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Artificial Intelligence in Healthcare Robots:
A Social Informatics Study of Knowledge Embodiment

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Abstract

Knowledge embodiment, taking a social informatics perspective, refers to the transformation of knowledge into a form in which its value becomes evident. Knowledge embodiment in robotic systems with artificial intelligence (AI robotic systems) actualizes the value of knowledge much more powerfully than other entities, potentially altering the connections among people or even displacing professionals. To understand the effects of knowledge embodiment in AI robotic systems on connections among people and technology, this study addresses two cumulative research questions: 1) What is the nature of knowledge embodiment, i.e., how are knowledge and AI robots assembled for knowledge work? 2) How does knowledge embodiment affect connections among people and technology (i.e., social informatics)? Case study of a large hospital that has employed different AI robotic systems in many parts of its healthcare service provision process indicates four forms of knowledge embodiment, each with a distinct focus. Further, a social informatics analysis suggests four ways knowledge embodiment affects connections among people and technology and reveals related social and institutional issues that go beyond technological determinism. Implications of these findings for research on social informatics and information science are discussed.

Artificial Intelligence in Healthcare Robots:
A Social Informatics Study of Knowledge Embodiment

1. Introduction

The social informatics perspective (Kling, McKim, & King, 2003; Meyer, 2006) is useful for understanding connections among people and the technologies they use. It is a powerful lens for understanding a wide variety of topics, especially those that are related to how knowledge practices can be better understood when looking at their social contexts (Fichman & Rosenbaum, 2014; Kling, 2007). One topic, in particular, is how knowledge and its practices are embedded within and enabled by technical systems (Hara & Fichman, 2014; Jan & Hazel, 2013).

Knowledge embodiment refers to the transformation of knowledge into a form in which its value becomes evident (Demarest, 1997; Johnston & Blumentritt, 1998). The concept looks beyond improving the accessibility and reuse of knowledge to emphasize realizing the value of knowledge (Elena, Noelia, & Carmen, 2017; Johnston & Blumentritt, 1998; Maria, Souad, & Vlatka, 2017; Subramaniam, 2006). Knowledge can be embodied in entities such as documents (Baptista, Annansingh, Eaglestone, & Wakefield, 2006), electronic repositories, expert systems (Bogers, 2011; Wei, Choy, & Yew, 2009), and increasingly, robotic systems with artificial intelligence (henceforth "AI robots"; Navarro-Gonzalez, Lopez-Juarez, Rios-Cabrera, & Ordaz-Hernández, 2015).

Knowledge embodiment in AI robotic systems actualizes the value of knowledge much more powerfully than embodiment in other entities such as expert systems, potentially altering the connections among people or even displacing human workers. By definition, an AI robotic system is an integrated system of software and hardware that possesses certain capabilities typically associated with humans, including processing or communicating in natural languages, perceiving the world from visual images, sounds, and other sensory inputs, logical reasoning, planning, or navigating the physical world (Russell & Norvig, 1995). McKinsey Global Institute predicted that revolutions in robotics and artificial intelligence will cause 375 million workers, including 38.6 million Americans, to switch occupations or learn new skills to hold down a job in 2030 (Manyika et al., 2017). Academics have made similar forecasts (e.g., Frey & Osborne, 2017). AI robotic systems capable of performing the work of professionals such as consultants, architects, lawyers, and doctors, are fast emerging and increasingly employed in practice (Meltzer, 2014; Susskind & Susskind, 2016). For example, as this study will show, AI-based medical imaging diagnostic systems that inspect computed tomography (CT) images and provide laboratory diagnoses like human radiologists, often with better efficiency and accuracy, are already employed in hospitals. The effects of AI robotic systems on people and connections among them are likely to vary depending on the nature of knowledge embodiment.

Understanding the effects of AI robotic systems on people and connections among them requires clarity in the concept of knowledge embodiment, which has largely remained obscure. Knowledge embodiment has often been treated as a black box and prior research has focused on identifying entities embodying knowledge and the performance effects of embodiment as an organizational capability (e.g., on competitive performance). As our literature review in the next section shows, the nature of knowledge embodiment is still understudied, little is known about the type of knowledge embodied, the form of body, how they are assembled for knowledge work, and how the assembly affects knowledge work.

This study addresses two cumulative research questions to understand how AI robotic systems affect people and connections among them:
1) What is the nature of knowledge embodiment, i.e., how are knowledge and AI robotic systems assembled for knowledge work?
2) How does knowledge embodiment in AI robotic systems affect people and connections among them (i.e., social informatics using the Socio-Technical Interaction Network (STIN) analytical strategy by Kling et al. (2003))?
These questions are addressed through a case study of Anhui Provincial Hospital, which has employed different AI robotic systems in many parts of its healthcare service process. The case offers an unprecedented opportunity to compare different forms of knowledge embodiment in different AI robotic systems, while most other organizations are still contemplating the employment of such technology. The case study reveals four forms of knowledge embodiment in AI robotic systems, each with a distinct focus in terms of the type of knowledge embodied (e.g., procedural knowledge), relationship between embodiment and human cognition (e.g., scaffold cognition), and transformation of knowledge work (e.g., augmentation of work). A social informatics analysis of the four forms of knowledge embodiment indicates four ways people (e.g., healthcare professionals, patients) and technology are interconnected. We observed that AI robotic systems could go beyond being technological tools used by humans to become more active social actors in knowledge work (e.g., competitor). The analysis also highlights social and institutional aspects of the connections that go beyond technological determinism and require careful management.

These findings have implications for research on social informatics and information science, in addition to clarifying the nature of knowledge embodiment. First, this study shows that the social informatics perspective is invaluable to our understanding of AI technology. AI technology embodies some human knowledge and human capabilities. By this very nature, examining AI technology’s social and institutional connections with people is essential for realizing its value. This study is one of the earliest to examine social informatics of knowledge embodiment in AI robotic systems and hopes to pave the ground for more social informatics studies of AI technology. Second, this study contributes to the social informatics perspective by identifying that advanced technology like AI robotic systems can go beyond being a tool used by humans to become a more active, autonomous social actor. This extends the findings of prior social informatics studies (Sawyer, 2005) and has implications for understanding connections as the human-technology distinction blurs. Third, our findings indicate new research questions for information science researchers that emerge as changes in connections among people and technology due to knowledge embodiment affects the flow of information in organizations.

2. Literature Review and Conceptual Background

To understand the state of research on knowledge embodiment, we first review studies on the topic. We then explain the theoretical concept of embodied cognition (Barsalou, 2008; Glenberg, Witt, & Metcalfe, 2013; Wilson, 2002), which served as a preliminary sensitizing device for analyzing the case data to understand knowledge embodiment in AI robotic systems. The social informatics perspective, which is used to understand connections among people and AI robotic systems in this study, is also described.

2.1 Knowledge Embodiment

Knowledge embodiment refers to the transformation of knowledge into a form in which its value becomes evident (Demarest, 1997; Johnston & Blumentritt, 1998). Our review (summarized in Table 1) indicates that it is regarded as an important knowledge practice in organizations (Baptista et al., 2006; Wei et al., 2009). It has been found to influence product development capability (Subramaniam, 2006) and other knowledge practices such as knowledge sharing (Bogers, 2011). Studies have also begun to identify its antecedents, such as contact with industry network (Elena et al., 2017). Prior studies have identified entities embodying knowledge, such as documents (Baptista et al., 2006), electronic repositories and expert systems (Bogers, 2011; Wei et al., 2009), work processes (Bogers, 2011; Demarest, 1997), social interactions (McAdam & Reid, 2001), products (Elena et al., 2017; Subramaniam, 2006), and more recently, AI robotic systems (e.g., Navarro-Gonzalez et al., 2015). Some examples of AI robotic systems used in knowledge work include financial process automation robots that can automate processes in banking, capital markets, and insurance; robot lawyers that can offer legal advices in areas ranging from bankruptcy to parking ticket appeals; and marketing robots that can devise marketing strategies (McKinsey, 2016).

Table 1. Review of Studies on Knowledge Embodiment

Study*	Definition of Knowledge Embodiment (KE)	Research Method and Context	Key Finding related to KE
Demarest (1997)	Transformation of knowledge that is tacitly held in the head of a knowledge worker and shared in relative secret among a small team of confederates into processes and practices, machinery, materials, and cultures	Conceptual discussion	KE is a key knowledge practice in firms
Johnston and Blumentritt (1998)	Transforming knowledge within an organization into a form in which its value becomes evident inside and outside the organization	Conceptual discussion	KE is a key knowledge process that affects competitive performance
McAdam and Reid (2001)	Capturing of knowledge through explicit programmes and social interchange	Survey of 95 organizations using the business excellence model and analysis of 8 workshop discussions	KE is more systematic at the senior-manager level; KE in large enterprises is more formal; KE is business rather than technology driven
Baptista et al. (2006)	Storage of knowledge within an organization	Case study of two enterprises in England	KE is perceived to be crucial in organizations
Subramaniam (2006)	Integration and incorporation of multisource knowledge into products	Survey of 57 multinational corporations	KE affects product development capability
Wei et al. (2009)	Put organizational knowledge into a form that makes it accessible to those who need it	Survey of 289 middle managers in Malaysian telecommunication companies	KE is perceived to be important in companies
Bogers (2011)	Codification of knowledge in intellectual property rights, technology, people, or routine	Case study of a firm involved in research and development collaborations	KE affects knowledge sharing and protection
Elena et al. (2017)	Ability to integrate and apply diverse knowledge and convert into marketable products	Survey of 167 Spanish academic spin-offs	KE is affected by industry network contact

* Studies are listed in chronological order

Knowledge embodiment in AI robotic systems has much potential to transform people's work and connections among them, but there has been a lack of studies on the topic in social informatics and information science research. Barrett, Oborn, Orlikowski, and Yates (2011) observed in an organization science study that the use of pharmaceutical-dispensing robots in two hospital pharmacies in the United Kingdom influenced the boundary relations among different occupational groups. This indicates the need to examine the phenomenon from the social informatics perspective and understand the implications for information science research. In robotics research, knowledge embodiment is a key long-term purpose and drives studies that synthesize cognitive tasks using available materials and methods (Mira & Delgado, 2006); Technical approaches for embodying knowledge into industrial robots have also been proposed (Navarro-Gonzalez et al., 2015). However, issues of interest to social informatics and information science, such as how knowledge embodiment affects knowledge work, people, and their connections, have been understudied.

