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A R T I C L E S

NEW INFORMATION TECHNOLOGY AND IMPLICIT BIAS

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In this paper, we perform a review of relatively recent empirical research that relates new information technology to biased thinking. Based on this review, we develop a framework that suggests a number of implicit associations (i.e., unconscious linkages between phenomena, such as “women are nurturing”) that relate new information technology to a variety of attitudes held by both organizational decision makers and average users of such information technology (e.g., “new information technology is superior to older information technology”). Our framework proposes a set of three underlying beliefs about new information technology (that new information technology is mysterious, nonhuman, and complex) that may underlie the implicit attitudes and biased thinking we identified. These underlying beliefs suggest that biases related to new information technology are distinct, in important ways, from most interpersonal biases studied in organizations. Given these findings, we suggest an agenda for future research that may enhance our ability to understand and mitigate biases related to new information technology in organizational settings.

“I’m interested in things that change the world or that affect the future and wondrous, new technology where you see it, and you’re like, ‘Wow, how did that even happen? How is that possible?’” —Elon Musk, inventor and founder of electric car firm Tesla¹

As this quote indicates, new technology is viewed, often implicitly, as something wondrous that can change the world. As the business world becomes increasingly defined by technological advances (especially in the area of information technology), we suggest that identifying and understanding biases associated with new information technology is increasingly important to effective management. Thus, in this article, we review evidence of implicit biases related to different forms of new information technology and attempt to understand their bases.

Implicit bias has been defined as prejudice based on attitudes or associations that are held internally

and unconsciously by individuals (Dietz & Hamilton, 2008; Uleman, Blader, & Todorov, 2005). In turn, new information technology may be defined (based on the research reviewed in this article) as any number of recently developed, nonhuman aids for decision making and information work, including personal computers, cell phones, and machine automation.²

In general, our review suggests a set of implicit associations and underlying beliefs related to new information technology that are distinct from the more widely studied implicit associations and beliefs related to people (Greenwald et al., 2002). In particular, while implicit associations regarding people tend to be based on concrete and visible characteristics (e.g., age, gender, race), we suggest that implicit associations related to new information technology are based on relatively abstract and

¹ From a March 30, 2014, interview on *60 Minutes*. Retrieved from <https://www.cbsnews.com/news/tesla-and-spacex-elon-musks-industrial-empire/>

² Like Orlikowski and Scott (2008), we find it difficult to explicitly define “new information technology.” Thus, we rely on the articles in our review to suggest a definition of the term.

unseen characteristics (e.g., mysteriousness, non-humanness, complexity) that are generally believed to define this form of technology. This notion suggests that biases related to new information technology may be developed and triggered in ways that are distinct from biases related to people and, as we discuss later, provide incentive for future research on information technology bias in organizations.

IMPLICIT ASSOCIATIONS AND BIAS

Before presenting our review and discussion, however, we provide a brief overview of the foundational research on implicit associations and bias from the study of interpersonal and intergroup attitudes. While this overview is important to understanding the general concept of implicit associations and bias, because our focus in this paper is information technology—not people—we have kept this section relatively brief. Our goal in the two subsections below is to outline the primary mechanisms involved in promoting and impeding implicit associations and bias, as well as some of the critical evaluations of this work.

Implicit Associations: Foundations and Mechanisms

Implicit associations may be defined as attitudes about objects “that are automatically activated by the mere presence of the object” (Hewstone, Rubin, & Willis, 2002, p. 577). For example, upon encountering a group of engineering students, one may unconsciously activate the attitude that “engineers are nerdy.” Implicit associations are, thus, distinguished from explicit attitudes—of which one is consciously aware and may readily admit (Hewstone et al., 2002). For example, through tests, such as the Implicit Association Test (Fazio & Olson, 2003), psychologists may identify unconscious associations between groups of people (e.g., women) and character traits (e.g., poor technical ability) to which people would not consciously admit. Further, when implicit associations are negative (as in the prior example), they may trigger “implicit bias,” the tendency to unconsciously evaluate a person or group in an unfavorable manner (Gawronski & Payne, 2011).

As in the above examples, psychological research on implicit associations has historically been dominated by the study of interpersonal and intergroup perceptions (Bargh, 2007; Greenwald & Krieger, 2006; Hewstone et al., 2002). This research suggests that unconscious impressions or attitudes about

people and groups are often based on salient features, such as physical characteristics (e.g., age, gender, race), noticeable behaviors (e.g., high or low performance), or markers of social categories (e.g., occupying the corner office or top floor of an office building, which often marks high status) (Uleman, Adil Saribay, & Gonzalez, 2008). Further, findings from this research indicate that these salient features lead observers to attribute to others—spontaneously and without intent—associated traits such as intelligence, ability, and trustworthiness (Uleman et al., 2005). In other words, implicit associations—sometimes called implicit trait inferences (Carlston & Skowronski, 1994)—are triggered when people notice any number of visible or salient characteristics of others (or groups of others). For example, researchers have shown that race-based implicit associations (e.g., Asians are good at math) may be triggered when a person encounters ethnic names or speaking accents during employment interviews (Purkiss, Perrewé, Gillespie, Mayes, & Ferris, 2006). While a full review of research on interpersonal and intergroup implicit associations is beyond the scope of this article, experimental studies by psychologists provide substantial evidence that such implicit attitudes exist and are commonly triggered (Dietz & Hamilton, 2008; Greenwald et al., 2002; Hewstone et al., 2002).

Subsequently, psychological research has shown that implicit associations influence judgments and decision making with regard to others. In organizational settings, these decisions may involve things like whom to hire and promote (Dietz & Hamilton, 2008). For example, in one of the most famous studies involving person perception and implicit bias, Bertrand and Mullainathan (2004) demonstrated that implicit associations between race and work traits (e.g., European Americans are hard workers, while African Americans are not) influenced judgments of job applicants and led hirers to follow up with applicants with European-sounding names much more frequently than those with African American-sounding names, even though both sets of applicants had identical experience and background according to their résumés.

In turn, psychological research has examined how individuals might reduce implicit bias and prejudice by inhibiting implicit associations. For example, some research indicates that having more contact with groups about whom we have prejudice may reduce implicit associations that lead to that prejudice (van Nunspeet, Ellemers, & Derks, 2015). Thus, in a study of inter-ethnic friendship and prejudice,

Abersson, Shoemaker, and Tomolillo (2004) found that individuals with close friends who were members of an ethnic target group exhibited less prejudice (i.e., less agreement with prejudiced statements about the ethnic target group) than those without close friends in the target group. This study provides support for the contact hypothesis of stereotype reduction (Pettigrew & Tropp, 2008), which suggests that the more we personally interact with members of a group, the harder it is to see them in terms of the broad generalizations that form the basis for stereotypes. More recent research has shown that merely imagining positive contact or collaboration with a stereotyped group can reduce implicit biases toward that group (Kuchenbrandt, Eyssel, & Seidel, 2013).

In addition to contact, other research has shown that motivation may reduce biased attitudes toward groups of people (Plant & Devine, 1998; Rudman, Ashmore, & Gary, 2001; van Nunspeet et al., 2015). For example, Devine, Plant, Amodio, Harmon-Jones, and Vance (2002) found that individuals who were high in internal motivation to be unprejudiced (e.g., they agreed with statements such as “I attempt to act in nonprejudiced ways toward [X group] because it is personally important to me”) exhibited lower levels of biased implicit associations toward a target group than those who were low in such motivation. Interestingly, however, individuals who were high in external motivation to be unprejudiced (e.g., they agreed with statements such as “I attempt to appear nonprejudiced toward [X group] in order to avoid disapproval from others”) did not exhibit lower levels of biased attitudes toward the group.

While these studies indicate strong support for the notion that humans form unconscious associations between people/groups and salient traits/characteristics, research on implicit associations is not without its criticisms. In particular, some research has shown that correlations between implicit and explicit (i.e., deliberate) evaluations can be relatively high when self-presentational concerns of evaluators are low (Cameron, Brown-Iannuzzi, & Payne, 2012). This research suggests that, when evaluators are not worried about how they are perceived by others, their implicit attitudes match closely with their explicit attitudes. Other research has shown that when evaluators are asked to focus on their “gut feelings” when making explicit evaluations, their responses increase in correlation to a corresponding implicit evaluation (Gawronski & LeBel, 2008).

Given these criticisms of implicit associations, researchers have begun to investigate the contexts in which measures of implicit attitudes may be most

distinct from explicit attitudes (Gawronski, LeBel, & Peters, 2007; Hofmann, Gawronski, Gschwendner, Le, & Schmitt, 2005). Research in this area suggests that implicit measures of attitude may be best suited to identifying biases related to ambiguous information or associations for which evaluators are not fully confident (Hugenberg & Bodenhausen, 2003). For example, Gawronski, Galdi, and Arcuri (2015) suggested that implicit measures are useful in assessing the “embryonic” political views of evaluators who are not confident enough in these views to express them explicitly.

Implicit Bias and New Information Technology

Given the strength of findings regarding implicit biases in interpersonal and intergroup perception, researchers have begun to investigate implicit biases in the context of nonhuman phenomena, such as information technology (Bhattacharjee & Premkumar, 2004; Clark, Robert, & Hampton, 2016). Findings from this research suggest that implicit associations might unconsciously influence attitudes about and use of a variety of information technologies, from smartphone apps (Pak, McLaughlin, & Bass, 2014) to decision aids for aircraft pilots (Parasuraman & Manzey, 2010). Further, given that evaluators are not likely to be fully confident in their assessments of new information technology (at least not in their initial evaluations), this context seems appropriate for using implicit measures to assess attitudes (Gawronski et al., 2015).

While recent research on implicit bias and new information technology confirms the relative generalizability of bias frameworks from person perceptions to other settings (Merritt, Heimbaugh, & LaChapell, 2012), it has not been reviewed to illuminate patterns in new information technology bias or how implicit attitudes toward information technology may differ, in important ways, from those regarding people. In particular, scholars have not reviewed extant research on new information technology and implicit bias in organizational settings as a means of better understanding attitudes toward and uses of such information technology at work, and how these attitudes might contrast with those related to people at work. As we show below, attitudes regarding new information technology may be irrational and lead to poor decision making by users (Venkatesh, Morris, Davis, & Davis, 2003). Thus, having a clear understanding of new information technology biases appears important to thoughtful decision making regarding new information technology in organizations.

In the following sections, we describe findings from a review of 96 relatively recent empirical research articles relating implicit attitudes and biases to new information technology use in organizations. We began our review by searching for publications on new information technology and bias available through online databases related to business and management (EBSCO Business Source Complete), psychology (PsychInfo), and engineering (ScienceDirect). Our search involved the keywords *information technology, automation, computers, digital, innovation, entrepreneur, bias, stereotype, implicit, association, and cognition*.

