded, **temporal dynamics**—such as learning effects or adaptation over time—are not directly observed. Third, while scenario-based items enhance ecological validity, they cannot fully reproduce the complexity and time pressure of clinical environments. Finally, the qualitative component, though rich, is based on a purposive subsample and may not capture the full spectrum of user strategies. These limitations are consistent with broader challenges in evaluating digital health systems, where controlled experimentation is often infeasible (Fan et al., 2023; Neter & Brainin, 2022).

**Future Research Directions**

**Cross-country and cross-system comparisons.** A priority for future work is **comparative, cross-country research** that examines how semantic challenges vary under different policy regimes, languages, and levels of standard adoption. Multi-site studies could leverage harmonized instruments to test measurement invariance and assess whether constructs such as semantic clarity and data consistency operate similarly across contexts. Such designs would clarify the extent to which findings are **structural versus context-contingent**, and inform internationally relevant governance strategies (van Kessel et al., 2022).

**AI-driven semantic solutions.** The growing integration of artificial intelligence in health information systems opens promising avenues for **semantic augmentation**. Natural language processing, knowledge graphs, and ontology-alignment algorithms can support **real-time disambiguation**, map local terminologies to standard vocabularies, and surface contextually relevant summaries. However, AI introduces its own risks—opacity, bias propagation, and overreliance—that must be rigorously evaluated. Future studies should investigate **human–AI co-interpretation**, examining how clinicians calibrate trust in AI-generated semantic cues and how these tools affect cognitive load and decision quality (Hu et al., 2025). Experimental and quasi-experimental designs could compare AI-assisted interfaces with conventional systems to assess gains in interpretability and safety.

**Longitudinal and process-oriented research.** To move beyond cross-sectional snapshots, **longitudinal studies** are needed to trace how semantic clarity, user adaptation, and decision outcomes evolve over time. Such work can capture **learning curves, habituation, and drift** in coding practices, as well as the impact of training or policy interventions. Embedding digital trace data (e.g., log files) with periodic surveys and interviews would enable fine-grained analysis of how users navigate ambiguity in situ. Process-oriented approaches, including ethnographic observation and time–motion studies, could further illuminate the **micro-dynamics of meaning-making** in clinical workflows.

**Linking semantics to patient outcomes.** A critical extension is to connect semantic constructs with **objective clinical outcomes**—diagnostic accuracy, medication safety, or care coordination metrics. While prior work suggests associations between information quality and performance, direct evidence linking **semantic clarity** to patient-level outcomes remains limited (Tangari et al., 2021). Integrating EHR analytics with clinical quality indicators would strengthen the case for investing in semantic improvements as a patient safety intervention.

**Intervention design and evaluation.** Finally, future research should move toward **design science and intervention studies**, developing and testing concrete solutions such as context-aware labeling, semantic validation at data entry, and adaptive interfaces. Randomized or stepped-wedge implementations can evaluate effectiveness while accommodating operational constraints. Importantly, interventions should be co-designed with end users to ensure alignment with clinical cognition and workflow realities (Richardson et al., 2022).

**Closing Remark**

Taken together, these directions underscore that advancing interoperability requires sustained attention to **how meaning is constructed, supported, and evaluated over time and across contexts**. By combining cross-context comparison, AI-enabled innovation, and longitudinal inquiry, future research can build a more robust evidence base for achieving not only interoperable systems, but **interpretable and trustworthy** digital health environments.

## Conclusion

Semantic challenges in Electronic Health Record (EHR) systems continue to represent a persistent yet often underestimated barrier to achieving meaningful interoperability in digital health environments. While substantial progress has been made in standardizing data structures and enabling system-level exchange, this study has shown that the core issue is not merely technical connectivity but the **interpretability of clinical data across diverse users and contexts**.

Across the quantitative and qualitative findings, a consistent pattern emerged: **semantic clarity plays a central mediating role between data consistency, perceived usability, and decision-making effectiveness**. Users do not interact with EHR systems as passive recipients of standardized data; rather, they actively interpret, reconstruct, and sometimes compensate for semantic gaps in real time. These interpretive processes shape workflow efficiency, cognitive load, and ultimately the quality of clinical decision-making. In this sense, semantic inconsistency is not an abstract data quality issue but a lived operational constraint embedded in everyday healthcare practice (Tangari et al., 2021; Fan et al., 2023).

Importantly, the study reinforces the argument that EHR effectiveness cannot be fully understood through technical metrics alone. A user-centric perspective reveals that meaning-making is central to system performance, and that usability is fundamentally contingent on how clearly and consistently information is semantically represented. This insight extends current digital health discourse by positioning semantic clarity as a core determinant of both user experience and clinical effectiveness, rather than a secondary concern of data standardization (Richardson et al., 2022; van Kessel et al., 2022).

Looking forward, the future of intelligent EHR systems will likely depend on the integration of **semantic-aware architectures**, where data representation, user cognition, and artificial intelligence converge to support shared understanding. Emerging technologies such as AI-driven ontology alignment, contextual data enrichment, and adaptive interfaces offer promising pathways toward reducing semantic friction. However, their success will depend not only on technical sophistication but also on how effectively they align with human interpretive practices in clinical environments (Hu et al., 2025).

Ultimately, advancing EHR systems requires a shift from viewing interoperability as the endpoint of digital transformation to understanding it as an ongoing process of **co-produced meaning between systems and users**. In doing so, health informatics can move closer to realizing digital infrastructures that are not only connected, but also truly comprehensible, trustworthy, and clinically actionable.

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