Information Systems for "Wicked Problems"

Research at the Intersection of Social Media and Collective Intelligence

The objective of this commentary is to propose fruitful research directions built upon the reciprocal interplay of social media and collective intelligence. We focus on "wicked problems" – a class of problems that Introne et al. (2013) call "problems for which no single computational formulation of the problem is sufficient, for which different stakeholders do not even agree on what the problem really is, and for which there are no right or wrong answers, only answers that are better or worse from different points of view". We argue that information systems research in particular can help to design appropriate systems due to benefits derived from the combined perspectives of both social media and collective intelligence.

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1 Relevance and Timeliness of the Topic for Business and Information Systems Engineering

Wicked problems (e.g., Churchman 1967, pp. B141–B142; Rittel and Weber 1973, pp. 155–169) are "problems for which no single computational formulation of the problem is sufficient, for which different stakeholders do not even agree on what the problem really is, and for which there are no right or wrong answers, only answers that are better or worse from different points of view" (Introne et al. 2013, p. 45). Many problems in management – including strategic decision-making, product design, and so on – are wicked in this sense, as are (unfortunately) most social and political problems, including "grand challenges" related to environment, health care, social welfare, education, and security (European Commission 2009; nA 2009; Mertens and Barbian 2013). We argue that there is a significant lack of appropriate information systems (and functionality) that contribute to addressing wicked problems successfully. More specifically and as an example, we may envision large-scale and function-rich information systems that support thousands if not hundreds of thousands of knowledge workers working simultaneously to solve wicked problems in close, cross-organizational collaboration. In a business context, IBM's Jam concept may serve as an early example of such a kind of information system (compare Bjelland and Wood 2008, p. 32). However, our envisioned large-scale information systems surpass the IBM system in their functionalities. The rich body of widely ranging social computing technologies that has emerged in the past few decades, is the informative basis for this quest; it includes (compare Klein 2012, pp. 449–473) email, chat, Web forums, wikis (e.g., Wikipedia), media sharing, open source software development efforts (e.g., Linux), solution competitions (such as Innocentive.com), idea-sharing systems (e.g., ideastorm.com), peer-filtering sites (e.g., Slashdot), group decision support systems (GDSS), and scientific collaboratories (Finholt 2002, pp. 73–107).

The central claim put forward in this research commentary is that research conducted at the crossroads of collective intelligence and social media can help us design appropriate information systems for wicked problems. The confidence that this claim can be met comes from recent advances in collective intelligence facilitated by the high level of participation of millions of people in social media environments.

"Social media" and "collective intelligence" have become research catchwords (see, e.g., Leimeister 2010, pp. 245–248). A search for "collective intelligence" in Thomson Reuters' Web of Science in the title, keywords, and abstracts fields resulted in 607 hits (July 1st 2013), and a similar search for "social media" resulted in 2,796 hits. Results from Google Ngram show the degree to which references to these two terms have increased in books in recent years and – notably – as far back as the early 1900s and the 1920–1950s (http://books.google.com/ngrams/graph). Further, there have also been special issues of academic journals devoted to collective intelligence (e.g., Kapetanios and Koutrika 2010, pp. 1–3) and social media (e.g., Boll et al. 2011; Chen and Yang 2011, pp. 826–827; Cortizo et al. 2011, pp. 5–7; Hiltz et al. 2011; Liang and Turban 2011, pp. 5–13; Schoder et al. 2013a, 2013b, pp. 9–15).

The proposed research also contributes to the longstanding academic discourse regarding the challenge of how to increase knowledge worker productivity. There have been repeated calls for advancing knowledge worker productivity over the years (Davenport et al. 1998, pp. 43–57; Davenport and Prusak 1998; Alavi and Leidner 2001, pp. 107–136). In information systems (IS) research in particular, we have examined how information systems can support knowledge workers in their knowledge creation, storage/retrieval, transfer, and application (see Alavi and Leidner, pp. 107–136 for a detailed discussion of each of these points). However, in the past we limited our studies to knowledge management within a firm. We have seldom analyzed how knowledge operates in large-scale information systems that cross organizational boundaries (such as social media), and how collective intelligence emerges or could be fostered.

