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Abstract:

Given the rapid advancements in information communication technology (ICT), researchers and practitioners need to understand the impact that emerging phenomena, such as artificial intelligence (AI), have on existing social and economic challenges. We conducted a hermeneutic literature review to present the current state of the digital divide, developments in AI, and AI's potential impact on the digital divide. We propose three theoretical framings: 1) conceptualizing the divide, 2) modeling the divide, and 3) analyzing the divide. These framings synthesize the digital divide's essence in relation to AI and provide the foundation for a socio-technical research agenda for the digital divide in light of the evolving phenomena of AI.

Keywords: Digital Divide, Artificial Intelligence, Socio-technical, Hermeneutic Literature Review, AI Divide.

Lionel P. Robert Jr. was the accepting senior editor for this paper.

1 Introduction

Advancements in artificial intelligence (AI) have begun to transform social interaction and business operations. These advancements have impacted diverse business functions, including financial fraud detection (Abbasi, Albrecht, Vance, & Hansen, 2012), risk profiling in healthcare (Lin, Chen, Brown, Li, & Yang, 2017), decision making (Meyer et al., 2014), and advertising (Gong, Abhisek, & Li, 2018). Organizations have increasingly invested financial and human resources in AI-related initiatives. In February, 2019, the United States (US) Federal Government made a commitment to dedicate more resources to AI research and initiatives (Pamuk & Shepardson, 2019). In addition to the US, other countries have also invested in developing AI technologies. For instance, Tianjin, a Chinese metropolis, has established a US$15.7 billion AI fund to develop AI-related projects and initiatives (Jing, 2018). McKinsey Global Institute (MGI)'s recent report concluded that AI may boost global economic output by US$13-15 trillion between now and 2030 (Wladawsky-Berger, 2019).

While digital innovations have delivered numerous benefits to society, they also result in unintentional, adverse effects—especially when these innovations result in inequity that separates those who have access to the technology (e.g., people, companies, and governments) and those who do not (Dewan & Riggins, 2005). Despite decades of initiatives that have focused on eliminating the digital divide, it has persisted (Bose, 2018) and evolved. Additional elements of the divide have emerged, such as skills (Bélanger & Carter, 2009) and outcomes (Scheerder et al., 2017).

AI innovations proliferate faster than policies and regulations that ensure their ethical and equitable diffusion through society. AI innovations result in pronounced advantages for individuals and organizations who can capitalize on this technology and disadvantages for individuals and organizations who lack the necessary technological skills to harness it effectively. In surveying more than 3,000 business managers, executives, and analysts in 112 countries, Columbus (2020) found that more than 80 percent of respondents expected AI to give their organization a competitive advantage and boost productivity.

The diffusion of AI initiatives will accelerate organizational transformation and introduce new business models. This revolution may generate new digital divide patterns. Given the growing investment in AI and its potential to revolutionize product and service delivery, Bryson and Winfield (2017) have highlighted the need for more research on the technology's potential challenges and consequences.

Researchers have started to explore AI ethics and fairness (Robert, Bansal, & Lütge, 2020a). However, few studies have systematically and comprehensively reviewed the digital divide in relation to AI. Dwivedi et al. (2019) have called for more research on AI's societal impacts in light of the digital divide. In response to this call, we conducted a hermeneutic review of the literature using a "specific theorizing review" (Leidner, 2018). We synthesized insights at the intersection between the digital divide and artificial intelligence.

With this study, we make several contributions to the information systems (IS) literature. First, we synthesize three theoretical framings at the intersection between the digital divide and AI. Second, we provide a comprehensive conceptual model of the digital divide in relation to AI. Finally, we use the theoretical framings to provide a research agenda for the digital divide in light of evolving phenomena, such as AI.

2 Methodology

In this study, we operationalize Boell and Cecez-Kecmanovic's (2014) literature review method. This approach encourages researchers to iteratively engage with and continuously discover a body of literature and, thereby, gradually develop deep understanding and insights. A hermeneutic literature review highlights two major hermeneutic circles: 1) a "search and acquisition" circle (inner circle) and 2) an "analysis and interpretation" circle (wider circle) (Boell & Cecez-Kecmanovic, 2014). In the hermeneutic framework, the two circles of literature review activities harmoniously intertwine: they follow each other not in a simple linear manner but in an iterative process and help researchers incrementally understand the literature they focus on.

