Why do users trust algorithms? A review and conceptualization of initial trust and trust over time

ABSTRACT

Algorithms are increasingly playing a pivotal role in organizations' day-to-day operations; however, a general distrust of artificial intelligence-based algorithms and automated processes persists. This aversion to algorithms raises questions about the drivers that lead managers to trust or reject their use. This conceptual paper aims to provide an integrated review of how users experience the encounter with AI-based algorithms over time. This is important for two reasons: first, their functional activities change over the course of time through machine learning; and second, users' trust develops with their level of knowledge of a particular algorithm. Based on our review, we propose an integrative framework to explain how users' perceptions of trust change over time. This framework extends current understandings of trust in AI-based algorithms in two areas: First, it distinguishes between the formation of initial trust and trust over time in AI-based algorithms, and specifies the determinants of trust in each phase. Second, it links the transition between initial trust in AI-based algorithms and trust over time to representations of the technology as either human-like or system-like. Finally, it considers the additional determinants that intervene during this transition phase.

Keywords: AI algorithms; trust; initial trust, trust over time, integrative review.

1. Introduction

AI-based algorithms are increasingly being deployed in contemporary work settings to support managerial and organizational decisions (Burton et al., 2020; Glikson & Woolley, 2020; Kellogg et al., 2019; Lepri et al., 2017; Prahl & Van Swol, 2017). They have been defined as systems with the ability "to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Kaplan & Haenlein, 2018, p. 15). The use of artificial intelligence to detect and predict the spread of coronavirus (OECD, 2020), algorithms that map the "brains" of CEOs to improve daily management (Copeland & Hope, 2016), self-driving vehicles, and AI agents that assist salespeople (Davenport et al., 2020) are a few notable examples of this.

Scholars have found that AI-based algorithms are more comprehensive than other technologies because they can collect, aggregate, and process large amounts of data from different sources (Leonardi & Contractor, 2018) and multiple parties (Majchrzak et al., 2013), and by so doing they expand the rationality of decision-makers. Perhaps more importantly, the power of AI-based algorithms stems from their ability to mimic human behavior and autonomously perform tasks that normally require human intelligence: that is, they are 'machines' that can learn from experience and improve the performance of their tasks over time (Lindebaum et al., 2020). On the other hand, they have a potential dark side linked to their ontological status as non-human decision-makers that combine the intelligence of the human brain with the power of the machine. They are programmed by humans to act on behalf of humans, but have autonomous agency. Like humans, they evaluate, rank, make decisions, bestow rewards, and hand out punishments quietly and anonymously. The lack of transparency in algorithmic decision-making has been associated with dynamics of control, power, and surveillance (Kellogg et al., 2020). For example, the use of algorithms in online customer evaluations that aggregate the 'wisdom of the crowd' has created a new form of employee monitoring through a coalition between customers and platform owners, who join together to evaluate the sellers of online services (Curchod et al., 2020). This means that while algorithms are trusted for their precision and objectivity in the "automation of data analysis" (Helbing et al., 2019, p. 74) and "replacement" of human intervention (Glikson & Woolley, 2020; Kaplan & Haenlein, 2020), they might also be experienced as a threat to autonomous decision-making, which ultimately reduces the level of trust in the technology.

In the interpersonal domain, trust has been defined as "a psychological state comprising the intention to accept vulnerability based upon positive expectations of the intentions or behavior of another" (Rousseau et al., 1998, p. 395). Like interpersonal trust, trust in technology is conceptualized as a belief that a technology artifact possesses certain desirable or favorable attributes that satisfy people's expectations (Gefen et al., 2008; McKnight et al., 2011; Teo et al., 2009). Specifically, the literature on trust in technology has distinguished between human-like trust constructs and system-like trust constructs (Lankton et al., 2015). Some researchers have conceptualized and measured trust in technology by using the same human-like constructs of integrity, ability and competence, and benevolence that researchers have traditionally used to measure interpersonal trust (Vance et al., 2008). In the algorithm domain, some researchers have linked trust to perceptions of fairness, accountability, and transparency (Shin and Park, 2019), while in contrast, others have operationalized trust by using system-like trust constructs such as reliability/predictability, functionality, and helpfulness (McKnight et al., 2011). These constructs are considered to be important antecedents of trust in algorithms and AI-based technologies (Hoff & Bashir, 2015). Finally, both human- and system-like constructs have been viewed as shaping both the cognitive and emotional trust of users in AI and algorithms (Glikson & Woolley, 2020).

