Original Paper

Assessing the Terminological Representation of Context Factors in Clinical Decision-Making Using SNOMED CT: Exploratory Analysis Study

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Abstract

Background: Clinical decision-making is inherently shaped by contextual factors that extend beyond guideline-based knowledge and objective clinical parameters. Although clinical decision support systems (CDSSs) aim to improve decision quality and safety, many existing systems insufficiently account for such contextual influences, limiting their effectiveness and acceptance. A prerequisite for a context-sensitive CDSS is the systematic and standardized representation of context factors. However, the extent to which existing clinical terminologies are capable of representing these factors remains unclear.

Objective: This study investigates the terminological representability of empirically identified context factors that influence clinical decision-making using SNOMED CT (Systematized Nomenclature of Medicine—Clinical Terms) as the semantic interoperability standard.

Methods: The analysis builds on a previously established set of context concepts identified through a scoping review of empirical literature and organized within a hierarchical conceptual structure. An exploratory manual semantic mapping of these context concepts to SNOMED CT was conducted. Mapping quality was assessed using standardized equivalence classifications (equal, equivalent, wider, narrower, inexact, and unmatched). An independent expert review and consensus process ensured harmonized mapping results. Context concepts not represented in SNOMED CT were also examined using alternative vocabularies via the OHDSI (Observational Health Data Sciences and Informatics) Athena platform.

Results: In total, 189 context concepts were analyzed. Of these, 81.5% (n=154) could be mapped to existing SNOMED CT concepts. Semantic correspondence varied across the analyzed context concepts: 36% (n=68) were classified as equal, 21.2% (n=40) as equivalent, 8.5% (n=16) as wider, 13.8% (n=26) as narrower, and 2.1% (n=4) as inexact. The remaining 18.5% (n=35) were classified as unmatched, indicating that no suitable SNOMED CT correspondence was identified. Patient-related context concepts demonstrated the highest coverage (70/75, 93.3%), whereas institution-related concepts showed substantially lower coverage (7/14, 50%). Mapped concepts were distributed across 11 SNOMED CT domains, most frequently observable entity and qualifier value. Entity-specific analyses revealed differences in both terminological coverage and equivalence status. A majority of nonrepresented concepts were identified in alternative vocabularies, primarily MeSH (23/35, 65.7%) and LOINC (Logical Observation Identifiers Names and Codes; 10/35, 28.6%), albeit often with inexact or partial correspondence.

Conclusions: The findings indicate that a substantial proportion of empirically identified context factors influencing clinical decision-making can be terminologically represented in SNOMED CT, although relevant gaps persist, particularly for organizational and social context factors. These results highlight both the potential and the limitations of existing clinical terminologies for supporting context-sensitive CDSSs and provide a foundation for future work on semantic standardization, ontology development, and the integration of standardized contextual information into CDSSs.

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Keywords: clinical decision-making; clinical decision support systems; Systematized Nomenclature of Medicine—Clinical Terms; SNOMED CT; semantic interoperability

Introduction

Physician decision-making constitutes a central element of medical practice, in which scientific evidence, clinical experience, and situational responsibility converge. The quality of these decisions substantially influences the effectiveness, safety, and patient-centeredness of health care delivery [1]. Clinical decision-making processes are characterized by a dynamic and iterative workflow in which information is continuously gathered, interpreted, and evaluated in light of situational constraints to derive diagnostic or therapeutic actions [2]. In real-world settings, clinical decisions are rarely made under idealized, strictly evidence-based conditions; instead, they are strongly shaped by contextual circumstances. A growing body of empirical research demonstrates that medical decisions are not solely based on objectively measurable clinical parameters but are substantially influenced by contextual factors, including physician experience [3], institutional conditions [4,5], team interactions [6,7], and individual patient preferences [8,9]. Accordingly, context factors extend beyond patient characteristics and disease management to include influences related to the treating physician, the professional and organizational environment, and the patient's family [10]. Evidence further indicates that such contextual influences can lead to variation in diagnostic or therapeutic decisions even among patients with comparable clinical presentations [11]. Clinical decision-making, therefore, extends beyond the mere application of guideline-based knowledge and represents a situational negotiation between medical expertise and the specific conditions of care delivery.

With the increasing digitalization of health care, the question of how contextual complexity can be represented within data-driven decision-making processes has gained growing relevance. Clinical decision support systems (CDSSs) are widely regarded as a key technology for making clinical decisions safer, more efficient, and more evidence-based [12,13]. CDSSs integrate patient-specific data, clinical knowledge, and decision rules to generate recommendations for diagnosis, therapy, or monitoring [13].

However, the potential of these systems can only be realized if they adequately account for the situational conditions under which clinical decisions are made [13]. In practice, many CDSSs insufficiently incorporate such contextual factors, resulting in inappropriate or redundant alerts and contributing to phenomena such as alert fatigue and declining system acceptance [14,15]. The lack of context sensitivity therefore represents a central limitation of existing systems, affecting not only technical performance but also usability, user acceptance, and successful clinical integration [13,16]. A context-sensitive CDSS is therefore essential and implies the system's ability to deliberately capture and process context factors as the situational conditions of a decision-making scenario in order to provide recommendations that are relevant to both the user and the clinical task [17]. To enable such a context-sensitive design of a CDSS, context factors must be systematically identified, formally structured, and made machine-interpretable. In clinical practice, however, contextual information is often incomplete, heterogeneous, or only available in unstructured formats, which substantially limits its reuse within a CDSS [18]. Moreover, there is still a lack of standardized representations of contextual information, further impeding the exchange of context-related data across different systems and settings [19].

