Human Information Interaction, Artificial Intelligence, and Errors

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Abstract

In a time of pervasive and increasingly transparent computing, humans will interact with information objects and less and less with the computing devices that define them. Artificial Intelligence (AI) will be the proxy for humans' interaction with information. Because interaction creates opportunities for error, the trend towards AI-augmented human information interaction (HII) will mandate an increased emphasis on cognition-oriented information science research and new ways of thinking about errors and error handling. A review of HII and its relationship to AI is presented, with a focus on errors in this context.

Introduction

Humans' interaction with information will only increase in the future and this interaction will likely be facilitated by artificial intelligent proxies. Because opportunities for errors most often occur at the intersections of system components, human or otherwise, the adoption of Artificial intelligence mechanisms will assuredly increase the amount of error that occur in information systems. The nature of these errors will likely manifest as latent errors and therefore be difficult to identify and resolve. Additional research in human information interaction (HII) is necessary and can positively improve the development of artificial intelligence innovations. By furthering our understanding of humans' interaction with information objects, HII research can provide advances in both the human and machine domains. Insights from this research will be necessary to understand errors that result from the actions of humans and artificial intelligence.

Often confused with human computer interaction (HCI) and human system interaction (HSI), human information interaction has a similar but distinctly differenced nuance from those other fields of study. HCI is a discipline concerned with the design, evaluation, and implementation of interactive computing systems for human use and with the study of major phenomena surrounding them (ACM SIGCHI, 1992). Similarly, HSI is defined as end user or customer interaction with technology-based systems through interaction styles or modalities such as reading, writing, touch, and sound (Chang and Bennamoun, 2012). Given these definitions, it is clear to see that the emphasis of both HCI and HSI is not on information, even though those phenomena form a foundational basis for both computers and systems. Information is the nuanced difference between HII and HCI/HSI. HII is the field of study that is concerned with how and why humans use, find, consume, and work with information in order to solve problems, make decisions, learn, plan, make sense, discover, and carry out other tasks and activities (Sedig and Parsons, 2015). It might be argued that HCI and HSI are supersets of HII, but the focus on humans' interaction specifically with information, as opposed to the computer platform, interfaces, and surrounding processes marks a significant differentiation, particularly critical for information systems. Information systems deal with symbolic or information-centric representations of reality. Figure 1 shows Liu's semiotic framework (Liu, 2000) that is synonymous with an information system.

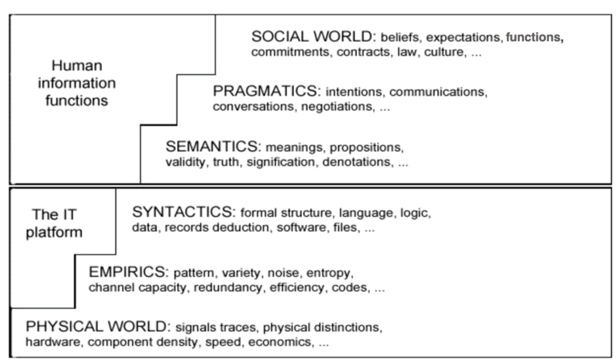

Figure 1. Semiotic framework (Liu, 2000)

Explicitly missing from Liu's framework, but implied in "the IT platform," is the processing layer that must exist to map from the information technology to the human. Within an information system, it is this processing layer where artificial intelligence (AI) finds its contributed value added. The implementations of AI are characterized by symbolic processing, non-deterministic computations, and knowledge management. Subsequently, innovations in AI are moderated by the advances in HII that directly impact the interdependence existing between humans and the AI-enabled information systems supporting them. When inconsistencies in that fundamental balance occur, errors may be generated. Nowhere is this balance more critical than in information processing environments.

The amount of complexity in the use of information has surpassed the intersection of simple computation and human's need for analytics. This has resulted in the emergent HII field of study; examining autonomous and computationally-aided problem solving within activity-context. The complexity of HII demands interoperability and compatibility between mixed initiative processes for information acquisition and processing in context to aid comprehension by humans' use of information. Artificial intelligence innovations are one of the primary means to automate and aid interaction with information.

