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Adaptive Knowledge Fusion for Care Navigation

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Abstract

The ability to monitor patients within their context and provide care-navigation guidance is a fundamental component of intelligent-care systems. Such context-aware care-navigation systems must be able to fuse large quantities of medical knowledge from heterogeneous sources. Knowledge fusion enables health-care services and applications to interrogate and search through data from a variety of sources tailored to a specific context, so that the sensed context as well as inferred and anticipated information can be mapped to the data resources required. Ontologies and terminologies of a healthcare domain constitute the knowledge layer and make it possible to understand, locate, and integrate raw data sources as well as reasoning services, either through lossless or lossy processes, and at different abstraction levels. However, the abundance of these resources poses challenges that to date have remained under-explored. Two main subsets of knowledge-fusion processes can be distinguished: the collection and integration of the various resources based on the intended goals and context; and the parsing and appropriate fostering and filtering of the information-flow pathways that convey the data, knowledge, and services. Strategies, methodologies, and requirements for context-aware care navigation are proposed.

Supporting patients and the elderly within their general environment care through effective navigation is among the oldest goals of health-care systems. More recently, the trend towards care in non-institutional contexts has grown, fostered in part by the drive to contain costs. However, the idea of placing a patient within an operative context that can sense its changes and provide appropriate guidance has only recently emerged. The trend towards the integration of various pieces of information into a unified framework, rather than into separate, ad hoc, semi-expert systems, is also relatively recent; yet, the two concepts correspond well in terms of implementation.

Keywords: Medical Knowledge Fusion; Intelligent Context-Aware Systems; Intelligent Context-Aware Systems; Electronic Health Records; Reasoning and Inference; Data and Knowledge Distribution and Sharing; Healthcare Middleware; Ontology-Based Complexity Management; User-Context Modeling; Medical Context Representation.

1. Introduction

With the rapid progress of knowledge representation, automated reasoning, and data extraction techniques, several models and frameworks for context-aware applications have emerged. Such systems employ various data-processing techniques and machine learning algorithms to provide appropriate care recommendations by taking care-navigation contexts into account. However, data-fusion approaches and context-reasoning techniques used in these systems strongly depend on the use case.

The wide range of data used in these approaches is usually acquired from heterogeneous sources originating from different domains, at different levels of abstraction, and in different formats. Thus, for context-aware care navigation systems, context-aware care recommendations must be expanded beyond the conventional context-aware systems focused on mobile devices. Data-fusion

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architectures need to support the integration of the various electronic health record and health-information-exchange data and combine them with other contextual information, such as health-related events, services and facilities, social media updates, and weather conditions. These diverse data sources need to be fused into a common model to provide improved and up-to-date context information for context-aware care navigation.

Table 1: Heterogeneous Medical Data Sources in Context-Aware Care Navigation

Data Source Type	**Description**	**Example Data Elements**	**Role in Knowledge Fusion**
Electronic Health Records (EHRs)	Patient-centric clinical repositories	Diagnoses, medications, allergies	Provides structured clinical history
Health Information Exchanges (HIEs)	Cross-organizational healthcare networks	Referral summaries, discharge records	Enables interoperability and distributed access
IoT and Context Sensors	Real-time environmental and physiological sensing	Heart rate, GPS, temperature	Supplies live contextual awareness
Social and Behavioral Data	External patient-related contextual information	Social activity, lifestyle indicators	Enhances personalized care recommendations
Healthcare Ontologies	Semantic medical knowledge repositories	SNOMED CT, LOINC, RxNorm	Supports semantic interoperability
Ambient Assisted Living Systems	Smart-care monitoring environments	Fall detection, mobility tracking	Improves elderly-care navigation

1.1. Data Integration and Interoperability

Due to the increasing diversification and specialization of healthcare, context-aware care navigation relies on a multitude of data sources, some of which are heterogeneous or imperfectly described. These realms of well-established research fields examine the challenges while presenting tested solutions. Knowledge fusion is a term coined in Artificial Intelligence that refers to the integration of multiple sources of knowledge and/or information in a systematic way. In healthcare, its main motivation is to acquire knowledge through the synthesis, fusion, and integration of many information sources to feed intelligent applications. Healthcare ontology-based systems often use knowledge fusion techniques.

In Information Systems, Data Integration represents the merging of data residing at different sources, the process of providing users with a unified view of these data, and the act of accepting the heterogeneity of the data. In care navigation systems, it is the merging of data residing in different health information systems in response to users' queries. Interoperability is a well-studied term in healthcare, emerging from the increasingly networked environment surrounding information technology in general. Governments and international organizations pose the goal of achieving interoperability across the healthcare sector, mainly fostered by the creation of Electronic Health Records and Health Information Exchanges that nurture such vision.

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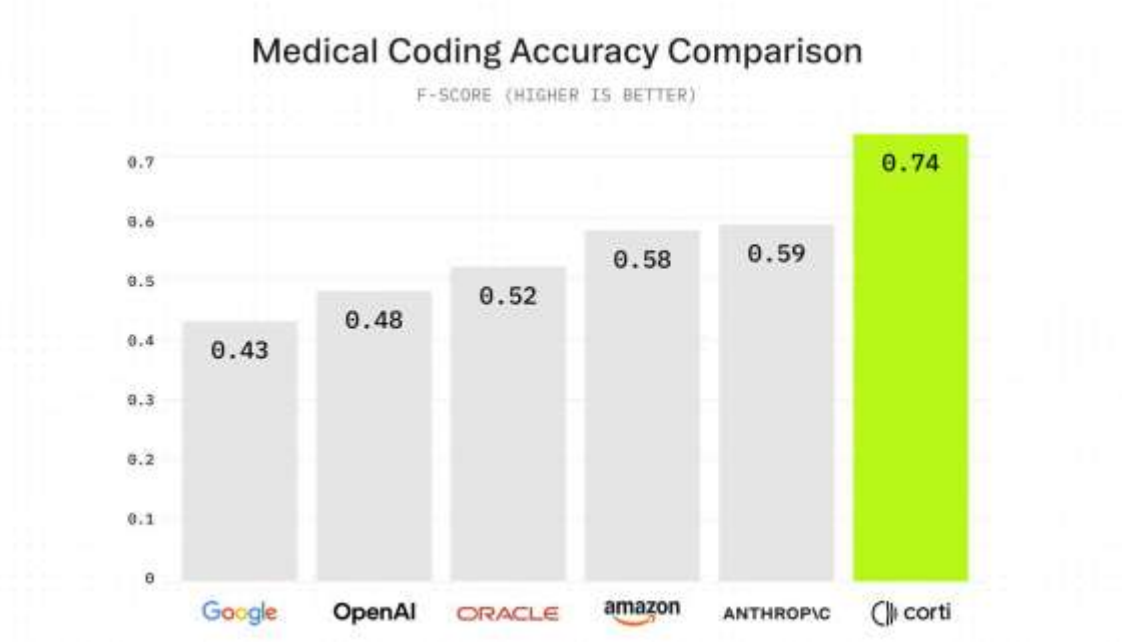