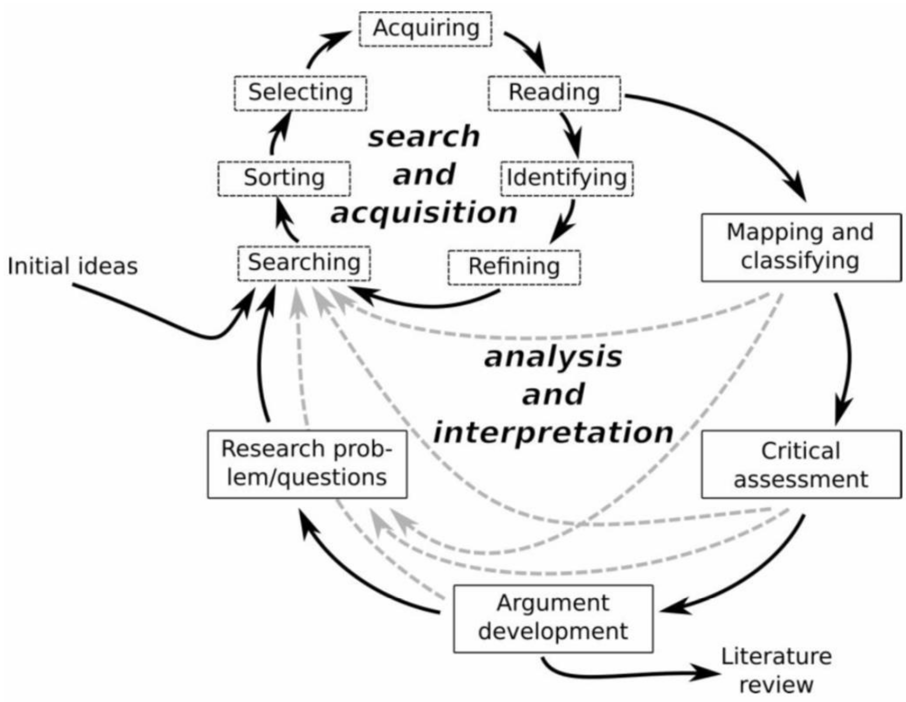

Figure 1. Hermeneutic Systematic Review (Boell & Cecez-Kecmanovic, 2014)

We used the hermeneutic approach in our study for three reasons. First, in the hermeneutic review process, one typically discovers and understands literature in an interpretive, iterative, and incremental manner (Boell & Cecez-Kecmanovic, 2014), which suited our study since many synonymous and relevant concepts associated with AI exist (e.g., deep learning, machine learning, robotics, natural language understanding, natural language processing, super intelligence, digital intelligence, and augmented intelligence) in the literature. Second, the hermeneutic review framework enables researchers to begin the review process by retrieving highly relevant publications rather than relying on huge sets of documents whose relevance they cannot sufficiently judge (e.g., ProQuest displays 2,902 results when searching for “AI” in the abstract field). The digital divide in relation to AI is an emerging rather than stable phenomena. Hence, we used the hermeneutic approach to iteratively identify relevant literature. Third, understanding the digital divide in relation to AI requires in-depth and multi-faceted insights from a socio-technical perspective, and the hermeneutic process allows one to discover such insights.

In the wider “analysis and interpretation” circle, we began by defining our research focus: “AI implications for the digital divide.” Then, we proceeded with the “search and acquisition” circle. Finally, we used literature mapping and classification, critical assessment, and argument development to help develop our research problems and support new circles of searching, reading, mapping, and classifying. We continued the process iteratively to formulate and refine our research questions and synthesize our research findings (Boell & Cecez-Kecmanovic, 2014). Per Boell and Cecez-Kecmanovic (2014), in conducting our mapping and classifying activity in the analysis and interpretation hermeneutic circle, we analyzed and classified relevant ideas (e.g., concepts) and obtained findings that pertain to our research question in the body of literature. In the critical-assessment stage, we addressed the body of literature by broadly analyzing and synthesizing what we know, how we have acquired such knowledge, how we can use such knowledge to understand our research problem, and the boundaries and weaknesses of existing research (Boell & Cecez-Kecmanovic, 2014).

In the search and acquisition circle, we identified highly relevant publications on the digital divide and AI in leading IS journals, which included papers that investigated some perspective of the digital divide and papers that articulated AI’s impact, consequences, and ethical issues. We started the first-round hermeneutic iteration with the Senior Scholars’ basket of eight journals. In that round, we identified 21 papers on the digital divide and 25 papers on AI. We summarize these papers in Appendices A and B (e.g., findings, theories, and technologies). In our review process, we passed through the hermeneutic circles (both the wider circle and the inner circle) three times in total. The final literature corpus comprised 118 papers (109 research papers such as academic journal papers, conference papers, and book chapters and nine newspaper articles). We identified all publications based on their relevance to our research focus.

Table 1. Summary of Reviewed Studies

Papers	Topics	Count
Research papers (academic journal papers, conference papers, and book chapters)	Digital divide (DD)	53
	Artificial Intelligence (AI)	56
Newspaper articles	DD or AI relevant	9
	Total	**118**

As Boell and Cecez-Kecmanovic (2014) suggest, we read the papers analytically to understand them. Accordingly, we mapped and classified the publications and their findings to identify the state of knowledge about our research problem. We synthesized the relevant literature into a compact classification based on their major concepts and views pertaining to our research interest based on the rationale that concept-centric classification and synthesis may help researchers structure literature to support critical assessment (Webster & Watson, 2002; Boell & Cecez-Kecmanovic, 2014).

From our initial search, we observed that review or theoretical papers synthesized the digital divide research in various ways. Dewan and Riggins (2005) provided a framework for conceptualizing research on the digital divide that differentiated between two inequality types (ICT access and ICT use) and three levels of analysis (global, organizational, and individual). Hilbert (2011) stated: "it is neither theoretically feasible, nor empirically justifiable to aim for one single definition of the digital divide" (p. 715). Instead, he proposed an approach to specify the essential elements when modeling the digital divide: to answer the questions "who," "with which kinds of characteristics," "connects how," and "to what." Hilbert's (2011) four-element model complements Dewan and Riggins' (2005) conceptualization framework to accommodate various digital inequities. Recently, Scheerder, van Deursen, and van Dijk (2017) posited that "digital divide research is largely limited to sociodemographic and socioeconomic determinants" (p. 1607).