Knowledge of different types could be embodied in AI robots, including declarative, procedural, conditional, and teleological knowledge (Hawkins & Woollons, 1998; Nilsson, 1991). *Declarative* knowledge is know-what in the form of facts, concepts, rules, or principles (Gourlay, 2006; Huber, 1991; Miguel Baptista, Fenio, Barry, & Richard, 2006). *Procedural* knowledge is know-how in the form of scripts, methods, processes, or operations. *Conditional* knowledge is knowledge of when to apply what knowledge and requires an understanding of the situation or circumstance at the point of action. *Teleological* knowledge is an understanding of the purpose, intention, rationale, or objective of using knowledge (Hawkins & Woollons, 1998; Kopp, Stark, & Fischer, 2008). To illustrate, an AI robot with declarative knowledge would store maps of the physical world and knowledge about the robot body's sensory and motor capabilities; one with procedural knowledge would be able to navigate from location A to B when a user specifies both; a robot with conditional knowledge would be able to make sense of its current location and navigate from anywhere to point B; a robot with teleological knowledge would be able to complete meaningful work, such as tidying up a room. It is important to note that declarative, procedural, conditional, and teleological knowledge are not always mutually exclusive categories in practice. For example, Anderson (1996) asserts that people are expected to acquire declarative knowledge before they can practice procedural knowledge. Similarly, utilizing conditional knowledge is likely to require declarative and procedural knowledge.

In sum, this review shows two research gaps: 1) the concept of knowledge embodiment remains a black box and prior research has mostly focused on its antecedents or effects on organizational performance. 2) There has been a lack of research on issues of interest to social informatics of knowledge, such as how knowledge embodiment affects knowledge work, people, and their connections. This study addresses these gaps. The typology of knowledge (i.e., procedural knowledge etc.) is likely to be useful for offering insight into the concept of knowledge embodiment.

2.2 Embodied Cognition

To understand the nature of knowledge embodiment in AI robotic systems, we reviewed theories of embodied cognition as part of our initial inquiry. Embodied cognition stands in contrast to symbolic cognition. *Symbolic cognition* views cognition as grounded in symbols comparable to words, and regards the sensory and motor centers in the brain to be input and output channels (Barsalou, 2008). Cognitive processes could therefore be studied without any reference to sensory and motor centers (Barsalou, 2008). On the other hand, *embodied cognition* views cognition as grounded in the body and its interaction with the environment, rather than as abstract, separately stored symbols (Barsalou, 2008). The fundamental tenet of embodied cognition is that "thinking is not something that is divorced from the body; instead thinking is an activity strongly influenced by the body and the brain interacting with the environment" (Glenberg et al., 2013, p. 573).

Embodied cognition is not a formalized theory, but rather a collection of theoretical perspectives all rejecting the symbolic cognition view. The *scaffolding perspective* emphasizes taking advantage of regularities in the environment, i.e., cognitive tools, to share cognitive load or aid cognitive actions in order to accomplish tasks beyond the capacity of an individual (see Table 2; Clark, 1997; Sutton, 2002). In other words, cognitive demand is off loaded or distributed to the environment as much as possible (Wilson, 2002). Examples of scaffolding include counting with fingers, using paper and pencil to store intermediate results in a long mathematical problem, or using abacus or computers.

Table 2. Theoretical Perspectives of Embodied Cognition

Perspective	Relationship between Cognition, Body, and Environment
Scaffolding	Cognitive load/demand is *shared by/distributed to* the body and/or environment
Enactive	Cognition is for action, and cognitive mechanisms such as perception and memory must be understood in terms of their ultimate contribution to *situation-appropriate, purposeful, or goal-based behavior*
Extended mind	Cognition is beyond the boundary of an individual. *External* and internal parts of a cognitive system are *complementary* rather than replicative.

The *enactive perspective* emphasizes dynamic sensorimotor activity that acts on or conditions the environment (Varela, Thompson, & Rosch, 1991). The environment is essentially enacted in that it emerges through bodily activities of the subject. In this perspective, cognition is for action (Wilson, 2002), and the function of cognition is to guide action. Cognitive mechanisms such as perception and memory should be understood in terms of their ultimate contribution to situation-appropriate, purposeful, or goal-based behavior. The cognitive system is, and evolves because it is a behavioral control system.

The *extended-mind perspective* asserts that the boundary of cognition is beyond the boundary of an individual (Clark & Chalmers, 1998). The perspective encompasses two principles. The parity principle states that cognitive states and processes extend beyond the brain and into the external environment. The relevant parts of the environment function in the same way as do cognitive processes in the brain (Clark & Chalmers, 1998). They become a wider cognitive system that "is formed across the group and the artifacts: this allows the ongoing social negotiation of the past, bringing certain events to the joint attention of people with quite different perspectives and stakes in the earlier events" (Sutton, 2006, p. 284). The complementarity principle states that in extended cognitive systems, external states and processes need not mimic or replicate the functions of internal states and processes. Rather, external and internal parts of the overall cognitive system can play different roles and contribute complementarily.

Research on embodied artificial intelligence has identified four notions of "body" to describe weak and strong forms of embodied artificial intelligence (Chrisley, 2003, p. 132; Ziemke, 2001):

1. Physical realization: The system must be realized in some physical substrate. This is the weakest form of embodied artificial intelligence.
2. Physical embodiment: The system must be realized in a coherent, integral physical structure. For example, a robotic system of integrated software and hardware.
3. Organismoid embodiment: The physical realization of the system must share some (possibly superficial) characteristics with bodies of natural organisms, i.e., somewhat human-like, but need not be alive in any sense.
4. Organismal embodiment: The physical realization of the system must not only be organism-like, but actually organic and alive. For example, the system should be able to learn or repair itself.

Regardless of the notion of body, embodied artificial intelligence should exhibit some characteristics associated with intelligence in human behavior, such as natural language processing, visual image processing, perception of the physical world based on input from sensors, motion, manipulation of physical objects, planning, problem solving, or learning (Nilsson, 1998; Poole, Mackworth, & Goebel, 1998; Russell & Norvig, 1995).

Overall, research on embodied cognition provides the basis for this study's analysis of the nature of knowledge embodiment in AI robotic systems, by identifying ways cognition is embodied and notions of body. Along with the types of knowledge described earlier, they are likely to be useful for clarifying the nature of knowledge embodiment.

2.3 Social Informatics Perspective

Social informatics of knowledge embodiment is the focus of this study. Social informatics is a lens for studying the social and institutional aspects of information and communication technologies that makes explicit the connections among people and technology (Fichman & Rosenbaum, 2014; Kling, 2007). Social informatics is grounded on the belief that technology does not exist in social or technological isolation (Kling, Rosenbaum, & Sawyer, 2005). Instead, they co-constitute one another and the interest is in the study of the relationships and interactions implied in the hyphen that separates the words in the term socio-technical (Meyer, 2014).

An important principle of social informatics is adopting a critical orientation (Kling et al., 2005), that is, challenging the basic assumptions around the use, design, or implementation of technology rather than automatically adopting the goals and beliefs of those who commission the technology. This helps to avoid simplistic technological determinism and encourages researchers to examine technology from multiple perspectives (such as the various people who use them in different contexts, as well as people who design, implement, or maintain them). In line with this, common findings that have been consistently revealed by prior social informatics studies include (Kling et al., 2005):

- the paradoxical effects of technology adoption and use,
- that technology uses shape action and thoughts that benefit some over others,
- that the design and implementation of technology have moral and ethical consequences, and
- that the phenomenon of interest will vary with level of analysis.

In this study, we use the social informatics perspective to analyze how knowledge embodiment in AI robotic systems affect connections among human workers and technology. Taking the critical orientation, we consider multiple social actors in our analysis.

3. Research Method

3.1 Data Collection

We used the case research methodology for several reasons. First, our research questions call for exploratory rather than confirmatory analyses as social informatics of knowledge embodiment is not yet well theorized. Second, knowledge embodiment in AI robotic systems is still an emerging rather than widespread phenomena and the interpretive approach is particularly suitable as it permits new, unexpected observations that were not identifiable at the outset of the inquiry to emerge (Klein & Myers, 1999). Third, clarifying the nature of knowledge embodiment in AI robotic systems and social informatics of knowledge embodiment requires in-depth and multifaceted investigations of social-technical issues in their real-life social contexts and a case study is therefore particularly suitable.

This case study focuses on Anhui Provincial Hospital. The hospital started using AI robotic systems in June 2016, and was the first in China to do so. AI robotic systems were employed in knowledge works such as managing patient flow, diagnosing medical images, and recommending treatments, and were used by physicians, nurses, as well as patients and visitors. The case offers a valuable opportunity to examine knowledge embodiment in different AI robotic systems and the effects of knowledge embodiment on different knowledge works, knowledge workers, and other social actors.

Data were collected in two steps. First, research access was negotiated and granted in September 2017. To prepare for data collection, we gathered secondary data from a variety of sources, including newspapers, magazines, and institutional websites. We retrieved news and magazine articles reporting the implementation and use of AI robotic systems by the hospital as well as the systems' development by the technology provider, iFlyTek Company Limited (iFlyTek). They provided background information on the case, such as the systems adopted, their uses in the healthcare service process, and the timing of implementation. We also gathered information about the hospital and iFlyTek from their websites, such as hospital size and announcements on the collaboration between the hospital and iFlyTek.