2. Theoretical Foundations of Knowledge Fusion in Healthcare

Formal ontologies, machine-readable representations of real-world concepts, instances, and relationships, enable heterogeneous and complex data integration across domains. Such structured knowledge fusion is often used in AI-enabled context-aware systems, since context knowledge provides information about the environment and users, thereby enabling more advanced, fault-tolerant, and user-centric applications. In healthcare, for example, context-aware systems can be used for personalized patient monitoring and care with better safety and quality. Such systems utilize layered ontologies to model both static area information (hospital data, patient locations, etc.) and dynamic contextual information (patient locations, states, and movements), making them suitable for contact tracing. The combination of dynamic area data with mobile phone tracking enables early detection of infection spreads, thus improving government responses.

Currently, new approaches exploit the idea of context fusion to provide recommender services in care navigation systems. Numerous context-aware services are made available to patients through mobile applications, improving care navigation in all stages of demand and supply, from finding healthcare resources and services to customized management of health conditions. Privacy and security are critical concerns of such systems, as access to context data can disclose sensitive personal information. Anonymization of context sharing, with respect to the context-sharing utility, is one way to address this issue, whereas a two-sided scheme enables patients to share only the necessary context with service providers.

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Intelligent Medical Knowledge Fusion Architecture

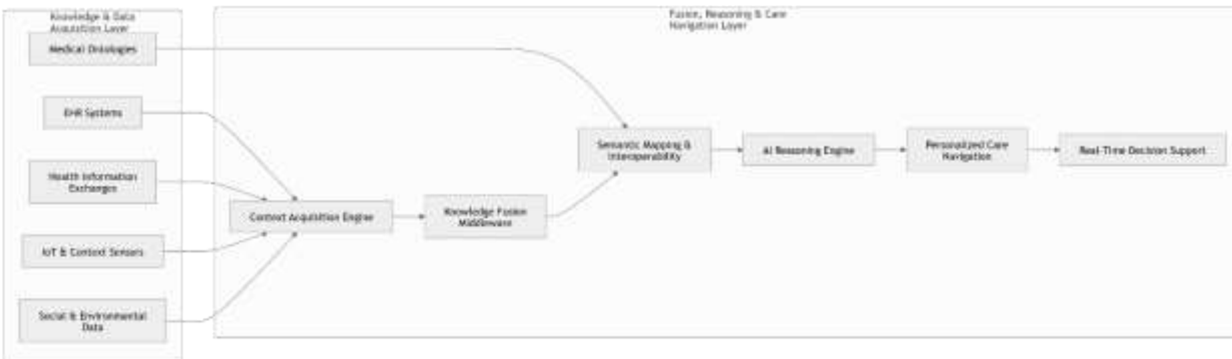

Table 2: Functional Layers of Intelligent Medical Knowledge Fusion Architecture

Layer	**Core Function**	**Technologies/Components**	**Expected Outcome**
Data Acquisition Layer	Collect heterogeneous healthcare data	EHR APIs, sensors, mobile devices	Continuous context collection
Integration Layer	Normalize and merge information	HL7, CCD, semantic mapping	Unified healthcare data model
Knowledge Fusion Layer	Perform ontology-driven fusion	OWL ontologies, reasoning engines	Context-aware intelligence
Middleware Layer	Manage interoperability services	Service-oriented middleware	Scalable service communication
Inference Layer	Execute reasoning and predictions	AI inference engines, rule systems	Personalized recommendations
Application Layer	Deliver care navigation services	Mobile apps, dashboards	Patient-centered guidance

2.1. Ontologies and Terminologies

Ontology and terminological expertise is crucial in creating intelligent medical knowledge fusion systems to navigate care context. Multiple medical source databases organize significant amounts of medical information. Making medical knowledge

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understandable and usable for machines involves developing a shared ontology using various ontologies and terminologies. Domain ontologies usually use separate top-level ontologies that describe very general concepts. Top-level ontologies are developed across many domains, and the reuse of the upper layer of a top-level ontology leads to its extension. Well-known recognized terminologies support the semantic unification in knowledge fusion systems for meaning disambiguation.

Although care navigation systems take advantage of these sources, the two aforementioned aspects of context modeling — knowledge representation and ontology-based concepts for knowledge fusion — are usually independent. Hence, different ontologies may represent the same concepts within layers in the layers, and contextual knowledge is not shared, tailored, and reusable. This section discusses differences between ontologies and terminologies, examines the role of ontologies and terminologies in context-aware care navigation, and identifies opportunities for extending context-aware care-navigation systems and the entire context-aware knowledge model within the context of navigation system consideration.

Ontologies are thus domain specific and overall goal driven. Thus, there exist different medical ontologies focusing on various aspects of health care Ontology design decisions and techniques can differ across purpose and units Apply ontology-based services rely on services that capture the essence of a domain and an ontology-plug-in module parse and perform requested operations using the ontology. The online medical care ontology service retrieves the right ontology in response to the context of the procedure. It exploits existing ontologies and these semantic relationships, which connect all medical ontologies, make their integration possible. Context ontologies represent a set of generic concepts concerning context and context properties. In addition to context recognition and information representation, agents can utilize context ontologies to share perceived context information and actively adapt their actions on the basis of context. In summary, interaction among communicating elements represents the context of communication and context ontologies enable agents to share the context of communication.