Synthesis in a review procedure ensures researchers can globally represent the literature, especially when they need a review framework to map research findings (Rowe, 2014). Researchers can either select or develop such a framework (Rowe, 2014). We propose a three-part review framework for synthesizing the literature: conceptualizing, modeling, and analyzing the AI divide. The first theoretical framing (i.e., conceptualizing the AI divide) defines the AI divide and research scope. The second framing (i.e., modeling the AI divide) highlights the technologies that contribute to and the entities impacted by the AI divide. The third framing (i.e., analyzing the AI divide) elucidates various determinants and metrics that researchers and practitioners have used to analyze and measure the AI divide. We used the three theoretical framings to map and classify emerging concepts. These framings synthesize the digital divide's essence, specifically in the AI context, and provide insight into its socio-technical dimensions.

3 Theoretical Framing 1: Conceptualizing the AI Divide

3.1 The Digital Divide

Early on, Rogers (1962) conceptualized the digital divide in recognizing a digital gap between users and potential users. However, Rogers's theory highlights only the impact that users' requirements have on ICT access and use. It does not include other factors such as individual attributes (e.g., demographics), technical conditions, and social environments (e.g., regulations) on users' behavior (Minghetti & Buhalis, 2010).

While academic investigations into the digital divide include various settings (e.g., the Internet, mobile device, e-government, and education-related technology), a widely adopted definition refers to the digital divide as "the gap between individuals, households, businesses and geographic areas at different socio-economic levels with regard both to their opportunities to access ICT and to their use of the Internet for a wide variety of activities" (OECD, 2001, p. 4). In other words, the digital divide implies that a portion of the population cannot access ICT that, like access to such public facilities as parks, museums, and libraries, everyone should be able to access (Robinson, DiMaggio, & Hargittai, 2003). This disparity differentiates life quality and opportunities between technologically enabled and non-technologically enabled individuals (Helbig, Gil-Garcia, & Ferro, 2009).

Researchers who conceptualized the digital divide early on explored the inequity in access to technologies such as computers and the Internet (Van Dijk, 2006). Going beyond "the distinction between the information haves and have-nots" (p.132), Bélanger and Carter (2009) focused on the gap between the literate and the illiterate that discriminates computer use. The digital divide is not a monolithic divide that exists only in computer and technology but any disequilibrium that may exist in any digital innovation. For example, Minghetti and Buhalis (2010) define the digital divide in tourism as the "unequal access and use of ICTs for tourists and destinations" (p. 267). In the healthcare context, an age-based digital divide may have significance in regard to accessing and using mobile health technology because, "despite having the ability to adopt, [older adults] nonetheless abstain or adopt selectively" (p. 1008). Wei, Teo, Chan, and Tan (2011, p. 170) identified three levels of the digital divide:

> *The digital access divide (the first-level digital divide) is the inequality of access to information technology (IT) in homes and schools. The digital capability divide (the second-level digital divide) is the inequality of the capability to exploit IT arising from the first-level digital divide and other contextual factors. The digital outcome divide (the third-level digital divide) is the inequality of outcomes (e.g., learning and productivity) of exploiting IT arising from the second-level digital divide and other contextual factors.*

Extant research on the digital divide has mainly addressed the first- and second-level effects (Dewan & Riggins, 2005). For instance, the second-level divide exists when apartment seekers may have access to the online portal Zillow Rentals via the Internet but cannot use it effectively due to reasons such as literacy, trust, and language skills. Scheerder et al. (2017) suggested a shift from a focus on the first-level digital divide and the second-level digital divide to a third-level digital divide in which one can highlight ICT's tangible impact and engagement. The third-level digital divide occurs when accessing and using ICT result in no beneficial outcomes. In other words, being able to access and use technologies does not necessarily result in positive engagement (Venkatesh & Sykes, 2013).

The extant literature explores the digital divide at various levels: global, organizational, and individual (Dewan & Riggins, 2005). Studies on the global digital divide have explored ICT penetration through various socio-economic variables, such as GDP per capita, technological infrastructure, economy structure, and policy (Dewan & Riggins, 2005). Global studies have also examined how the digital divide impacts various geographic areas, such as countries and regions. For example, Norris (2001) investigated inequality in ICT access and usage between developing and industrialized countries. At the organizational level, studies have frequently focused on analyzing the divide between companies that gain a competitive advantage through using technology in innovative ways and companies that do not. At the individual level, studies have often focused on personal demographics such as income, occupation, and education.

3.2 An Artificial Intelligence (AI) Divide

The AI concept builds on the notion that "every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it" (McCarthy, Minsky, Rochester, & Shannon, 2006, p. 1). AI features a machine that mimics human minds' "cognitive" functions, such as learning, reasoning and decision making, and problem solving (Dietterich & Horvitz, 2015; Luger, 2005).

Researchers and practitioners have designed AI-enabled artifacts to facilitate various business applications and operations, such as search advertising (Gong et al., 2018), copycat detection (Wang, Li, & Singh, 2018), risk profiling in chronic care (Lin et al., 2017), dynamic decision making (Meyer et al., 2014), financial fraud detection (Abbasi et al., 2012), customer social networks analysis (García-crespo, Colomo-palacios, Gómez-berbís, & Ruiz-mezcua, 2010), knowledge management (Li, Chen, Zhang, Li, & Nunamaker, 2009), user emotion recognition (Derrick, Jenkins, & Nunamaker, 2011), and user performance prediction (Buettner, Sauer, Maier, & Eckhardt, 2018). AI has become commonplace in our daily lives (Müller & Bostrom, 2016). AI innovations encompass various subfields that range from general tasks, such as natural language understanding, to specific tasks, playing chess (e.g., AlphaZero), writing poetry (He, Zhou, & Jiang, 2012), driving a car in a crowded city (e.g., Tesla's autopilot system), and making clinical decisions (e.g., IBM Watson Health).