While the prior research has provided a valuable starting point when it comes to identifying the main antecedents of human trust in AI-based algorithms, less attention has been paid to how users' trust in algorithms develops over time, and what the consequences are. This issue merits consideration because from a theoretical perspective, explaining how continued experience of AI-based algorithms affects trust in this sphere extends our processual understanding of this technology and how it is used. We expect trust in AI-based algorithms to evolve because as an intelligent technology, they have the ability to change their functional capacities through machine learning (Glikson & Woolley, 2020). Over time, their actions will become more indeterminate and difficult to predict, and trust beliefs will become more complex and harder to understand (Thiebes et al. 2021). In addition, the user experience will evolve: users with a low level of algorithm literacy or knowledge may have a low level of trust in algorithms, but by interacting with them over the course of time, they develop expertise and skill levels that could affect the trustworthiness of their technology (Burton et al., 2020).

In this article, we review the literature on trust in AI-based algorithms with the aim of developing an integrated framework that portrays users' changing perceptions of trust over time. Review articles provide unique opportunities for making a theoretical contribution and advancing scientific knowledge (Post *et al*., 2020). They organize a knowledge space with the purpose of making it more accessible while extending the field of possibilities (Patriotta, 2020). In novel or emergent research areas, such as AI-based algorithms, review articles can help other researchers understand the research topic and discern important, under-examined areas, take stock of research findings from various disparate sources, connect existing concepts and empirical findings in original ways so that a new perspective or phenomenon emerges, and build a platform for future research in the reviewed domain.

Our review highlighted six main determinants of trust in AI algorithms: users' propensity to trust, IT acceptance levers, the human-like characteristics of the AI-based algorithm, social influence, familiarity, and the system-like characteristics of the AI-based algorithm. We subsequently considered the extent to which these drivers of trust are particularly relevant in influencing initial judgements of trust that occur quite early in user interactions with the technology and those that operate as users interact with the technology over time. Based on our findings, we develop an integrative framework that extends current understandings of trust in AI-based algorithms in the following ways: First, it distinguishes between the formation of initial trust and trust over time in AI-based algorithms, and specifies the determinants of trust in each phase. Second, it links the transition between initial trust in AI-based algorithms and trust over time to representations of the technology as either human-like or system-like. Third, it considers the additional determinants that intervene during this transition phase.

The paper is structured as follows. After a short section on trust in technology and AI-based algorithms, we describe the methodology adopted in this study. We then present our integrative framework and develop theoretical propositions from it (Davis, 1971). The final section concludes the paper by summarizing the contributions to research and outlining directions for future research.

2. Theoretical background

Artificial intelligence has been characterized as a new generation of digital technologies capable of interacting with the environment and aiming to simulate human intelligence (Glikson & Wooley, 2020; Schwab, 2017). Hence, the introduction of AI-based algorithms in organizational settings has reignited debates on the future of work and professions by raising questions about workers' trust in AI technology (Frey & Osborne, 2017; Susskind & Susskind, 2015).

Early research on trust was carried out in the field of interpersonal relationships between people and organizations (Mayer et al., 1995). From this perspective, interpersonal trust results from "the expectancy held by an individual or a group that the word, promise, verbal or written statement of another individual or group can be relied upon" (Rotter, 1967, p. 651). By overcoming the initial theories that posited that "people trust people, not technology" (Friedman et al., 2000, p. 36), the concept of trust was then extended to the context of technology (McKnight et al., 1998; Wang & Benbasat, 2005), and researchers began to recognize that humans do, in fact, trust technology (Lankton et al., 2015). In this context, prior studies investigated what theoretical foundation is best suited for studying trust relationships between people and an information system (IS) (Paravastu et al., 2014), the mechanisms of trust in such systems (Söllner et al., 2016), and the differences in users' trust beliefs between first-time use and post-adoption of technology (Bhattacherjee, 2001; Bhattacherjee & Lin, 2014; Gao & Waechter, 2017; McKnight et al., 2020).

Within this stream of research, the social presence theory (Short et al., 1976) claims that a technology's attributes affect individuals' perception of technology as more human-like than system-like (Lankton et al., 2015). Thus, in line with the social response theory (Nass et al., 1994), people interact with a technology as if they are dealing with humans because of its social cues (Gefen & Straub, 2003; Reeves & Nass, 1996). The affordance theory also offers an explanation of trust in technology (Gibson, 1977), referring to aspects known as "social affordances" that can lead to different degrees of "humanness" associated with technology. Indeed, a technology provides certain actions to a person and may support different outcomes, depending on whether it is perceived as being more or less human-like (Lankton et al., 2015). Finally, other researchers have used trust beliefs that relate more to a technology's system-like characteristics, including its functionality and reliability (McKnight et al 2011).

