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RESEARCH AGENDA IN DEVELOPING CORE REFERENCE ONTOLOGY FOR HUMAN-INTELLIGENCE/MACHINE-INTELLIGENCE ELECTRONIC MEDICAL RECORDS SYSTEM

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Abstract
Beginning around 1990, efforts were initiated in the medical profession by the U.S. government to transition from paper based medical records to electronic medical records (EMR). By the late 1990s, EMR implementation had already encountered multiple barriers and failures. Then President Bush set forth the goal of implementing electronic health records (EHRs), nationwide within ten years. Again, progress toward EMR implementation was not realized. President Obama put new emphasis on promoting EMR and health care technology. The renewed emphasis did not overcome many of the original problems and induced new failures. Retrospective analyses suggest that failures were induced because programmers did not consider the medical socio-technical communications structures that had evolved around paper records. Transition to electronic records caused breakdowns in the medical socio-technical communications systems; induced inconsistencies in information exchanges among clinics, physicians, hospitals, laboratories, pharmacies, and health insurance providers; and resulted in the incorrect administration of prescriptions, errors in patient care, and unnecessary treatments and surgeries. With the rapid integration of machine intelligence (MI) in medical socio-technical systems, there is a potential to repeat the failures of EMR implementation. To address the MI integration issue, this paper reports research design into the development of a human-intelligent/machine-intelligent (HI-MI) EMR core reference ontology around which EMR-MI knowledge can be encoded to form the basis for informed transition to artificially intelligent electronic medical records.

Keywords
Electronic Medical Records, HealthCare, Human Intelligence, Machine Intelligence

Introduction
The use of electronic medical records (EMRs) has increased significantly over the past few years. In the health industry and in medical research, EMRs have proven to be a critical source of information for pharmaceutical, diagnostic research, insurance purposes, coding enhancement for billing, and understanding of an overall patient encounter and history. Studies to date have revealed that the text content in EMRs may contain important additional information relevant to outcomes, concomitant diseases, procedures, interventions or test results in observational studies (Call, B., 2013). Public demand for flexible access to health information and services is growing as well, encouraged by internet trends and policies promoting patient rights and empowerment (Cayton H., 2004).

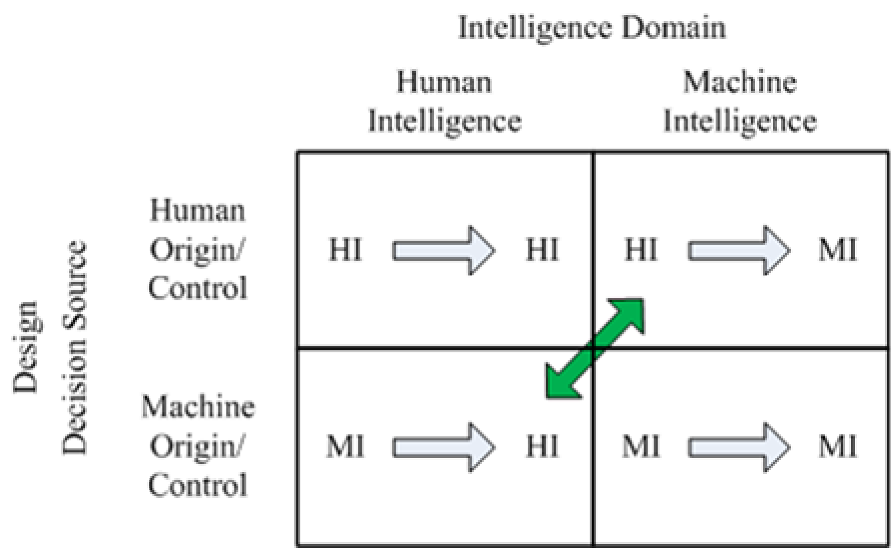
Beginning around 1990, efforts were initiated in the medical profession to transition from paper based medical records to electronic medical records (EMR). In 1991, the Institute of Medicine (IOM) issued a report which also called for paperless health records within ten years (Institute of Medicine, 1991). However, the more medical information becomes available in electronic form, the need for more complete security implementations becomes necessary. The National Research Council (NRC) of the National Academy of Sciences was charged in 1995, with evaluating the practical measures that can be used to reduce the risk of improper disclosure of confidential health information while providing justified access to those interested in improving the quality and reducing the cost of care (National Research Council. 1997). In 1996 the Health Insurance Portability and Accountability Act (HIPAA) was introduced in response to growing issues facing healthcare coverage, privacy and security in the United States. In the 1997 State of the Union address, then President Clinton noted that "we should connect every hospital to the Internet, so that doctors can instantly share data about their patients with the best specialists in the field." (Clinton, William. 1997). However, the security and confidentiality of the clinical data are a major impediment to realizing this noble goal. By the late 1990s, EMR implementation had already encountered multiple barriers: (1) isolated and structurally disparate paper and electronic data sources {clinics, physicians, hospitals, laboratories, pharmacies, and health insurance providers}, (2) governmental versus private medical entities, (3) differing data granularities, (4) differing network interfaces, (5) differing code systems (McDonald, 1997). Interoperability has been a concern since at least the mid-1990s, when a growing clinician user base made it necessary for systems to communicate with each other to effectively coordinate care (Institute of Medicine, 1997). To address these barriers, then President Bush established the Office of the National Coordinator for Health Information Technology (ONCHIT) in 2004 with the goal of implementing electronic health records (EHRs), nationwide, within ten years. Progress toward EMR implementation was slow, however. By 2006, less than 18% of physicians had transitioned to EMRs (Ford, Menachemi, and Phillips, 2006). Again, emphasis was put on implementation of EMRs under then President Obama's American Recovery and Reinvestment Act with the inclusion of $19 billion in incentives and $50 billion to promote health care technology. Throwing money at EMR implementation, however, did not overcome many of the problems and actually induced other problems.