The MGI has stated that AI can significantly boost overall economic productivity (Bughin, Seong, Manyika, Chui, & Joshi, 2018). Meanwhile, some thought-leaders have expressed concern that individuals and organizations do not share these benefits equitably; accordingly, resulting "AI divides" may reinforce and fuel existent digital divides. From individuals' perspective, AI's dispersion may turn labor demand away from repetitive tasks that AI can fully or partially automate. The MGI report (Bughin, Seong, Manyika, Chui, & Joshi, 2018) indicates that jobs that involve low-level digital skills could fall by 10 percent in the coming decade; in contrast, jobs that involve high-level digital skills will likely rise (Bughin et al., 2018). This shift in demand could result in wage increases for jobs that require digital skills and literacy and create inequity between individuals who have AI literacy and individuals who do not. In industry, innovative companies equipped with AI-enabled technologies may be able to harness big data more effectively and analyze customer-generated content in real time without incurring additional labor expenses. Inevitably, these companies are most likely to outperform competitors who do not wish to or cannot adopt AI technologies. Late AI-adopters may experience a decline in their competitiveness (e.g., market responsiveness agility, scalability) and, accordingly, cash flow and revenues due to diminishing market share. At the country level, the digital divide refers to inequity “between those with ready access to the tools of information and communication technologies and the knowledge that they provide access to and those without such access or skills” (Cullen, 2001, p. 311). AI divides at the country level have become increasingly apparent as countries that lead the world in AI take advantage of AI to seek economic benefits and magnify social welfare (Barton, Woetzel, Seong, & Tian, 2017).

Given the evolving ways in which researchers have conceptualized the digital divide and perpetual advancements in AI, we highlight the need for research on the emerging AI divide in diverse disciplines, such as information science, artificial intelligence, political science, economic science, social science, and communication science. We identified a need to explore AI-related inequalities about access to AI (the first-level divide), the ability to use AI (the second-level divide), and the outcomes of AI engagement (the third-level divide) (Scheerder et al., 2017). The third-level divide may result from imbalanced outcomes of AI engagement beyond AI access and use. For example, bias in training data (e.g., facial recognition) may result in systems that work well for certain groups but not others even when users have access to and choose to use this new AI technology (e.g., false positives for criminals among minority populations). The way in which we conceptualize the AI divide highlights the multi-level interrelatedness of social (e.g., various stakeholders) and technical aspects (e.g., such AI features as data and algorithms). Future research needs to explore the impact of an AI divide across access level, capacity level, and outcome level.

4 Theoretical Framing 2: Modeling the AI Divide

Various disciplines have explored AI technologies, such as computer science (Ramos, Augusto, & Shapiro, 2008), statistics (Gale & Pregibon, 1984), cognitive science (Dupoux, 2018), linguistics (Liu, Li, & Thomas, 2017), and information systems (Ågerfalk, 2020). People generally recognize Alan Turing as originating artificial intelligence concept (French, 2000). Turing (1950) described “thinking machines” that can reason at the level of a human being. The “Turing Test” stipulates “computers need to complete reasoning puzzles as well as humans in order to be considered ‘thinking’ in an autonomous manner” (West, 2018). John McCarthy first used the term “artificial intelligence” in the mid-1950s to denote machines that could think autonomously. He described the criterion as “getting a computer to do things which, when done by people, are said to involve intelligence” (West, 2018).

AI enables a program or a machine to complete tasks that a human would normally perform, such as planning, reasoning, problem solving, and even acting. Russell and Norvig (2016) identified four types of AI: thinking humanly, thinking rationally, acting humanly, and acting rationally. Cognitive scientists have used psychology theories to imbue AI with “humanness” (Gratch & Marsella, 2005), while computer scientists and mathematicians have emphasized AI’s logical and unemotional “rationality.” Rationality, the capability to produce ideal solutions, and humanness, the extent to which technology mimics humans, represent two sides of the same coin (Russell & Norvig, 2016).

AI techniques are vast. Some frequently used techniques include natural language processing, knowledge representation, automated reasoning, machine learning, computer vision, and robotics (Russell & Norvig, 2016). Natural language processing enables AI to interact with people using human language. For example, Apple’s smartphone assistant, Siri, leverages several natural language processing techniques (i.e., speech recognition, lexical analysis, and semantic analysis) to understand speech and even intentions. Knowledge representation annotates and stores digital information. Automated reasoning refers to drawing inferences from stored information to solve problems and make predictions. Machine learning “focuses on applications that learn from experience and improve their decision-making or predictive accuracy over time” (IBM, 2020). Computer vision refers to technology that can recognize objects to interpret and understand the visual world. Robotics designs, constructs, operates, and uses robots and machines to replicate human actions (e.g., driving, lifting, speech) (Russell & Norvig, 2016). Many AI-enabled innovations use the aforementioned techniques in combination. We can find AI innovations in mobile applications such as Facebook or Google Photos, which use machine learning to recognize faces in pictures (LeCun, Bengio, & Hinton, 2015).