2 Problem Description and Research Challenges

Before describing the research problem and highlighting the research challenges, it is important to define the terms social media and collective intelligence. As a minimal consensus, "social media" is used as a generic term for social interactions built on a multitude of digital media and technologies that allow users to create and share content and act collaboratively (Schoder et al. 2013a, pp. 9–15).[1] Prominent examples of companies offering these types of services include online social networking platforms such as Facebook, LinkedIn, and Google+; microblogging sites such as Twitter, Sina Weibo, and Tumblr; and platforms for exchanging visual media such as YouTube and Flickr.

While there are more than 500 published papers on collective intelligence (CI), research has not yet converged on a common definition. While some can help us find a definition for "collective intelligence", many use the term "collective intelligence" to refer to different phenomena. For example, Woolley et al. (2010, p. 687) define CI as "the general ability of the group to perform a variety of tasks. Empirically, collective intelligence is the inference one draws when the ability of a group to perform one task is correlated with that group's ability to perform a wide range of other tasks." Vanderhaeghen et al. (2010, p. 17) define CI as "the fact that the locally controlled behavior of a number of individuals leads to successful problem solving". Gregg (2009, p. 456) defines CI as "intelligence that emerges from the collaboration and competition of many individuals". Hiltz et al. (1991, p. 92) define CI as "the ability of a group to arrive at a solution that is better than any of the members achieved individually". Leimeister (2010, pp. 245–248) deconstructs "collective intelligence" etymologically and concludes with a definition of collective intelligence from the MIT Center for Collective Intelligence, that is, "groups of individuals doing things collectively that seem intelligent". Finally, Luo and colleagues (2009, p. 204) define collective intelligence of human groups as "the idea that a human group may manifest higher capabilities of information-processing and problem-solving than any individual participant of that group does, especially when the participants densely interact with each other through the computerized communication channels such as the Internet and the World Wide Web".

Many IS researchers (e.g., Kapetanios and Koutrika 2010, p. 1; Leimeister 2010, p. 246) quote the main question of collective intelligence research that was formulated by a research group led by Tom Malone at the Massachusetts Institute of Technology: "How can people and computers be connected so that – collectively – they act more intelligently than any individuals, groups, or computers have ever done before" (see http://cci.mit.edu). It is important to note that this notion of CI encompasses people *and* computers.

Our understanding of how information systems may help to resolve wicked problems is still in its infancy. Research has shown that wicked problems typically cannot be resolved by pure computing power. Computing power is effective on well-defined problems, which can be formalized, but wicked problems are poorly defined, with some aspects of the relevant knowledge being tacit, unstructured, and neither easily captured nor easily codified. The underlying complexity of wicked problems comes from the fact that they are problems complicated by social interactions that are fluid, evolving, and involve conflicting interests. Resolving wicked problems requires parallel discourse, multiple iterations, changes of beliefs, and unpredictable revisions. Outcomes may be emergent and depend on the intensity, quality, and perception of contributions over time and may never be final or "true" in an absolute, agreed-upon sense.

Given the complexity of wicked problems, it should come as no surprise that more recent research streams such as "human computation", "human sensing", "the human grid", "citizen science" (Cohn 2008; Bonney et al. 2009) and so on show that humans are better suited for many tasks than computers (popular examples include Amazon's mechanical Turk) (Brynjolfsson and McAfee 2012, pp. 53–60). Still, information systems can contribute a lot, not by pursuing the automation paradigm of IS but by extending the support paradigm as exemplified by Computer-Supported Cooperative Work (CSCW).

[1] For different interpretations of the term "social media" see Kaplan and Haenlein (2010, pp. 59–68); Kietzmann et al. (2011, pp. 241–251).

Table 1 Research challenges

Systems engineering for large-scale CI applications
Measuring, such as discourse and CI
Big Data management
Semantic content analysis
Human-computer interfacing
Commercialization of CI applications and application scenarios

Examples of needed functionality as part of information systems with regard to wicked problems include (Schoder et al. 2013b):

- Supporting deliberation, that is, the "process where communities (1) identify possible solutions for a problem, and (2) select the solution(s) from this space that best meet(s) their diverse needs" (Klein 2012, p. 449);
- helping knowledge workers navigate social graphs (link prediction, identifying relevant individuals, assessing the strength of ties, assessing the embeddedness and position of individuals, etc.);
- highlighting relevant documents based on their processing through social interactions (who is using or working on documents, in which social position and context, and does this indicate relevance?);
- exploiting human computation;
- creating individualized information cockpits that monitor topical domains in a customized way (including hot topic identification and predictive capabilities of how things, items, issues, people, etc. may evolve); and
- coping with large collections of semi-structured or unstructured data, technically as well as semantically.