Embedding human contextual decision logic into a CDSS therefore requires a structured and standardized representation of relevant context factors. Although many technological approaches aim to improve clinical decision-making primarily through data-driven model optimization, the present work places the human dimension of clinical decision-making at the center of analysis. Accordingly, the focus is not on technical system development but on examining the extent to which existing clinical terminologies are capable of representing the contextual influences that shape real-world decision processes.

Various medical terminologies and classification systems exist to support the standardized representation of clinical information, each with different design purposes and levels of semantic expressiveness. LOINC (Logical Observation Identifiers Names and Codes) primarily focuses on the standardization of laboratory observations and measurements, with contextualization largely limited to attributes such as timing or specimen type [20]. The International Classification of Diseases (ICD), while extended in ICD-11 (Revision 11) to increase expressiveness [21], remains mainly oriented toward disease classification and coding for statistical and billing purposes. In contrast, SNOMED CT (Systematized Nomenclature of Medicine—Clinical Terms) is designed as a comprehensive clinical reference terminology with a formal ontological structure and extensive support for semantic relationships. It provides specific mechanisms for representing contextual information, such as the "situation with explicit context" hierarchy and postcoordination, enabling flexible modeling of clinical statements [22]. Given these characteristics, SNOMED CT was selected as the reference terminology for the present study to assess the terminological representability of context factors in clinical decision-making.

The objective of this study is to systematically assess the terminological coverage and semantic representability of these context factors within SNOMED CT and to identify areas in which conceptual gaps persist.

Based on this objective, this study addresses the following research questions:

> Research question 1: To what extent can empirically identified context factors influencing clinical decision-making be semantically represented by existing concepts in SNOMED CT?

Research question 2: What differences can be observed in the terminological coverage of context factors within SNOMED CT?

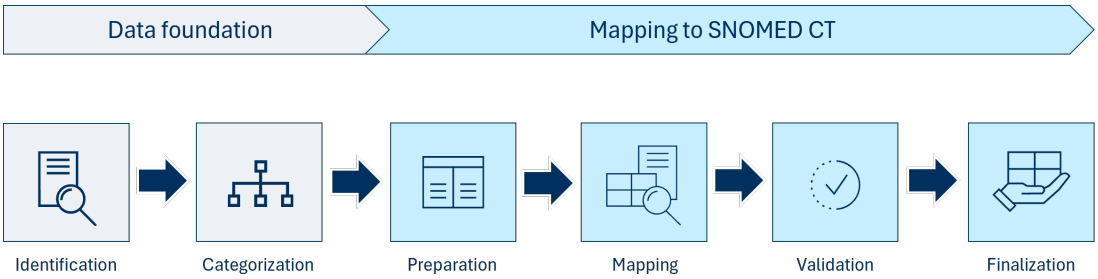
Existing terminology mapping studies have predominantly focused on aligning structured clinical data elements or domain-specific concepts with SNOMED CT. However, clinical decision-making is not solely determined by such structured data but is substantially shaped by contextual factors that are often implicit, heterogeneous, and not formally represented. To date, the terminological representability of these empirically grounded context factors has not been systematically investigated. By mapping a comprehensive, literature-derived set of context factors influencing clinical decision-making to SNOMED CT, this study introduces a novel, human-centered perspective on terminology evaluation. It thereby bridges a critical gap between the situational logic of clinical decision-making and its formal representation in interoperable knowledge systems. The results are intended to provide a foundation for the future development of semantically consistent, context-sensitive CDSSs and to contribute to the standardization and interoperability of context-related information in clinical decision support.

Methods

Study Design

The methodological workflow of the study is illustrated in Figure 1. The analysis builds on a data foundation developed in previous work, in which context factors of clinical decision-making were systematically identified through a scoping review and subsequently organized within a hierarchical conceptual structure [10,23]. Building on this conceptual framework, the present study applies an exploratory semantic mapping approach to systematically assess the terminological coverage and semantic representability of these context factors within SNOMED CT.

Figure 1. Overview of the methodological approach. Gray elements indicate preceding work, whereas blue elements represent the methods applied in this study. SNOMED CT: Systematized Nomenclature of Medicine—Clinical Terms.



Data Foundation

The present study builds on a previously established set of evidence-based context factors relevant to clinical decision-making. These factors were identified through a scoping review of the empirical literature and subsequently organized within a structured conceptual framework, as reported in earlier publications [10,23]. The review focused on empirical studies addressing physician decision-making and applied a systematic search across multiple bibliographic databases (eg, PubMed, Web of Science, and Scopus). To support synthesis and consolidation, the identified context factors were iteratively structured and categorized based on the contextual model of Zimmermann et al [24] using a multistage expert-based card sorting approach [25].

This process aimed to establish a coherent and clinically meaningful conceptual structure while preserving the semantic richness of the identified factors. The outcome of this process was a hierarchical representation of context factors, referred to in this study as context concepts. This conceptualized dataset serves as the methodological foundation for the semantic mapping of context factors to SNOMED CT conducted in the present work.

Mapping to SNOMED CT

Overview of the Mapping Process

The defined context concepts constitute the data basis for the terminological mapping conducted in this study. The objective of this step is to systematically examine the extent to which these context concepts can be semantically represented within an established clinical reference terminology. This analysis directly addresses the first research question by quantifying the degree of terminological coverage and identifying areas of limited or missing representation.

SNOMED CT was selected for the mapping process because it represents the most comprehensive and internationally established clinical reference terminology currently available. The mapping was conducted as an exploratory manual process with independent review by 2 reviewers, both researchers with expertise in medical informatics. The procedure comprised 4 steps adapted from the mapping approach described by Ehrsam et al [26]: (1) structuring of the data foundation, (2) exploratory mapping, (3) assessment of semantic coverage, and (4) validation of the results. Each step is described in detail in the following sections and was designed to progressively refine the semantic analysis while maintaining transparency and reproducibility.