4.1 Visible AI and Invisible AI

We can categorize AI innovations as visible and invisible. When users can readily recognize AI's presence, we refer to that innovation as visible AI. Visible AI innovations, which have discernible outcomes (e.g., self-driving navigation systems and voice-recognition agents such as Amazon's Alexa and Apple's Siri), also have a "user-invisible" side. According to Robert et al. (2020a), "the algorithms used to reach decisions are often treated as a black box and lack transparency" (p. 101). Invisible AI refers to the system's imperceptible components (e.g., the underlying algorithms and training data) that support and determine how it performs. For example, machine learning enables a system to use algorithms (e.g., deep learning, recurrent neural network, random forest) to analyze data and make intelligent decisions based on what it learns. These machine learning algorithms enable AI systems to continuously and automatically learn from large data sets to improve their decision quality and the accuracy of their predictive results without human intervention.

The user-invisible algorithms that power AI's visible capabilities play an essential role in AI's success or failure. Invisible AI faces numerous challenges. For example, Siri or Alexa may sometimes frustrate users with their "matter-of-fact" responses—these supposedly intelligent assistants lack emotional intelligence (Krakovsky, 2018). Also, AI can generate decisions from training data, which may comprise biased observations. Data scientists can create mismatched training data and operational data by inappropriately applying a trained machine learning model to an unanticipated context. Data measurement bias, data variable collection bias, data sample bias, or model bias can cause this mismatch (Robert, Pierce, Marquis, Kim, & Alahmad, 2020b).

4.2 Components of the AI Divide

As we mention earlier in the paper, much research on the digital divide exists (Bélanger & Carter, 2009; Dewan & Riggins, 2005; Friemel, 2016; Hilbert, 2011; Sung, 2016; Van Deursen & Van Dijk, 2014). Hilbert (2011) used four factors to describe the digital divide: 1) the subject who accesses the technology (who?), 2) the subject's characteristics (of what characteristics?), 3) the mode by which the subject connects (how?), and 4) the systems the subject connects to (to what?). The four-factor model reflects the interrelatedness of social and technical components that pertain to the digital divide.

One can also apply Hilbert's (2011) model to the AI divide. However, a new component emerges in the AI context: subjects' perceptions and beliefs. Public beliefs about AI's future and impact vary. Proponents often highlight AI innovations' benefits, such as tutoring students or performing surgeries, while others warn about their potential negative consequences. For example, AI-aided surveillance technologies introduce various challenges for individual privacy (Fast & Horvitz, 2017). AI may displace human workers or roboticize warfare (Markoff, 2014). AI may become super intelligent and recursively design and refine itself and evolve beyond human control (Dietterich & Horvitz, 2015).

Other envisioned risk perceptions that researchers and practitioners have raised include the hazards that could emerge from an autonomous system that AI enables without human oversight. For instance, AI-enabled facial recognition may watch the public, which would result in a loss of individual privacy (Marr, 2018). AI-enabled systems have the ability to detect and target floating voters, obtain and analyze public emotions, mine public opinions, and, accordingly, manipulate election outcomes (Bryson & Winfield, 2017).

Invisible AI also has potential risks (Hawking, Russell, Tegmark, & Wilczek, 2014). Machine learning algorithms enable AI systems to mimic human rationality or intelligence via learning from data (Pedregosa et al., 2011). However, while copious datasets often help to improve AI performance, actors who inappropriately use individual's data and inadequate data protection will increase users' risk perceptions and reduce their willingness to access AI-enabled systems and, thereby, affect the AI divide.

We recommend extending the four-factor model that Hilbert (2011) proposed to include five factors. Specifically, we suggest adding "subjects' perceptions and beliefs" to highlight the importance of individuals' risk perceptions and trusting beliefs to the AI divide (see Figure 2). AI is a nascent field in science and engineering (Russell & Norvig, 2016); as AI evolves, it inspires scholars to investigate potential risks (Bostrom, 2013; Müller & Bostrom, 2016). Scholars in diverse disciplines such as biometry (Prabhakar, Pankanti, & Jain, 2003), healthcare (Kumar & Patel, 2014; Zhang et al., 2015), automated vehicles (Jayaraman et al., 2019), and cloud computing (Zhou, Zhang, Xie, Qian, & Zhou, 2010) have raised concerns about AI-related risks. As Fox and Connolly (2018) have indicated, the digital divide may deepen when individuals do not wish to adopt new technology due to mistrust, high-risk perceptions, and the intense desire for information privacy.