This paper presents a contemporary overview of HII and discusses the need for research in this field of study that necessarily investigates the implications of AI and human error. It provides a background on HII, considers artificial intelligence and information processing, analyzes how the convergence of HII research and AI will require new notions of errors, and finally identifies potential research areas that are important to advancing human information interaction and artificial intelligence for error mitigation.

Human Information Interaction

The general trend towards pervasive computing will naturally result in less focus on computing devices and the boundary between them and humans' access to the benefits they provide. Consider how people think of their desktop order laptop computers and contrast this view with tablets and cellphones. The mobile devices are still computers in the same context as the desktop, just more portable. When this contrast is thought of in the context of cloud computing, the diminishing emphasis on computing devices and increasing spotlight on information or information objects becomes blatantly apparent. Further blurring of the device-information distinction will only continue, as the pervasiveness of computing and information continue to dissolve the barriers between the physical world (Limkar et al., 2016; Barnaghi et al., 2015; Bolotin, 2015; Wiberg, 2015).

The commercialization of the Internet of Things marks the marketization of the focal transition away from human computer/machine/system interaction to humans' information-centric interactions (Soldatos, 2015). This perspective makes sense, because the world is an integral whole in which the things that exist in it are interdependent; not a collection of distinct elements isolated from each other (Fidel, 2012). Moreover, information is arguably ubiquitous now and will only become more so in the future as the commercialization of Internet "things" continues to cross boundaries of business, physics, biology and other fields of science. Thus the convergence of fields of study, already interdisciplinary in nature, mandates a similar concentration on topics of human information interaction.

Gershon (1995) was the first to establish the phrase "human information interaction" when examining HCI research, differentiating the label as placing more focus on "how human beings interact with, relate to, and process information regardless of the medium connecting the two." Marchionini (2008) extends this notion to suggest that human information interaction (HII) shifts the foci of all aspects of information work; blurs boundaries between information objects, technology, and people; and creates new forms of information. This is a significant departure from human computer (HCI) or human system (HSI) interaction, which considers technology more broadly and places equal emphasis on physical aspects of interaction.

When considering HII, it is important to have functional definitions for the terms: human, information, and interaction. From a definitive perspective human is the best understood… it is us: individuals and people. Relative to HII, humans are the individuals or people who interplay with information and its related environments. Often considered "users" of information systems (Dervin and Reinhard, 2006), humans fulfill the role of "actors" when their scope of examination includes tasks (Lamb and King, 2003; Match, 2002). When the interdependence of the world is factored into the definition of human, it is important to think of the second order effects, where community of actors, teamed or seemingly operating independently impact one another through their information-centric functions. Therefore, in this sense, humans include cooperative and non-cooperative individuals and teams; bound by the scope of information.

Within HII, both human and information must be considered as nouns and therefore information is considered a "thing" of a physical nature. This is consistent with the bit-based form of information, as defined by Shannon (1948). Although a distinct and formal definition of information has been and remains the subject of extensive philosophical debate, when the physical definition of information is adopted anything that is experienced by humans (sight, sound, taste, smell, and feel) can be considered information. Within HII, this physical definition is extended to give information context within the human experience. Therefore, information (Buckland, 1991) can be thought of as a symbolic representation that has meaning, is communicated, has an effect, and is used for decision making. Meaning implies some degree of understanding. Communicated requires transmission (not necessarily receipt). Effect mandates acknowledgement in the minima and action in the maxima. Decision making signifies purpose, relative or not (Fidel, 2012). These requirements for the definition of information give information-objects state within HII.