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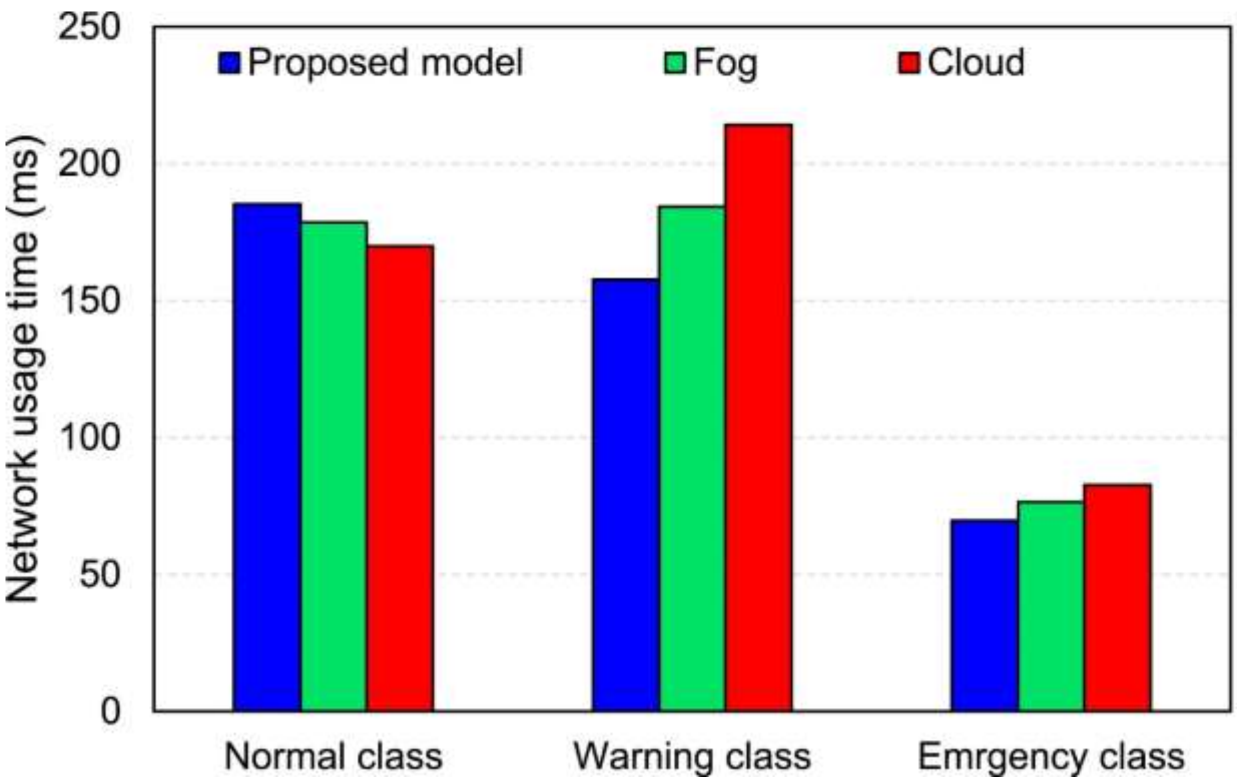

3. Context-Aware Care Navigation: Concepts and Requirements

Navigation is defined as the determination of one's position and directed motion toward a destination. Navigating in care is about receiving health or social services and collecting relevant health or nonhealth information. Intelligent care navigation systems provide system-to-user and user-to-system navigation support during the entire navigation process. Context-aware care navigation systems exploit contextual information about the users, their environment, and the services or information delivery channels to improve the quality of the navigation support.

The concept of context embraces everything that can be known about the user and the user environment at any moment in time. Effective support may require continuous context modeling, where context is modeled, but not necessarily stored, in a system or component. Context-aware care navigation services usually rely on the availability of context models that contain temporally and spatially scoped sets of context properties that describe the users, the user's environment, and the desired service. Context-aware

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systems may acquire or generate contextual knowledge, but context sensing may also be performed as a joint operation between users and systems.

Table 3: Ontologies and Terminologies Used in Healthcare Knowledge Fusion

Ontology / Terminology	Primary Purpose	Healthcare Domain	Knowledge Fusion Benefit
SNOMED CT	Clinical terminology standardization	Clinical events	Semantic consistency
RxNorm	Drug normalization	Medication systems	Medication interoperability
LOINC	Laboratory test coding	Diagnostic testing	Unified lab representation
OWL Ontology	Formal semantic modeling	Multi-domain healthcare	Machine-readable reasoning
Context Ontologies	User and environmental modeling	Context-aware systems	Dynamic context adaptation
Custom Care Ontologies	Institution-specific knowledge	Local healthcare workflows	Personalized navigation logic

Mathematical Formulas:

1. Context Fusion Equation

This equation models the aggregation of heterogeneous healthcare context sources into a unified contextual representation.

$$C_{fused}(t) = \sum_{i=1}^{n} w_i \cdot C_i(t)$$

Where:

- $C_{fused}(t)$= Unified healthcare context at time t
- $C_i(t)$= Context information from source i
- w_i= Weight assigned to source reliability
- n= Number of context sources

Applications:

- EHR integration
- Sensor fusion

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- Patient-state aggregation

2. Ontology Similarity Mapping Function

Used for semantic interoperability between heterogeneous healthcare ontologies.

$$Sim(O_a, O_b) = \frac{|\, Concepts(O_a) \cap Concepts(O_b) \,|}{|\, Concepts(O_a) \cup Concepts(O_b) \,|}$$

Where:

- O_a, O_b= Two healthcare ontologies
- $Concepts(O)$= Set of semantic concepts in ontology