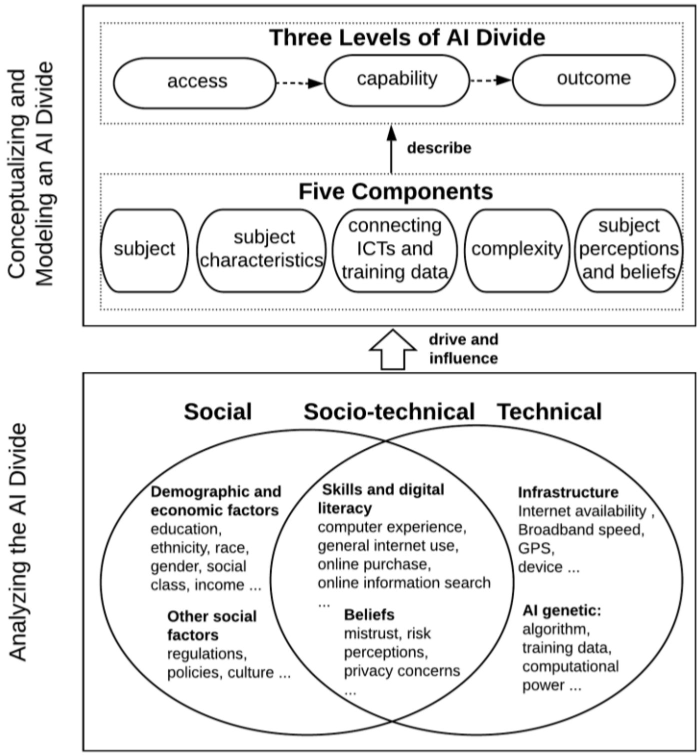

Figure 2. A Comprehensive Framework for AI Divide Research

In addition to adding a fifth factor to Hilbert's (2011) model, we also propose including "training data" in the third factor, which highlights the significance of "underlying ICTs and training data" to the AI divide. Artificial Intelligence technologies such as machine learning and natural language processing require a massive volume of high-quality data to train models in order to achieve desirable results. AI-equipped systems often need access to training data to build AI models. Training data may be publicly accessible data (e.g., the data in UCI Machine Learning Repository) or private data labeled through customized services (e.g., Labelbox). Future research needs to examine individuals' perceptions, concerns, beliefs, and ethics in relation to visible and invisible AI.

5 Theoretical Framing 3: Analyzing the AI Divide—A Socio-technical Framework

AI applications permeate global, organizational, and individual interactions. However, actors will not likely share AI innovation's benefits in an impartial manner. Developing economies with insufficient digital infrastructure and limited capacity for innovation may not realize the same benefits and convenience from AI innovation as developed countries. Similarly, companies that fully adopt AI technologies may gain an advantage over companies that do not. For instance, an organization may deploy AI to replace human labor and, hence, lower operational costs. At the individual level, we will see variance in AI access, comfort, and outcomes.

The socio-technical view posits that one can better understand IS phenomena when one considers both "social" and "technical" perspectives and treats them as interacting components of a complex system (Lee, 2004). The AI divide describes inequality that concerns accessing and using AI-enabled technology and that technology's impacts. In modeling and investigating an AI divide, one needs to not only delineate the components in the five-factor progression model but also analyze the driving socio-technical factors.

The social dimension includes demographic and socio-economic factors (e.g., gender, age, yearly economic outcomes, family size, and education level) (Ferro, Helbig, & Gil-Garcia, 2011; Fuchs & Horak, 2008;

Niehaves & Plattfaut, 2014; Payton, 2003; Ragnedda & Muschert, 2013; Shirazi, Ngwenyama, & Morawczynski, 2010; Venkatesh & Sykes, 2013; Wareham, Levy, & Shi, 2004) and other social factors such as culture, regulations, and policies (Borgida et al., 2002; Chinn & Fairlie, 2007; Philip, Cottrill, Farrington, Williams, & Ashmore, 2017). The technical dimension includes determinants such as infrastructure (Lee, Park, & Hwang, 2015; Philip, Cottrill, & Farrington, 2015; Riddlesden & Singleton, 2014) and AI-specific factors (e.g., AI algorithms and training data). Socio-technical determinants influence how users interact with and perceive AI innovations (Levy, Janke, & Langa, 2015; Radovanović, Hogan, & Lalić, 2015) and beliefs (Fox & Connolly, 2018).

5.1 Demographic and Socio-economic Factors

Extant research has highlighted the relevance of demographic and socio-economic factors to the digital divide (Scheerder et al., 2017). Factors such as income, gender, education, ethnicity, and age (Friemel, 2016; Helsper, 2010; Ragnedda & Muschert, 2013; Sung, 2016) differentiate who can access and use ICTs. These factors may also differentiate who can access and use AI. Future research needs to examine the impact that demographic and socio-economic factors have on the AI divide.

5.2 Other Social Factors

Studies on the digital divide have also explored social factors such as culture (Borgida et al., 2002), regulations (Chinn & Fairlie, 2007), and policies (Philip et al., 2017). Borgida et al. (2002) explored the role of cooperation norms and political culture in influencing the digital divide in computer and Internet access. In the AI context, scholars should explore the effect that diverse social factors, such as policies, have on AI innovations.

5.3 Infrastructure

System developers and designers build “intelligence” into information systems. For example, Google Photos can use facial recognition to allow users to search their photos by people, things, and places. AI-enabled facial recognition helps Google Photo identify a person from a digital image or a video source by analyzing features and building a machine learning model. A prerequisite to accessing an online facial recognition system exists: the Internet. Hence, the Internet directly affects whether one can access and use AI; in other words, successful access to an online AI service depends on Internet connectivity and bandwidth. In addition to the Internet, other infrastructure barriers may include physical devices (e.g., smartphones), GPS (e.g., autonomous driving), the Internet of things (IoT), and cloud computing.

5.4 AI-specific Factors

Algorithms (e.g., machine learning algorithms) and data enable AI (Ananny, 2016). In accordance, AI-specific factors will impact the AI divide—algorithm and data. For example, if one trained a machine learning algorithm for clinical decision support with data in one country, the system may not perform with the same level of accuracy when applied to citizens in a different country. A recent facial recognition study at MIT found that, when a photo contained a male with light skin, the system had an accuracy rate of approximately 99 percent; however, when it attempted to recognize a female with darker skin, the error rate rose to 21 to 35 percent (Lohr, 2018). These disparate results suggest that bias encoded in AI algorithms and/or training data may generate an AI divide.

5.5 Skills and Digital Literacy

Computer-based skills and digital literacy, which contribute to the existent digital divide, will also impact the AI divide. Van Deursen and Van Dijk (2011) argued that as the digital divide evolves, differences in skills using a technology may create inequity in technology use. We posit that, as AI innovations evolve, we will see a widening gap among individuals, organizations, and countries that can effectively access, use, and understand these innovations.