We then followed Rousseau, Manning, and Denyer's (2008) approach of "synthesis by explanation," which seeks to create explanations for phenomena by discerning patterns in published articles. As Rousseau et al. (2008, p. 499) noted:

[A]n explanatory approach . . . treats the vital evidence from primary studies incorporating the original researchers' interpretations and explanations, not just results. The scope of the review includes a wide range of research types and data forms to promote a full understanding of the phenomena of interest. Its product is a revised model intended to explain for whom, under what circumstances, in what respect and why, certain causes or interventions produce preferred outcomes.

This approach has led us to include additional literatures on the technology acceptance model and human-computer interaction as well as additional journals (e.g., *Behavior and Information Technology, Human Factors, Journal of Human-Computer Studies*). After this extended search process, we had collected 137 articles.

Upon a more careful reading of these 137 articles, we identified 96 that were clearly related to our research objectives (i.e., they were empirical and provided evidence of implicit associations related to new information technology). We summarize these 96 articles in an appendix (see Supplementary Materials in the online version of this article), including the full citation, methods, primary findings, and apparent implicit associations indicated. We detail our review of these articles next.

NEW INFORMATION TECHNOLOGY AND IMPLICIT BIAS IN ORGANIZATIONS: A REVIEW OF EXTANT RESEARCH

Through our review of the 96 empirical articles described above, we found substantial evidence of

biased attitudes by users or potential users of new information technology. In turn, these findings suggested a number of implicit associations related to new information technology, as well as three general beliefs that appear to underlie these implicit associations. These general beliefs are that new information technology is (a) mysterious/unknown, (b) nonhuman/alien, and (c) complex/difficult to understand. Together, our findings regarding biased attitudes, implicit associations, and general beliefs related to new information technology comprise a framework of information technology and implicit bias. This framework is depicted in Figure 1.

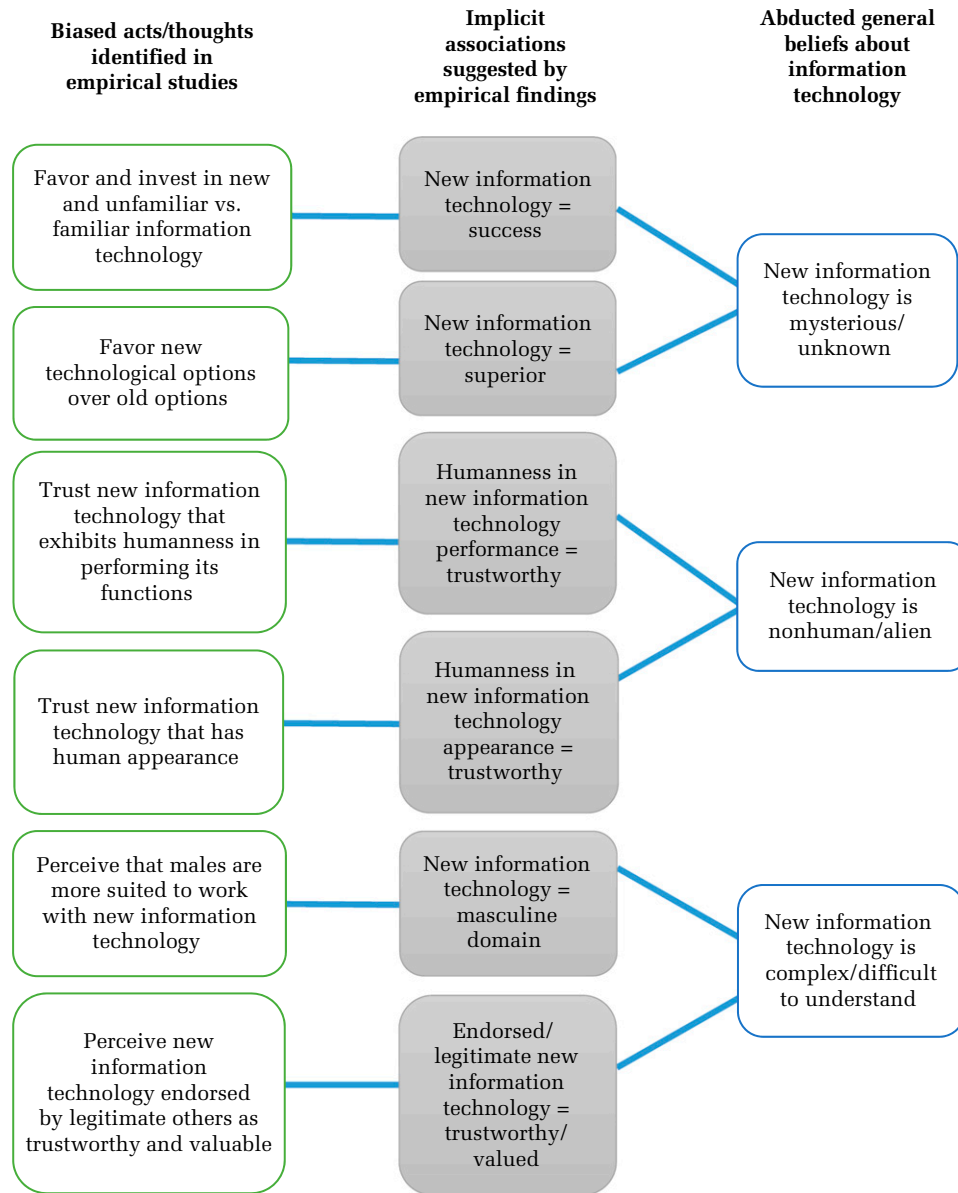
It is important to note that, as shown in the figure, the general beliefs in this framework arose from our review rather than from a formal empirical investigation, and thus might be thought of as the result of "abductive thinking" (Kolko, 2010). As Kolko (2010, p. 19) noted: "Abduction can be thought of as the step of adopting a hypothesis as being *suggested* by the facts . . . a form of inference [emphasis added]." In other words, abduction might be thought of as the "logic of what *might* be [emphasis added]" (Kolko, 2010, p. 20). As such, the general beliefs we outline represent what *could* be underlying the patterns we observed in the empirical articles we reviewed, but they have not been formally tested.

As shown in Figure 1, these general beliefs arose from our review as follows: *evidence from empirical research* about user perceptions and experiences with new information technology → *suggested implicit associations* between specific types of new information technology and characteristics of innovations → *abducted general beliefs* about new information technology. We discuss this stream of evidence, suggestions, and abductions in the following sections.

EVIDENCE SUGGESTING THE GENERAL BELIEF THAT NEW INFORMATION TECHNOLOGY IS MYSTERIOUS/UNKNOWN

Our abduction that people hold a general belief that new information technology is mysterious/unknown began with empirical research examining support from potential investors and users for new information technology (e.g., Agarwal & Prasad, 1998; Clark et al., 2016; Lockett, Murray, & Wright, 2002; Madhavan & Wiegmann, 2004; Simon & Houghton, 2003; Sveiby et al., 2009). For example, Lowe and Ziedonis (2006) found that continued investment in failing projects was more likely in firms investing in new information technology than in

FIGURE 1
A Framework of New Information Technology and Implicit Bias



other types of investments. Similarly, Lafferty and Goldsmith (2004) found that potential users had more positive attitudes toward and were more willing to purchase technology that was viewed as “new” (versus old or preexisting). Additional examples of such biases toward investing in or adopting new information technology are given in our appendix (in the Supplementary Materials).

In general, these studies provided evidence that those who must decide whether or not to invest in or use a new information technology are biased in their

predictions about the potential success of these technologies and the superiority of these technologies over existing ones. In this manner, these studies suggest two implicit associations that we define as “new information technology = success” and “new information technology = superior.” In the following sections, we describe empirical evidence from our review for both of these implicit associations. Following this evidence, we explain how these implicit associations led us to our abducted general belief that *new technology is mysterious/unknown*.

Findings Suggesting the Implicit Association of New Information Technology = Success

We found a number of research studies indicating that members of the general public implicitly associated new information technology with “success” (e.g., Clark et al., 2016; Mordini, 2007; Moynihan & Lavertu, 2012; Shane, 2002; Vishwanath & LaVail, 2013). Findings from these studies suggest that general audiences associate new information technology with success based on oft-repeated stories that exaggerate the successes of previous technological breakthroughs (e.g., how DNA sequencing has completely changed disease management).

In this vein, Clark et al. (2016) performed a series of experimental studies with undergraduates that examined attitudes about new and unfamiliar information technology. The authors found that participants (a) invested in new information technology stocks more than noninformation technology stocks, (b) were more optimistic about the future of an unfamiliar versus familiar information technology, and (c) unconsciously associated success with new technological industries and products. Further, the authors predicted that, because successful information technology introductions were so familiar and well-known to most people, the mere mention of new information technology was often enough to trigger the new information technology = success implicit association, or what they called “the information technology effect.”

In support of this notion, Clark et al. (2016) found that biases toward new information technology were most pronounced when participants in their studies were given evidence about the past success of new information technologies, triggering the new information technology = success implicit association. By contrast, it appeared difficult for participants in their studies to think of *unsuccessful* information technologies (who can remember the name of early voice-recognition software?)—possibly because technology firms have been reluctant to discuss and publicize failures that might be detrimental to their viability (Lundholm & Van Winkle, 2006).

In a related manner, Vishwanath and LaVail (2013) used survey methods to examine attitudes about new personal computer technology (either PCs or Macs) that had been adopted by individual users. Their findings showed that early adopters of such information technology (those who adopted when the technology was relatively new and unknown) showed biased optimism toward the new information technology—consistent with the “new information technology = success” implicit association—and

blamed any failures on user error rather than on the technology itself. In turn, this thinking was associated with continued use of the information technology even after it failed. Vishwanath and LaVail (2013) contrasted these findings with the lower optimism displayed by later adopters (those adopting the information technology when it was more well-known), who were more likely to blame failures on the technology itself and discontinue its use after failures occurred.

While Vishwanath and LaVail’s (2013) findings may be attributed, in part, to self-enhancement motives by early adopters (e.g., blaming failures on other users protects their self-esteem by suggesting they were correct to adopt the new information technology), they are also consistent with the notion that implicit associations exist between new and unfamiliar information technology and success. This latter argument makes even more sense when one considers that later adopters, who, like early adopters, would have been motivated to protect their self-esteem by blaming failures on user error, nevertheless blamed these failures on the information technology itself (which, at the time of the adoption, was no longer “new”).

Similar optimism biases about new and unfamiliar technologies have been shown in other organizational studies (Lowe & Ziedonis, 2006; Simon & Houghton, 2003). For example, Garud and Ahlstrom (1997) found that developers of three new medical technologies (the artificial heart, cochlear implants, and the FK 506 immunosuppressive drug) overestimated patient benefits and underestimated the time and cost for development. In these cases, the researchers suggest that overoptimism was related to the newness and ambiguity of the new technology as well as the need to move quickly, which encouraged the use of simplifying biases (Shane, 2002). Again, these findings are consistent with a “new information technology = success” implicit association and decision making that was overly optimistic as a result.