Interaction is the actionable (verb) part of HII, being defined as the activity that involves both parts, humans and information. The nature of interaction extends beyond the concept of interface, which is merely the doorway to true interaction. Given this distinction, interaction is the interplay between different components (humans and information in HII), rather than a fixed and pre-specified path (Moore, 1989). This view of interaction is reasonable because there are degrees of interaction and humans can inject stochasticity into a process. Yet by omitting pre-specified paths, Moore's definition is too restrictive to hold in HII because information systems, where humans and information interact, often follow pre-specified (via a-priori programming) paths. Dourish (2004) offers a more applicable definition of interaction as: the what and the how of something being done; the means of by which activity is accomplished, dynamically, and in context.

It is this notion of dynamic activity or work that has found grounding in the HII literature. It is important to note that within HII there is an implicit understanding that information already exists, does not need to be "created," and that it is being transformed from one state to another for the purposes of human interaction and comprehension. This orientation on work allows HII to apply notions of Shannon's (1948) information theory to second order concepts such as uncertainty, context, causality, and reasoning. We note that a purely quantitative approach to information is far from satisfactory. The small message criterion (Moskowitz, et al., 1994) shows the danger of relying on solely bit counting measures of information leakage. As way of example, consider the ride of Paul Revere. One bit of information was enough to tell the Colonialists that the British were coming (one if by road, two if by sea). Furthermore, in Moskowitz et al. (2002) the use of bit counting metrics of hidden images is also shown to be lacking due to the way the human mind interprets images, already noisy images. Allwein (2004) attempted to give a qualitative framework of Shannon-type theories. This paper was the first to marry Barwise-Seligman (Barwise and Seligman, 1997) approaches to Shannon's using the tools of channel theory from logic.

Despite some work applying Shannon's theories in logic and computational methods, applications of Shannon's information theory have found little traction, beyond an initial foray in the 1950's, within the psychology domain (Luce, 2003). Two notable early works illustrate the application of Shannon's theories to human information interaction. McGill's (1954) "Multivariate Information Transmission" and Miller's (1956) "The Magical Number Seven, Plus or Minus Two: Some Limits on Our Capacity for Processing Information" sought to address phenomena that bounded information capacity limitations, including absolute judgments of stimuli and short-term memory (Luce, 2003). The idea of the human mind being an information processing network with capacity limitations has remained as a concept in the literature (Marois and Ivanoff, 2005; Rabinovich et al., 2015; Serruya, 2015), but these works view the human mind and its processes in more complex ways than pure information theory as quantitatively defined by Shannon. British mathematician Devlin (2001, p. 21) points out the seeming inapplicability of Shannon's information theory to complex psychological concepts and research by minimizing the notion of information to simply data:

> Shannon's theory does not deal with "information" as that word is generally understood. Instead, it deals with data—the raw material out of which information is obtained.

The lack of confluence between information theory and psychology is readily apparent in Skilling's (1989) book on Entropy and Bayesian methods. Table 1 summarizes the book's table of contents. Noticeably missing are any topics involving human or cognitive applications. If information is something that the human mind commonly interacts with and Shannon's theory is the grounding for one side of that interaction, more occurrences of Shannon's theories should appear in the psychology literature.

Topic	No. Articles
Statistical fundamentals	17
Physical measurement	6
Time series, power spectrum	6
Thermodynamics & quantum mechanics	5
Crystallography	5
Astronomical techniques	3
Neural networks	2

Table 1. Summary of topics (adapted from Luce, 2003)

We have discussed two important situations where Shannon's information theory is lacking: one is using channel capacity as a metric for information knowledge, and the other is the use of Shannon theory in the psychological sciences. Moreover, there is ample evidence in the literature. Shannon himself warned of the shortcomings of his information theory, and cautioned researchers in his famous and short Bandwagon paper (Shannon, 1956). The incompatibilities between Shannon's quantitative information theory and our understanding of human cognition underscore the need for further fundamental research in HII. Moreover, current work in HII often avoids, or obfuscates, the processing layer between the information and humans.

Our understanding of HII would seem to be in its early stages. Yet advances in computational and the information sciences are driving humans' dependence on and use of information at an accelerating pace. The speed of this trend is readily apparent in the prevalence of information analytics and processing. Assuming that all of the information in the world is already in existence and only requires contextual transformation to make it "interactable" with humans, processing is essential and particularly critical. This processing is the domain of modern artificial intelligence research.