Second, we collected data on site at Anhui Provincial Hospital and iFlyTek. We interviewed 34 informants, including physicians, nurses, patients, accompanying visitors, hospital administrators, as well as managers and staff members of iFlyTek (see the list of interviewees in Table 3). The interviews were semi-structured, with question prompts around the use of AI robotic systems in the hospital, the role of robots in physicians' and nurses' work, changes in work after the robots were deployed, and opinions or concerns about the use of robots in the hospital's service provision (see Table 4). Each interview lasted 30 to 90 minutes and was voice recorded and transcribed. All interviews were conducted and analyzed in Chinese and were translated into English by the bilingual researchers for the purpose of reporting. We also observed the use of all the AI robotic systems on site and recorded key information with written notes and photographs. Specifically, we observed how different patients or visitors interacted with a receptionist robot for about 60 minutes and how two registered nurses used the speech-based electronic health records (EHR) system. We also watched a demonstration of the medical imaging diagnostic system and the medical diagnostic and treatment assistant robot, "Yizhi". The transcripts, observation notes, photographs, and secondary data allowed triangulation of data during analysis and served to substantiate our findings (Klein & Myers, 1999).

Table 3. List of Interviewees

Organization	**(Job) Role**	**AI robotic system used/ managed**	**Number interviewed**
Anhui Provincial Hospital	Reception nurse	Receptionist robot	2
	Registered/ practitioner nurse	Speech-based electronic health records (EHR) system	3
	Radiologist	Medical imaging diagnostic system	5
	Physician	Medical diagnostic and treatment assistant robot, "Yizhi"	4
	Head of hospital's information department	All systems	1
	Staff member of hospital's information department		2
Not applicable	Patient/ accompanying visitor	Receptionist robot	7
iFlyTek (technology provider)	Engineer of AI robotic system	All systems	5
	Head of iFlyTek-hospital collaboration		1
	Staff member of iFlyTek-hospital collaboration		2
	Staff member of marketing department		2

Table 4. List of Key Questions in the Interview Guide

Organization	Job role	Key questions
Anhui Provincial Hospital	Reception nurse Registered/ practitioner nurse Radiologist Physician	- How do you work with the AI robotic system? - Has the system changed the way you work/use knowledge? If so, how? - Has the system changed the way you work with other people? If so, how? - Do you find the system useful? Why/why not? - What difficulties/challenges do you face when using the system? - Have you attempted to address the difficulties/challenges? If so, how?
	Head of hospital's information department Staff member of hospital's information department	- Why did the hospital adopt AI robotic systems? - How does the department manage the use of AI robotic systems in the hospital? - Have the systems changed the way employees work with one another? If so, how? - How does the hospital promote the use of the systems? - What difficulties/challenges were encountered when managing/promoting the systems and what has been done to address them?
Not applicable	Patient/ accompanying visitor	- What did you use the receptionist robot for? - Do you find the robot useful? Why/why not? - What difficulties do you face when using the robot? - How does the robot compare to a human reception nurse?
iFlyTek (technology provider)	Engineer of AI robotic systems Head of iFlyTek-hospital joint laboratory Staff member of iFlyTek-hospital joint laboratory Staff member of marketing department	- How does each AI robotic system support the targeted user? - How is each system expected to change the way users work? - How is each system expected to change the way users work with other people? - What information or knowledge are needed for the systems to function? What knowledge is incorporated/embodied in the systems? - What difficulties/challenges were encountered when developing the systems and what has been done to address them?

3.2 Data Analysis

This study focuses on the social informatics of knowledge embodiment. Specifically, our research questions are 1) What is the nature of knowledge embodiment, i.e., how are knowledge and AI robotic systems assembled for knowledge work? 2) How does knowledge embodiment in AI robotic systems affect people and connections among them (i.e., social informatics using the Socio-Technical Interaction Network (STIN) analytical strategy by Kling et al. (2003))? For the first research question, we followed the approach advocated by embodied cognition researchers to analyze the type of knowledge, relationship between embodiment and human cognition (embodied cognition), and how AI robotic systems transform human knowledge work (see Figure 1). This approach is recommended because it "place[s] embodiment at the center of the organism's solution to a given task, rather than on the periphery" (Wilson & Golonka, 2013, p. 11) and "fully engage[s] with the implications of embodiment" (Wilson & Golonka, 2013, p. 1). Theoretical perspectives and concepts related to embodied cognition and embodied artificial intelligence were used as sensitizing devices for analyzing data (Pan & Tan, 2011). These analyses eventually indicated several distinct forms of knowledge embodiment.

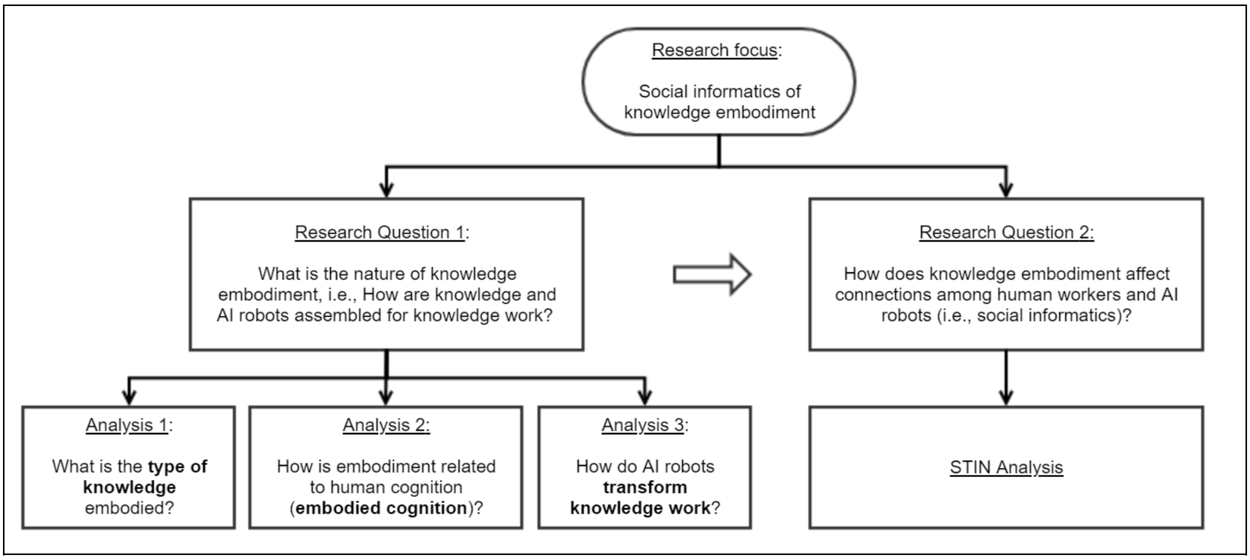

Figure 1. Research Questions and Overview of Data Analysis

For the second research question, we followed the Socio-Technical Interaction Network (STIN) analytical strategy for social informatics (Kling et al., 2003; Meyer, 2006). We analyzed how different forms of knowledge embodiment affected connections among humans and AI robotic systems. The social informatics perspective has been used to study social interactions among human and robots, but the focus has mostly been on affective robots (e.g., Lee, Kim, Kim, & Kwon, 2017) rather than robots engaging in cognitively demanding work. Specifically, the STIN strategy suggests considering the following for each knowledge work:

- A relevant population of social actors related to the use of AI robotic systems
- Excluded actors and undesired interactions
- Incentives/motivations of use and resource flow
- Salient socio-technical characteristics
- Robot design choice points and mapping of design to socio-technical characteristics

As mentioned earlier, we consider multiple social actors in our analysis and take a critical orientation to avoid technological determinism.

All data were examined and interpreted through multiple and independent readings by the authors and two post-graduate research assistants. The first author developed initial frameworks by summarizing the narratives in a tabular form, and categorized data into emerging themes. The others played the role of devil's advocates by questioning the analyses, prompting discussions that led to refinements of the initial frameworks and better agreement among data, analyses, and the resultant frameworks.

3.3 Case Description – Anhui Provincial Hospital and AI Robotic Systems Employed

Founded in 1898, Anhui Provincial Hospital is a tertiary public hospital (i.e., general hospital with more than 500 beds) that is also affiliated with the University of Science & Technology to support medical education and medical research. The 476,800-square-meter hospital provides a comprehensive range of medical and surgical specialties, including cardiology, dermatology, endocrinology, nephrology, neurology, oncology, ophthalmology, otolaryngology, and psychology. As of January 2018, the hospital had 6,347 employees and 7,650 beds. It served more than 3,684,000 outpatients and 193,500 inpatients in 2017 (Anhui Provincial Hospital, 2017). To put its size in perspective, the largest hospital in the United States, Florida Hospital Orlando, had 3,391 beds, 615,490 outpatients, and 130,879 inpatients as of January 2018 (Florida Hospital, 2018).

The implementation of AI robotic systems in Anhui Provincial Hospital is a key part of a joint research laboratory on medical AI with iFlytek, set up in 2016. In a press release, the president of iFlytek explained the collaboration's goal (iFlyTek, 2016):

> *"The establishment of the joint research laboratory is worth looking forward to, and will speed up the application of speech and artificial intelligence technology in the medical field and realize smart healthcare, for the benefit of hundreds of millions of people."*

The collaboration has led to the implementation of three AI robotic systems in 2016: receptionist robot named Xiaoyi, speech-based electronic health records (EHR) system, and imaging diagnostic system. A medical diagnostic and treatment assistant robot named Yizhi has been developed and pilot tested in early 2018 (see Table 5). As of May 2018, the use of all four systems was not mandatory and a user had the choice of using the traditional option. More details about each of these systems are described next.