Finally, research on investment by venture capitalists (VCs) or entrepreneurs in new businesses provides support for a new information technology = success implicit association (Palich & Bagby, 1995; Simon & Shrader, 2012). For example, in a study examining investment decisions by VC firms in small and medium-sized enterprises, Riquelme and Watson (2002) found that perceptions that the new enterprises had products that were “technologically advanced” were part of the VCs’ mental models for enterprise success. That is, they implicitly associated new information technology with success in new ventures,

and were biased in their willingness to fund them over other ventures.

Findings Suggesting the Implicit Association of New Information Technology = Superior

Related to the new information technology = success implicit association, we found a number of studies that suggested an implicit association between new information technology and “superiority” over existing information technology (e.g., Kambil & Martins, 1999; Lafferty & Goldsmith, 2004; Riquelme & Watson, 2002; Smith, Zhang, & Colwell, 1996). In these studies, decision makers were typically comparing newly created technologies to preexisting technologies, and they appeared to be biased in favor of the information technology that was new.

This implicit association is related to the new information technology = success implicit association in that it is accompanied by overoptimism for new information technology. Yet it is distinct from the new information technology = success implicit association (which is grounded in predictions about the future performance of the new information technology) because it is grounded in implicit *comparisons* between new and preexisting technologies (Fu & Elliott, 2013). In this way, the new information technology = superior bias is closer to what Rogers (1976, p. 295) described as a “pro-change” or “pro-innovation” bias, which suggests that anything new is superior to anything preexisting. This is also related to the “recency bias” that has been suggested to lead firms to focus on newer innovations over historical knowledge (De Massis, Frattini, Kotlar, Petruzzelli, & Wright, 2016).

In particular, this general tendency to perceive new information technology as superior to preexisting information technology has been demonstrated, consistently, in marketing studies of new products (Fu & Elliott, 2013; Fuhrman, 2007; Lafferty & Goldsmith, 2004; Szymanski, Kroff, & Troy, 2007). For example, in an experimental study rating a new cell phone model (Lafferty & Goldsmith, 2004), participants’ ratings of the cell phone’s perceived “newness” (e.g., “unlike all others,” “innovative,” “new”) was significantly predictive of their positive attitudes toward the cell phone brand and their intentions to buy the cell phone. Similarly, in an experimental study involving a new type of portable media player, Fu and Elliott (2013) found that participants’ perceptions of the player’s innovativeness (e.g., “first of its kind,” “totally new to the market,”

“new product category,” “innovative”) predicted attitudes regarding the player’s favorability and usefulness, and in turn, mediated the effects of these attitudes on intentions to purchase the player.

In other cases, new product adoptions *within* an organization have been shown to be influenced by a new information technology = superior implicit association (Kraiczy, Hack, & Kellermanns, 2014). For example, one study examined the introduction of a new content management system designed to help technical writers collaborate on documentation tasks (Coggio, 2015). In this study, the author found that the internal change agents tasked with introducing the new system had a strong bias in favor of the new system, even though they did not have expertise in how the new system would be used by employees. This pro-innovation bias led the change agents to emphasize technical considerations (what is called “technocratic rationality”) over other considerations (e.g., ease of use), which ultimately led many workers to resist the system.

Abducted General Belief That New Information Technology Is Mysterious/Unknown

“Any sufficiently advanced technology is indistinguishable from magic.” —Arthur C. Clarke (Clarke, 1973).

In line with the above quote, we argue that our findings about the implicit associations of “new information technology = success” and “new information technology = superior” indicate that potential investors or users of these technologies hold the general belief that new information technology is mysterious and unknown (Heidegger, 2010; Postman, 2011). We believe that this general belief explains why potential investors would be willing to forgo careful analysis of new technology (Clark et al., 2016), and why potential users are willing to discount failures of new technology as “user error” versus technology problems (Vishwanath & LaVail, 2013). That is, we suggest that, if new technology is perceived in the abstract, as a “wonder” to behold but not a tool to understand (Mordini, 2007), these types of reactions to new technology may be explained (why try to carefully evaluate the potential of a new technology if one can’t really do this accurately?).

The general belief that a new technology is mysterious is further supported by the ease with which these potential users or investors appear to conjure up thoughts of technological advances that seem miraculous (e.g., using nanotechnology to treat

cancer) as well as those that have changed our everyday lives (e.g., mobile phone apps with real-time maps that are updated by satellites). Clark et al. (2016) suggested that this ease is related to the abstract nature of information technology, which is most often equated with unfamiliar or “mysterious” technologies. Thus, they argued that new information technologies hold “all of the abstract promise . . . that is facilitated by lack of understanding” (Clark et al., 2016, p. 98).

EVIDENCE SUGGESTING THE GENERAL BELIEF THAT NEW INFORMATION TECHNOLOGY IS ALIEN/NONHUMAN

Our abduction that people hold the general belief that new information technology is alien/nonhuman began with empirical research relating trust in information technology to humanness in appearance and performance (e.g., Hoff & Bashir, 2015; Lankton, McKnight, & Tripp, 2015; Pak et al., 2014; Qiu & Benbasat, 2009; Schaefer, Chen, Szalma, & Hancock, 2016). In these studies, humanness in appearance involved using a human voice and image, while humanness in performance involved politeness and friendliness in the way in which the technology interacted with users. Researchers found that these “human” characteristics led users to be more trusting of information technology. For example, in a meta-analysis of more than 30 studies involving automation information technology, Schaefer and colleagues (2016) found that information technology that appeared more human and interacted in a human way was more trusted than information technology that did not appear and perform in a human-like manner. Additional findings supporting this notion are summarized in the appendix (Supplemental Materials).

As a result of these findings, our review suggested two implicit associations: (a) humanness in new information technology performance = trustworthy, and (b) humanness in new information technology appearance = trustworthy. We discuss these two implicit associations and their associated behaviors next, and follow this discussion with an explication of our abducted general belief.

Findings Suggesting the Implicit Association of Humanness in New Information Technology Performance = Trustworthy

A number of empirical studies suggest that people view new information technology that performs its

functions in a “human-like” manner to be more trustworthy than information technology that is less human in its performance (e.g., Lankton et al., 2015; Montague, Winchester, & Kleiner, 2010; Sauer, Chavaillaz, & Wastell, 2016; Schaefer et al., 2016; Verberne, Ham, & Midden, 2012). In these studies, humanness in performance might include allowing input by humans, taking turns with humans in decision making, expressing shared goals with human operators, or exhibiting politeness and friendliness in responding to human users. When these types of “human behaviors” are evident in new information technology, research suggests that users tend to trust it more. As Lankton and colleagues (2015, p. 885) explained with regard to humanness in computer information technology:

Whenever computer information technology exhibits humanlike behaviors, such as language production, taking turns in conversation, and reciprocal responding, the user is more likely to personify the information technology (Moon, 2000; Nass, Moon, Fogg, Reeves, & Dryer, 1995). For example, people may make kind comments about a computer that demonstrates courtesy (Wang, Baker, Wagner, & Wakefield, 2007).

Further, Lankton et al. (2015, p. 884) suggested that trust in these types of behaviors can be explained by social presence theory (Rettie, 2003), which posits that “the attributes of an information technology influence whether it is perceived as being more sociable, warm, and personal than other technologies based on the extent to which it allows a user to experience other individuals as being psychologically present.” In turn, social presence has been argued to build trust in new information technology because it reduces uncertainty and risk associated with interacting with an unfamiliar technology (Kumar & Benbasat, 2006).

Extant research also suggests that implicit trust in new information technology that performs in human ways is often triggered when individuals interact with such technology in decision-making contexts (Verberne et al., 2012). In these situations, users may conjure implicit beliefs related to human interactions in decision making (e.g., I trust other decision makers that share my goals) and apply these beliefs to their interactions with information technology (e.g., I trust information technology decision aids that share my goals), even though they are aware that information technology is different from humans (Reeves & Nass, 1996). In turn, users may be biased in favor of information technology that performs in ways that mimic desired human behaviors. As Schaefer and colleagues

(2016, p. 383) noted with regard to automation in information technology that “collaborates” in a human way:

Individuals exhibit greater trust in automation that provides some level of collaboration. For example, users typically trust manually adjustable automation when it provides explicit control (i.e., the human has the authority over system function allocation), compared to implicit control (i.e., the system is given the authority).

In a typical study showing support for an implicit association between humanness in new information technology performance and trust, Verberne and colleagues (2012) used experimental methods to study user trust in a new adaptive cruise control (ACC) system on automobiles. In this study, the ACC system was designed to maintain a safe following distance and speed when activated by an auto’s driver. Verberne and colleagues (2012) found that users indicated more trust in the ACC if they were given information that the new information technology shared in their goals (e.g., related to comfort, speed, energy efficiency, or safety) and provided information about why it was taking over driving functions when it did so.

In a similar manner, Lankton and colleagues (2015) performed a survey study involving user attitudes about new social communication technologies (e.g., Microsoft Access, a classroom information technology, and Facebook). Findings showed that users rated Facebook as significantly more “human” than Microsoft Access because Facebook allowed users to experience others as more psychologically “present” (through “likes”) and to interact socially through the ability to post and view comments, photos, and videos. In turn, Lankton and colleagues (2015) found that users rated Facebook relatively higher in human-like trust (i.e., perceptions that the information technology was competent and benevolent and had integrity—in line with Mayer, Davis, & Schoorman’s [1995] model of interpersonal trustworthiness in organizations).

Finally, in an experimental study examining the effects of etiquette on trust in automated advice given by new information technology for diagnosing aircraft engine problems, Parasuraman and Miller (2004) found that advice given in a polite (vs. rude) manner increased trust in the new information technology to such an extent that it could overcome poor reliability of the information technology. Thus, trust in new information technology that was polite but reported to have only 60% reliability was equal

to trust in new information technology that was reported to have 80% reliability but engaged users in a rude manner.

Findings Suggesting the Implicit Association of Humanness in New Information Technology Appearance = Trustworthy

Related to the above findings, we found evidence of implicit associations between humanness in the appearance of new information technology (information technology that looks and sounds human) and trustworthiness (e.g., Cyr, Head, & Pan, 2009; Hassanein & Head, 2007; Pak et al., 2014; Qiu & Benbasat, 2009). As noted above, information technology that behaves as humans do may increase trust through social presence (i.e., the feeling that another is psychologically present in interactions with information technology; Rettie, 2003). Similarly, research in this area has shown that social presence (and subsequently trust) may be enhanced by information technology that appears human, including information technology that has humanoid embodiment and voice (Qiu & Benbasat, 2009), as well as use of emotive text and human images (Cyr et al., 2009; Hassanein & Head, 2007). Further, this research indicates that implicit associations between human appearance and trust may be triggered when the reliability of new information technology is uncertain or ambiguous.

For example, several studies have shown that new information technology that includes human images is more trusted than that which does not contain such images (Cyr et al., 2009; Kim & Moon, 1998). In an experimental study of reactions to human images in website design, Cyr and colleagues (2009) found that websites with human images containing facial features were seen as more appealing and warm to potential users. In turn, perceptions of warmth and appeal led to more trust in the website. Similarly, in a study of trustworthiness in cyber banking, Kim and Moon (1998) found that a human image in the interface improved users’ trust in the banking system.