Applications:

- HL7-FHIR semantic mapping
- SNOMED CT alignment
- Cross-domain terminology fusion

3. Context-Aware Recommendation Score

Used to determine optimal care-navigation recommendations.

$$R(u,s) = \alpha M_u + \beta L_s + \gamma P_c$$

Where:

- $R(u,s)$= Recommendation score
- M_u= Medical relevance for user
- L_s= Location/service accessibility
- P_c= Patient contextual priority
- α, β, γ= Tunable coefficients

Applications:

- Intelligent hospital navigation
- Personalized care routing

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- Emergency triage assistance

4. Knowledge Confidence Estimation

Measures confidence in fused healthcare knowledge.

$$K_c = \frac{\sum_{i=1}^{n} r_i \times d_i}{n}$$

Where:

- K_c= Knowledge confidence score
- r_i= Reliability of source i
- d_i= Data quality score
- n= Number of integrated datasets

Applications:

- Trustworthy AI healthcare systems
- Clinical decision validation
- Multi-source evidence fusion

5. Context Reasoning Probability

Bayesian inference for predicting patient context state.

$$P(H \mid D) = \frac{P(D \mid H) \times P(H)}{P(D)}$$

$$P(H \mid D) = \frac{P(D \mid H) \times P(H)}{P(D)}$$

Where:

- H= Hypothesized health condition
- D= Observed patient data

Applications:

- Disease-risk estimation

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- Clinical reasoning
- Predictive healthcare analytics

6. Multi-Layer Middleware Communication Delay

Models communication latency in layered healthcare middleware systems.

$$T_{total} = T_{acq} + T_{proc} + T_{trans} + T_{resp}$$

Where:

- T_{acq}= Context acquisition delay
- T_{proc}= Processing delay
- T_{trans}= Transmission delay
- T_{resp}= System response delay

Applications:

- Real-time care navigation
- Smart healthcare middleware optimization
- Distributed healthcare systems

7. Healthcare Data Integration Cost Function

Optimization function for minimizing integration complexity.

$$J = \sum_{i=1}^{n} (E_i + S_i + C_i)$$

Where:

- J= Total integration cost
- E_i= Extraction cost
- S_i= Semantic transformation cost
- C_i= Communication overhead

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Applications:

- Health Information Exchange optimization
- Cloud healthcare integration
- Enterprise medical interoperability

8. Patient Risk Prediction Function

Machine-learning inspired healthcare risk estimation.

$$Risk(x) = \sigma(Wx + b)$$

$$Risk(x) = \sigma(Wx + b)$$

Where:

- x= Patient feature vector
- W= Weight matrix
- b= Bias term
- σ= Sigmoid activation function

Applications:

- Chronic disease prediction
- ICU risk monitoring
- Preventive healthcare analytics

9. Privacy Preservation Function

Used for anonymized healthcare context sharing.

$$P_{privacy} = 1 - \frac{I_{shared}}{I_{total}}$$

Where:

- $P_{privacy}$= Privacy preservation ratio
- I_{shared}= Shared sensitive information

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- I_{total}= Total patient information

Applications:

- HIPAA-compliant data sharing
- Secure context dissemination
- Privacy-aware care systems

10. Context Dissemination Efficiency

Measures effectiveness of healthcare context propagation.

$$E_{ctx} = \frac{N_{successful}}{N_{total}}$$

Where:

- E_{ctx}= Dissemination efficiency
- $N_{successful}$= Successful context deliveries
- N_{total}= Total dissemination attempts

3.1. Context Modeling and Representation

The entire design of context-aware care navigation systems revolves around context, which serves as the basis for decision making. Accordingly, context modeling and representation approaches have gained much attention in recent years. Context can be characterized in various dimensions, including the source and type of knowledge, the range of addressed users, and the problem of data security and privacy. Context-related knowledge can be acquired from users, devices, and the surrounding environment, and it should be represented in an appropriate format for the target application. Models such as the Object-Process Methodology and context-aware Event-Condition-Action systems are used in various context-aware applications.

In the context of the care navigation problem, context comprises medical knowledge as well as the characteristics of care seekers, service providers, and the care provision environment. Medical knowledge to assist care seekers in navigating and receiving appropriate services has been modeled previously using controlled vocabularies, ontologies, and semantic networks. Elements such as the health knowledge of care seekers and providers, the contents and requirements of health services, available .

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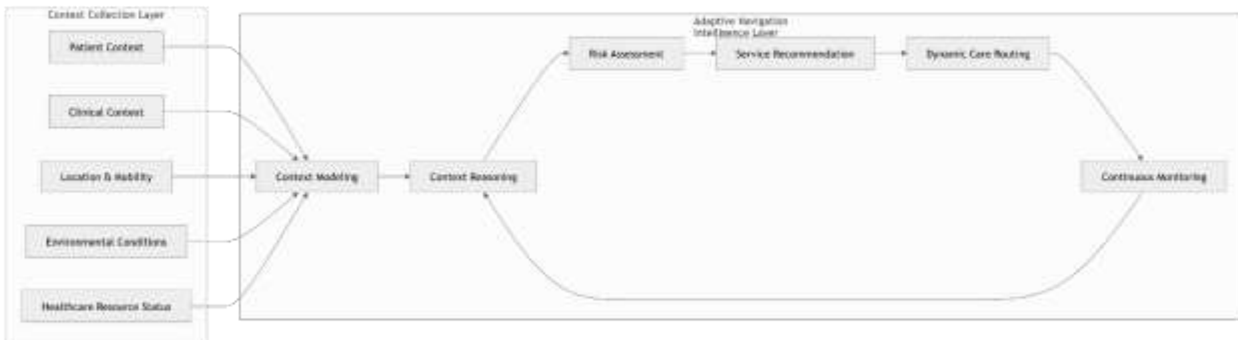