The receptionist robot “Xiaoyi” answers non-emergency patients’ and visitors’ inquiries about healthcare services in standard Mandarin as well as 22 dialects of Chinese. It can direct a patient visitor to the relevant physician and room based on the patient’s verbal description of symptoms and availability of medical facilities and staff. For patients with scheduled appointment, Xiaoyi will direct them to the self-registration kiosks. The robot is developed based on machine learning of 53 professional medical books and a large amount of patient flow data (Sun, Sun, Tan, Xie, & Huang, 2014). It is able to answer inquiries about physicians’ schedule in 47 medical departments, navigate to 618 locations within the hospital, and answer 260 frequently-asked questions with 90.81% accuracy. All users had the alternative option of asking human reception nurses’ assistance. The robot had significantly reduced the number of human reception nurse on duty. The robot also learns continuously, as a reception nurse explained during an interview:

“The robot analyzes all inquiries received at the end of every day. For inquiries that it could not answer, a human reception nurse would enter the correct answer to help improve its capability.”

The speech-based EHR system is an AI robotic system that integrates hardware and software (i.e., microphone and speech-recognition software) to process natural languages (Wei, Wang, Hu, Ge, & Wu, 2017). It is used by nurses to update EHR during clinical examination, ultrasound examination, and ward inspection rounds. Before the system was deployed, a nurse would record patients’ health data based on physicians’ examination on paper, and manually type the data into the EHR system afterwards. The speech-based system allows nurses to enter data at the point of examination using speech recognition. Its logical natural language processing algorithm automatically filters out noise and irrelevant data and converts unstructured speech into structured text with up to 97% accuracy. As of 2017, the system was used by about 1,000 nurses a day, and has reduced data entry time from dozens of minutes to a few minutes. It was not mandatory to use the system and nurses had the option of using the traditional paper-based method based on their personal preference.

Table 5. AI Robotic Systems in Anhui Provincial Hospital

AI robotic systems (integrated system of hardware and software that possesses certain capabilities typically associated with humans)	Receptionist robot, “Xiaoyi” 	Speech-based electronic health records (EHR) system 	Medical imaging diagnostic system 	Medical diagnostic and treatment assistant robot, “Yizhi” 
Key AI robotic functions	Recognize human (e.g., patients’) speech queries in natural languages, direct patients to the relevant physician while optimizing patient flow and utilization of treatment facilities, accompany patients to the relevant area/room	Recognize human (i.e., nurses’) speech in natural languages and convert it into structured text entries in EHR (i.e., natural language processing)	Visually analyze medical images and suggest laboratory diagnosis	Interpret information integrated from various sources to suggest medical diagnosis and treatment
Similar system in the market	Softbank Pepper Robot (BBC News, 2016)	Nuance’s Dragon Medical Speech Solutions (Nuance, 2018)	Watson Health Imaging (IBM, 2018)	No similar system found

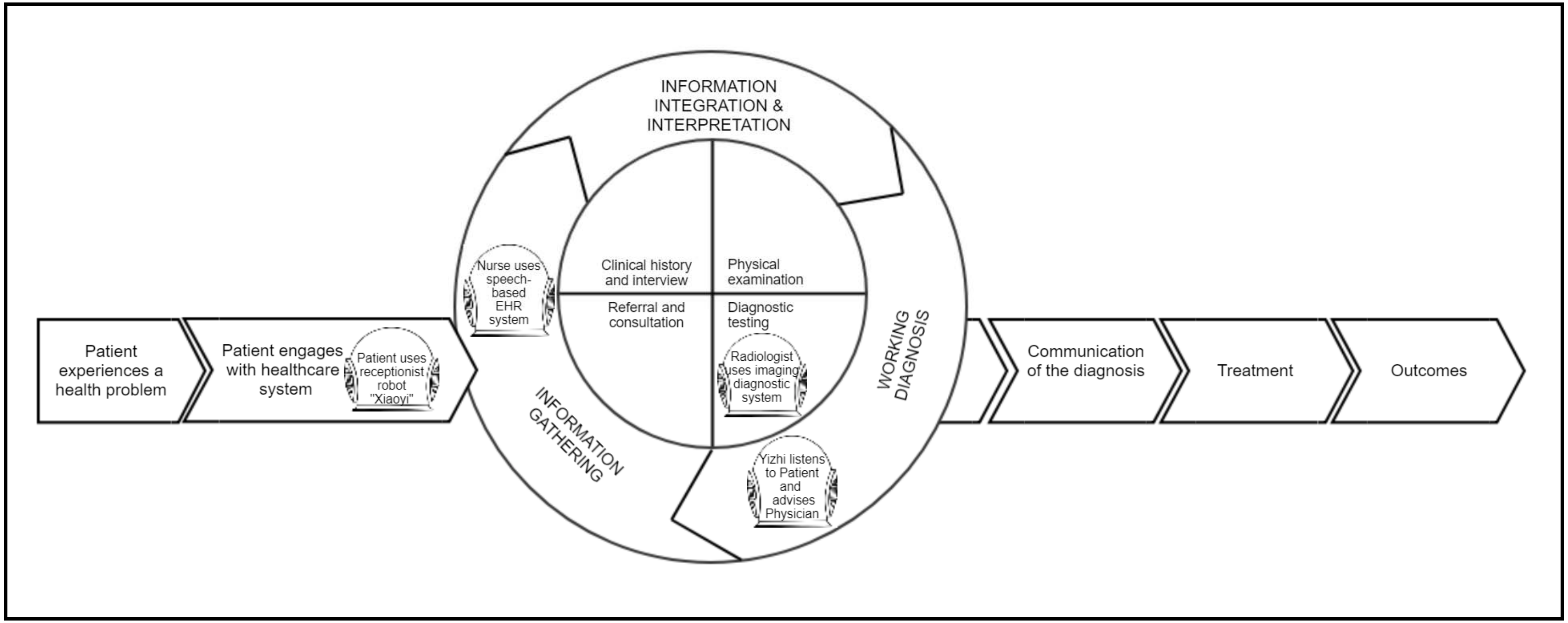

Figure 2. AI Robotic Systems in Anhui Provincial Hospital's Healthcare Process (adapted from Balogh, Miller, & Ball, 2015)

The imaging diagnostic system integrates computer hardware and image processing software to visually analyze CT images of the lung (Yin, 2017). It can identify pulmonary nodules with high sensitivity (3mm to 8mm), analyze their surroundings, automatically classify them as malignant or benign, and recommend diagnosis to radiologists, who then conclude the final diagnosis and report to physicians. The system is developed based on machine learning of more than 680,000 lung CT images, 53 professional medical books, 2,000,000 electronic health records, and 400,000 medical cases. It has diagnosed about 11,800 CT images in the hospital, with an accuracy of 94.9%. Its use was not mandatory and radiologists had the option of manually analyzing images. The system has also learned more than 20,000 mammography images and 200,000 magnetic resonance images and the hospital plans to use the system for diagnosing breast cancer and Alzheimer's disease in the near future. The head of iFlyTek-Anhui Provincial Hospital collaboration explained the system’s advantage during an interview:

> *“The system is much more sensitive and is tireless, compared to humans. It is difficult for radiologists to stay focused for 8 to 24 hours, but the system does not have this limitation. Most radiologists screen about 100 images a day. In contrast, the system screens and learns from a massive amount of images continuously and its learning ability far exceeds that of humans.*

The medical diagnostic and treatment assistant robot “Yizhi” can recommend diagnosis and treatment to physicians by interpreting information integrated from various sources, including laboratory diagnosis, patient medical history, past medical cases, and speech conversation between the physician and patient during clinical examination. The robot is developed based on semantic machine learning of medical textbooks, 2 million medical records, and 400,000 articles (patent to be filed). The robot has passed China’s national medical licensing written examination with a score of 456, which is well above the passing score of 360 and the national average. More than half of the examination questions were about patient cases and it was impossible to rely solely on memorization and search. Instead, Xiaoyi had to be able to see links between words, sentences, and paragraphs to develop a capacity to reason and make judgment like a human candidate. The hospital is currently field testing the robot with patient volunteers. The robot “listens” to the conversation between the physician and patient during clinical examination and integrates the information gathered with that from other sources to recommend diagnosis and treatment to the physician, who then communicates with the patient. The robot is expected to help physicians conclude diagnosis faster and reduce errors.

Overall, Anhui Provincial hospital employs AI robotic systems in many parts of its healthcare service provision process (see Figure 2). The receptionist robot, Xiaoyi, is used when a patient visits the hospital; The speech-based EHR system and imaging diagnostic system are used in the diagnosis process, for gathering patient information and in laboratory diagnostic testing respectively; "Yizhi", suggests diagnosis and treatment by interpreting information integrated from different sources.

AI robotic systems offering similar functions by other vendors are available in the market, except for Yizhi (see the last row of Table 5). Specifically, the Dragon Medical Speech Solutions can transcribe speech to text in EHRs (Nuance, 2018); The Watson Health Imaging system (IBM, 2018) launched in 2017 also inspects medical images and suggests diagnosis like iFlyTek's system; Softbank's Pepper Receptionist Robot had been used in two Belgian hospitals (BBC News, 2016). The existence of systems with similar capabilities in the market indicates that much of our findings can serve as a reference for other hospital organizations as they begin to implement AI robotic systems. There is much to learn from Anhui Provincial Hospital as it already uses AI robotic systems much more extensively in the healthcare process than many other hospitals. Nevertheless, it is important to note that more studies of systems offered by different vendors in different contexts are needed to establish the generalizability of the findings, especially when the focus is social informatics.

4. Analyses and Findings

4.1 Nature of Knowledge Embodiment (Research Question 1)

We followed the analysis approach outlined in section 3.2 (see Figure 1). We first analyzed the type of knowledge embodied for each knowledge work, embodied cognition, and transformation of knowledge work due to each AI robot, in the order of healthcare process shown in Figure 2. These analyses indicated four distinct forms of knowledge embodiment.