In another study, involving an online shopping context, Qiu and Benbasat (2009) examined how both humanoid embodiment and voice influenced shoppers’ trust in a computerized salesperson offering advice about digital cameras. In this study, the authors used the presence (vs. absence) of an animated face and the use of a human voice (vs. text or computer-generated voice) to assess the effects of salesperson appearance on user trust. In an experiment using actual online shoppers, they found that,

compared to a sales agent represented by text only or by computer-generated voice only, a sales agent represented by an animated face and human voice led to ratings of higher social presence of the salesperson, which in turn led to higher trust in the salesperson. While participants were not given information about the reliability of the salesperson, the complexity of the items being sold (digital cameras), the rapidness of new model introduction, and the large number of models sold were hypothesized to lead most users to feel unsure about the reliability of the advice being given.

Abducted General Belief That New Information Technology Is Alien/Nonhuman

We argue that findings about the implicit associations of “humanness in new information technology appearance = trustworthy” and “humanness in new information technology performance = trustworthy” indicate that potential users of these technologies hold the general belief that *new information technology is nonhuman and alien* (Goddard, Roudsari, & Wyatt, 2012). In particular, we believe that this general belief explains why users are especially attentive to the degree to which information technology appears and performs like humans. That is, because information technology is thought to be nonhuman, any performance or appearance features of the technology that make it seem more human are noticed.

This general belief is further supported by findings supporting the “automation bias,” which indicate that many users believe in the inherent superiority of new information technology over humans in performing complex analyses and diagnoses (Mosier & Skitka, 1996; Skitka, Mosier, & Burdick, 2000). Together, these findings suggest that new information technology is seen as clearly distinct from humans—that is, it is seen as nonhuman.

EVIDENCE SUGGESTING THE GENERAL BELIEF THAT NEW INFORMATION TECHNOLOGY IS COMPLEX/ DIFFICULT TO UNDERSTAND

Finally, our abduction that people hold the general belief that new information technology is complex/difficult to understand began with research showing that users were more likely to trust and value new information technology that was endorsed by legitimate others (e.g., Amin, Hamid, Lada, & Anis, 2008; Bonardo, Paleari, & Vismara, 2011; De Vries & Midden, 2008; Fu & Elliott, 2013; Subramanian, Lim, & Soh, 2013), as well as evidence that users

perceived new information technology to be more of a masculine (vs. feminine) domain (Cooper, 2006; Pinkard, 2005; Selwyn, 2007). For example, Zucker and Darby (1996) found that if “rock star” scientists (i.e., well-known and admired scientists) were attached to a new technology proposal, it was more likely to be developed than a proposal without such endorsement. Further, as we discuss below, numerous studies suggest that people tend to view new information technology as the domain of men (vs. women), who also tend to dominate science and technology fields that are viewed as complex and difficult (e.g., computer and software engineering). Additional examples of such biases related to new information technology are given in our appendix (Supplementary Materials).

Together, these studies provide evidence of two implicit associations among users and developers of information technology: (a) endorsed/legitimate new information technology = trustworthy/valued and (b) new information technology = masculine domain. We discuss findings suggesting these implicit associations next, and follow this discussion with an explication of our abducted general belief.

Findings Suggesting the Implicit Association of Endorsed/Legitimate New Information Technology = Trustworthy/Valued

Our review highlighted a number of studies suggesting the implicit association that new information technology that is endorsed by legitimate others is trustworthy and valued (e.g., Bromley-Trujillo, Stoutenborough, Kirkpatrick, & Vedlitz, 2014; Stoutenborough & Vedlitz, 2016; Wang & Guan, 2011). This implicit association is consistent with the traditional view of new technology as the application of complex, scientific knowledge to specific purposes (e.g., Fox, Jasanoff, Markle, Petersen, & Pinch, 1995; Pinch & Bijker, 1984). In this vein, numerous studies have shown that the existence of scientific knowledge about new information technology, as well as scientists’ or other experts’ approval of the information technology, lowers the perceived risks and increases the perceived benefits associated with that information technology (Higgins, Stephan, & Thursby, 2011; Siegrist, 2000, 2008; Siegrist, Stampfli, Kastenholz, & Keller, 2008; Wang & Guan, 2011). In addition, researchers have shown that such legitimate endorsement contributes to the perceived trustworthiness of new information technology (e.g., Stoutenborough & Vedlitz, 2016), which predicts its use (Guo & Ren, 2017).

Dominant in this literature is the deficit model of public acceptance that assumes that most members of the public have “deficient” knowledge of new technology, while scientists or other experts possess “sufficient” knowledge (Gross, 1994; Wynne, 1991). This model explains why the public can be initially hostile to new technologies, but also may be more trusting of technologies that are vetted and endorsed by experts (e.g., Stoutenborough, Sturgess, & Vedlitz, 2013; Stoutenborough & Vedlitz, 2016; Sturgis & Allum, 2004; Zoellner, Schweizer-Ries, & Wemheuer, 2008).

In support of this model, a number of studies provide evidence that reliance on social trust in experts, such as scientists, will occur “when an individual lacks knowledge about an [information technology]” (Siegrist & Cvetkovich, 2000, p. 713). For example, a study by Dzindolet, Pierce, Beck, and Dawe (2002) showed that an automated system for visual detection that was endorsed by a university was seen as more trustworthy than humans for the same task. Similar endorsement by experts has also been shown to enhance trust in automated decision systems in studies of unmanned vehicles (Clare, Cummings, & Repenning, 2015) and route planners (DeVries & Midden, 2008).

In addition to increasing trust in information technology, researchers have also found that endorsement by experts leads to high valuation of information technology. For example, Bonardo and colleagues (2011) studied the effects of university academics on the valuation of 499 high-tech firms that went public between 1995 and 2003. Their findings showed that firms that had academics on their top management teams (an apparent endorsement of the firm) were valued higher in initial stock offerings than those who did not have such endorsements. Similar effects have been found in other studies examining the effects of research scientists’ endorsement on venture capital funding for high-tech ventures (Fuller & Rothaermel, 2012; Higgins et al., 2011). For example, Fuller and Rothaermel (2012) found that endorsement from “star scientists” helped new information technology ventures to reach an initial public offering. In these cases, the scientists’ endorsement of the venture appeared to provide a “credible signal about the unobserved quality of the new venture” (Fuller & Rothaermel, 2012, p. 232).

Relatedly, research on the technology acceptance model (Davis, Bagozzi, & Warshaw, 1989) has shown that perceived value of new information technology is enhanced when legitimate others endorse that

technology (Agarwal & Prasad, 1997; Clare et al., 2015; DeVries & Midden, 2008; Macedo, 2017; Ranjan & Athalye, 2009; Venkatesh & Davis, 2000; Wang & Benbasat, 2005). For example, in a field study involving adoption of a new automated scheduling system, Venkatesh and Davis (2000, p. 201) found that those who perceived that “others who are important to me think that I should use the system” were more likely to perceive the new information technology as valuable and accept it. This finding has been replicated in numerous other studies, including those examining perceptions of the value of the Internet (Macedo, 2017), mobile banking information technology (Amin et al., 2008; Riquelme & Rios, 2010; Sripalawat, Thongmak, & Ngramyarn, 2011; Yu, 2012), and consumer electronics (Fu & Elliott, 2013).

Findings Suggesting the Implicit Association of New Information Technology = Masculine Domain

Another implicit association suggested by our review is that new information technology = masculine domain. Scholars in the tradition of social construction of technology (e.g., MacKenzie & Wajcman, 1985; Wajcman, 1991, 2000) have suggested that relationships with information technology are gendered, and that information technology itself cannot be fully understood without reference to gender issues (Dixon et al., 2014). In particular, feminist scholarship within the field of information technology studies has extensively investigated the role of women in information technology (Faulkner, 2000) and the relationship between women and information technology (Faulkner, 2001). This body of work has documented the persistence of a gender gap manifested in fewer women working in the so-called STEM fields—science, technology, engineering and mathematics—(e.g., Robnett, 2016; Sotudeh & Khoshian, 2014; Verbick, 2002; Wang & Degol, 2016), and hence, fewer women involved in the development of new technologies (e.g., Leach & Turner, 2015; Selwyn, 2007).

Scholars have attributed women’s limited participation in science and technology, in part, to the implicit association between masculinity and technology (Faulkner, 2001), and to the notion of new technology as a “male-centered world” (Kilbourne & Weeks, 1997) or as a key source of male power (Wajcman, 2006). The origins of this implicit association have been traced back to the Industrial Revolution, when the patriarchal nature of science and technology was formed as a consequence of the shift

from the organic, female worldview to a male, mechanical worldview. As Wajcman (2006, p. 8) noted:

The very definition of information technology has had a male bias. The emphasis on machines dominated by men conspired in turn to diminish the significance of women's technologies, such as horticulture, cooking and childcare, and so reproduced the stereotype of women as technologically ignorant and incapable. The history of information technology still represents the prototype inventor as male.

According to these perspectives, the implicit association between men and new information technology is the result of the historical, social, and cultural construction of gender that started with the formation of engineering as a white, male, middle-class profession that led "male machines rather than female fabrics to become markers of information technology" (Wajcman, 2010, p. 144).

We found evidence of an implicit association between new technology and masculinity in studies of attitudes toward computers and, in general, to technologies in modern society. For instance, in a study of 406 undergraduate students, Selwyn (2007) found that gender stereotypes influenced how young people perceived aspects of new information technology. They found that only communicative and creative applications of information technology, such as graphics, emailing, and e-learning, were perceived as feminine, while all other applications, such as digital music, digital cameras, laptop computers, and online banking, were perceived as masculine. These findings are consistent with the notion of computers as eminently "toys for boys" and with the stereotype that women are inferior to men when it comes to technological skills (e.g., Cooper, 2006; Faulkner, 2001; Verbick, 2002).

In turn, a number of studies have investigated the reinforcing consequences that such implicit associations have on women's attitudes toward computers. For instance, Smith, Morgan, and White (2005) showed that the general association between computers and men (and not women) led to lower computer information technology domain identification for women, and forced women still considering the information technology field to create strategies for overcoming stereotypes related to gender by either downplaying their female status or emphasizing their masculine traits. In a similar vein, Cooper (2006) showed that female students primed with their gender identity immediately before a computer task performed worse than those who were primed with their student identity. They explained these

findings as a result of the pressure of the negative stereotypes—what's been called stereotype threat (Steele & Aronson, 1995)—related to women's technological skills. Further, Koch and colleagues (2008) found that after having been exposed to negative stereotypes related to their technological abilities, women were more likely to attribute failure in performing a computer task to their own inability than did men (who were more likely to blame faulty equipment).