5.6 Beliefs

Individual concerns about AI-related risks may reduce users’ willingness to engage with AI tools or systems. For example, facial recognition can identify human faces in photos (e.g., Google Photo, Facebook). While some users may enjoy the convenience of unlocking their smartphone with a smile, other users may have concerns about the technology's potential to enable unwanted surveillance.

The social-technical framework we propose identifies how actors can generate, mitigate, or bridge the AI divide as AI permeates society. Our findings in the third theoretical framing (see Section 5) complement our findings from the first two (see Sections 3 and 4). By coherently integrating these framings, we construct a comprehensive framework to conceptualize, model, and analyze the AI divide (see Figure 2). In light of the proposed theoretical framing, future research should investigate AI divide drivers and explore strategies to abate the AI divide.

6 Conclusion

Acknowledging the digital divide's sociodemographic and socioeconomic determinants (Scheerder et al., 2017), we use a socio-technical view to provide a comprehensive framework of the digital divide in an era of technological transformation. Traditionally, the digital divide has focused on human access, skills, and capacity. However, invisible AI complicates the interaction between humans and AI-enabled systems. AI innovations interact with users via both front-end interfaces and the training data that actors select and manage.

Despite our best efforts to investigate the implications that AI will have on the digital divide, we acknowledge some limitations. First, while we made efforts to review the literature and theoretically synthesize the influential factors of the AI divide in the socio-technical framework, some factors that the presented social-technical paradigm does not list may exist. Second, although we provide the theoretical framework to investigate the digital divide in the AI context, research needs to empirically test and validate the influential factors' practical and statistical significance.

With this paper, we make several significant contributions to the extant literature. Informed by a hermeneutic process, we propose an AI divide research framework that accounts for both visible and invisible AI. The framework highlights divide determinants associated with the socio-technical view, such as determinants that reflect how users perceive AI (i.e., risks, trust, and concerns), which, in turn, may impact other human-AI interactions (e.g., correcting inappropriate learning models).

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Appendix A: Digital Divide Research

Table A1. Digital Divide Research

Source	Topics or findings	Publication	Theories identified and literature referenced	Technology
Fox & Connolly (2018)	Provides recommendations for narrowing the m-health digital divide to ensure that older citizens can and will adopt.	*Information Systems Journal*	Protection motivation theory and social cognitive theory	Mobile health (m-health) technologies
Andrade & Doolin (2016)	Moves beyond the conventional discussion on the digital divide by exploring what people can do and achieve with ICTs.	*MIS Quarterly*	N/A	ICT used for refugees' social inclusion
Srivastava & Shainesh (2015)	Investigates the prevailing differences in the level of services that different population segments (service divide) in developing countries consume.	*MIS Quarterly*	N/A	Indian healthcare service providers
Niehaves & Plattfaut (2014)	Explores factors that influence the elderly's intentions to use the Internet.	*European Journal of Information Systems*	TAM, UTAUT, MATH	Internet
Venkatesh, Sykes, & Venkatraman (2014)	Develops a model of e-government portal use and investigates individual characteristics in impacting e-government portal use.	*Information Systems Journal*	Innovation diffusion theory	E-government portal
Venkatesh & Sykes (2013)	Uses social networks as the lens through which to investigate technology use and economic outcomes of digital divide initiatives in developing countries.	*Information Systems Research*	The theory of planned behavior	Personal computers that were enabled with Internet access
Racherla & Mandviwalla (2013)	Uses an interpretive case study approach to investigate the Philadelphia wireless initiative.	*Information Systems Research*	Innovation diffusion theory	Information infrastructure
Wei et al. (2011)	Examines three levels of the digital divide (the digital access divide, the digital capability divide, and the digital outcome divide) and develops a model to investigate their associations.	*Information Systems Research*	Social cognitive theory	computer
Sipior, Ward, & Connolly (2011)	Employs the technology acceptance model to explore the digital divide and transformational government (t-government) in the United States.	*European Journal of Information Systems*	TAM	Transformational government (t-government)
Dewan, Ganley, & Kraemer (2010)	Investigates how the cross-country diffusions of personal computers and the Internet affect the evolution of the global digital divide.	*Information Systems Research*	Innovation diffusion theory	Computer and the Internet
Agarwal, Animesh, & Prasad (2009)	Explores whether and how social influence affects individual choice.	*Information Systems Research*	N/A	Internet
James (2007)	Explores the ways in which the impact of innovations depends on how they are generated and diffused.	*Journal of Information Technology*	N/A	Internet, mobile
Rensel, Abbas, & Rao (2006)	Investigates transactional website use in public environments and explores how to bridge the digital divide.	*Journal of the Association for Information Systems*	Modified theory of reasoned action	Public transactional website