Step 1: Structuring

First, the previously identified context concepts were systematically prepared in a structured Microsoft Excel spreadsheet [27]. A hierarchical overview was created to represent all context factors within the overall conceptual framework according to their entity-specific assignments. The data were then organized into separate worksheets, with each hierarchical level (entity, category, and subcategory) represented on its own sheet. This structuring step was intended to support consistent semantic interpretation across hierarchy levels and to reduce the risk of context loss during the mapping process. Subsequently, the spreadsheet was extended in accordance with the SSSOM (Simple Standard for Sharing Ontology Mappings) guidelines [28] by adding structured metadata fields, including concept ID, domain, reviewer ID, date, and equivalence status. The inclusion of these metadata elements enabled systematic and transparent documentation and later analysis of mapping decisions. A detailed description of the corresponding metadata elements is provided in Table 1.

Table 1. Metadata extracted during the mapping process.

Metadata	Description
Context concept	Source context concept to be mapped
SNOMED CT[a] concept	Target concept identified in SNOMED CT
Concept ID	Unique ID associated with the SNOMED CT concept
Domain	Semantic domain of the SNOMED CT concept
Reviewer ID	Identifier of the reviewer who performed the mapping
Date	Date on which the mapping was conducted
Equivalence status	Degree of semantic correspondence between context concept and SNOMED CT concept

[a]SNOMED CT: Systematized Nomenclature of Medicine—Clinical Terms.

Step 2: Exploratory Mapping Using SNOMED CT

In the second step, an exploratory semantic search of the SNOMED CT hierarchy was conducted to align the context factors with existing SNOMED CT concepts. Each term was manually queried using the SNOMED CT Browser [29]. The mapping was based on the SNOMED CT UK Edition (release v20250409), which includes the full content of the International Edition as well as UK-specific extensions. The use of the UK Edition ensured comprehensive coverage while allowing access to additional context-relevant concepts not available in the International Edition alone. Each category was assessed individually by systematically exploring parent and child concepts within the SNOMED CT hierarchy. This hierarchical exploration was used to evaluate both direct matches and semantically related concepts within the broader ontological context. A context concept was classified as "mapped" if at least one of the 4 predefined criteria in Table 2 was met. Where more than one potentially relevant concept was identified, the concept with the highest semantic correspondence was selected. If none of these criteria was met, no valid correspondence was assumed, and the context concept was classified as "not mapped" (not representable in SNOMED CT).

Table 2. Mapping decision criteria.

Criterion	Definition
Lexical correspondence	A SNOMED CT[a] concept carried a designation identical to that of the context concept.
Synonym correspondence	The context concept matched a synonym or alternative designation formally recorded for a SNOMED CT concept.
Conceptual correspondence	The designations differed lexically, but a SNOMED CT concept was judged to denote the same underlying concept.
Hierarchical correspondence	No lexical, synonymous, or conceptual correspondence existed, but a superordinate or subordinate SNOMED CT concept preserved the essential meaning of the context concept.

[a]SNOMED CT: Systematized Nomenclature of Medicine—Clinical Terms.

As the SNOMED CT Browser [29] returns active concepts by default, the mapping was based on active concepts, and inactive (retired) concepts were not considered. Postcoordination was deliberately not applied, as the aim of this study was to identify potential terminological gaps rather than to bridge them by combining multiple SNOMED CT concepts. All identified concepts were recorded in a Microsoft Excel [27] mapping table along with their concept ID, domain, and subtype. Context categories for which no correspondence was found were classified as not representable in SNOMED CT. To visualize the mapping results, Sankey diagrams were created using SankeyMATIC [30].

Step 3: Assessment of Semantic Coverage

For all mapped categories, an equivalence status was subsequently assigned to characterize the degree of semantic correspondence between the original category (source concept) and the assigned SNOMED CT concept (target concept). This step served as the primary analytical mechanism for evaluating semantic coverage and mapping quality

beyond binary match/nonmatch decisions. Classification was performed in accordance with the definitions implemented in Usagi (version 1.4+) [31], which are based on Health Level Seven International (HL7) specifications for conceptual equivalence [32,33]. The semantic correspondence between source and target concepts was classified using 6 predefined equivalence levels, namely, equal, equivalent, wider, narrower, inexact, and unmatched, with their formal definitions provided in Table 3. Among these levels, equal, equivalent, wider, narrower, and inexact differentiate the degree of semantic correspondence between an identified source and target pair, whereas unmatched denotes the absence of a suitable target concept.

Table 3. Equivalence definition[a].

Equivalence level	Definition
Equal	The concepts are exactly the same (ie, intensionally identical).
Equivalent	The concepts mean the same thing (ie, extensionally identical).
Wider	The target contains more information than the source.
Narrower	The target contains less information than the source.
Inexact	The target overlaps with the source, but both source and target cover additional meaning.
Unmatched	There is no match for this concept in the target code system.

[a]The equivalence definitions were adapted from Usagi (version 1.4+) [31].