Researchers have also documented that, in general, women suffer from lower perceptions of technological self-efficacy and higher levels of anxiety than men when using computers and digital technologies (e.g., Cooper, 2006; Cooper & Weaver, 2003; Huffman, Whetten, & Huffman, 2013). In particular, in their study of 750 undergraduate students, Huffman and colleagues (2013) found that in addition to biological sex, perceived gender roles affected technological self-efficacy. Specifically, they found that perceived masculinity as a gender role was a strong predictor of information technology self-efficacy. This finding is consistent with the implicit association between computers and men (but not women). In turn, numerous studies suggest that this implicit association undermines the success of women in information technology fields. For example, several studies have shown that, perhaps as a result of the implicit association between men and information technology, women receive insufficient encouragement and support in school for careers in information technology (Kanny, Sax, & Riggers-Piehl, 2014; Robnett, 2016) and lack positive female role models in technological fields (Cheryan, Siy, Vichayapai, Drury, & Kim, 2011; Wang & Degol, 2016).

Abducted General Belief That New Information Technology Is Complex/Difficult to Understand

We argue that our findings about the implicit associations of "endorsed/legitimate new information technology = trustworthy/valued" and "new information technology = male domain" indicate that potential users of these technologies hold the general belief that new information technology is complex/difficult to understand. In particular, we believe that this general belief underlies the strong association between trustworthy and valued information technology and legitimate experts in male-dominated fields (i.e., science and engineering). Said another way, because endorsement by experts in male-dominated fields leads users to trust and value new

information technology, it follows that these users hold the general belief that new information technology *requires* endorsement by such experts if it is to be valued and trusted. In turn, it follows that users believe such information technology must be complex and difficult to understand by most people (otherwise it wouldn't require expert endorsement).

This belief appears to stem from the strong relationship between new information technology and science advocated by early sociologists of science (e.g., Pinch & Bijker, 1984). Such notions have been corroborated by science and technology studies,³ which have conceived of technology as the application of scientific discoveries from basic research to specific purposes (e.g., Fox et al., 1995; Pinch & Bijker, 1984). The recent development of advanced and complex technologies based on the latest scientific discoveries in chemistry, biology, physics, and computing—such as nanotech, fin-tech, block chain, and artificial intelligence—have certainly reinforced this belief.

In sum, our review of research related to technology biases suggests three general beliefs that people hold about information technology: (a) new information technology is mysterious/unknown, (b) new information technology is nonhuman/alien, and (c) new information technology is complex/difficult to understand. In the following sections, we discuss how these general beliefs suggest directions for future research.

NEW INFORMATION TECHNOLOGY BIAS IN ORGANIZATIONS: UNANSWERED QUESTIONS AND AN AGENDA FOR FUTURE RESEARCH

As a whole, our review indicates that audiences may hold a number of biased attitudes and implicit associations related to new information technology, and that these biased attitudes and implicit associations are grounded in a set of underlying general beliefs about such technology. Further, our review suggests that these underlying beliefs are different from those commonly found to underlie interpersonal biases and implicit associations. As noted earlier, interpersonal biases and implicit associations tend to be related to concrete and salient human characteristics, such as gender, race, and age (Gilovich, Griffin, & Kahneman, 2009). In contrast, our review

and framework suggest that many biases related to new information technology involve abstract and unseen characteristics, such as mysteriousness, nonhumanness, and complexity. These distinctions between new information technology biases and interpersonal biases suggest a number of unanswered questions and conundrums for organizational scholars. We outline these issues next, organized around the three underlying beliefs we abducted from our review.

New Information Technology Is Mysterious/Unknown

One important implication of our suggestion that new information technologies are viewed as mysterious or unknown (i.e., unexplained or mystifying) is that implicit associations and biases related to this view may be triggered merely by thinking about technological advances. In other words, we may need only *imagine* mysterious, future information technologies (e.g., aircraft technologies that can fly us around the world without a human pilot) to trigger implicit associations about the success and superiority of new, cutting-edge technologies. Given the strong association between new technology and science fiction novels and films, it may be easy, in fact, for people to trigger biases related to new information technology based on completely fictional images and thoughts. Furthermore, choices about the design of new technologies might play a key role in activating such associations. For example, the modern or even futuristic design of some new devices (e.g., the first flip phones that looked like Star Trek communicators, or the Apple Watch that reminded users of scenes from the TV show *Knight Rider*) might trigger associations between new information technology and success or superiority.

Yet these ideas are merely speculative. One might argue that the empirical findings relating new information technology and success/superiority might be explained by the newness of the information technology as much as its mysteriousness. For example, biases in favor of new technologies might be influenced by public discourse that creates feelings of anticipation about potential technological developments. Such anticipation may be stoked by the media or through organizational communication campaigns (e.g., the Samsung advertisement that linked its new watch-phone to the comic strip detective Dick Tracy). Future research, thus, needs to tease apart how mysteriousness versus newness of new information technology relates to implicit associations with success and superiority.

³ Science and information technology studies refer to the study of how social, political, and cultural values affect scientific research and technological innovation, and how these, in turn, affect society, politics, and culture.

Moreover, future research is needed to understand the apparent contradiction between findings that, on one hand, show that mysteriousness and newness of information technologies lead audiences to view them as more likely to be successful, and on the other hand, show that information technology that appears familiar to audiences may be viewed as more likely to be successful. In this respect, a handful of studies have shown that past positive experiences with a certain information technology leads users to view new information technology that appears similar to this past information technology to be more likely to be successful (Bailey & Scerbo, 2007; Johnson, Bardhi, & Dunn, 2008; Kambil & Martins, 1999). These findings suggest that, in addition to implicit associations, the “representativeness” heuristic (Tversky & Kahneman, 1973, p. 207) may influence audiences’ perceptions of new information technology. In judging potential success, the representativeness heuristic predicts that decision makers will evaluate any information technology as more likely to be successful the more it appears similar to previous technologies they have known to be successful (Kiesler & Sproull, 1982). For example, Kambil and Martins (1999) found that tax filers’ prior success with an information technology (i.e., e-filing for tax returns) predicted their perceptions of potential success with a new information technology that appeared similar to this past information technology (e.g., online network-based tax filing).

While this evidence is at odds with what our review has brought to the fore about the mysteriousness and newness of technologies, it may suggest an important contextual factor that influences implicit biases regarding new information technology. Specifically, it suggests that the type of *audience* is important to whether new information technology (vs. familiar information technology) is viewed as potentially successful. In the studies in our review, audiences who were *high-status decision makers* (e.g., entrepreneurs, investors, or top managers) displayed a bias for new information technology. This finding is consistent with research showing that entrepreneurs in technological fields are more prone to risk taking than nonentrepreneurs (Palich & Bagby, 1995; Simon & Shrader, 2012), and may result from the implicit association between new information technology and success. In contrast, the few studies we found demonstrating a preference for familiar technologies (à la the representativeness heuristic) involved audiences who were everyday users of information technology (e.g., employees, and especially more risk-averse, less technologically

savvy users). These findings indicate that future research needs to carefully consider the type of audience that is perceiving information technology to better predict whether they might employ the “new information technology = success/superiority” implicit associations.

New Information Technology Is Alien/Nonhuman

The underlying belief that new information technology is alien and nonhuman appears to explain many of the fears about new information technology (i.e., that it cannot be trusted and may make decisions counter to human interests). Nevertheless, our review suggests that biases related to this general belief can be mitigated, if not overcome, by infusing new information technology with “humanness” in its performance or appearance. This finding has interesting implications for the choices engineers in technology companies make regarding the design characteristics of new information technologies. These choices become even more important if one considers that such technologies are often embodied in physical objects that can be visibly salient (e.g., due to size or contrast with surroundings) and repeatedly observed (due to their permanence). As a result, noticeable characteristics of new information technology may become “chronically accessible” (Macrae & Bodenhausen, 2000, p. 102) in the memories of users.

In this respect, research on bias in person perception (Uleman, Newman, & Moskowitz, 1996) suggests that salient characteristics of human beings (e.g., gender, race, age, ability, speaking accent, etc.) can trigger biases by eliciting spontaneous trait inferences (i.e., unconscious linking of traits to groups defined by salient characteristics—such as that elderly persons are slow). When applied to technologies, these findings raise some empirical questions: Are the salient characteristics of technology different, in important ways, from those related to human beings? And if so, how do these differences influence the triggering of implicit associations and bias? For example, there is little research examining how human-like characteristics of technologies might interact with implicit stereotypes of humans. In other words, are machines that look and act like elderly people perceived as old, or rather as reassuring and more trustworthy? Do interactions with machines that embody certain racial and gender features (e.g., female Asian or male Muslim) trigger related implicit associations? We could find only one study that examined these issues. Specifically, Pak and colleagues (2014) showed that gender

stereotypes may come into play when evaluating the trustworthiness of a medical advice application (e.g., they found that a virtual male doctor was rated as more trustworthy than a virtual female doctor). Future research should take this research further by examining other types and contexts where human stereotypes and biases may be related to new information technologies.

In turn, as noted earlier, increased experience with individuals from a variety of ethnic groups, as well as imagined positive contact with these groups, has been shown to inhibit negative implicit associations related to such groups (Abersson et al., 2004; Devine et al., 2002). Yet whether these same tactics can be used to inhibit negative implicit associations related to human-like information technology is an empirical question that future studies will have to answer.

The increasing resemblance of new information technologies to human beings also raises an interesting conundrum. If, on one hand, human-like information technologies are considered more trustworthy and less scary than nonhuman-like ones, will the proliferation of humanoid technologies lead to an irrational overtrusting of these technologies and an overreliance on information technology versus human decision making? We read almost every day about machine learning and machine-assisted decision making and the ability of robots to replace human beings in performing most tasks (Chui, Manyika, & Miremadi, 2016; Yeomans, 2015). This is at the same time both exciting and scary news. While businesses invest in these technologies to reduce costs and increase efficiency, there is a mounting fear among the workforce that they might be replaced by these technologies. Although a full discussion of the ethical implications of such business decisions is beyond the scope of this article, scholars may need to further explore how humanness in information technology has both positive and negative moral implications.

A related challenge comes from how the general public interacts with new information technology and how the Internet and social media can fuel unhealthy discussion online. This was the case with the launch of Microsoft's chatbot, Tay. Within a few hours of its public launch, Tay started expressing a racist, sexist, and homophobic personality (Hunt, 2016). Internet users realized that Tay would learn from its interactions, so they purposely tweeted insulting comments at it. Tay incorporated that language into its mental model and started using the same language. Recent research in computer science (Caliskan, Bryson, & Narayanan, 2017) has confirmed that as machines acquire human-like language

abilities (through word embedding), they also absorb the implicit biases concealed within the patterns of language use. As Caliskan and colleagues (2017) warned, these effects could have serious consequences for businesses that might want to use machine-learning technologies to perform tasks such as résumé screening, as this could result in prejudiced outcomes. Future technological developments, therefore, will have to focus on giving machines human-like abilities such as common sense and logic while also taking care to program acceptable behaviors through mathematical formulations of non-discrimination in decision making (Caliskan et al., 2017).