Table A1. Digital Divide Research

Kvasny & Keil (2006)	Analyzes how the target populations and service providers in Atlanta and LaGrange Georgia reacted to two initiatives, how these reactions reproduced the digital divide, and the lessons for future digital divide initiatives.	*Information Systems Journal*	Theoretical constructs from Bourdieu	E-commerce
Dewan, Ganley, & Kraemer (2005)	Studies the country-level digital divide across successive generations of IT to explore the changing nature of the divide.	*Journal of the Association for Information Systems*	Theory of reasoned action	Multi-technology
Kauffman & Techatassanaso-ontorn (2005)	Examines digital wireless phone adoption among nations and regions and portrays the current global digital divide.	*Journal of the Association for Information Systems*	A regional contagion theory of technology diffusion	Digital wireless phone
Dewan & Riggins (2005)	Examines the digital divide at three levels of analysis: the individual level, the organizational level, and the global level.	*Journal of the Association for Information Systems*	Innovation diffusion theory	E-commerce
Riggins (2004)	Investigates how the digital divide, where high-type consumers dominate the online channel and low-type consumers dominate the offline channel, artificially segments the marketplace.	*Journal of Management Information Systems*	N/A	E-commerce
Dutton, Sharon Eisner, McKnight, & Peltu (2004)	Analyzes how outcomes linked to ICT innovation are impacted by choices about whether and how to use, or not use, the technology to reconfigure access to people, services, information, and technologies. Presents a framework to assist in redressing digital divides.	*Journal of Information Technology*	N/A	Broadband Internet
James (2004)	Investigates how poor, illiterate persons in developing countries benefit from the Internet without using computers and the Internet.	*Journal of Information Technology*	N/A	Internet
Corrocher & Ordanini (2002)	Develops a model for measuring the digital divide in a set of countries or geographical areas.	*Journal of Information Technology*	N/A	Internet

Appendix B: AI Research

Table B1. AI Research

Source	Topics or findings	Publication	AI application area
Gong et al. (2018)	Examines the effect of keyword ambiguity on the performance of search advertising.	*MIS Quarterly*	Search advertising
Wang et al. (2018)	Uses machine learning techniques to build a copycat-detection method.	*Information Systems Research*	Copycat-detection
Hao, Padman, Sun, & Telang (2018)	Develops a hierarchical Bayesian learning model to examine the impact of social learning through targeted early adopter effects and general peer effects.	*Information Systems Research*	Social learning
Guo, Wei, Chen, Zhang, & Qiao (2017)	Proposes a framework for extracting representative information from intra-organizational blogging platforms.	*MIS Quarterly*	Blogging platforms
Lin et al. (2017)	Designs a Bayesian multitask learning approach for healthcare predictive analytics.	*MIS Quarterly*	Risk profiling in chronic care
Aleksander (2017)	Assesses the actual level of competence that robotics achieves and reviews the role of robots in the foreseeable future.	*Journal of Information Technology*	Robots
Larsen & Bong (2016)	Designs a tool using natural language processing algorithms to address construct identity in literature reviews	*MIS Quarterly*	Construct identity in literature review
Müller, Junglas, Brocke, & Debortoli (2016)	Discusses the use of big data analytics tools (e.g., predictive modeling, natural language processing) as an enquiry strategy for IS research.	*European Journal of Information Systems*	Big data analytics
Shollo & Galliers (2016)	Develops a conceptual framework of organizational knowing and synthesizes the literature to understand the role of business intelligence.	*Information Systems Journal*	Organizational knowing
Meyer et al. (2014)	Designs a machine learning approach for improving dynamic decision making.	*Information Systems Research*	Dynamic decision making
Elkins, Dunbar, Adame, & Nunamaker (2013)	Investigates whether counter-attitudinal expert system recommendations threaten experts.	*Journal of Management Information Systems*	Credibility assessment
Abbasi et al. (2012)	Designs a meta-learning framework for detecting financial fraud.	*MIS Quarterly*	Detecting financial fraud
García-crespo et al. (2010)	Designs a semantic-based framework for customer social networks analysis.	*Journal of Information Technology*	Social networks analysis
Greenwald, Kannan, & Krishnan (2010)	Designs a Markov decision process approach for evaluating information revelation policies in procurement auctions.	*Information Systems Research*	Procurement auctions
Kayande, Bruyn, Lilien, Rangaswam, & van Bruggen (2009)	Evaluates two design characteristics of decision support systems: 1) feedback on the upside potential and 2) feedback on corrective actions.	*Information Systems Research*	AI-aided decision making
Li et al. (2009)	Investigates citation network-based patent classification in managing knowledge.	*Journal of Management Information Systems*	Knowledge management
Druckenmiller & Acar (2009)	Designs an agent-based collaborative approach for graphing causal maps.	*Journal of the Association for Information Systems*	Graphing causal maps

Table B1. AI Research

Bansal, Sinha, & Zhao (2009)	Investigates tuning data mining methods for cost-sensitive regression in loan charge-off forecasting.	*Journal of Management Information Systems*	Loan charge-off forecasting
Arazy & Woo (2007)	Investigates the effect of three key parameters on collocation indexing performance in information retrieval—directionality, distance, and weighting.	*MIS Quarterly*	Information retrieval
Nissen & Sengupta (2006)	Investigates the comparative performance of human and software agents in the procurement domain.	*MIS Quarterly*	Procurement in supply chains
Aleksander (2004)	Presents a personal view talking about the forces driving AI's development.	*Journal of Information Technology*	N/A
Sinha & May (2004)	Conducts an empirical analysis of the performance of five popular data mining methods.	*Journal of Management Information Systems*	Data mining
Wei, Hu, & Dong (2002)	Designs an evolution-based approach for managing document categories in e-commerce environments.	*European Journal of Information Systems*	Document categories management
Murugan (2002)	Designs a behavior-based artificial intelligence approach for profiling web usage in the workplace.	*Journal of Management Information Systems*	Web usage profiling
Walczak (2001)	Investigates data requirements for financial forecasting with neural networks.	*Journal of Management Information Systems*	Financial forecasting

About the Authors

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