HII and Artificial Intelligence

Artificial intelligence (AI) is a program, which in an arbitrary world, will cope no worse than a human (Dobrev, 2005). While clearly denoting AI as a "program," this definition sets the standard as being bounded by a human reference. Given the range of all AI definitions, and there are many, they all consistency frame AI as a proxy for humans. Thus, HII research is relevant for not only AI but also the relationship that AI has with true humans. Wah (1987) characterizes AI processing as requiring symbolic processing, deterministic computations, dynamic execution, parallel processing, open systems, and knowledge management. While HII as a field of study was not given much thought at the time of Wah's work, his description of AI is indicative of the necessary processing to facilitate humans' interaction with information. Wah (1987) points to knowledge management as an important element of AI as a problem reduction requirement.

Due to its inherent complexity AI problems demand significant computational power and complex problems require exceedingly large amounts of useful knowledge (Du and Pardalos, 2013). Advances in AI allow increasingly difficult reasoning problems to be addressed (Bond and Gasser, 2014; Nilsson, 2014) and advanced cognitive activities, such as those that exist in naturally in the human brain represent some of the most difficult reasoning problems to artificially re-create.

Learning and adaptation are critical capabilities for both AI and HII and it is in these areas where the two fields find a significant overlap. With the advance of big data analytics and the overwhelming prevalence of available information, machine learning has emerged as a trendy method of giving humans greater interaction with information and a driver for increased innovations in AI. As an example, content analysis, a fundamental activity in HII, employs a myriad of machine learning approaches to enable artificial intelligence to perform content analysis in volume and autonomously. General definitions of machine learning focus on the design and development of algorithms to create reapplicable models based on generalizations from limited sets of empirical data in order to adapt to new circumstances and to detect and extrapolate patterns (Russell and Norvig, 2003). Therefore, machine learning is the way AI implements the human learning, reasoning and adapting functions relative to information in order to perform human-like tasks.

Artificial intelligence encompasses other areas apart from machine learning, including knowledge representation, natural language processing/understanding, planning and these areas also have overlap with HII, particularly when one considers work or activity context. The purpose of AI is often to automate HII for the purposes of decision making or work. However, no AI-enabled autonomous system is completely autonomous because at some point a human enters the loop. Ideally, at the end points of the autonomous functionality, the ultimate purpose of any contemporary autonomous activity is to aid or augment a human process.

Automation emphasizes efficiency, productivity, quality, and reliability, focusing on systems that operate autonomously, often in structured environments over extended periods, and on the explicit structuring of such environments (Goldberg, 2012). However, information environments vary broadly in terms of their structure, they form the rules and association of information objects that artificial intelligence operations act on (Stonier, 2012). In this manner, artificial intelligence is a proxy for humans in their interaction with information with the added dimension that humans interact with the artificial intelligence, essentially creating a recursive HII loop. AI interacts with information and humans interact with AI, which is itself information. This recursive relationship can both minimize and amplify opportunities for errors.

Ideally, an AI implementation delivers a seamless interaction with the information environment and the real world (in some cases) to accomplish humans' intent of all sorts. Because AI is driven by machines, the number of information transactions will be much higher than those generated by humans. As a proxy for humans, AI's interaction with information will similarly increase, if only in the encoding and translation of representations. Within the AI-proxy, there is a potential for errors in the interdependence between information and intent. Since system errors occur at the intersection of logic and data, increases in information interaction (human or otherwise) can increase the potential for errors.