New Information Technology Is Complex/Difficult

Finally, the general belief that new information technology is difficult/complex, as well as its related implicit associations, may have serious repercussions for the use and implementation of modern information technologies. As previously mentioned, one implicit association that supports this general belief is that new information technology = masculine. The studies in our review suggest that this implicit association has created a vicious circle that perpetuates a lack of women using and designing technology. In particular, these studies suggest that if few women use technologies and few women are involved in the design and development of new technologies, chances are that new technologies will be designed by men to appeal, primarily, to men. For example, researchers have found that computer design is mostly based on the video arcade model, which is appealing to most men but threatening to many women (Selwyn, 2007; Verbick, 2002; Wajcman, 2004). If these types of outcomes reinforce the implicit association of new information technology = masculine, it may further prevent women from using and designing new technologies. Future research, thus, needs to examine more specifically how design choices that are naturally appealing to men (versus women) might reinforce (versus neutralize) the implicit association that new information technology = masculine.

A related area for future research is the domain of artificial intelligence (Oana, Cosmin, & Valentin, 2017). As popular press has emphasized, most artificial intelligence is designed by men, and this may lead to software that perpetuates implicit associations between information technology and masculinity (Clark, 2016). In this respect, recent research in computer science has shown that image-recognition

software may learn a sexist view of women (Zhao, Wang, Yatskar, Ordonez, & Chang, 2017). The authors in this study tested two collections of labeled photos used to train image-recognition software and found a predictable gender bias in their depiction of activities such as cooking and sports. Similarly, images of shopping and washing were linked to women, while coaching and shooting were tied to men. Interestingly, machine-learning software trained on the datasets did not just mirror those biases; it also amplified them. Given these findings, future research should investigate how the design of artificial intelligence might be monitored to guard against the learning and amplification of implicit associations between information technology and masculinity.

In addition, as noted earlier, the general belief that new information technology is complex appears to be related to implicit associations between endorsed or legitimate new information technology and trust in that information technology. These implicit associations suggest that, because many users do not possess the technological expertise, they trust new information technology that has been vetted by legitimate others. As we reported, these legitimate others might be technological experts such as university researchers (Fuller & Rothaermel, 2012), or supervisors or managers who are respected by their subordinates (Fu & Elliott, 2013).

One interesting implication of the implicit association between endorsed information technology and perceived trustworthiness of that information technology is that many experts trust only new information technology that is endorsed by experts in their same field (Breschi & Catalini, 2010)—leading to a very insular network of experts supporting each other's technological developments while eschewing outsiders' information technology. This type of technological "inbreeding" can inhibit breakthrough developments that often incorporate disparate ideas into research projects (Harvey, 2014). Thus, future research should examine how to increase trust in information technology from outside of a scientist's personal domain or social network.

At the same time, our review indicates that users may overtrust new information technology that is endorsed by legitimate others, such as "star scientists" (Fuller & Rothaermel, 2012) or Nobel laureates (Higgins et al., 2011). As a consequence, such information technology may not be scrutinized as carefully as it should be, and poor decisions may be made regarding investments in it. In this vein, future research needs to consider how to present

information technology to decision makers in ways that encourage deliberate scrutiny but do not lead to premature rejection.

CONCLUSION

Our review illustrates a number of general beliefs and implicit associations that may arise from biased perceptions of new information technology. As our lives are increasingly linked to such technologies, understanding these beliefs and implicit associations and their effects on perception and decision making becomes increasingly important. Our hope is that this review motivates future research that may help to further illuminate how users may manage implicit biases so that new information technology is most positively leveraged in our lives and work.

REFERENCES

- Aberson, C. L., Shoemaker, C., & Tomolillo, C. (2004). Implicit bias and contact: The role of interethnic friendships. *Journal of Social Psychology, 144*, 335–347.
- Agarwal, R., & Prasad, J. (1997). The role of innovation characteristics and perceived voluntariness in the acceptance of information technologies. *Decision Sciences, 28*(3), 557–582.
- Agarwal, R., & Prasad, J. (1998). The antecedents and consequents of user perceptions in information technology adoption. *Decision Support Systems, 22*(1), 15–29.
- Amin, H., Hamid, M. R. A., Lada, S., & Anis, Z. (2008). The adoption of mobile banking in Malaysia: The case of Bank Islam Malaysia Berhad (BIMB). *International Journal of Business and Society, 9*(2), 43–53.
- Bailey, N. R., & Scerbo, M. W. (2007). Automation-induced complacency for monitoring highly reliable systems: The role of task complexity, system experience, and operator trust. *Theoretical Issues in Ergonomics Science, 8*(4), 321–348.
- Bargh, J. A. (2007). Social psychological approaches to consciousness. In P. D. Zelazo, M. Moscovitch, & E. Thompson (Eds.), *The Cambridge handbook of consciousness* (pp. 555–569). New York: Cambridge University Press.
- Bertrand, M., & Mullainathan, S. (2004). Are Emily and Greg more employable than Lakisha and Jamal? A field experiment on labor market discrimination. *American Economic Review, 94*, 991–1013.
- Bhattacharjee, A., & Premkumar, G. (2004). Understanding changes in belief and attitude toward information technology usage: A theoretical model and

- longitudinal test. *Management Information Systems Quarterly*, 28(2), 229–254.
- Bonardo, D., Paleari, S., & Vismara, S. (2011). Valuing university-based firms: The effects of academic affiliation on IPO performance. *Entrepreneurship Theory and Practice*, 35(4), 755–776.
- Breschi, S., & Catalini, C. (2010). Tracing the links between science and information technology: An exploratory analysis of scientists' and inventors' networks. *Research Policy*, 39(1), 14–26.
- Bromley-Trujillo, R., Stoutenborough, J. W., Kirkpatrick, K. J., & Vedlitz, A. (2014). Climate scientists and environmental interest groups: The intersection of expertise and advocacy. *Politics, Groups & Identities*, 2, 120–134.
- Caliskan, A., Bryson, J. J., & Narayanan, A. (2017). Semantics derived automatically from language corpora contain human-like biases. *Science*, 356(6334), 183–186.
- Cameron, C. D., Brown-Iannuzzi, J. L., & Payne, B. K. (2012). Sequential priming measures of implicit social cognition: A meta-analysis of associations with behavior and explicit attitudes. *Personality and Social Psychology Review*, 16(4), 330–350.
- Carlston, D. E., & Skowronski, J. J. (1994). Savings in the relearning of trait information as evidence for spontaneous inference generation. *Journal of Personality and Social Psychology*, 66(5), 840–856.
- Cheryan, S., Siy, J. O., Vichayapai, M., Drury, B. J., & Kim, S. (2011). Do female and male role models who embody STEM stereotypes hinder women's anticipated success in STEM? *Social Psychological & Personality Science*, 2, 656–664.
- Chui, M., Manyika, J., & Miremadi, M. (2016, July). Where machines could replace humans—and where they can't (yet). *McKinsey Quarterly*. Retrieved from <https://www.mckinsey.com/business-functions/digital-mckinsey/our-insights/where-machines-could-replace-humans-and-where-they-cant-yet>
- Clare, A. S., Cummings, M. L., & Reppenning, N. P. (2015). Influencing trust for human–automation collaborative scheduling of multiple unmanned vehicles. *Human Factors*, 57(7), 1208–1218.
- Clark, B. B., Robert, C., & Hampton, S. A. (2016). The information technology effect: How perceptions of information technology drive excessive optimism. *Journal of Business and Psychology*, 31, 87–102.
- Clark, J. (2016, June 23). Artificial intelligence has a “sea of dudes” problem. *Bloomberg*. Retrieved from <https://www.bloomberg.com/news/articles/2016-06-23/artificial-intelligence-has-a-sea-of-dudes-problem>
- Clarke, A. C. (1973). *Profiles of the future: An inquiry into the limits of the possible* (rev. ed.). New York: Harper & Row.
- Coggio, G. L. (2015). Technical communicators as agents and adopters of change: A case study of the implementation of an early content-management system. *IEEE Transactions on Professional Communication*, 58(3), 271–288.
- Cooper, J. (2006). The digital divide: The special case of gender. *Journal of Computer Assisted Learning*, 22, 320–334.
- Cooper, J., & Weaver, K. D. (2003). *Gender and computers: Understanding the digital divide*. Mahwah, NJ: Lawrence Erlbaum.
- Cyr, D., Head, M., & Pan, B. (2009). Exploring human images in website design: A multi-method approach. *Management Information Systems Quarterly*, 33, 539–566.
- Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer information technology: A comparison of two theoretical models. *Management Science*, 35(8), 982–1003.
- De Massis, A., Frattini, F., Kotlar, J., Petruzzelli, A. M., & Wright, M. (2016). Innovation through tradition: Lessons from innovative family businesses and directions for future research. *Academy of Management Perspectives*, 30(1), 93–116.
- Devine, P. G., Plant, E. A., Amodio, D. M., Harmon-Jones, E., & Vance, S. L. (2002). The regulation of explicit and implicit race bias: The role of motivations to respond without prejudice. *Journal of Personality and Social Psychology*, 82, 835–848.
- De Vries, P., & Midden, C. (2008). Effect of indirect information on system trust and control allocation. *Behaviour & Information Technology*, 27(1), 17–29.
- Dietz, J., & Hamilton, L. K. (2008). *Subtle biases and covert prejudice in the workplace* (Case 9B08C005). London, Ontario, Canada: Ivey Publishing.
- Dixon, L. J., et al. (2014). Gendered space: The digital divide between male and female users in internet public access sites. *Journal of Computer-Mediated Communication*, 19, 991–1009.
- Dzindolet, M. T., Pierce, L. G., Beck, H. P., & Dawe, L. A. (2002). The perceived utility of human and automated aids in a visual detection task. *Human Factors*, 44(1), 79–94.
- Faulkner, W. (2000). The power and the pleasure? A research agenda for “making gender stick” to engineers. *Science, Technology & Human Values*, 25, 87–119.
- Faulkner, W. (2001). The information technology question in feminism: A view from feminist information technology studies. *Women's Studies International Forum*, 24, 79–95.