4.1.1 Analysis 1: Type of Knowledge Embodied

The type of knowledge embodied is identified by examining the knowledge needed for work by the respective AI robotic systems. The knowledge works enacted by AI robotic systems are reception of non-emergency patient visitors, editing EHR, diagnosing medical images, and determining treatment (see Table 6).

The hospital reception work involves advising patient visitors through the wide range of healthcare services and directing them to the relevant physician, while optimizing patient flow. The key problem addressed is "Which physician should this patient see and where to go *now*?" The appropriate solution depends on a patient's symptoms, as well as availability of physicians and medical facilities at the time a patient visits. The AI robot "Xiaoyi" embodies this *conditional* knowledge) and is designed to complete reception work by itself without human reception nurses' intervention (see Table 6). A reception nurse described during an interview*:*

"When inquired, Xiaoyi can give timely feedback or ask the visitor for more information and recommend the relevant doctor according to the patient's symptoms."

In editing EHR, the AI-based EHR system takes over nurses' task of transcribing physicians' spoken assessment of patients' condition from speech to structured text. The work task addressed by the robotic system is primarily linguistic, that is, "what does a speech sound mean in a language"? The type of knowledge embodied in the EHR system is thus *declarative*, since a language is essentially a set of symbols and grammar rules. A nurse using the system regularly explained during an interview:

"The speech-based system can process spoken language very well and is more natural and efficient than keyboard entry. This is the main reason some nurses prefer the speech-based system."

The work of diagnosing medical images focuses on determining an accurate laboratory diagnosis. The diagnostic process involves three basic steps: visually inspecting images to identify anomalies (visual perception), rendering an interpretation (cognition), and reporting the concluded diagnosis to physicians (Krupinski, 2010). The AI-based imaging diagnostic system can carry out the first two steps and suggest potential diagnoses for radiologists' consideration before reporting to physicians. The knowledge embodied is *procedural* rather than declarative, since the system needs to go beyond knowing what abnormalities look like to analyze and then infer potential diagnoses indicated by them. During a demonstration of the system, a radiologist described the process through which the system works:

"Like a human radiologist, the system first needs to acquire medical images through a CT scanner. This is followed by visual inspection of the images to identify anomalies. The system then quantifies the anomalies in a preliminary report for the radiologist."

A physician's work of diagnosing and determining medical treatment requires knowledge that is *teleological*, considering that getting treatment is the key purpose of a patient's hospital visit. The AI robot "Yizhi" addresses the problem of "how should this patient be treated?" by integrating and analyzing a patient's medical history, laboratory diagnosis, and clinical examination, as well as an enormous collection of medical cases treated by other physicians, to recommend potential medical diagnoses and treatments to the physician. A physician who had used Yizhi commented that:

"Yizhi is like a junior doctor qualified in clinical training and recommending diagnosis but should work under the supervision of a more senior physician."

Table 6. Type of Knowledge Embodied in AI robotic systems

Knowledge Work and AI Robotic System Employed	Work/Task Done by AI Robotic System	Type of Knowledge Embodied
Advise patient visitors through healthcare services and optimize patient flow: “Xiaoyi”	Recognize human (e.g., patients’) speech queries in natural languages, direct patients to the relevant physician while optimizing patient flow and utilization of treatment facilities, accompany patients to the relevant area/room	Conditional: Which physician should a patient see and where to go *now*?
Edit EHR: Speech-based EHR system	Recognize and convert human speech sound into structured text entries in EHR	Declarative: What does a speech sound mean in a language?
Diagnose medical images: Medical imaging diagnostic system	Visually analyze medical images and then suggest laboratory diagnosis	Procedural: What laboratory diagnosis is indicated by a set of medical images?
Determine treatment: Medical diagnostic and treatment assistant robot, “Yizhi”	Suggest medical diagnosis and treatment by interpreting information integrated from various sources	Teleological: How should a patient be treated?

4.1.2 Analysis 2: Embodied Cognition and Relationship between Embodiment and Human Cognition

Embodied cognition theories are useful for understanding the effects of embodiment in AI robotic systems on human’s cognition. The receptionist robot “Xiaoyi” accounts for patient-specific and time-sensitive information in its work, such as a patient’s symptoms and the availability of physicians and medical facilities at the time a patient visits. It thus has an enactive effect (see Table 7), that is, acts to affect patients in a situation-appropriate way, based on embodied cognition theories (see section 2). A reception nurse provided examples of the robot’s usage during an interview:

> *“The robot can handle queries independently and respond to questions such as ‘I have a headache and have been feeling dizzy. Which doctor should I see?’ by prompting for further information and suggesting the relevant department and available doctor to see…many visitors now skip the human reception desk.”*

The speech-based EHR system reduces physical effort (of typing) rather than cognitive effort. Therefore, it is not relevant to consider the system in terms of embodied *cognition* theories (Barsalou, 2008; Glenberg et al., 2013). A nurse who regularly uses the system identified its key benefit during an interview:

> *“The system mainly reduces the need for typing and helps us save a lot of effort and time.”*

The medical imaging diagnostic system affects human workers' (i.e., radiologists) cognition by sharing some of the cognitive load of diagnosing images (i.e., visual inspection, identification, and quantification of anomalies), and thus has a scaffolding effect. A radiologist elaborated this during an interview:

"We often take tens of minutes to inspect a set of CT scans. Now the imaging diagnostic system does the visual inspection for us within seconds and can easily identify nodules that are difficult to detect with naked eyes.

Yizhi not only analyzes information related to a patient, but also integrates information from other medical cases treated by other physicians. This increases the knowledge and experience available to a physician, and thus has an "extended mind" effect based on embodied cognition theories. An engineer involved in the development of Yizhi described:

"Yizhi has 'learned' from an enormous amount of medical textbooks, clinical guidelines, and medical cases. It can provide physicians with the fuller medical knowledge and experience needed for diagnosis."

Table 7. Embodied Cognition

AI Robotic System	Effect of Embodiment on Human Cognition
Receptionist robot, "Xiaoyi"	Enactive – cognition is embodied in a robot to act in a situation-appropriate way
Speech-based EHR system	Not applicable. Robot reduces physical effort rather than cognitive effort
Medical imaging diagnostic system	Scaffolding – cognitive load is distributed to a robot
Medical diagnostic and treatment assistant robot, "Yizhi"	Extended Mind – cognition is complemented by other physicians' knowledge and experiences of other medical cases

4.1.3 Analysis 3: Transformation of Knowledge Work

Xiaoyi accomplishes knowledge work autonomously, working as one of the reception nurses (rather than just taking subtasks of a work), thereby reducing the workload of other human reception nurses. We label this effect of AI robotic systems reducing human workload as "actuation" to capture the notion of robots completing an identifiable instance of work. A reception nurse noted during an interview:

"After the robot is implemented, we get less visitor inquiries even though the number of visitors has been increasing."

The speech-based EHR system changes nurses' work by allowing them to verbally update EHR instead of typing, thereby reducing physical effort (rather than cognitive effort). We label this effect of AI robotic systems on the physical effort of work as "automation" (see Table 8). A nurse regularly using the system commented during an interview:

"The system has eliminated most of the typing needed to update an EHR…even for corrections, we could use speech input instead of typing."

The imaging diagnostic system greatly reduces the cognitive effort needed for the work of laboratory diagnosis by scanning through a large number of images and shortlisting the potential diagnoses for radiologists. We label this effect of AI systems reducing the cognitive effort for knowledge work as "assistance". A radiologist explained during an interview:

"The system helps with the mentally demanding parts of a diagnosis…that is, visually identifying anomalies and quantifying them…the final diagnosis is still decided by the human radiologist."

Yizhi goes beyond reducing workload to enhance a physician's work by providing access to and integrating a large amount of other physicians' experience and knowledge. This boosts the work of human physicians in a way that is difficult or even impossible to achieve without the robot. We label this effect of AI robotic systems enhancing knowledge work in unprecedented ways as "augmentation". An engineer involved in the development of Yizhi highlighted:

"The robotic system can "learn" much more knowledge…and process a large amount of data to recommend diagnosis much faster than a human [physician], in the matter of seconds…These are very difficult for humans to achieve."

Table 8. Transformation of Knowledge Work

Knowledge Work and Robotic System Employed	Effect of AI Robotic System on Work
Advise patient visitors through healthcare services and optimize patient flow: "Xiaoyi"	Actuation: *Reduces* human *workload* by autonomously completing work
Edit EHR: Speech-based EHR system	Automation: Reduces the *physical effort* of human work
Diagnose medical images: Medical imaging diagnostic system	Assistance: Reduces the *cognitive effort* of human work
Suggest diagnosis and treatment: "Yizhi"	Augmentation: *Enhances* human *work* by integrating experiences of other knowledge workers/ experts

Overall, these findings indicate that AI robotic systems eliminate routine, repetitive, time-consuming, and tedious tasks/works that are loath to knowledge workers and allow them to focus on more meaningful and high-order work. Specifically, reception nurses now conducts the "training" work, teaching Xiaoyi to answer more and varied queries with better accuracy based on their experience and intimate understanding of patient needs. Freed from the burdensome tasks of integrating information from different sources and backed by experience drawn from an enormous collection of medical cases, physicians can now focus more on the “communication” work, explaining diagnosis and treatment to patients, and engage with them on a deeper, more compassionate level, improving the human touch in physician-patient relationship.