Context-Aware Care Navigation Workflow

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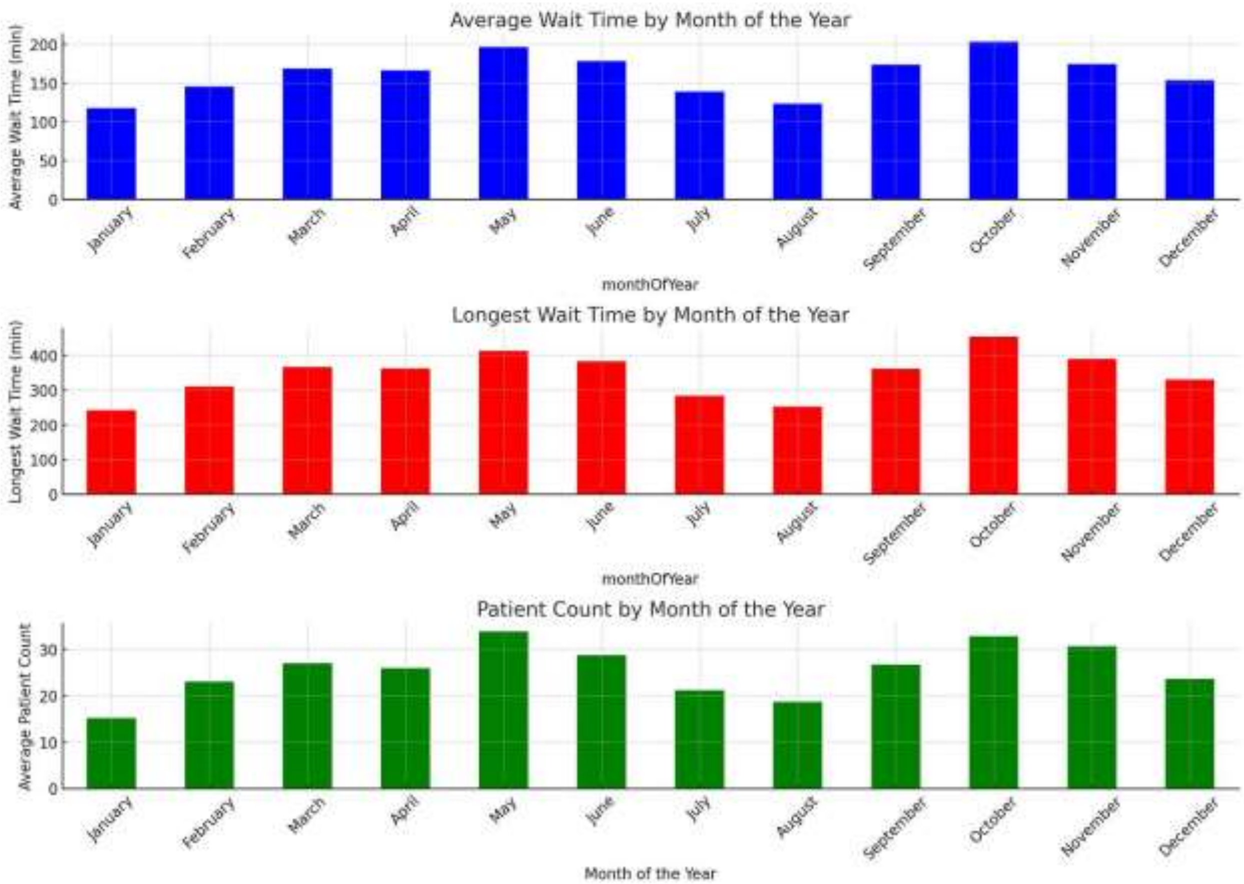

4. Data Sources, Privacy, and Security Considerations

Care navigation systems lie at the intersection of the care provider and care consumer acknowledging the concerns from both perspectives. On the care provider side such systems require real-time multimedia data about the consumers situation context health status and other related attributes. From the care consumer side dynamically capturing context information can raise significant privacy concerns. Therefore sound security mechanisms for context acquisition context sensing and context validation require careful integration for effective context-aware care navigation.

The primary data sources for such context-aware care navigation systems are electronic health records EHRs and health information exchanges HIEs. EHRs are confidential collections of electronically stored data for an individual patient organized around key clinical concepts. EHRs are provided by a single healthcare organization for the exclusive use of its affiliated providers and health

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plans. HIEs in contrast facilitate the sharing of information among multiple healthcare organizations. HIEs are real-time computerized networks that transmit patient information across the spectrum of care. By gathering information from EHRs and other health systems related to patients underlying medical conditions HIEs are populated with context-sensitive health information. Thanks to works such as these patients can feel more secure sharing their health status with third-party context providers. Since consent to share any EHR data must be obtained from the patient as per HIPAA guidelines EHR data combined with HIE data that are external to patient health status can integrate for care navigation with minimal privacy intrusion.

Table 4: Context Categories in Intelligent Care Navigation Systems

Context Category	Context Elements	Example Usage	System Impact
Patient Context	Health condition, disability status	Wheelchair-accessible routing	Personalized navigation
Environmental Context	Weather, traffic, hospital occupancy	Emergency rerouting	Improved service accessibility
Temporal Context	Visiting hours, appointment timing	Schedule optimization	Reduced delays
Clinical Context	Disease severity, medications	Specialist recommendation	Better treatment coordination
Social Context	Caregiver support, social conditions	Community-care referrals	Holistic patient management
Device Context	Sensor availability, battery state	Mobile health monitoring	Continuous care support

4.1. Electronic Health Records and Health Information Exchanges

Health information exchanges offer the potential to access electronic health records stored in different databases if patient consent is obtained. Nevertheless, the actual fusion of records normally takes place at the application level, based on extracted clinical information such as medication lists, allergies, and recent hospital discharges. The use of standardized formats (e.g., HL7, CCD) for exchanging this data further facilitates semi-automatic knowledge-fusion processes.