- Fazio, R. H., & Olson, M. A. (2003). Implicit measures in social cognition research: Their meaning and use. *Annual Review of Psychology, 54*(1), 297–327.
- Fox, M. F., Jasanoff, S., Markle, G. E., Petersen, J. C., & Pinch, T. (1995). *Handbook of science and technology studies*. Thousand Oaks, CA: SAGE.
- Fu, F. Q., & Elliott, M. T. (2013). The moderating effect of perceived product innovativeness and product knowledge on new product adoption: An integrated model. *Journal of Marketing Theory and Practice, 21*(3), 257–272.
- Fuhrman, E. (2007). Consumer trends driving new products: Sales look good for innovative categories. *Beverage Industry, 98*(4), 4–8.
- Fuller, A. W., & Rothaermel, F. T. (2012). When stars shine: The effects of faculty founders on new technology ventures. *Strategic Entrepreneurship Journal, 6*(3), 220–235.
- Garud, R., & Ahlstrom, D. (1997). Technology assessment: A socio-cognitive perspective. *Journal of Engineering and Technology Management, 14*(1), 25–48.
- Gawronski, B., Galdi, S., & Arcuri, L. (2015). What can political psychology learn from implicit measures? Empirical evidence and new directions. *Political Psychology, 36*(1), 1–17.
- Gawronski, B., & LeBel, E. P. (2008). Understanding patterns of attitude change: When implicit measures show change, but explicit measures do not. *Journal of Experimental Social Psychology, 44*(5), 1355–1361.
- Gawronski, B., LeBel, E. P., & Peters, K. R. (2007). What do implicit measures tell us? Scrutinizing the validity of three common assumptions. *Perspectives on Psychological Science, 2*(2), 181–193.
- Gawronski, B., & Payne, B. K. (Eds.). (2011). *Handbook of implicit social cognition: Measurement, theory, and applications*. New York: Guilford Press.
- Gilovich, T., Griffin, D. W., & Kahneman, D. (2009). *Heuristics and biases: The psychology of intuitive judgment*. New York: Cambridge University Press.
- Goddard, K., Roudsari, A., & Wyatt, J. C. (2012). Automation bias: A systematic review of frequency, effect mediators, and mitigators. *Journal of the American Medical Informatics Association, 19*(1), 121–127.
- Greenwald, A. G., Banaji, M. R., Rudman, L. A., Farnham, S. D., Nosek, B. A., & Mellott, D. S. (2002). A unified theory of implicit attitudes, stereotypes, self-esteem, and self-concept. *Psychological Review, 109*, 3–25.
- Greenwald, A. G., & Krieger, L. H. (2006). Implicit bias: Scientific foundations. *California Law Review, 94*(4), 945–967.
- Gross, A. G. (1994). The roles of rhetoric in the public understanding of science. *Public Understanding of Science, 3*, 3–23.
- Guo, Y., & Ren, T. (2017). When it is unfamiliar to me: Local acceptance of planned nuclear power plants in China in the post-Fukushima era. *Energy Policy, 100*, 113–125.
- Harvey, S. (2014). Creative synthesis: Exploring the process of extraordinary group creativity. *Academy of Management Review, 39*(3), 324–343.
- Hassanein, K., & Head, M. (2007). Manipulating perceived social presence through the web interface and its impact on attitude towards online shopping. *International Journal of Human-Computer Studies, 65*, 689–708.
- Heidegger, M. (2010). The question concerning technology. In C. Hanks (Ed.), *Technology and values: Essential readings* (pp. 99–113). West Sussex, UK: Wiley-Blackwell.
- Hewstone, M., Rubin, M., & Willis, H. (2002). Intergroup bias. *Annual Review of Psychology, 53*(1), 575–604.
- Higgins, M. J., Stephan, P. E., & Thursby, J. G. (2011). Conveying quality and value in emerging industries: Star scientists and the role of signals in biotechnology. *Research Policy, 40*(4), 605–617.
- Hoff, K. A., & Bashir, M. (2015). Trust in automation: Integrating empirical evidence on factors that influence trust. *Human Factors, 57*(3), 407–434.
- Hofmann, W., Gawronski, B., Gschwendner, T., Le, H., & Schmitt, M. (2005). A meta-analysis on the correlation between the Implicit Association Test and explicit self-report measures. *Personality and Social Psychology Bulletin, 31*(10), 1369–1385.
- Huffman, A. H., Whetten, J., & Huffman, W. H. (2013). Using technology in higher education: The influence of gender roles on technology self-efficacy. *Computers in Human Behavior, 29*, 1779–1786.
- Hugenberg, K., & Bodenhausen, G. V. (2003). Facing prejudice: Implicit prejudice and the perception of facial threat. *Psychological Science, 14*(6), 640–643.
- Hunt, E. (2016, March 24). Tay, Microsoft's AI chatbot, gets a crash course in racism from Twitter. *The Guardian*. Retrieved from <https://www.theguardian.com/technology/2016/mar/24/tay-microsofts-ai-chatbot-gets-a-crash-course-in-racism-from-twitter>
- Johnson, D. S., Bardhi, F., & Dunn, D. T. (2008). Understanding how information technology paradoxes affect customer satisfaction with self-service information technology: The role of performance ambiguity and trust in information technology. *Psychology and Marketing, 25*(5), 416–443.
- Kambil, A., & Martins, L. L. (1999). Looking back and thinking ahead: Effects of prior success on managers' interpretations of new information technologies. *Academy of Management Journal, 42*(6), 652–661.

- Kanny, M. A., Sax, L. J., & Riggers-Piehl, T. A. (2014). Investigating forty years of STEM research: How explanations for the gender gap have evolved over time. *Journal of Women and Minorities in Science and Engineering, 20*, 127–148.
- Kiesler, S., & Sproull, L. (1982). Managerial response to changing environments: Perspectives on problem sensing from social cognition. *Administrative Science Quarterly, 27*(4), 548–570.
- Kilbourne, W., & Weeks, S. (1997). A socio-economic perspective on gender bias in information technology. *Journal of Socio-Economics, 26*, 243–260.
- Kim, J., & Moon, J. Y. (1998). Designing towards emotional usability in customer interfaces—trustworthiness of cyber-banking system interfaces. *Interacting with Computers, 10*(1), 1–29.
- Koch, S. C., Müller, S. M., & Sieverding, M. (2008). Women and computers. Effects of stereotype threat on attribution of failure. *Computers & Education, 51*, 1795–1803.
- Kolko, J. (2010). Abductive thinking and sensemaking: The drivers of design synthesis. *Design Issues, 26*(1), 15–28.
- Kraiczy, N. D., Hack, A., & Kellermanns, F. W. (2014). New product portfolio performance in family firms. *Journal of Business Research, 67*(6), 1065–1073.
- Kuchenbrandt, D., Eyssel, F., & Seidel, S. K. (2013). Cooperation makes it happen: Imagined intergroup cooperation enhances the positive effects of imagined contact. *Group Processes & Intergroup Relations, 16*, 635–647.
- Kumar, N., & Benbasat, I. (2006). The influence of recommendations and consumer reviews on evaluations of websites. *Information Systems Research, 17*, 425–429.
- Lafferty, B. A., & Goldsmith, R. E. (2004). How influential are corporate credibility and endorser attractiveness when innovators react to advertisements for a new high-technology product? *Corporate Reputation Review, 7*(1), 24–36.
- Lankton, N. K., McKnight, D. H., & Tripp, J. (2015). Technology, humanness, and trust: Rethinking trust in technology. *Journal of the Association for Information Systems, 16*(10), 880–918.
- Leach, L., & Turner, S. (2015). Computers users do gender: The co-production of gender and communications technology. *SAGE Open, 1–14*. doi:10.1177/2158244015604693
- Lockett, A., Murray, G., & Wright, M. (2002). Do UK venture capitalists still have a bias against investment in new technology firms. *Research Policy, 31*(6), 1009–1030.
- Lowe, R. A., & Ziedonis, A. A. (2006). Overoptimism and the performance of entrepreneurial firms. *Management Science, 52*(2), 173–186.
- Lundholm, R., & Van Winkle, M. (2006). Motives for disclosure and non-disclosure: A framework and review of the evidence. *Accounting and Business Research, 36*, 43–58.
- Macedo, I. M. (2017). Predicting the acceptance and use of information and communication technology by older adults: An empirical examination of the revised UTAUT2. *Computers in Human Behavior, 75*, 935–948.
- MacKenzie, D., & Wajcman, J. (1985). *The social shaping of technology: How the refrigerator got its hum*. Milton Keynes, UK: Open University Press.
- Macrae, C. N., & Bodenhausen, G. V. (2000). Social cognition: Thinking categorically about others. *Annual Review of Psychology, 51*(1), 93–120.
- Madhavan, P., & Wiegmann, D. A. (2004, September). A new look at the dynamics of human-automation trust: Is trust in humans comparable to trust in machines? *Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 48*(3), 581–585.
- Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. *Academy of Management Review, 20*(3), 709–734.
- Merritt, S. M., Heimbaugh, H., & LaChapell, J. (2012). I trust it, but I don't know why: Effects of implicit attitudes toward automation on trust in an automated system. *Human Factors, 55*, 520–534.
- Montague, E. N. H., Winchester, W. W., III, & Kleiner, B. M. (2010). Trust in medical technology by patients and healthcare providers in obstetric work systems. *Behaviour & Information Technology, 29*, 541–554.
- Moon, Y. (2000). Intimate exchanges: Using computers to elicit self-disclosure from consumers. *Journal of Consumer Research, 26*, 323–339.
- Mordini, E. (2007). Technology and fear: Is wonder the key? *Trends in Biotechnology, 25*(12), 544–546.
- Mosier, K. L., & Skitka, L. J. (1996). Human decision makers and automated decision aids: Made for each other. In R. Parasuraman & M. Mouloua (Eds.), *Automation and Human Performance: Theory and Applications* (pp. 201–220). Mahwah, NJ: Lawrence Erlbaum Associates.
- Moynihan, D. P., & Lavertu, S. (2012). Cognitive biases in governing: Technology preferences in election administration. *Public Administration Review, 72*(1), 68–77.
- Nass, C. I., Moon, Y., Fogg, B. J., Reeves, B., & Dryer, C. (1995). Can computer personalities be human personalities? *International Journal of Human-Computer Studies, 43*, 223–239.
- Oana, O., Cosmin, T., & Valentin, N. C. (2017). Artificial intelligence: A new field of computer science which