Step 4: Validation of the Mapping

To ensure quality and validate the mapping results, an independent expert review was conducted. For validation, a second reviewer with demonstrated expertise in semantic interoperability and extensive experience in terminological mapping independently performed a separate mapping of all categories and assessed the corresponding equivalence levels. The results of both reviewers were systematically compared to verify consistency in concept assignment and equivalence classification. Initial interreviewer agreement was quantified descriptively as the proportion of context concepts for which both reviewers independently made the same decision, calculated separately for concept assignment and for equivalence-level classification. Any discrepancies were addressed through a structured consensus process. A discrepancy was defined as any case in which the 2 reviewers assigned a different SNOMED CT concept or a different equivalence level to the same context concept. All discrepant cases were reviewed jointly by both reviewers in a consensus meeting, in which the reviewers revisited the source concept, the candidate SNOMED CT concepts, the mapping decision criteria (Table 2), and the equivalence definitions (Table 3), before agreeing on a final concept assignment and equivalence classification. All discrepancies were resolved through discussion, and no third-party arbitration was required. The combination of independent dual mapping, standardized equivalence criteria, and structured consensus discussion strengthened the robustness and reproducibility of the results.

Management of Concepts Not Represented in SNOMED CT

For context categories for which no suitable concept could be identified in SNOMED CT, an additional search was conducted using Athena [34]. Athena [34] is a searchable vocabulary platform provided by Observational Health Data Sciences and Informatics (OHDSI) that enables cross-vocabulary concept identification across multiple standardized terminologies (eg, MeSH, LOINC, and Nebraska Lexicon). This supplementary step was included to assess whether nonrepresentability was specific to SNOMED CT or reflected a broader lack of terminological coverage. Each term was manually entered into the Athena [34] search interface and screened for potentially corresponding concepts. Identified candidate concepts were then documented in accordance with the SSSOM guidelines [28], as previously described in Step 2, and assessed using the same predefined equivalence levels (Table 3) applied to the SNOMED CT mappings to reflect the degree of semantic correspondence.

Results

Dataset Description and Structuring

The data basis for the terminological mapping consisted of the structured context concepts derived from the preceding work. These concepts were organized within a 3-level hierarchical structure in Microsoft Excel [27]. The first level consisted of the entity level, encompassing 6 overarching context concepts: patient, physician, institution, patient's family, peers, and disease treatment. Each entity represents a distinct context concept at the highest level of the hierarchy. At the second hierarchical level, a total of 101 categories were assigned across the entities, while the third level comprised 82 subcategories. For example, the patient entity represents a context concept at the first hierarchical level, demographic characteristics constitute a category at the second level, and gender represents a corresponding subcategory at the third level. Similarly, within the physician entity, personal state constitutes a category at the second hierarchical level, with workload represented as a corresponding subcategory at the third level. To illustrate the thematic scope of the analyzed dataset and to support the interpretation of the subsequent entity-specific mapping results, Table 4 provides representative context concepts for each of the 6 entities, together with the number of concepts analyzed per entity.

Table 4. Representative context concepts per entity (illustrative excerpt)[a].

Entity (N=189)	Representative context concepts (with subcategories)
Patient (n=75)	Demographics (eg, age, gender, ethnicity, socioeconomic status, and insurance), health status (eg, disease condition, comorbidities, and quality of life), wants and needs (eg, preferences and expectations), history (eg, medical history and social history), behavior (eg, compliance)
Physician (n=55)	Demographics (eg, age, education), work-related (eg, position and profession), personal states (eg, workload, stress, and sleepiness), emotions and feelings (eg, trust and confidence), perception (eg, perceived risks and benefits), decision-making (biases)
Patient's family (n=18)	Demographics, abilities, knowledge, emotions and feelings, attitude, behavior (family support), decision-making, time constraints, and parental absence
Institution (n=14)	Hospital factors (hospital structure, clinical load, resources, legal, and finance), culture, guidelines, scope of practice, management, and geographics
Peers (n=16)	Opinion, perception, experience, involvement, team structure, interaction (communication), decision-making, and behavior (support)
Disease treatment (n=11)	Severity, complexity, course, evidence, treatment options, treatment costs, treatment time, and history

[a]The entity column corresponds to level 1 (overarching context concepts). In the right-hand column, the unenclosed terms denote level 2 categories, while the terms in parentheses denote the associated level 3 subcategories, shown where available.

Due to the relational structure of the context model, some context concepts (eg, demographics) may be associated with multiple entities and appear at different hierarchical and relational levels. A detailed overview of the complete hierarchical structure is provided in Multimedia Appendix 1.

Results of Steps 2 to 4: Mapping, Coverage, and Validation

The described hierarchical organization of context concepts served as the empirical basis for the subsequent semantic mapping to SNOMED CT. Overall, 189 context concepts across all 3 hierarchical levels were included in the analysis.

First, the results of the 2 reviewers prior to consensus were analyzed. This analysis showed an agreement on concept assignment of 68.8% (130/189); for these concepts, the assigned equivalence level agreed in 89.2% (116/130) of cases. All remaining discrepancies were subsequently resolved through the consensus process. The mapping results reported below refer to the consolidated mapping for all 189 context concepts examined. Of these, 154 (81.5%) concepts were successfully mapped to an existing SNOMED CT concept, whereas 35 (18.5%) concepts could not be assigned a suitable terminological correspondence. A complete list of all mapped context concepts, including assigned SNOMED CT identifiers, domains, and equivalence classifications, is provided in Multimedia Appendix 2.

For each context concept, semantic correspondence with the assigned SNOMED CT concept was evaluated using predefined equivalence levels. Of all 189 analyzed context concepts, 36% (n=68) were classified as equal; for example, "abilities" was classified as equal to "14671000000105 | Abilities," and 21.2% (n=40) as equivalent, as in the case of "comorbidities" assigned to "398192003 | Co-morbid conditions." Furthermore, 8.5% (n=16) were classified as wider, exemplified by "social history" and "160476009 | Social / personal history observable," 13.8% (n=26) as narrower, as in "performance status" and "278844005 | General clinical state," and 2.1% (n=4) as inexact, exemplified by "interests" and "225469004 | Interested." The remaining 18.5% (n=35) of context concepts were classified as unmatched, indicating the absence of a suitable SNOMED CT concept.