The desired functionality and required improved understanding of appropriate information systems can be expressed in at least six sets of research challenges (see **Table 1**):

Systems Engineering for Large-Scale CI Applications The first set of research challenges concerns systems engineering which tackles functionality, technical design, and modeling aspects: Which models, methods and languages are the most appropriate for designing IS for wicked problems? Although there is a plethora of articles dealing with system design for small- and medium-size platforms for collaboration (e.g., in the domain of computer-supported cooperative work), our understanding is still limited regarding CI applications suitable to support interaction among thousands if not hundreds of thousands of people collaborating simultaneously and cross-organizationally on a single issue. Prediction market research is a notable exception (e.g., Tziralis and Tatsiopoulos 2007, pp. 75–91); prediction markets try to harness collective intelligence of a large number of (rather independent) trading agents. Nevertheless, gaining an understanding of how to harness collective intelligence of large groups of people is as relevant as how to harness collective intelligence of small groups.

Measuring, such as Discourse and CI The second set of research challenges, in general terms, concerns measurement. "The better we measure, the better we manage", as the old adage goes. It seems crucial to measure what is going on in a discourse concerned with wicked problems. Also, it would be helpful to have measures specific for people with particular expertise aimed at best allocation of knowledge; this could or should be part of specific discourse. For example, insight into how CI can be measured may help with classic knowledge worker tasks including team formation and assigning and tailoring workloads in an effective way. The motivation for measuring collective intelligence is similar to the motivation for measuring individual intelligence (cf. Deary 2000). Measuring individual intelligence is undoubtedly one of the prominent tasks in psychology research. However, there have been very few efforts to measure group intelligence (Woolley et al. 2010, pp. 686–688). Social psychologists have not yet attempted to measure group intelligence in the same way in which they measure individual intelligence (Woolley et al. 2010, pp. 686–688).

Big Data Management The third set of research challenges concerns data handling: How can we cope with (large) amounts of discourse-induced data in terms of quantity, flow characteristics, and (most often weak) structuring? In the context of social media, the increasing amount of data is reflected in various phenomena. For example, statistics published by Wikipedia claim that the number of articles in the English-language Wikipedia increased from 3.8 million in January 2012 to 4.1 million in January 2013. This corresponds to about 800 articles per day (http://en.wikipedia.org/wiki/Wikipedia:Size_of_Wikipedia). The micro-blogging platform Twitter claims that more than 400 tweets are sent each second, and the Chinese micro-blogging service Sina Weibo reports more than 300 million registered users in just three years (Schoder et al. 2013b, pp. 9–15). However, techniques for the analysis of such data (e.g., text mining, Web mining, social network analysis, and spatial-temporal analysis) are not yet well integrated into existing collaborative work systems. Furthermore, methods for the analysis of social media data that are generated in the "Web 3.0" (i.e., data from mobile phones, tablets, and other sensor-based systems) are still far from being well developed (Chen et al. 2012, pp. 1165–1188).

Semantic Content Analysis The fourth set of research challenges focuses on dealing semantically with content. Content analysis at a semantic level has many facets, each of which poses quite diverse challenges. Computer vision and speech recognition aim to detect and analyze content and context, but can also be the starting point for translating non-textual audio-visual content (such as video or speech) to text as an intermediate representation for analysis. Information extraction, natural language processing, or related sub-disciplines (such as opinion mining) provide research fields which focus on the quest for semantic meaning in textual content. Here, challenges such as detecting topics or semantic orientation (sentiment) are often modeled as text classification problems to be addressed by machine learning algorithms (Sebastiani 2002, pp. 1–47) such as Naive Bayes or Support Vector Machines (Joachims 1998). These operate on different levels of supervision (supervised, semi-supervised, or unsupervised) and may include "relevance feedback" loops. Challenges in deriving semantic meaning also occur at different levels of granularity, such as the level of the complete document collection itself, of the document, of the section, or even at the level of individual phrases. Fields are the detection of topic (Brants et al. 2002, pp. 211–218), genre (Kessler et al. 1997, pp. 32–38), as well as subjectivity and/or sentiment (Liu 2010, pp. 627–666; Pang et al. 2002, pp. 79–86; Turney 2002, pp. 417–424), whereas the complexity of human language leads to multiple challenges such as detecting negations (Councill et al. 2010, pp. 51–59), sarcasm and irony (Carvalho et al. 2009, pp. 53–56), or opinion spam (Jindal and Liu 2008, pp. 219–230), and the detection/resolutions of synonyms (Baroni and Bisi 2004) or anaphora (Lappin and Leass 1994, pp. 535–561) and co-references (Soon et al. 2001, pp. 741–757).