- any business should consider. *Ovidius University Annals, Economic Sciences Series*, 17, 356–360.
- Orlikowski, W. J., & Scott, S. V. (2008). Sociomateriality: Challenging the separation of technology, work and organization. *Academy of Management Annals*, 2(1), 433–474.
- Pak, R., McLaughlin, A. C., & Bass, B. (2014). A multi-level analysis of the effects of age and gender stereotypes on trust in anthropomorphic technology by younger and older adults. *Ergonomics*, 57, 1277–1289.
- Palich, L. E., & Bagby, D. R. (1995). Using cognitive theory to explain entrepreneurial risk-taking: Challenging conventional wisdom. *Journal of Business Venturing*, 10(6), 425–438.
- Parasuraman, R., & Manzey, D. H. (2010). Complacency and bias in human use of automation: An attentional integration. *Human Factors*, 52, 381–410.
- Parasuraman, R., & Miller, C. A. (2004). Trust and etiquette in high-criticality automated systems. *Communications of the ACM*, 47(4), 51–55.
- Pettigrew, T. F., & Tropp, L. R. (2008). How does intergroup contact reduce prejudice? Meta-analytic tests of three mediators. *European Journal of Social Psychology*, 38, 922–934.
- Pinch, T. J., & Bijker, W. E. (1984). The social construction of facts and artifacts: Or how the sociology of science and the sociology of information technology might benefit each other. *Social Studies of Science*, 14, 399–441.
- Pinkard, N. (2005). How the perceived masculinity and/or femininity of software applications influences students' software preferences. *Journal of Educational Computing Research*, 32, 57–78.
- Plant, E. A., & Devine, P. G. (1998). Internal and external motivation to respond without prejudice. *Journal of Personality and Social Psychology*, 75, 811–832.
- Postman, N. (2011). *Technopoly: The surrender of culture to technology*. New York: Vintage.
- Purkiss, S. L. S., Perrewé, P. L., Gillespie, T. L., Mayes, B. T., & Ferris, G. R. (2006). Implicit sources of bias in employment interview judgments and decisions. *Organizational Behavior and Human Decision Processes*, 101, 152–167.
- Qiu, L., & Benbasat, I. (2009). Evaluating anthropomorphic product recommendation agents: A social and relational perspective to designing information systems. *Journal of Management Information Systems*, 25, 145–182.
- Ranjan, R., & Athalye, S. (2009). Drought resilience in agriculture: The role of technological options, land use dynamics, and risk perception. *Natural Resource Modeling*, 22(3), 437–462.
- Reeves, B., & Nass, C. (1996). *The media equation: How people treat computers, television, and new media like real people and places*. Chicago: University of Chicago Press.
- Rettie, R. (2003). Connectedness, awareness and social presence. *Proceedings of the 6th Annual International Workshop on Presence*. Aalborg, Denmark, October 6–8. Retrieved from <https://eprints.kingston.ac.uk/2106/>
- Riquelme, H. E., & Rios, R. E. (2010). The moderating effect of gender in the adoption of mobile banking. *International Journal of Bank Marketing*, 28(5), 328–341.
- Riquelme, H., & Watson, J. (2002). Do venture capitalists' implicit theories on new business success/failure have empirical validity? *International Small Business Journal*, 20(4), 395–420.
- Robnett, R. D. (2016). Gender bias in STEM fields: Variation in prevalence and links to STEM self-concept. *Psychology of Women Quarterly*, 40, 65–79.
- Rogers, E. M. (1976). New product adoption and diffusion. *Journal of Consumer Research*, 2(4), 290–301.
- Rousseau, D. M., Manning, J., & Denyer, D. (2008). Evidence in management and organizational science: Assembling the field's full weight of scientific knowledge through syntheses. *Academy of Management Annals*, 2(1), 475–515.
- Rudman, L. A., Ashmore, R. D., & Gary, M. L. (2001). "Unlearning" automatic biases: The malleability of implicit prejudice and stereotypes. *Journal of Personality and Social Psychology*, 81, 856–868.
- Sauer, J., Chavaille, A., & Wastell, D. (2016). Experience of automation failures in training: Effects on trust, automation bias, complacency and performance. *Ergonomics*, 59(6), 767–780.
- Schaefer, K. E., Chen, J. Y., Szalma, J. L., & Hancock, P. A. (2016). A meta-analysis of factors influencing the development of trust in automation: Implications for understanding autonomy in future systems. *Human Factors*, 58(3), 377–400.
- Selwyn, N. (2007). Hi-tech = guy-tech? An exploration of undergraduate students' gendered perceptions of information and communication technologies. *Sex Roles*, 56, 525–536.
- Shane, S. (2002). Selling university information technology: Patterns from MIT. *Management Science*, 48(1), 122–137.
- Siegrist, M. (2000). The influence of trust and perceptions of risks and benefits on the acceptance of gene technology. *Risk Analysis*, 20, 195–204.
- Siegrist, M. (2008). Factors influencing public acceptance of innovative food technologies and products. *Trends in Food Science & Technology*, 19, 603–608.

- Siegrist, M., & Cvetkovich, G. (2000). Perception of hazards: The role of social trust and knowledge. *Risk Analysis*, *20*, 713–720.
- Siegrist, M., Stampfli, N., Kastenholz, H., & Keller, C. (2008). Perceived risks and perceived benefits of different nanotechnology foods and nanotechnology food packaging. *Appetite*, *51*, 283–290.
- Simon, M., & Houghton, S. M. (2003). The relationship between overconfidence and the introduction of risky products: Evidence from a field study. *Academy of Management Journal*, *46*, 139–149.
- Simon, M., & Shrader, R. C. (2012). Entrepreneurial actions and optimistic overconfidence: The role of motivated reasoning in new product introductions. *Journal of Business Venturing*, *27*(3), 291–309.
- Skitka, L. J., Mosier, K., & Burdick, M. D. (2000). Accountability and automation bias. *International Journal of Human-Computer Studies*, *52*(4), 701–717.
- Smith, D. W., Zhang, J. J., & Colwell, B. (1996). Pro-innovation bias: The case of the Giant Texas Smoke-Scream. *Journal of School Health*, *66*(6), 210–213.
- Smith, J. L., Morgan, C. L., & White, P. H. (2005). Investigating a measure of computer technology domain identification: A tool for understanding gender differences and stereotypes. *Educational and Psychological Measurement*, *65*, 336–355.
- Sotudeh, H., & Khoshian, N. (2014). Gender differences in science: The case of scientific productivity in nano science and technology during 2005–2007. *Scientometrics*, *98*, 457–472.
- Sripalawat, J., Thongmak, M., & Ngramyarn, A. (2011). M-banking in metropolitan Bangkok and a comparison with other countries. *Journal of Computer Information Systems*, *51*(3), 67–76.
- Steele, C. M., & Aronson, J. (1995). Stereotype threat and the intellectual test performance of African Americans. *Journal of Personality and Social Psychology*, *69*, 797–811.
- Stoutenborough, J. W., Sturgess, S. G., & Vedlitz, A. (2013). Knowledge, risk, and policy support: Public perceptions of nuclear power. *Energy Policy*, *62*, 176–184.
- Stoutenborough, J. W., & Vedlitz, A. (2016). The role of scientific knowledge in the public's perceptions of energy technology risks. *Energy Policy*, *96*, 206–216.
- Sturgis, P., & Allum, N. (2004). Science in society: Re-evaluating the deficit model of public attitudes. *Public Understanding of Science*, *13*, 55–74.
- Subramanian, A., Lim, K. H., & Soh, P. H. (2013). When birds of a feather don't flock together: Different scientists and the roles they play in biotech R&D alliances. *Research Policy*, *42*(3), 595–612.
- Sveiby, K. E., Gripenberg, P., Segercrantz, B., Eriksson, A., & Aminoff, A. (2009, June). *Unintended and undesirable consequences of innovation*. Paper presented at the XX ISPIM Conference, The Future of Innovation, Vienna.
- Szymanski, D. M., Kroff, M. W., & Troy, L. C. (2007). Innovativeness and new product success: Insights from the cumulative evidence. *Journal of the Academy of Marketing Science*, *35*(1), 35–52.
- Tversky, A., & Kahneman, D. (1973). Availability: A heuristic for judging frequency and probability. *Cognitive Psychology*, *5*(2), 207–232.
- Uleman, J. S., Adil Saribay, S., & Gonzalez, C. M. (2008). Spontaneous inferences, implicit impressions, and implicit theories. *Annual Review of Psychology*, *59*, 329–360.
- Uleman, J. S., Blader, S. L., & Todorov, A. (2005). Implicit impressions. In R. R. Hassin, J. S. Uleman, & J. A. Bargh (Eds.), *The new unconscious* (pp. 362–392). New York: Oxford University Press.
- Uleman, J. S., Newman, L. S., & Moskowitz, G. B. (1996). People as flexible interpreters: Evidence and issues from spontaneous trait inference. *Advances in Experimental Social Psychology*, *28*, 211–279.
- van Nunspeet, F., Ellemers, N., & Derks, B. (2015). Reducing implicit bias: How moral motivation helps people refrain from making “automatic” prejudiced associations. *Translational Issues in Psychological Science*, *1*(4), 382–391.
- Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the information technology acceptance model: Four longitudinal field studies. *Management Science*, *46*(2), 186–204.
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *Management Information Systems Quarterly*, *27*(3), 425–478.
- Verberne, F. M. F., Ham, J., & Midden, C. J. H. (2012). Trust in smart systems: Sharing driving goals and giving information to increase trustworthiness and acceptability of smart systems in cars. *Human Factors*, *54*, 799–810.
- Verbick, T. (2002). Women, technology, and gender bias. *Journal of Computing Sciences in Colleges*, *17*, 240–250.
- Vishwanath, A., & LaVail, K. H. (2013). The role of attributional judgments when adopted computing technology fails: A comparison of Microsoft Windows PC user perceptions of Windows and Macs. *Behaviour & Information Technology*, *32*(11), 1155–1167.
- Wajcman, J. (1991). *Feminism confronts technology*. State College, PA: Penn State Press.
- Wajcman, J. (2000). Reflections on gender and technology studies: In what state is the art? *Social Studies of Science*, *30*, 447–464.

- Wajcman, J. (2004). *Technofeminism*. Cambridge, UK: Polity.
- Wajcman, J. (2006). Technocapitalism meets technofeminism: Women and technology in a wireless world. *Labour & Industry: A Journal of the Social and Economic Relations of Work*, 16, 7–20.
- Wajcman, J. (2010). Feminist theories of technology. *Cambridge Journal of Economics*, 34, 143–152.
- Wang, G., & Guan, J. (2011). Measuring science–technology interactions using patent citations and author–inventor links: An exploration analysis from Chinese nanotechnology. *Journal of Nanoparticle Research*, 13, 6245–6262.
- Wang, L. C., Baker, J., Wagner, J. A., & Wakefield, K. (2007). Can a retail web site be social? *Journal of Marketing*, 71, 143–157.
- Wang, M. T., & Degol, J. L. (2016). Gender gap in science, technology, engineering, and mathematics (STEM): Current knowledge, implications for practice, policy, and future directions. *Educational Psychology Review*, 29(1), 1–22.
- Wang, W., & Benbasat, I. (2005). Integrating TAM with trust to explain online recommendation agent adoption. *Journal of the Association for Information Systems*, 6, 72–101.
- Wynne, B. (1991). Knowledges in context. *Science, Technology & Human Values*, 16, 111–121.
- Yeomans, M. (2015, July 7). What every manager should know about machine learning. *Harvard Business Review*. Retrieved from <https://hbr.org/2015/07/what-every-manager-should-know-about-machine-learning>
- Yu, C. S. (2012). Factors affecting individuals to adopt mobile banking: Empirical evidence from the UTAUT model. *Journal of Electronic Commerce Research*, 13(2), 104–121.
- Zhao, J., Wang, T., Yatskar, M., Ordonez, V., & Chang, K. W. (2017). Men also like shopping: Reducing gender bias amplification using corpus-level constraints. *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing* (pp. 2979–2989), Copenhagen, Denmark.
- Zoellner, J., Schweizer-Ries, P., & Wemheuer, C. (2008). Public acceptance of renewable energies: Results from case studies in Germany. *Energy Policy*, 36, 4136–4141.
- Zucker, L. G., & Darby, M. R. (1996). Star scientists and institutional transformation: Patterns of invention and innovation in the formation of the biotechnology industry. *Proceedings of the National Academy of Sciences*, 93(23), 12709–12716.



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