When information from multiple sources must be merged, one way to do so is to map these sources to a common ontological model. As clinical terms often possess different meanings in different domains, proper external mapping of local classes to shared ontological classes is suggested. By using several terminologies and ontologies, such as SNOMED CT (clinical events), RxNorm (drugs), LOINC (lab tests), and custom ontologies for the local establishment of care requirements, it becomes possible to derive the addresses of specific entities that match expressed requirements, even when the requirements contain terms from different ontologies, with the assistance of external mappings. Nevertheless, such methods have an inherent limitation: the indexes of those selected entities cannot be guaranteed to contain compatible information in their records.

A richer intermediary view based on clinical ontologies can offer a promising solution. Such undermined indexes would allow the selection of pertinent entities matching expressed requirements, even when the latter contained terms from different ontologies.

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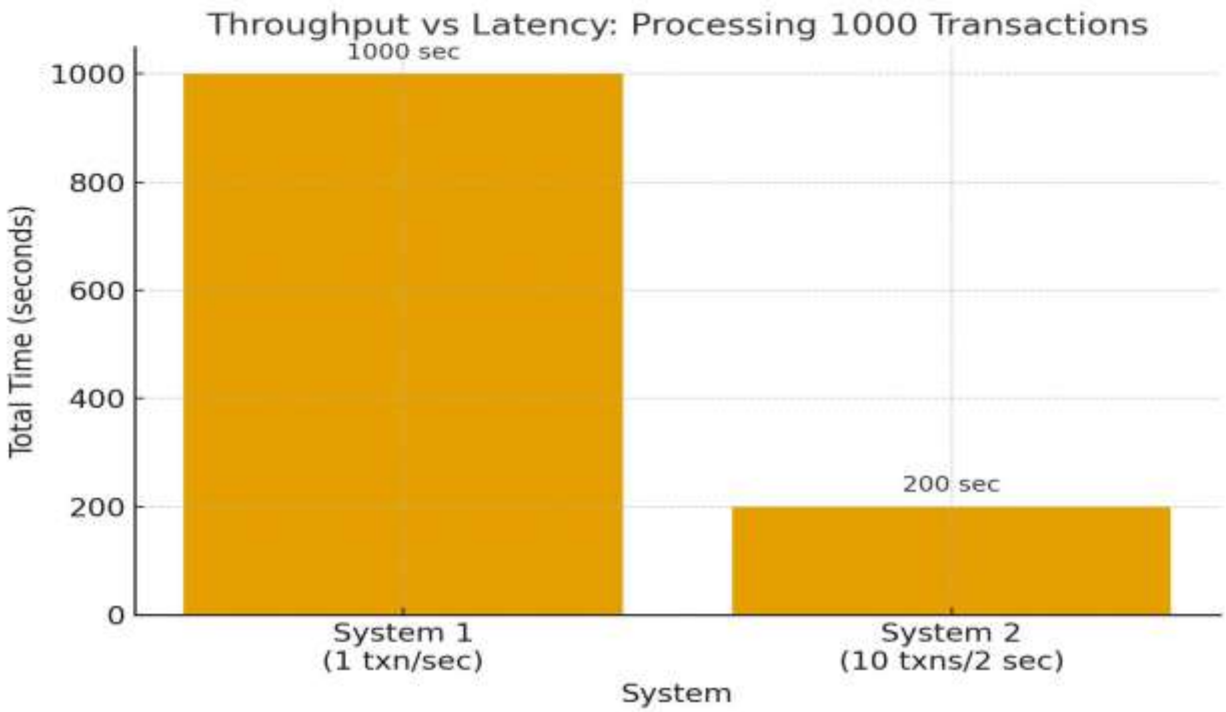

5. Architectural Approaches for Knowledge Fusion Systems

Layered systems and service-oriented approaches are the most widely used solutions for knowledge fusion. Perhaps their main advantage lies in their efficient and adaptive integration of a multitude of data sources and services, following a unique layered architecture. The service-oriented architecture of the HealthBridge white-paper provides a possible model for intelligent medical knowledge fusion. The solution focuses on the specification of the system as a design reference, although different implementations are currently used in hospital processes. A layered architecture provides a service abstraction model based on clustering of the information and knowledge sources in four simplified system layers. The specific clustering of the service capabilities follows the Reference Model of Open Distributed Processing from the International Telecommunication Union and uses specialized knowledge for service composition and service discovery tools to automate service connection at runtime. Providing a knowledge fusion infrastructure as a middleware platform takes the advantages of such a layered data source model to the next logical conclusion.

The data and information stored in ontologies, data warehouses, and databases can also be seen as services. In this sense, the services are data repositories that publish their data in a semantically enriched way. This platform uses a layered architecture to provide an integrated, simplified view of the services-level specification, followed by the presentation level that does not concern the knowledge fusion itself but any public service over the infrastructure.

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Table 5: Privacy and Security Challenges in Context-Aware Healthcare Systems

Challenge	Description	Potential Risk	Mitigation Strategy
Unauthorized Data Access	Exposure of sensitive health records	Privacy violations	Role-based access control
Context Information Leakage	Disclosure of patient activities	User profiling	Context anonymization
Cross-System Interoperability Risks	Insecure data exchange channels	Data tampering	Secure HL7 communication
Sensor Data Vulnerabilities	Compromised IoT devices	Incorrect health monitoring	Secure sensing protocols
Consent Management Complexity	Improper sharing permissions	Regulatory non-compliance	HIPAA-compliant consent workflows
Ontology Mapping Errors	Semantic inconsistencies	Incorrect recommendations	Standardized ontology mapping

5.1. Layered Architectures and Middleware

Multi-layered design patterns allow separating the different levels of information and knowledge processing, hiding the complexity of higher-level requirements to the user and developer. A typical architecture comprises data sources connected to a middleware that provides a set of generic services (e.g. access control, integration and fusion) to the applications using the intelligent knowledge fusion capabilities. The services include context acquisition and sensing, knowledge maintenance, context reasoning and massive knowledge reasoning and inference with knowledge discovery. These services can be used to build context-aware applications for care navigation and intervention.

Middleware architectures can be considered a special case of proxy-based architectures where a proxy must be created on each upper layer in order to manage the lower layer locations. Context-aware service-oriented architectures are an extension of traditional service-oriented architectures where context is not used only in the service discovery phase, but is an integral part of the request and reply message processing.