Human-Computer Interfacing The fifth set of research challenges focuses on linking humans and computers: How can humans and computers be combined in problem-solving networks? The motivation for this research question is twofold. On the one hand, we are heading towards a good understanding of human networks (e.g., Wasserman and Faust 1994) as well as of computer networks. On the other hand, we do not yet know much about "two-mode networks" consisting of humans and computers (von Ahn 2005).

Commercialization of CI Applications and Application Scenarios The sixth set of research challenges concerns the commercialization (i.e., business models) of applications and application scenarios. For the given context, Zott et al. (2011, pp. 1019–1042) provide an extensive literature review of business model research. In their stream of thought, IS researchers can contribute in particular to research on "e-business model archetypes". Such research has its origin in e-Commerce research and can be organized around two complementary streams of thought: one aims to provide typologies (and describes generic e-business models); the other focuses on the components of e-business models. It is evident that social media facilitate new business models. For example, several authors examine Facebook's business model (e.g., Krombholz et al. 2012, pp. 175–212). However, little is known about business models that focus on harnessing collective intelligence with social media, and thus we may miss the potential of creating incentives for economic players that induce a infrastructure for wicked problems.

In the next section, we point to prospective scientific methods suitable for tackling the research challenges.

3 Prospective Scientific Methods

Taking on some of the aforementioned exemplary features as part of information systems with regard to wicked problems, a vast set of very promising scientific methods is already deployed.

The support of knowledge workers in navigating social graphs can be tackled with methods from social network analysis (SNA) (e.g., Cross et al. 2005), an interdisciplinary research paradigm that mainly utilizes graph theory to examine how people are connected. Five particular areas of SNA research are of interest. The first research area includes algorithms for the visualization of networks and calculation of network statistics (e.g., Borgatti et al. 2002; Brandes 2001, pp. 163–177; De Nooy et al. 2005; Krempel 2005). The second area comprises models that examine the evolution of networks (e.g., Doreian and Stokman 1997; Robins et al. 2007, pp. 192–215; Snijders et al. 2009, pp. 44–60; Wasserman and Pattison 1996, pp. 401–425). The third includes work dealing with scale free networks and complex systems (e.g., Barabasi and Albert 1999, p. 509; Newman 2006, p. 8577; Watts et al. 2007, pp. 22–23; Watts and Strogatz 1998, pp. 440–442). The fourth, mostly undertaken by IS researchers, uses network analysis to analyze electronic communication networks (e.g., Ahuja and Carley 1999, pp. 741–757; Ahuja et al. 2003, pp. 21–38; Ashworth and Carley 2006, pp. 43–75; Fischbach et al. 2009, pp. 1–8; Wasko et al. 2009, pp. 254–265; Kane et al. forthcoming). Finally, the fifth area of research comprises research in management science and sociology that focuses on the association between network structure and the performance of actors embedded in the networks (see Borgatti and Foster 2003, pp. 991–1013; Brass et al. 2004, pp. 795–817, for a literature review of these works in organizational research).

Highlighting relevant documents based on their processing by social interactions can be tackled with methods from CSCW. For example, in the context of groupware, researchers examined the performance of different technologies for creating context awareness in Web browsers (Gutwin et al. 2011, pp. 167–176). These findings can help us develop the envisioned super large-scale group decision support systems using Web technologies.