4.1.4 *Findings: Four Forms of Knowledge Embodiment*

The preceding analyses indicate four forms of knowledge embodiment in AI robotic systems, each with a distinct focus. “Expediting” involves embodying *declarative* knowledge to *automate* work (i.e., reduce human workers’ physical effort); “Equipping” is embodying *procedural* knowledge to *scaffold* human cognition, thereby *assisting* work (i.e., reduce cognitive effort); “Emancipation” refers to embodying *conditional* knowledge to *enact* human cognition, thereby *actuating* human work (i.e., reduces workload by completing work autonomously); “Expansion” involves embodying *teleological* knowledge to *extend* cognition, thereby *augmenting* human work. It is important to note that these four forms of knowledge embodiment are not meant to be mutually exclusive categories. Instead, they seek to highlight the distinct focus of different forms of knowledge embodiment. To illustrate, while Expansion could be used to automate work, the resultant AI robot is likely to be unnecessarily complicated; Expediting would not be sufficient for knowledge work that requires conditional knowledge.

4.2 Knowledge Embodiment’s Effects on Connections among People and AI robotic systems (Research Question 2)

As outlined in section 3.2, we followed the STIN analytical strategy for social informatics (Kling et al., 2003; Meyer, 2006) to understand connections among people and AI robotic systems. We analyze multiple social actors and take a critical orientation to avoid technological determinism. The key findings are discussed next.

Analysis of relevant social actors in each knowledge work indicates that different forms of knowledge embodiment connect human workers and AI robotic systems differently. In the work of advising patient visitors, the “emancipating” AI robot Xiaoyi is embodied to work as if it is one of the human reception nurses. Other than reception nurses, patient visitors are also aware of its presence and interact with it directly. We call this role of AI robotic systems relative to humans “competitor”, because technically this form of knowledge embodiment can substitute humans (see Figure 3a). Although Xiaoyi is technically capable of interacting and handling inquiries like a human reception nurse, we observed that many patient visitors did not yet perceive Xiaoyi as an equivalent of human nurse. For example, a male patient visitor aged 28 noted during an interview that it was “fun” to use Xiaoyi, which is an emotion that is rarely associated with human reception nurses:

“Xiaoyi is quite fun to use. It is also very convenient”

Some patient visitors also expressed distrust of Xiaoyi when compared to a human nurse:

"I doubt robots can replace human nurses…they work based on algorithms. I can't trust them." – male patient visitor aged 36

"The robot is quite smart and can answer quite a lot of questions…but I am not sure whether the answers are correct." – male patient visitor aged 34

To demonstrate Xiaoyi's ability to work independently and promote its usage by patient visitors, the hospital plans to organize a "No-Reception-Nurse Day" during which only receptionist robots would be available at the reception desk in 2018.

In editing EHR, "expediting" with the speech-based system affects human nurses through *division of labor* (see Figure 3b). We label this role of AI robotic system relative to human workers "cooperator". The presence of a cooperator is not apparent to social actors other than the actor it automates, as patients did not interact with the system directly and were not aware that nurses were using the system. Not all the nurses were using the system, as it was not mandatory. One reason for not adopting the system is the lack of awareness of its usefulness, as a nurse who had worked more than five years in the hospital recalled her experience leading towards adoption during an interview:

"I didn't pay much attention to the system. I didn't have time to explore…I started using it only after seeing another nurse use it… It was then I realized how convenient and useful it is."

The head of the hospital's information department also noted:

"People are busy and we don't want to force them to use the system…we try to demonstrate and promote the system whenever there is an opportunity…most people who have opportunity to see how useful it is say they want to start using it."

This suggests that the adoption of cooperator systems are inhibited by the lack of awareness rather than resistance.

In diagnosing medical images, the "equipping" system work together with human radiologists to *construct a shared conception* of a problem (i.e., laboratory diagnosis). The AI system's presence is clear to radiologists, but not to the other social actors (i.e., physicians and patients). We label this role of AI systems as "collaborator" to capture the idea that it goes beyond the division of labor (see Figure 3c). Radiologists appreciate the "collaborator" and find it easy to work with. A radiologist who had worked more than ten years in the hospital expressed during an interview:

"It's like having someone to help…a pair of eyes that focus on inspecting the images…while I confirm the analysis and determine the final diagnosis."

When asked about the difficulties or challenges of using the system, the radiologist commented:

"Not much. The system feels quite intuitive and not much learning is needed."

In determining medical treatments, the "expansion" system Yizhi works with human physicians as if it is an associate, as a physician commented during an interview:

> *"The AI robot works as well as an associate physician. It cannot take over the work of communicating with patients. The final medical diagnosis and treatment are still decided by human physicians."*

The presence of Yizhi is apparent to not just human physicians, but also patients. It is embodied as a human-like organismoid and "listens" to the conversation between the physician and patient in clinical examinations (see Figure 3d). An engineer involved in the robot's development explained:

> *"Yizhi is a physician's clinical assistant, focusing on supporting physicians in clinical diagnoses and treatments."*

AI robotic systems are viewed by patients as useful for seeking second opinions:

> *"I am already undergoing treatment, but it would be good to get a second opinion from a more objective robot physician, just to make sure."*

We name this role of AI robotic systems "coopetitor". They are competitors to human physicians to the extent that they are viewed as alternative physicians offering second opinions. At the same time, they cooperate and augment the work of human physicians by suggesting treatment options based on an enormous database of medical cases and knowledge. Most doctors interviewed acknowledge the augmenting benefit of Yizhi and agreed that it could compete with human physicians in some cases, but also resisted the idea that it could displace physicians. A physician who has worked in the hospital for more than ten years explained during an interview:

> *"For simpler, more common diseases, Yizhi works quite well. However, for more complex cases that are clinically difficult to diagnose, Yizhi will need more work to close the gap."*

This suggests that in its coopetitor role, Yizhi's performance could depend on its ability to "learn" new knowledge continuously.

Although Yizhi does not interact directly with patients, there is some indication that it can improve the physician-patients interaction, as the physician noted:

> *"The system increases efficiency and allows me to spend more time focusing on the patient and giving more humane care."*

In sum, the social informatics analysis leads to four salient socio-technical concepts (Kling et al., 2003) that describe the connections among human workers and AI robotic systems: cooperator, collaborator, competitor, and coopetitor. Among them, competitors and coopetitors have the greatest social impact in that multiple social actors are aware of their presence, and their organismoid form renders them as one of the social actors in knowledge work, rather than simply a technology tool used by human workers.

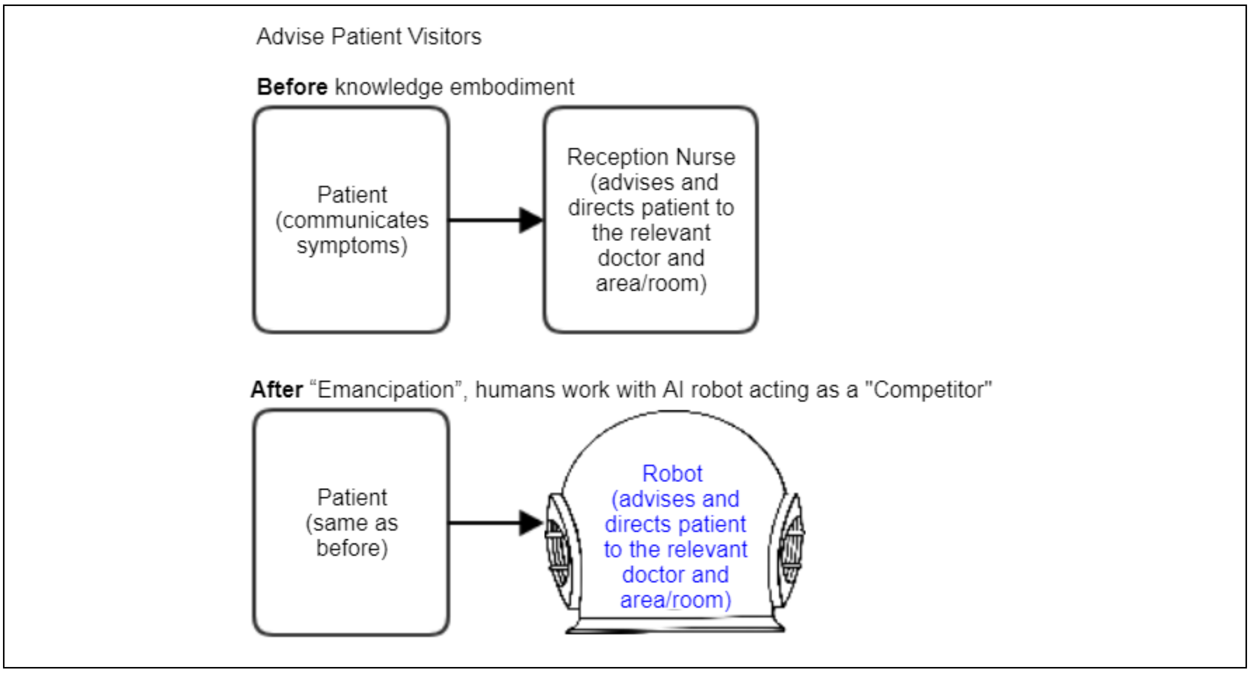

Figure 3a. Change to Social Actors due to Knowledge Embodiment (KE) in Advising Patient Visitors