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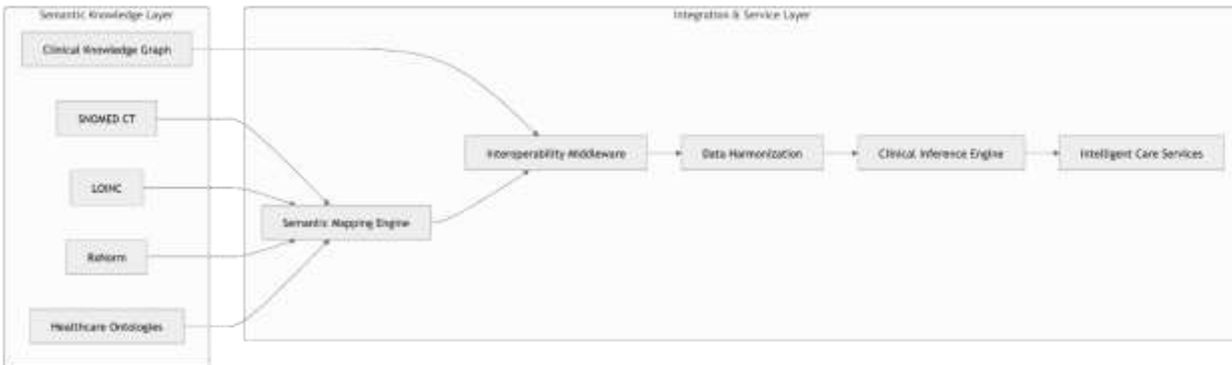
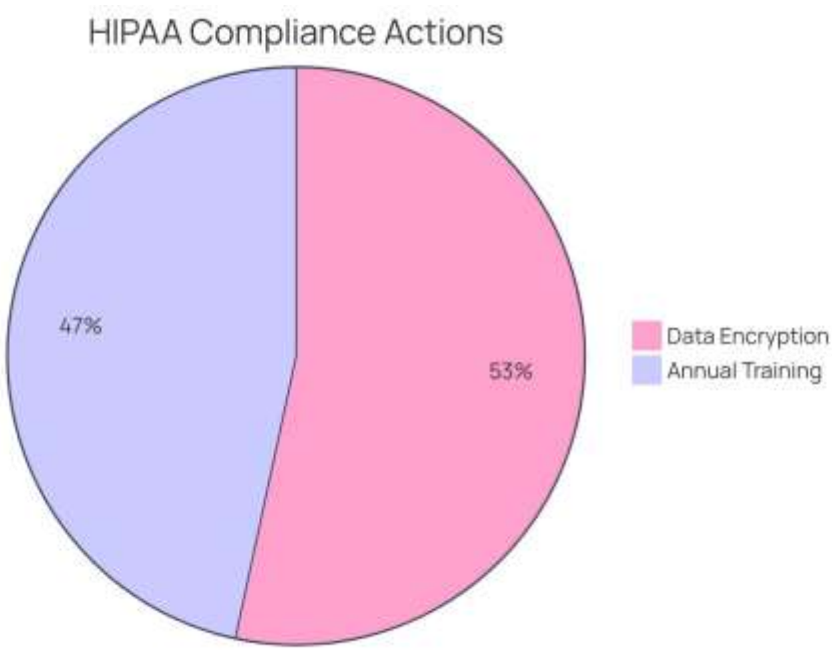


Ontology-Based Healthcare Interoperability Framework



6. Methodologies for Context-Aware Care Navigation

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In general, context-aware systems consist of four main functions. An effective context acquisition function is essential to sensing context information from the environment. The context modeling function organizes the context information in a structured form that the system can use. The context interpretation function analyzes and interprets the acquired context information, including context reasoning and inference. Lastly, the context dissemination function makes all or part of the context information available to other components or processes of the system.

More specifically, context acquisition for context-aware care navigation systems gathers context information related to physical places, people, and events. Places contain physical location information (e.g., GPS coordinates) and attributes that affect the navigation (e.g., Visiting hours for different departments). People provide information about patients—type of patient (e.g., patient in wheelchair), mental state (e.g., mentally impaired)—and staff—moving staff and staff on duty. Events are departing and arriving events of external agents such as shuttle services. A proper selection of available context sensors is a core requirement for the acquisition process. In addition to predefined sensors, sensor-near devices may also act implicitly as context sensors that are based on their location and resources. Context-acquisition agents gather the sensor readings of individual sensors, carry out the necessary conversions into a normalized context model, and distribute the readings to relevant context consumers.

Table 6: Classification of Context Sensors in Care Navigation Systems

Sensor Type	**Information Captured**	**Example Device**	**Healthcare Application**
Identification Sensors	User identity and location	RFID tags	Patient tracking
Environmental Sensors	Ambient conditions	Temperature sensors	Infection monitoring
Physiological Sensors	Patient vital signs	ECG monitors	Remote patient monitoring
Interaction Sensors	User-device interactions	Smart wearable interfaces	Behavioral monitoring
Motion Sensors	Mobility and movement	Accelerometers	Fall detection
Reflexive Context Sensors	Event-triggered responses	Emergency alert systems	Real-time intervention

6.1. Context Acquisition and Sensing

Context awareness is inherently tied to the acquisition of context information in the environment of the user. In this subsection, the context acquisition methods and approaches have been summarized. Sensing usually refers to the use of specialized sensors, but in a broader context, the component providing the context information is often called a context sensor. A context sensor can provide real-time information about the user and its environment.