The integration of humans into computational tasks can be addressed with methods from human computation, defined as "a paradigm for utilizing human processing power to solve problems that computers cannot yet solve" (von Ahn 2005, p. 3). Its power comes from its use of games designed to engage humans in collaborating, sometimes without their knowledge, which may be one of its main distinctions from the other methods mentioned above (Quinn and Bederson 2011, pp. 1403–1412; Kearns 2012, pp. 58–67). An adjacent avenue of research scrutinizes human beings acting as sensors, thus exercising what is called human sensing, crowd data sensing or public data sensing (Austen 2013, pp. 48–51). Conti et al. (2012, pp. 2–21) frame a broader picture in terms of convergent cyber-physical systems. They discuss the phenomenon that a wave of (human) social networks and structures are emerging as important drivers for the development of novel communication and computing paradigms.

The task to create individualized information cockpits that monitor topical domains in a customized way can be tackled with methods from data mining such as association rules, clustering, decision trees, k-nearest neighbor, or neural networks (see Park et al. 2012, pp. 10059–10072, for a literature review).

The problem of coping technically with large collections of semi- or unstructured data can be tackled with methods and programming models such as MapReduce (e.g., Dean and Ghemawat 2008, pp. 107–113) (e.g., Apache Hadoop) that facilitate the analysis of large amounts of data, often called "Big Data" (see Chen et al. 2012, pp. 2265–1188, for an overview of these methods). There is a large body of research on how to cope semantically with large collections of semi- or unstructured data (i.e., text), including methods from machine learning (e.g., Bishop 2006), data mining (e.g., Liu 2007), text mining (Feldman and Sanger 2006), and sentiment analysis (Pang and Lee 2008). These methods open up unprecedented opportunities for the analysis of (social) media and collective intelligence.

4 Examples of Initial Results

Among the papers at the intersection of social media and collective intelligence with respect to information systems research for "wicked problems", several research domains have attracted particular attention in IS research and may provide examples of initial results. We would here like to highlight four research domains.

(1) The first research domain comprises deliberation technologies. Klein (2012, pp. 449–473) reviews a wide range of social computing technologies that have emerged in the past few decades. To understand the strengths and limitations of deliberation technologies more fully, he groups functionality as either "time-centric" or "topic-centric". Obviously, there is a lot of significant research on deliberation technology. However, to leverage and extend this research to large-scale argumentation systems, there is a need for more argumentation-centric approaches (e.g., Gürkan et al. 2010, pp. 3686–3702).

(2) The second domain comprises work that proposes methods and artifacts for harnessing collective intelligence from wikis. For example, researchers have proposed an alternative search interface for Wikipedia (Hahn et al. 2010, pp. 1–11); others examined the influence of the number of editors on the collective knowledge created in Wikipedia (Kittur et al. 2009, pp. 1495–1504). Other authors used methods from machine learning to improve the quality of an organization's corporate wiki and, in doing so, assigned wiki articles to experts for further review and contribution (Lykourentzou et al. 2010, pp. 18–38). Researchers have examined wiki-like systems such as a collective intelligence system for crime reports (Furtado et al. 2010, pp. 4–17) and a system for real-time traffic information (Lee et al. 2010, pp. 62–70). Finally, Passant & Laublet (2008, pp. 58–69) present a wiki-farm system to produce ontology-based data that are understandable for humans and computers, which leads to the third research domain.

(3) The third research domain is collective intelligence and data categorization. According to Levy (2010, pp. 71–94), one of the most prominent researchers in the domain of CI, useful data categorization is a core problem of CI management in commercial enterprises. Hence, several researchers regard social tagging and the resulting folksonomies as a main CI research question (e.g., Floeck et al. 2011, pp. 75–91; Gregg 2010, pp. 134–138; Gruber 2007, pp. 1–11; Hsieh et al. 2009, pp. 9513–9523; Vanderhaeghen et al. 2010, pp. 15–28). Social tagging refers to the process by which users bookmark objects – often on the Internet and thus – identified by their Unified Resource Locators (URLs) – and annotate those objects with metadata, or so-called tags. The set of tags that results over all users' annotations is denoted folksonomy, a neologism derived from folk and taxonomy (see Gruber 2007, pp. 1–11, for a discussion of the ontology of folksonomy). There is some dispute in the literature over the contexts in which folksonomies are more or less appropriate for content classification and categorization than taxonomies created by experts (see, e.g., Hsieh et al. 2009, pp. 9513–9523, for a comparison of taxonomies and folksonomies). Therefore, design science approaches suggest artifacts that employ social tagging for harnessing the collective intelligence in enterprises. For example, Vanderhaeghen et al. (2010, pp. 15–28) illustrate how social tagging can be applied in process management. They propose and discuss a structure, model, and prototype.