Four broad problem categories emerged. First, technical differences between network interfaces and EMR code systems were magnified. Second, the unplanned transition from paper based medical records to EMRs caused breakdowns in the socio-technical communications and knowledge exchange systems that had evolved around the paper records. Third, inconsistencies in information needs between clinics, physicians, hospitals, laboratories, pharmacies, and health insurance providers prohibited full integration. Fourth, implemented EMR systems actually obstructed, rather than facilitated, learning from aggregated medical data inhibiting the ability to improve health care quality (D'Avolio, 2009). In a study of EMR adoption rates, Decker, Jamoom, and Sisk (2015) found that only 54% of physicians, ranging from 39.5% for small practices to 81.2% for large practices, had a minimal level of EMR implementation, and only 35% of physicians, ranging from 22.4% for small practices to 60% for large practices, had fully switched to EMRs. After billions of dollars investment, EMR failures are still common and the adaptation rate remains low.

Fit of EMR Research within Human-Intelligence/Machine-Intelligence Framework

Cotter (2015) summarized 21st century human and artificial intelligence research along two domains: the intelligence domain and the decision source domain as shown in Figure 1.

Exhibit 1. EMR within HI-MI Decision Domain.



Noted failures in EMR implementation can be linked directly to failures to design the HI $\rightarrow$ MI and MI $\rightarrow$ HI knowledge exchange interfaces. The EMR focus of governmental initiatives (Clinton, Bush, and Obama) was in the MI $\rightarrow$ MI domain of linking hospital computer systems over the internet. Traditionally, the information and communications technology (ITC) community has assumed that knowledge is recorded in paper format, databases, e-mails, and online libraries. The only effort needed was to convert paper records to electronic format, capture information in e-mails and online libraries, and integrate these disparate information sources into a searchable database. The ITC perspective fit well within governmental EMR initiatives.

Conversely, the existing HI → HI medical socio-technical knowledge exchange was built on human to human communications and tacit, as well as explicit, knowledge exchange around paper-based records. Krogh, Ichijo, and Nonaka (2000) provide a Knowledge Enabling 5 × 5 Grid that permit characterization of the root causes of HI → HI communications and tacit knowledge exchange failures of categories two through four of the above four broad problem categories under the MI → MI EMR implementation.

Exhibit 2. Knowledge Enabling: The 5 × 5 Grid (Krogh, et. al., 2000, p. 9)

	KNOWLEDGE-CREATION STEPS				
KNOWLEDGE ENABLERS	**1 Sharing Tacit Knowledge**	**2 Creating a Concept**	**3 Justifying a Concept**	**4 Building a Prototype**	**5 Cross-Leveling Knowledge**
Instill a Vision		√	√√	√	√√
Manage Conversations	√√	√√	√√	√√	√√
Mobilize Activists		√	√	√	√√
Create the Right Context	√	√	√√	√	√√
Globalize Local Knowledge					√√

Krogh, Ichijo, and Nonaka specify that knowledge creation proceeds in a five-step process: "…(1) sharing tacit knowledge, (2) creating concepts, (3) justifying concepts, (4) building a prototype, and (5) cross-leveling knowledge." (p. 8) Further, they emphasize that "… knowledge enabling involves both deliberate activities – those that can be planned and directed by management – and emergent ones – the unintended consequences of intended actions." (p.8) They define the knowledge enablers as follows:

- *Instilling a knowledge vision* legitimizes knowledge creation initiatives throughout the company.
- *Manage conversations* requires tacit knowledge creation to occur in positive atmosphere where all organizational members actively contribute to and apply shared insights. This enabler is "… connected most closely with relationships and care in the organization … strongly affects all five knowledge-creation steps."
- *Mobilize activists* achieves broader participation by reinforcing tacit knowledge contribution.
- *Creating the right context* requires designing and implementing organizational structures that reinforce informal group and team communication and knowledge sharing.
- *Globalize local knowledge* promotes communication of tacit knowledge across all organizational levels. This enabler "… matters most when knowledge creation and utilization are separated in time and space." (pp. 9-10)

Wachter (2015) provides multiple examples of EMR failures that can be used to illustrate the root causes of HI → HI communications and tacit knowledge exchange failures

Category 2, breakdowns in the socio-technical communications and knowledge exchange paper-based systems:

> "Steve Polevoi is the director of quality for the Emergency department at UCSF Medical Center. In pre-digital days, … ER nurses and doctors lived and breathed teamwork, constantly chatting as they went about their work. Now everything gets reported and ordered in the EHR, and it's on to the next task. Even worse, each "side" retreats to its own corner of the department to do its computer work." (p. 77)

> This example illustrates complete breakdown of the five-step knowledge-creation process due to violation of enabler two, creating a positive atmosphere, enabler four, designing and implementing supporting organizational structures, and enabler five, communication of tacit patient knowledge across ER levels.

Category 3, inconsistencies in information needs between clinics, physicians, hospitals, laboratories, pharmacies, and health insurance providers:

> "Lucca's (the doctor) admission orders for Pablo Garcia reached Benjamin Chan's (the pediatric pharmacist) screen moments after the doctor had electronically signed them. As Chan reviewed the orders, he saw that Lucca had ordered 5 mg/kg of Septra. Because the resulting dose of 193 mg was more than 5 percent greater than the 160-mg Septra tablets, hospital policy did not allow Chan to simply approve the order. The pharmacist texted Lucca: "Dose rounded by >5%. Correct dose 160 mg. Please reorder." After receiving the text page, Lucca reopened the medication-ordering screen…. She typed "160" into the dose box and clicked "Accept." She just then moved to the next task …, believing that she had just ordered the one Septra tablet …. Since doses can be ordered in either milligrams or milligrams per kilogram, the computer program … used the default setting … "mg/kg" …. in typing 160, Lucca was actually ordering 160 mg per kg—not one double-strength Septra, but 38 ½ of them." (pp. 139-140)
>
> This example illustrates violation of enabler four, creating the right context by designing and implementing organizational structures, and enabler five, communication of tacit patient knowledge across hospital organizational levels.

Category 4, obstruction, rather than facilitation, of learning from aggregated medical data inhibiting the ability to improve health care quality:

> "Shahram Ebadollahi, IBM's chief science officer for healthcare …finds that the biggest problem he and his Watson team are facing is not too much data—but too little. In large healthcare datasets, there might be 1,000 pieces of data collected on at least one of the patients…. But 90 percent of the cells in the spreadsheet are bare, meaning that a piece of data that's available for some patients is missing for others. On top of that, many data points are "noisy"—potentially inaccurate for a variety of reasons, ranging from keystroke errors to sensor malfunctions." (p. 117)
>
> This example illustrates violation of all five enablers; lack of organizational vision for the purpose of accurate data collection, managed conversations across organizational silos, involved activists promoting the importance of accurate data collections, designed organizational structures to support accurate data collections, and globalized understanding of the importance of the explicit knowledge to be gleaned from data analytics.

EMR Ontology Development Objective

Almost no research has addressed the question of how should HI $\rightarrow$ MI and MI $\rightarrow$ HI cognitive interactions be designed to maintain system decision integrity and assure mission accomplishment. This lack of design intent contributed to or was the root cause of noted breakdowns in and medical failures of EMR implementation. This research will develop a core reference ontology and core body of knowledge for Human-Intelligence/Machine-Intelligence (HI-MI) electronic medical records system.