Mapped context concepts were assigned to 11 distinct SNOMED CT domains. Table 5 summarizes the domain distribution of the mapped 189 context concepts. The largest proportion was assigned to the domain observable entity (n=62, 32.8%), followed by qualifier value (n=30, 15.9%) and clinical finding (n=19, 10%). Additional domains represented at lower frequencies included procedure, situation with explicit context, social context, environment or geographical location, person, physical object, record artifact, and event. Context concepts without a suitable SNOMED CT correspondence were categorized as not applicable.

Table 5. Distribution of all analyzed context concepts (N=189) across SNOMED CT[a] domains, including definitions, absolute values (n), and relative (%) frequencies[b].

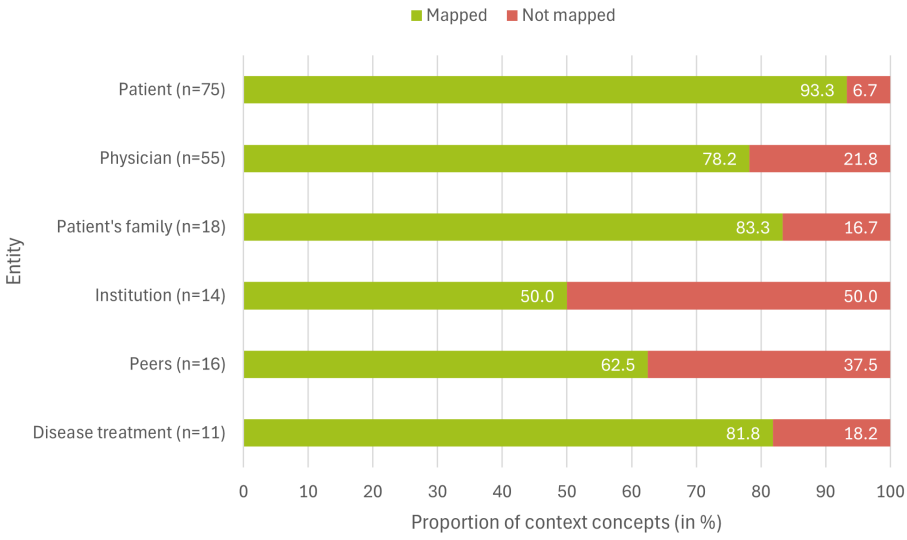
Domain	Definition of domain according to SNOMED CT model [35]	Value, n (%)
Observable entity	Questions or assessments which can produce an answer or result	62 (32.80)
Not applicable	Context concepts for which no suitable SNOMED CT mapping could be identified	35 (18.52)
Qualifier value	Values for some SNOMED CT attributes, where those values are not subtypes of other top-level concepts	30 (15.87)
Clinical finding	Result of a clinical observation, assessment, or judgment and includes normal and abnormal clinical states	19 (10.05)
Social context	Social conditions and circumstances significant to health care	17 (8.99)
Situation with explicit context	Concepts in which the clinical context is specified as part of the definition of the concept itself	7 (3.70)

Domain	Definition of domain according to SNOMED CT model [35]	Value, n (%)
Record artifact	Content created for the purpose of providing other people with information about record events or states of affairs	6 (3.17)
Environment	Types of environments as well as named locations such as countries, states, regions, or other geographic areas	5 (2.65)
SNOMED CT model component	Technical metadata supporting the SNOMED CT release	5 (2.65)
Physical object	Natural or human-made physical objects	1 (0.53)
Procedure	Activities performed in the provision of health care	1 (0.53)
Special concept	Concepts outside the formal description logic of the concept model of the terminology, but which may be useful for specific use cases	1 (0.53)

[a]SNOMED CT: Systematized Nomenclature of Medicine—Clinical Terms.
[b]Context concepts without a suitable SNOMED CT correspondence are reported as not applicable. Relative frequencies are based on all analyzed context concepts (N=189).

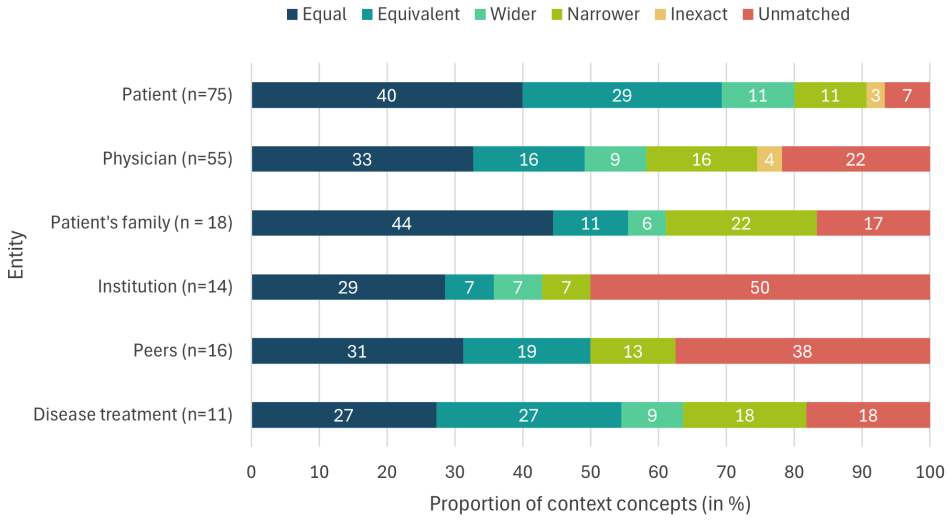
To address the second research question ("What differences can be observed in the terminological coverage of context factors within SNOMED CT?"), the context concepts were further analyzed. To assess whether terminological coverage varied with conceptual granularity, mapping outcomes were first analyzed, stratified by hierarchical level. Mapping rates were largely comparable across the 3 levels: at the entity level, 83.3% (5/6) of concepts were successfully mapped to SNOMED CT, compared to 80.2% (81/101) at the category level and 82.9% (68/82) at the subcategory level. A more differentiated picture emerged when mapping outcomes were stratified by the 6 entities of the context framework (patient, physician, institution, patient's family, peers, and disease treatment). This entity-based analysis revealed marked differences in terminological coverage. Although patient-related context concepts (n=75) were largely mappable to SNOMED CT (n=70, 93.3%), only 50% (n=7) of institution-related context concepts (n=14) were successfully mapped. The relative distribution of mapped and unmapped concepts across entities is shown in Figure 2.