HII, AI, and Error

Interaction is an opportunity for error and automation that increases interactions has the potential to increase errors. There is little insight in the revelation that people make errors when using information systems. Nonetheless, errors can be serious, both in the sense that they can lead to significant mishap and even physical harm, and in the social sense that they frustrate or inconvenience humans (Norman, 1983). Figure 2 illustrates classes of errors that result from interactions. From an information interaction perspective, regardless of whether the interaction involves humans or their AI proxies, the implications of the classification on error understanding, handling and mitigation apply. Referring to Figure 2, mistakes characterize the direct results of information interaction. Even slips mark the domain of AI outcomes, as well as human decision making resulting from information interaction. Moreover, as noted previously, humans are never completely removed from AI-enhanced automated processes. Thus, humans are always responsible for system disasters, if only because they are the visible element of system performance. While generalized notions of errors would spur debate about trust, blame, and culpability when errors are considered in the abstraction of information interaction and AI automation, the distinction of active and latent errors will become increasingly difficult to partition.

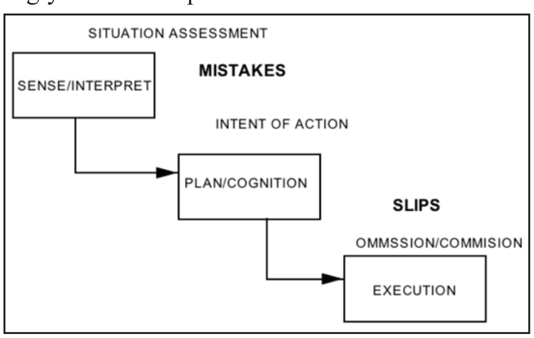

Figure 2. Classes of errors (Norman, 1983)

Active errors are those associated with the performance of frontline operators/actors and latent errors are those related to activities removed in time and/or space from the direct control interface (Reason, 1990). Moreover, active and latent errors in the context of information interaction and AI will conflate the two approaches to the problem of human fallibility: the person and the system. The person approach focuses on the errors of individuals, e.g. forgetfulness, inattention, moral weakness, etc. The system approach concentrates on the conditions under which individuals work (Reason, 2000).

Detailed analysis from recent accidents, many of which resulted in a loss of life and extensive long-lasting damage, have made it apparent that latent errors pose the greatest threat to the safety of a complex system (Reason, 1994). The amalgamation of the person approach and system approach will make error understanding and mitigation more difficult. Consider how errors in information interaction may be perceived or attributed when the device boundaries are dissolved and the information objects are given focus. Issues of misinformation, misuse, improper processing, and out-of-context alignment will increasingly be the norm. The promise of artificial intelligence will find its grounding in machine learning, which can obfuscate as well as enhance human information interaction. The susceptibility of machine learning techniques to their underlying information (data and distribution) cascades into the AI that depends on it and thus is transferred to the automation and humans that rely on it; manifesting as latent errors.

Conclusion

The lack of agreed upon definitions in the emergent HII domain presents a significant impediment to understanding the interdisciplinary complexity of the research area. However, the trending computational nature of all sciences (e.g. physics, biology, chemistry, etc.) will force the need for a better theoretical and practical understanding of HII. The idea of designing information as an activity, separate from the design of the machines containing the information will move beyond an emergent research area to one that defines not only information science, but other sciences as well. A world characterized by computation will drive the notion of “things” made from information and shift humans’ models of artificial intelligence and its application for autonomous and seamless work.

AI will be a key enabler as humans’ information interaction expands. Advances in AI will accelerate the need for fundamental research in HII. Increasingly fulfilling the role of humans, AI will not ever likely completely remover humans from information interactions. Thus, the interdependence between humans, AI and information processing will result in increased latent errors and conflation of system and person errors. It is not unreasonable to expect exceeding occurrences of latent errors in information system interaction, resulting from increased AI usage. Greater understanding of information interaction can reduce latent errors and potentially minimize interdependence between person and system approaches to fallibility.

This paper provided a review of HII and showed how AI is a proxy for humans in that context. The opportunity for AI to address (and potentially cause) errors will force the demand for new models of human error. Human information interaction is where the intersection of AI and human error will occur. Given these trends, increased research focus on applying Shannon’s seminal theories to psychological advances, providing theoretical grounding for HII, will be progressively important.

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