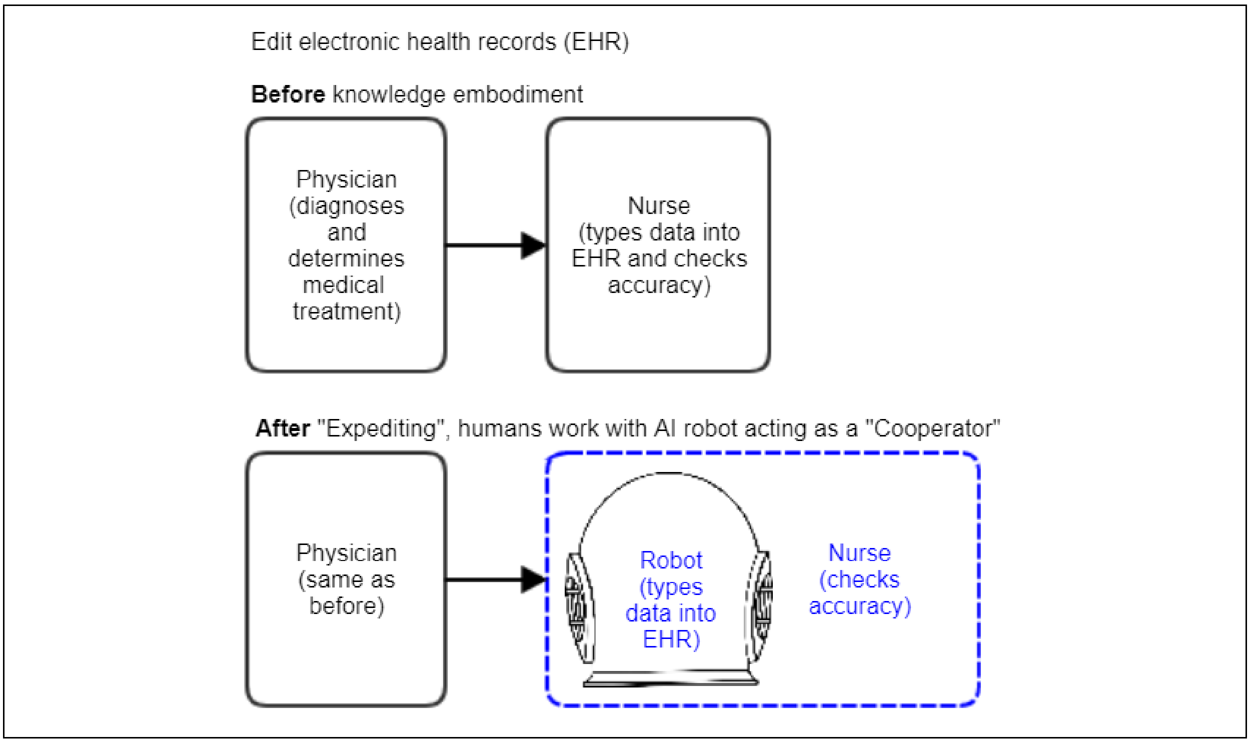

Figure 3b. Change to Social Actors due to KE in Editing EHR

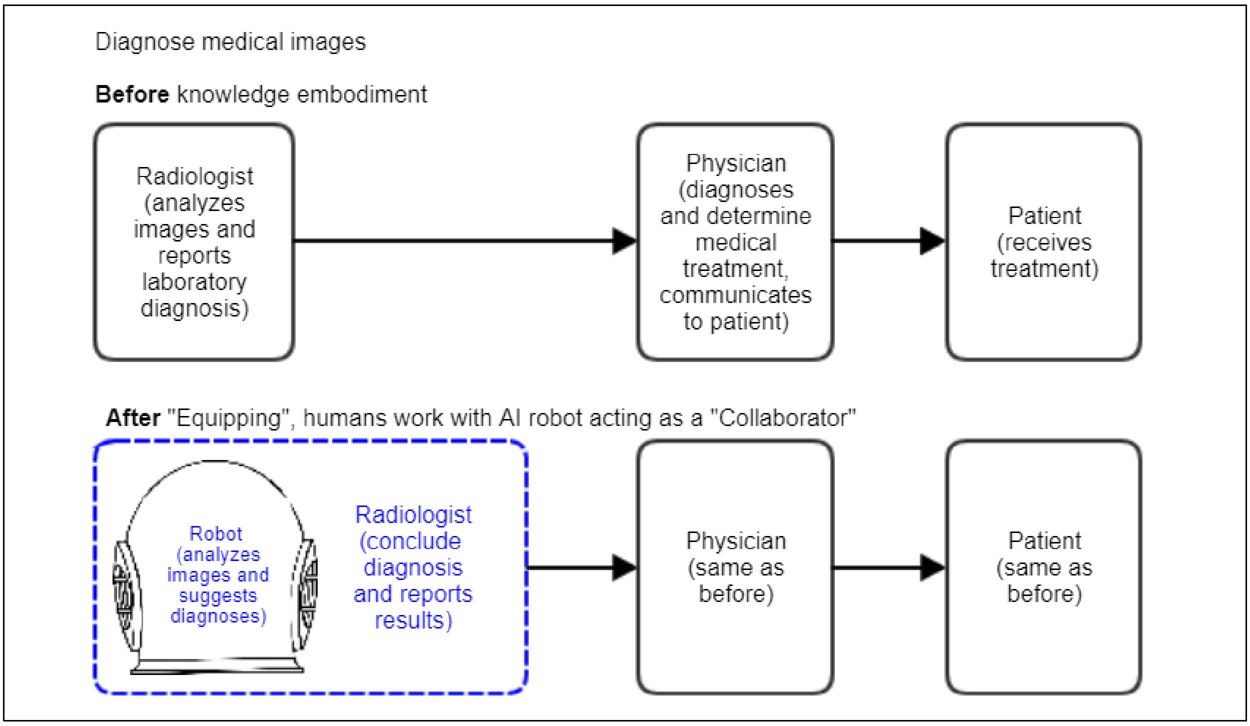

Figure 3c. Change to Social Actors due to KE in Diagnosing Medical Images

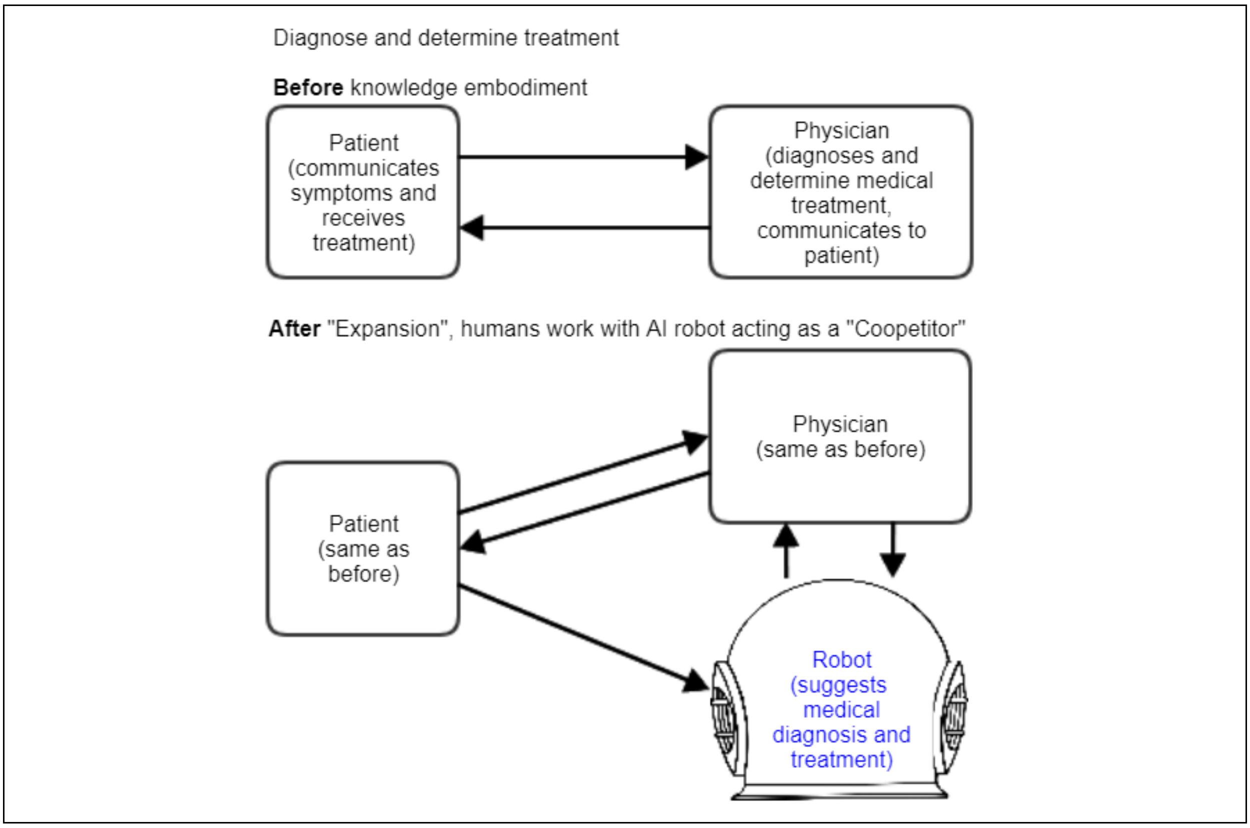

Figure 3d. Change to Social Actors due to KE in Diagnosing and Determining Treatment

Following STIN, a key system design choice point matching robot design to socio-technical characteristics indicated by our analysis is the notion of “body”. Embodied AI research has identified four notions, namely, physical realization, physical embodiment, organismoid embodiment, and organismal embodiment (described in section 2; Chrisley, 2003; Ziemke, 2001). “Competitors” and “coopetitors” take the role of a social actor and interact with multiple social actors and therefore tend to require at least organismoid embodiment. In the case study, Xiaoyi and Yizhi are both human-like organismoid that have some distinctly human characteristics, including eyes, limbs, ears, and the ability to move in physical space (see *Table 9*). In contrast, “cooperators” and “collaborators” take up subtasks and work with a single social actor. Embodiment in the form of physical embodiment tends to be adequate. In the case study, the “cooperator” speech-to-text EHR system manifests as an app that is installed on a physical mobile device; The medical imaging diagnostic system consists of a collection of computer hardware and AI software with a logical and well-aggregated structure. They are thus more than physical realization and are instead instances of “physical embodiment”.