Figure 2. Proportion of mapped and not mapped context concepts per entity, based on whether a suitable Systematized Nomenclature of Medicine—Clinical Terms (SNOMED CT) concept could be identified.



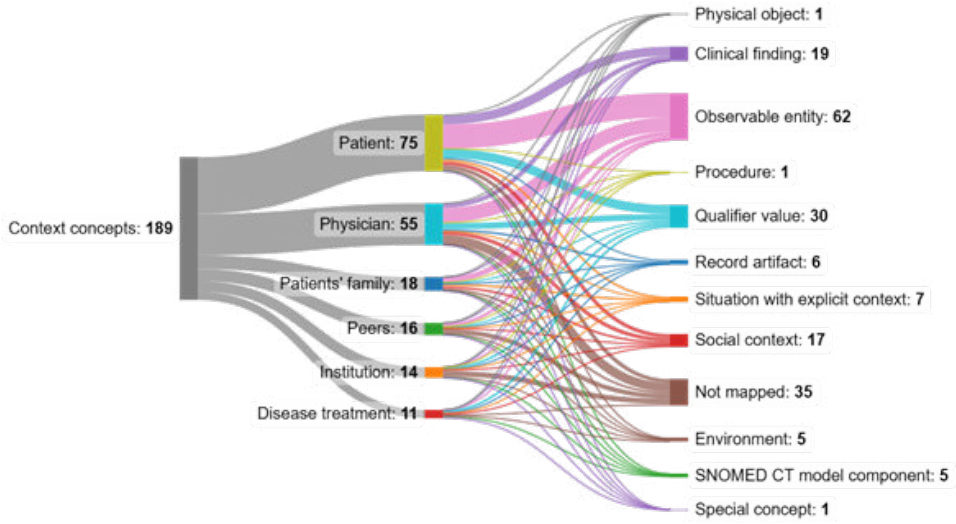
An entity-specific analysis of equivalence status demonstrated differences in mapping quality across the 6 entities (Figure 3). Here, the equivalence levels equal, equivalent, wider, narrower, and inexact jointly represent the semantic mapping quality of the mapped concepts, whereas the unmatched equivalence status corresponds to unmapped context concepts. The results indicate that the entities—patient, patient's family, and disease treatment—showed the highest proportions of equal and equivalent classifications. Mappings associated with the physician entity were distributed more across multiple equivalence categories. The institution and peers entities exhibited the highest proportions of unmatched context concepts. Across all entities, the inexact equivalence status occurred least frequently, while wider and narrower classifications were observed in nearly all entities with varying frequencies.

Figure 3. Proportion of context concepts per entity according to their semantic mapping quality, differentiated by equivalence level.



Subsequently, a domain-specific analysis stratified by entity was performed to examine the allocation of mapped context concepts to SNOMED CT domains. Figure 4 illustrates the distribution of entity-specific context concepts across SNOMED CT domains, with unmapped concepts displayed separately.

Figure 4. Distribution of context concepts by entity and corresponding Systematized Nomenclature of Medicine—Clinical Terms (SNOMED CT) domain.



Among mapped patient-related context concepts, 45.7% (32/70) were assigned to the observable entity domain. A similar pattern was observed for mapped physician-related context concepts, with 44.2% (19/43) assigned to the same domain. For context concepts related to the patient's family, 46.7% (7/15) were assigned to the observable entity domain. Peer-related mapped context concepts were likewise most frequently assigned to this domain (4/10, 40%). In contrast, institution-related mapped context concepts were most frequently assigned to the qualifier value domain (3/7, 42.9%). The same domain predominated among mapped disease treatment–related context concepts, accounting for 33.3% (3/9) of assignments.

Concepts Not Represented in SNOMED CT

In a final analysis step, 35 context concepts not represented in SNOMED CT were cross-referenced with alternative vocabularies using the Athena [34] search function. Among these, 65.7% (n=23) were mapped to MeSH concepts, while an additional 28.6% (n=10) were mapped to LOINC concepts. Single context concepts were mapped to the Nebraska Lexicon (n=1) and the UK Biobank (n=1), respectively. Most of these alternative mappings were assigned an equivalence status of inexact (n=12, 34.3%), followed by equivalent (26%, n=9), narrower (14%, n=5), equal (14%, n=5), and wider (11%, n=4). A detailed overview of these results is provided in Multimedia Appendix 3.

Discussion

Discussion of Results

The aim of this study was to examine the extent to which empirically identified context factors that influence clinical decision-making can be semantically represented in SNOMED CT. Based on a previously established set of evidence-based context concepts, the present analysis assessed their terminological coverage and semantic correspondence within SNOMED CT using an exploratory manual mapping approach.