The sensing of context information is one of the mashup components in a context-aware system that provides continuous context information, even with a change in the context source. Context can come from multiple environment and detection sources and is sensed either by specialized hardware, software services, or data mined from databases. Sensors can be categorized based on the

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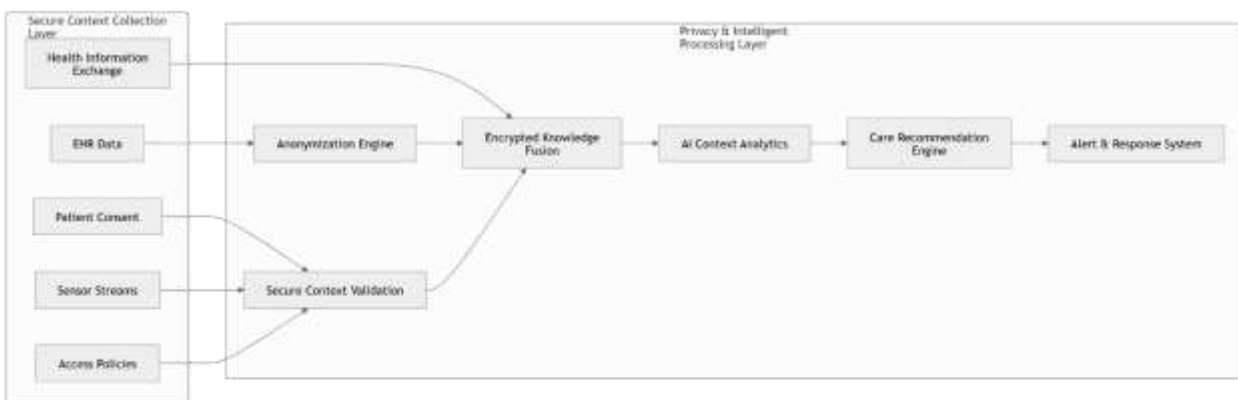
type of context information, such as environmental, identifications, conditions, or even interactions. Identification sensors provide information about the user, sickness, and location. Environmental sensors provide context information about the environment, while interaction sensors provide interaction information about user and device, user and user, and user and space interaction. Environmental and condition sensors provide context regarding the environment, whether the user is in a safe or dangerous environment. A detailed classification of context sensors is presented in. The context sources can also be classified following the software agent technology, such as active, passive, and reflexive context sources, as shown. Active context sources are those that might immediately provide context information when a user asks for it. For example, the battery state of a mobile phone can be monitored.

Privacy-Aware Medical Context Fusion System



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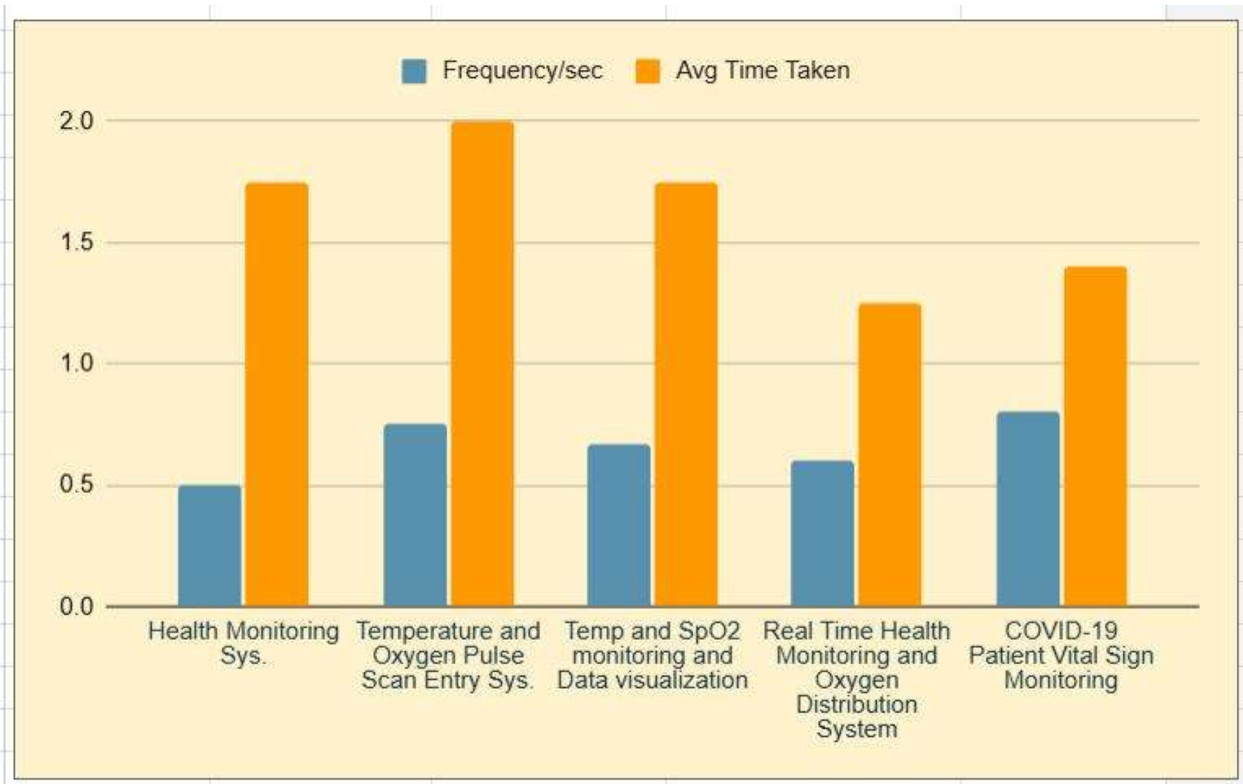

7. Conclusion

The design and implementation of context-aware care navigation systems demands the integration, combination, and interpretation of a wide range of heterogeneous data sources, including health information exchanges, electronic health records, smart home and ambient-assisted living environments, social networks, and the web. Issues of interoperability and data integration arise at various levels: from the syntactic to the semantic via the layer of terminology and vocabulary The availability of medical knowledge in machine-interpretable formats enables the use of this knowledge for intelligent guidance through the navigation process and assists in the interpretation of sensor data acquisition and fusion.

An overview of specific categories of data sources required for context-aware care navigation are considered. The relationship of context-aware care navigation systems and issues of data privacy and security is also examined. Care navigation systems are introduced as an example of application-specific context-aware systems with a focus of context fusion for care navigation independently of other sources of context knowledge.

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