EMR Ontology Development Methodology

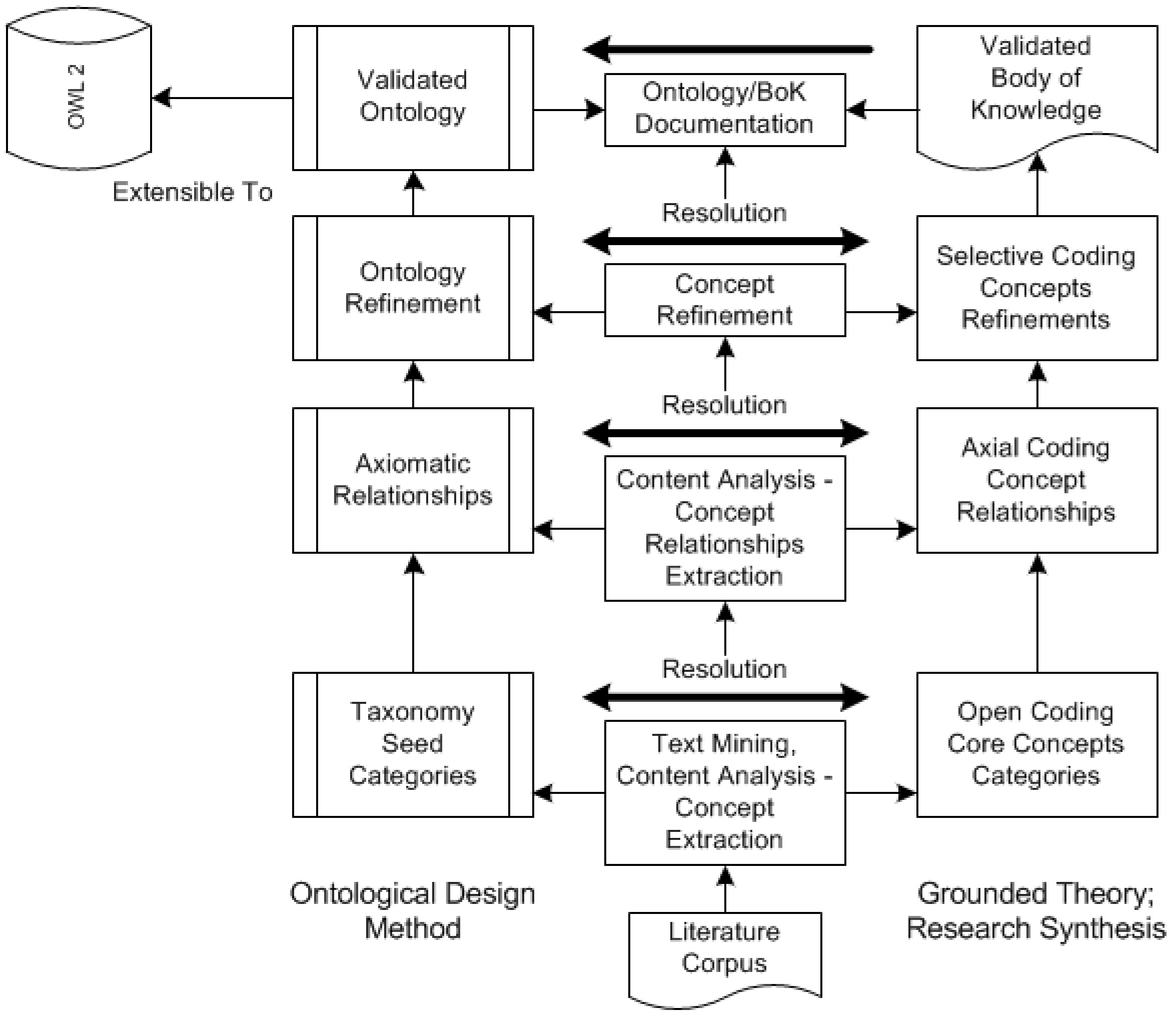
Considering the required knowledge scope, this research will seek to build a core reference ontology and knowledge base for HI-MI electronic medical records systems in the following major phases.

1. Creating corpus of peer reviewed journal articles on healthcare, medical, emergency care units, pharmaceutical, organizational, knowledge, and information technology,
2. Performing text mining to identify structural commonalities and differences in the EMR corpus,
3. Using the identified structural commonalities and differences, conduct open coding in grounded theory analysis in order to establish the taxonomical basis for the HI-MI EMR body of knowledge,
4. Performing content analysis to identify taxonomical relationships within and between structural relationships,
5. Using the taxonomical relationships, conduct axial coding in grounded theory analysis in order to establish the axiomatic relationships,
6. Using grounded theory selective coding to refine taxonomical structure and axiomatic relationships,

7. Validation of the core reference ontology against developed foundational HI-MI theoretical body of knowledge.

Text mining, concept extraction, and content analysis will be integrated with and link current ontological engineering best practice and grounded theory to evolve the core reference ontology and core body of knowledge jointly from a corpus of peer-reviewed electronic medical records literature. The general EMR ontological and body of knowledge development framework is presented in Exhibit 3.

Exhibit 3. EMR Ontological and Body of Knowledge Development Framework (adapted from Mahmud and Cotter, 2017)



Conclusions

Patient beneficial electronic medical records will require integration of the information systems development within Krogh, Ichijo, and Nonaka's knowledge enabling framework to overcome prior and continuing implementation failures. This work has set forth a research design into the development of a human-intelligent/machine-intelligent (HI-MI) EMR core reference ontology around which EMR-MI knowledge can be encoded to form the basis for informed transition to artificially intelligent electronic medical records.

Recommendations

Constructive public review and comment is invited for the purpose of strengthening the research design.

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