Principal Findings

The findings of the present analysis show that a large proportion of the identified context concepts (81%) could be terminologically represented in SNOMED CT. However, this coverage rate does not fully reflect the degree of semantic correspondence between the context concepts and their assigned SNOMED CT concepts. While equal and equivalent classifications indicate close semantic correspondence, wider, narrower, and inexact classifications indicate that the source and target concepts differ in scope or meaning. The overall mapping rate should therefore be interpreted as an indicator of terminological coverage rather than evidence of uniform semantic correspondence. This generally supports the suitability of SNOMED CT as a reference terminology for representing context-related factors in clinical decision-making. At the same time, mappings with partial semantic correspondence may require further refinement or additional modeling before they can be operationalized in a specific implementation context. This consideration is particularly relevant for institution-related, peer-related, and social context factors, for which partial semantic correspondence may be insufficient to support reliable system-level decision support. Furthermore, a relevant proportion of concepts (19%) could not be adequately represented in SNOMED CT, indicating the presence of persisting terminological gaps. The findings therefore suggest that evidence-based context factors of clinical decision processes are, in principle, amenable to formal modeling, but are not yet fully covered by SNOMED CT. Incomplete mapping rates have also been reported in other studies using comparable manual terminology-mapping approaches [36-38]. For example, Thandi et al [38] reported an unmatched rate of 11% in a manual mapping of eCGA (electronic Comprehensive Geriatric Assessment) elements to SNOMED CT, while Tavakoli et al [37] reported a coverage of 82% for ophthalmological infection and trauma concepts. The findings of the present study therefore fall within a range comparable to those reported in published mapping studies and further underline that even in established clinical domains, complete terminological representation in SNOMED CT cannot be assumed.

Entity-Specific Differences in Terminological Coverage

With regard to the entity-specific analysis, the results revealed marked differences in representability across context concepts related to the 6 investigated entities: patient, physician, patient's family, institution, peers, and disease treatment. Since mapping outcomes were largely consistent across the 3 hierarchical levels (entities, categories, and subcategories), these differences can be attributed to characteristics of the entities themselves rather than to the conceptual granularity of the underlying concepts, supporting the interpretation of entity-specific terminological coverage as a substantive finding. In particular, coverage was highest for patient-related context concepts (mapping rate: 93%) and disease treatment–related context concepts (mapping rate: 82%), whereas the coverage of institution-related context concepts was substantially lower (50%). These findings underscore the clinical and patient-centered orientation of SNOMED CT and are consistent with its primary practical use as a standard for electronic health records (EHRs), where data are collected primarily to support patient care [39,40]. Consistent with the overall representability of patient-centered context concepts, their semantic fit to SNOMED CT concepts was also comparatively strong, with 40% classified as equal and 29% as equivalent, whereas institution-related concepts showed substantially lower semantic alignment (29% equal and 9% equivalent). Taken together, the findings regarding the semantic fit between evidence-based context factors derived from the literature and SNOMED CT concepts further highlight the strong suitability of SNOMED CT for representing clinical, patient-centered information. By contrast, physician-related context information and information concerning the patient's family showed a more heterogeneous distribution across equivalence levels, suggesting that physician states, working conditions, and family-related influences are not yet adequately captured in SNOMED CT. In addition, the high proportion of unmatched assignments among intention-related and peer-related context factors points to a systematic weakness in the representation of organizational and social contexts. This again reflects the strong focus of SNOMED CT as a standard for clinical information systems such as EHRs and its ability to effectively represent the types of data that are routinely captured in such systems [41], where information is documented primarily for patient care purposes [40]. However, contextual factors that shape clinical decision-making are often not documented in EHRs or other health information systems, meaning that the clinical reality of medical decision-making is not fully represented in current digital infrastructures [42-44]

Domain-Specific Patterns Across Entities

With regard to the domains of the identified SNOMED CT concepts, a clear predominance of the observable entity domain was found for context information related to the patient, physician, patient's family, and peers. This pattern suggests that, within SNOMED CT, context is frequently represented as an observable characteristic or state. In contrast, institution-related and disease treatment–related concepts were most often assigned to the qualifier value domain, indicating that these context-related information elements are primarily modeled as modifying attributes rather than as independent clinical concepts [45]. By comparison, only a small proportion of concepts fell within the situation

with explicit context domain, suggesting that the potential of this subhierarchy for representing contextual information has not yet been fully realized. However, this heterogeneity in concept representation should not be interpreted solely as a limitation of the terminology itself. Rather, it reflects the more fundamental challenge of defining and formally representing context as a multidimensional, dynamic, and situation-dependent construct [10,41,46]. At the same time, a more consistent domain assignment of context-related concepts within SNOMED CT could improve the conceptual clarity, structural coherence, and retrievability of contextual information within the terminology [47].

Interpretation of Nonmappable Context Concepts

Concepts that could not be represented in SNOMED CT were identified in other vocabularies, most notably MeSH (23/35, 65.7%) and, to a lesser extent, LOINC (10/35, 28.6%). This finding indicates that context-related information is, in principle, terminologically representable, but remains fragmented across multiple vocabularies. The high proportion of MeSH concepts suggests that a substantial share of the identified context factors is located primarily at a conceptual or knowledge-based level, which can plausibly be explained by the underlying data source, as the mapped context factors were extracted from the scientific literature. Whereas MeSH is designed to structure and index biomedical literature [48], SNOMED CT is intended for the formal representation of clinical information in care settings [49]. The distribution of context-related concepts across multiple vocabularies should therefore be understood as a reflection of this functional specialization. At the same time, however, it results in a fragmentation of relevant information that complicates consistent semantic integration and thus constitutes a major challenge for both interoperability [37] and effective data management [41]. Accordingly, the identification of a candidate correspondence in MeSH, LOINC, or another vocabulary should be interpreted as evidence of conceptual availability rather than direct operational readiness. Depending on the intended use case, further semantic modeling, terminology binding, and specification of the relevant data elements may be required before such concepts can be incorporated into EHR-based CDSSs.