Table 9. Notions of Body Manifested in AI robotic systems

AI Robotic System	Notion of “Body”
Receptionist robot, “Xiaoyi”	Organismoid (human-like)
Speech-based EHR system	Physical embodiment
Medical imaging diagnostic system	Physical embodiment
Yizhi	Organismoid

STIN also suggests exploring other social actors. Our analysis revealed that it is also important to consider the robotics technology provider, iFlytek, and the press covering AI topics. There has been much media speculation on AI robotic systems displacing human workers, including medical professionals. To alleviate related concerns in Anhui Provincial Hospital, iFlyTek proclaim that the medical AI robotic systems were developed as human-in-the-loop systems that support rather than displace human workers, in regular meetings within the hospital as well as press releases. The head of iFlyTek-hospital collaboration explained during an interview:

> *“Our intention has never been to replace human physicians with robots… For a comprehensive discipline like medicine, we hope Yizhi can be a helpful assistant to physicians, providing them with up-to-date medical knowledge and diagnosis recommendations.”*
>
> *“Experienced physicians can hardly be replaced. The intention of developing Yizhi is to improve the performance of junior physicians, while allowing experienced physicians to devote more time and energy to high-value work.”*

5. Limitations and Implications for Research and Practice

This study has several limitations that present opportunities for further research. First, in this case study we focused on analysing the use of AI robotic systems developed by iFlyTek in Anhui Provincial Hospital. To establish the findings' generalizability, more studies are needed to examine systems developed by other vendors (e.g., Watson Health Imaging system) and their use in different hospital organizations. We conjectured that our analysis of the type of knowledge embodied (see analysis 1) is applicable to other similar systems as they function similarly. However, more field studies of healthcare professionals and patients are needed to collect data and understand whether our findings in other analyses (e.g., transformation of work) are applicable to systems developed by other vendors and hospitals. Second, in our social informatics study of knowledge embodiment, we focused on AI robotic systems and did not consider other entities such as electronic repositories. Technically, AI robotic systems have the potential of altering the use of other entities or even superseding them, though this has not occurred in our case study. Further research may compare knowledge embodiment in different entities to understand how they complement or substitute one another. Third, we have not examined knowledge workers' motivation to use or work alongside AI robotic systems. The four forms of knowledge embodiment we identified can be the generative basis for identifying relevant motivators. Understanding the motivation should contribute towards a more comprehensive theorization of knowledge embodiment.

Addressing the first research question, we identified four distinct forms of knowledge embodiment (i.e., expediting, equipping, emancipation, and expansion). For the second research question, we found four ways knowledge embodiment affects social connections among people and AI robotic systems (i.e., as cooperators, collaborators, competitors, or coopetitors). Our findings are summarized in Figure 4. These findings add new insights into research on how robotic systems could reconfigure relationships among people and technology (Barrett et al., 2011). Our study extends the findings of prior studies by analyzing the use of multiple robotic systems within an organization, including systems that work autonomously.

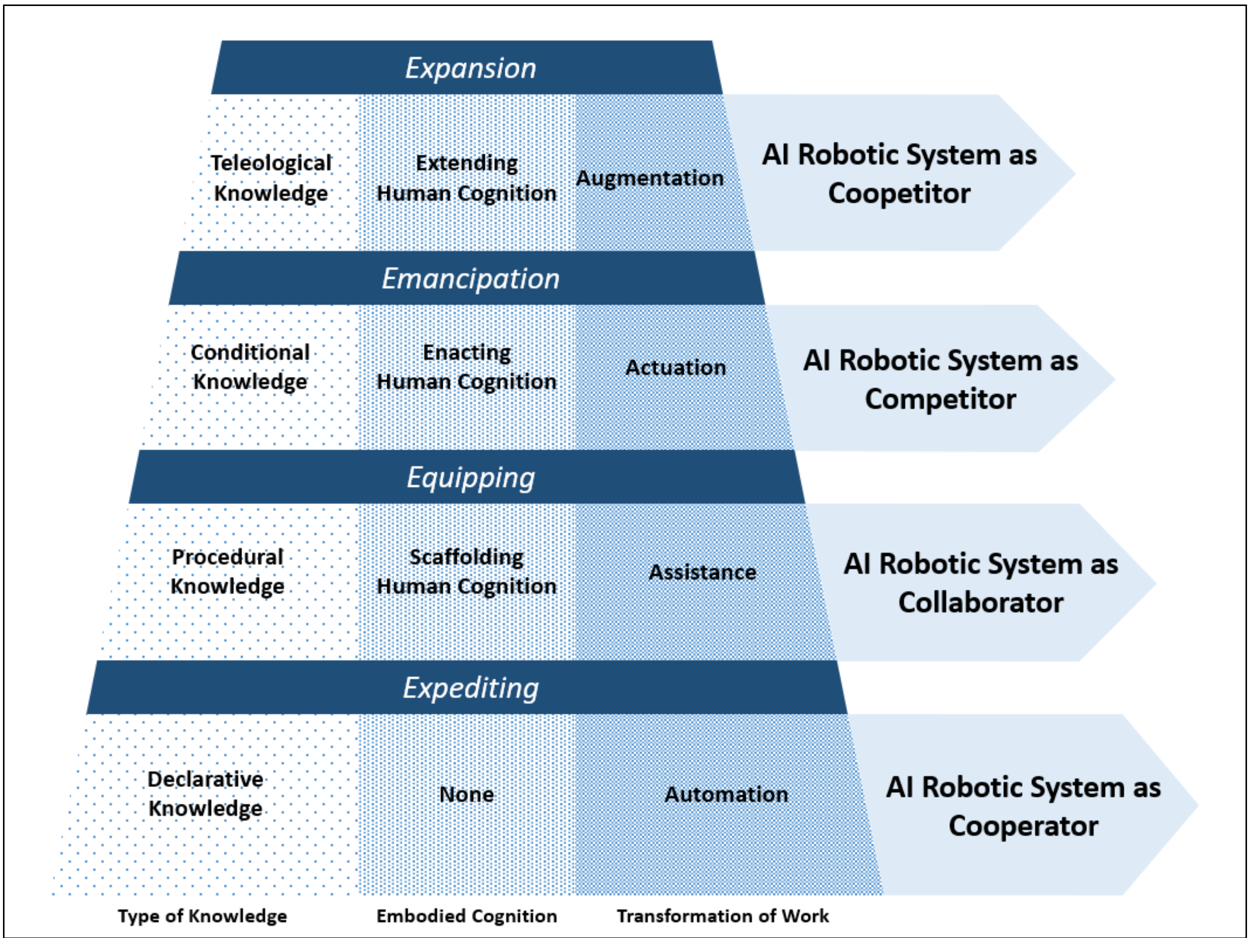

Figure 4. Overview of Findings on Social Informatics of Knowledge Embodiment

This study contributes to research on knowledge management, social informatics, and information science in several ways. First, the four forms of knowledge embodiment are useful for further research on the topic, addressing perennial questions such as: How does knowledge embodiment affect work performance or organizational performance? What factors influence the effectiveness of knowledge embodiment? These questions could not be meaningfully addressed with a black-box view of knowledge embodiment and the four forms of embodiment identified in this study provide a fertile ground for identifying relevant antecedent and performance factors.

Second, this study shows that the social informatics perspective is invaluable to our understanding of AI technology. AI technology mimics humans in many ways and understanding its social and institutional connections with people is essential for realizing its value. As demonstrated in this study, the STIN analytical strategy is especially useful as it provides a guiding framework for going beyond technology determinism and understanding technology from multiple social actors' perspective. For example, our STIN analysis indicated that AI robotic systems that work as competitors and coopetitors face more resistance from social actors than systems that work as cooperators and collaborators, even though they were all designed to improve people's work and performance. STIN analysis also revealed the peripheral yet important influence of the robotics technology provider. The provider fostered early adoption of AI robotic systems by highlighting their complementary and non-threatening nature to relieve the general apprehension of knowledge workers. This study shows that the social informatics perspective is not just applicable, but necessary to our understanding of the use of AI robotic systems in knowledge work.

Third, this study contributes to the social informatics perspective and extend prior findings (Sawyer, 2005) by identifying that advanced technology like AI robotic systems can go beyond being a tool used by humans to become a more active, autonomous social actor. As human-computer interface becomes more natural and intuitive and AI robotic systems become more human-like, the human-technology distinction could fade. This could require further development of the concept of connections in social informatics as human-human connections and human-technology connections converge.

Fourth, our findings indicate new research questions for information science researchers. Knowledge embodiment transforms knowledge work and is likely to change or create new information practices. For example, in the case study, reception nurses' work was transforming to focus on "training" Xiaoyi to handle a greater variety of queries, make fewer errors, and perform better. This training work may require new ways of collecting, analyzing, and managing information at work, which could be further investigated as information science researchers understand the implications of artificial intelligence.

Also, knowledge embodiment affects knowledge workers socially (e.g., as coopetitors) and human workers increasingly need to work alongside robots. The resultant change in organizational structure is likely to affect information flow. For example, the coopetitor robot Yizhi integrates information from difference sources (e.g., patient history, laboratory diagnosis) and eases the human physicians' task of managing different information flows. Yizhi also facilitates the flow of information from outside the organizational boundary, in terms of medical cases handled by doctors in other hospitals. The change to and management of information flows due to knowledge embodiment is a fruitful topic for further research.

For practice, the social informatics analysis highlights a design choice point for implementing knowledge embodiment in AI robotic systems: matching the notion of "body" (e.g., organismoid) to a robot's expected social role (e.g., coopetitor). A robot's social role can be determined by identifying the form of knowledge embodiment necessary for a particular knowledge work, through analyzing the type of knowledge to be embodied (e.g., procedural), intended effects of a robot on human cognition (e.g., scaffolding) and work (e.g., assistance). Coopetitor and competitor systems are likely to require more organismoid, human-like embodiment than collaborator and cooperator systems.

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