(4) The fourth research domain comprises papers that deal with prediction markets, which many CI researchers cite as a prime example for harnessing collective intelligence (e.g., Bonabeau 2009; pp. 45–52; Bothos et al. 2009, pp. 26–41; Malone et al. 2010, pp. 21–31). Research into predictions is a mature field of study of its own. For example, The Journal of Prediction Markets debuted in 2007. Therefore, we do not review this field of study in this commentary, but rather point to the literature review by Tziralis and Tatsiopoulos (2007, pp. 75–91) as well as the contributions by Forsythe, Nelson, Neumann and Wrigt (1992, pp. 1142–1161), Spann and Skiera (2003, pp. 1310–1326), Servan-Schreiber, Wolfers, Pennock and Galebach (2004, pp. 243–251), and Arrow and colleagues (2008, pp. 877–878).

5 Conclusion

Wicked problems are one of the most challenging problem classes ever encountered, and we are only in an early phase of understanding their complexities. Unfortunately, most grand challenges share characteristics of wicked problems. The need for appropriate information systems or – more specifically – useful functionality to harness the collective intelligence of crowds is not disputed and can constitute a solid research claim. The scale and scope of the proposed research calls for interdisciplinary approaches. We can expect that IS/Business and Information Systems Engineering (BISE) research will benefit from academic discourse with computer science, sociology, psychology, anthropology, and media studies – to name only the most prominent fields, but not ruling out additional disciplines.

For example, computer scientists have developed methods and tools that include data capture, curation, storage, search, sharing, transfer, analysis, and visualization. Sociologists can contribute to our understanding of the interplay of social media and collective intelligence. As highlighted above, (social) network analysis is a core methodology for understanding how humans (and computers) need to be connected to act more intelligently than individuals, groups, or computers have ever done before. Like many other theories that help us understand the social processes leading to collective intelligence, social network analysis has its roots in sociology (e.g., Scott 2010, pp. 21–26). From psychology, we can borrow motivational theories; from anthropology, ethnographic approaches; from media studies, for instance, agenda-setting theories, content analysis, discourse analysis, effects theories, theories of persuasion, or uses and gratifications theory.

IS as a scientific discipline may be applauded for being in a pole position likely to contribute significantly to the proposed research: IS research takes a two-pronged perspective that is particularly fruitful given the rich research questions that almost always simultaneously include "man" and "machine" aspects as well as socioeconomic dimensions. IS research needs to undertake the difficult balancing act of combining behavioristic research approaches with design-oriented research approaches. In doing so, it tends not to favor one over the other, which makes it particularly vulnerable to criticism from both research communities, since both communities use the same language to describe different phenomena and have different beliefs about

Abstract

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The objective of this commentary is to propose fruitful research directions built upon the reciprocal interplay of social media and collective intelligence. We focus on "wicked problems" – a class of problems that Introne et al. (Künstl. Intell. 27:45–52, 2013) call "problems for which no single computational formulation of the problem is sufficient, for which different stakeholders do not even agree on what the problem really is, and for which there are no right or wrong answers, only answers that are better or worse from different points of view". We argue that information systems research in particular can aid in designing appropriate systems due to benefits derived from the combined perspectives of both social media and collective intelligence. We document the relevance and timeliness of social media and collective intelligence for business and information systems engineering, pinpoint needed functionality of information systems for wicked problems, describe related research challenges, highlight prospective suitable methods to tackle those challenges, and review examples of initial results.

Keywords: Collective intelligence, Knowledge work, Research agenda, Research commentary, Social media, Wicked problems

what constitutes rigorous and relevant research (see, for example, the discussion in Baskerville et al. 2011, pp. 11–15; Buhl et al. 2012a, pp. 307–315; Buhl et al. 2012b, pp. 236–253; Junglas et al. 2011, pp. 1–6; Österle et al. 2010, pp. 7–10). To understand and build effective artifacts, both approaches are complementary and both are indeed necessary.

We hope that the two-pronged perspective of IS research in particular will be extended to the intersection of social media and collective intelligence, stimulating the design of function-rich information systems for wicked problems.

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