Implications

Overall, these findings highlight both the limitations of existing terminologies and the need for more formal representations of contextual information in clinical decision support. In particular, context factors beyond traditional clinical parameters require explicit modeling to address persistent limitations of CDSSs, including the insufficient consideration of clinical workflows and organizational contexts [13,50]. Previous studies have shown that the standardized capture of contextual information remains limited [51,52], partly because such information often remains implicit, is not formally documented [53,54], or is recorded in free-text fields that hinder automated processing [55]. The results of this study suggest that a substantial subset of these context factors can be represented using existing terminological structures and may provide a basis for their integration into CDSS logic. For example, contextual information such as physician workload, institutional resources, or patient-related social factors could be used to modulate system behavior, for instance, by adapting alert frequency, prioritizing recommendations, or tailoring decision support to specific situational conditions. To illustrate this more concretely, consider a medication-safety alert triggered by a potentially nephrotoxic drug combination in a patient with declining renal function. Drawing on the local formulary, the system could recommend a renally safer alternative that is actually stocked at the institution rather than one it does not carry. Drawing on the on-site availability of services, it could adapt the suggested follow-up, proposing therapeutic drug monitoring or a nephrology consultation where these are available, or prompting timely referral where they are not. Physician workload, in turn, derived from routinely available signals such as the active patient census, could be used to adapt alert frequency by deferring low-severity advisories during high-workload periods, while high-priority safety alerts remain unaffected. For a CDSS to make meaningful use of contextual information, these data must therefore be captured in a standardized and interoperable way. In this regard, the integration of terminologies into EHRs appears promising [52], but this requires extending existing terminologies to incorporate contextual dimensions [56]. The present findings provide an empirically grounded basis for such extensions and for the development of formal context ontologies and semantically coherent, context-sensitive information models. More broadly, they contribute to ongoing efforts to formally represent clinical decision logic for use in digital support systems.

Limitations

Several limitations should be considered when interpreting these findings. The analysis was restricted to SNOMED CT and therefore does not allow conclusions about the representability of the identified context concepts in other terminologies. In addition, the mapped concepts were derived from literature-based context factors rather than real-world clinical data and may therefore not fully reflect the breadth of contextual information used in routine care. Although measures such as dual-independent mapping and consensus procedures were applied, some degree of subjectivity in the mapping process cannot be completely excluded. The practical applicability of the mapped concepts in operational CDSSs or interoperable health information systems was not evaluated, meaning that the results inform terminological representability rather than clinical utility or implementation performance. This study should therefore be understood as an exploratory mapping rather than an implementation proposal. Finally, the findings depend on the specific SNOMED CT edition and release used, and reported coverage rates may differ in jurisdictions without comparable national extensions. Despite expert review, some degree of subjectivity in the manual mapping process remains unavoidable.

Future Research Directions

Future research should build on these results by moving from terminological representability toward implementation-oriented modeling of contextual information. This includes the development of formal context ontologies, context-sensitive information models, and strategies for the structured capture of contextual factors in clinical systems. In this context, future studies should assess whether concepts with partial or no correspondence can be more precisely represented through SNOMED CT postcoordination or require new concept authoring. In addition, further studies are needed to investigate which contextual factors are actually documented or can feasibly be captured in routine care, and how such information can be linked to decision support logic in a clinically meaningful way. It will also be important to examine how contextual concepts are represented across different SNOMED CT editions and how they can be consistently integrated across terminologies, ontologies, and information models in order to support semantic interoperability beyond isolated concept mapping. Finally, evaluation studies in real-world settings are required to determine whether improved formalization of contextual information can contribute to more relevant, acceptable, and practice-oriented CDSSs.

Conclusions

This study shows that a substantial proportion of empirically identified context factors influencing clinical decision-making can be linked to existing concepts in SNOMED CT. At the same time, the observed gaps in coverage, particularly for organizational and social context factors, indicate that current terminological structures do not yet fully reflect the contextual complexity of clinical decision-making. The findings therefore support the view that SNOMED CT can provide an important terminological basis for formalizing contextual information, while also highlighting the need for complementary work on semantic modeling, terminology development, and implementation-oriented context representation. Advancing these areas will be important for enabling more context-sensitive and semantically robust digital decision support.

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Data Availability

The authors declare that the data supporting the findings of this review are available within the paper.

Authors' Contributions

Conceptualization: KS
Data curation: KS
Formal analysis: KS
Funding acquisition: MS
Investigation: KS, EH
Methodology: KS, EH
Resources: KS
Supervision: MS
Validation: KS
Visualization: KS
Writing – original draft: KS
Writing – review & editing: EH, MS

Conflicts of Interest

None declared.

Multimedia Appendix 1

Overview of the hierarchical structure of contextual factors.
[XLSX File (Microsoft Excel File), 16 KB-Multimedia Appendix 1]

Multimedia Appendix 2

Mapped context concepts.
[XLSX File (Microsoft Excel File), 21 KB-Multimedia Appendix 2]

Multimedia Appendix 3

Unmatched context concepts.
[XLSX File (Microsoft Excel File), 12 KB-Multimedia Appendix 3]

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Abbreviations

CDSS: clinical decision support system
EHR: electronic health record
HL7: Health Level Seven International
ICD: International Classification of Diseases
LOINC: Logical Observation Identifiers Names and Codes
OHDSI: Observational Health Data Sciences and Informatics
SNOMED CT: Systematized Nomenclature of Medicine—Clinical Terms
SSSOM: Simple Standard for Sharing Ontology Mappings

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