Scholars have also pinpointed the fact that in order to understand user trust in algorithms, it is particularly important to distinguish between automated systems and intelligent systems based on AI algorithms (Glikson & Woolley, 2020). Automated systems are systems that perform repetitive tasks following programmed rules. They operate in a deterministic way, without any learning process. AI-based algorithms, on the other hand, can simulate human intelligence and adjust their behavior based on their experience. The outcomes produced by automated systems are generally well understood, and users have no difficulty trusting them. Conversely, although AI-based algorithms can use data to a greater extent than humans and are trusted for their precision (Helbing et al., 2019), their behavior is perceived as risky because of their complexity and non-deterministic nature (Glikson & Woolley, 2020; Kaplan & Haenlein, 2020). In particular, there are concerns regarding algorithmic fairness, accountability, and transparency (Shin and Park, 2019). Fairness in algorithms is related to algorithmic bias, which occurs when algorithms create unfair outcomes that arbitrarily favor certain groups over others, reflecting the implicit values of the humans who trained the algorithm (Beer, 2017; Shrestha et al., 2019). The concept of algorithmic accountability raises questions about who should be held accountable for the possible unintentional consequences of algorithm outcomes (Diakopoulos, 2016). Finally, the problem of transparency in algorithmic contexts revolves around the problem that the generation of results by the use of algorithms is usually proprietary and undisclosed, so that the decision-making process is opaque for users (Shin et al., 2020). Furthermore, AI-based algorithms can take multiple forms – both physical and intangible – (for example, robots, virtual agents, bots, or AI embedded in a technology), with the result that their level of sophistication is not always explicit, and the logic behind a human-AI relationship is often unclear, complex, and difficult to explain (Glikson & Woolley, 2020; Shin, 2021). As such, AI algorithms may provide limited, or different, signals on which both human-based trust (that is, a limited social presence on which to base judgments of benevolence) and system-based trust (for example, the provision of limited information from which to evaluate reliability) can be established.

Owing to the specific features of AI-based algorithms, established theories of technology acceptance, such as the technology acceptance model (TAM) (Davis, 1989) are not sufficient to understand the determinants of initial trust and trust over time in algorithms. This is because the use antecedents that apply across IT – namely perceived usefulness and ease of use (Davis, 1989; Gefen et al. 2003) – can only partially apply in the algorithm context. In fact, AI-based algorithms, which perform tasks autonomously, are not simple tools, and users may be more likely to perceive them as being useful where their outcomes are fair, transparent, accurate, and explainable (Shin & Park, 2019; Wolker & Powell, 2020). Research therefore needs to model trust in the context of algorithm systems by emphasizing the issues around their use. Furthermore, AI-based algorithms can display certain human characteristics (learning from experience and performing tasks autonomously) that can lead users to attribute human-like trusting beliefs to them, which in many cases does not fit with other technologies (Glikson & Woolley, 2020; Lankton et al. 2015). For example, users may trust AI-based algorithms that can solve complex tasks because of their competence – a human-like capability – rather than their functionality, a classification that is usually used for trust in technologies.

Finally, the growing literature on algorithm aversion has explored the conditions that lead to the acceptance or rejection of algorithmically generated insights by individual users of decision aids (Burton et al., 2020; Dietvorst et al., 2015). The phenomenon of algorithm aversion refers to "the reluctance of human forecasters to use superior but imperfect algorithms" (Burton et al., 2020, p. 221), which reveals that people tend to trust their own judgment more than algorithmic decisions, especially after an algorithm has erred. Allowing people to adjust an algorithm's forecasts increases their satisfaction with their prediction process, prevents them from losing trust in the algorithm after it makes a mistake, and increases their willingness to continue using it after they have received feedback (Dietvorst et al., 2015; Michelman, 2017).

Overall, previous studies on AI-based algorithms have effectively explained how this particular category of digital technologies differs from other technologies and articulated the determinants of human trust in AI. By and large, however, trust has been mainly considered as resulting from the synchronic encounters between AI-based algorithms and their users. Less attention has been paid to how this encounter evolves over time. In this regard, prior studies have suggested that initial trust in technology is extremely "fragile" because it is based on an initial experience or what others say (McKnight et al., 1998). Further experience, new stimuli, and knowledge-based trust can lead users to change their opinions over time (Jones & George, 1998; McKnight et al., 2011). In the context of AI-based algorithms, scholars have begun to address the trajectory of human trust in the various forms of AI representation (robots, virtual reality, and embedded). For example, while in robotics cognitive trust starts at a low level and develops over time with experience, in the case of virtual agents (such as a chatbot) and embedded AI, an initially high level of trust is followed by a decrease following interaction, when users' expectations of high-level machine intelligence do not fit the technological reality (Glikson & Woolley, 2020). This literature, however, is still in its incipient phase and there is a need for both consolidating current understandings and creating new ones. In the reminder of this paper, we review the literature on AI-based algorithms to develop a framework that distinguishes between initial trust formation and trust over time in AI-based algorithms, and specifies the determinants of trust in each phase.

3. Methodology

The purpose of our review is to synthesize the existing research on trust in algorithms and develop a comprehensive framework that captures the fundamental building blocks of human trust in AI-based algorithms and their interrelationships. Drawing on theories of technology adoption that underline how the determinants of initial adoption differ from the determinants of use over time (Karahanna et al., 1999), we outline the basic building blocks of an initial conceptual framework of trust in algorithms. We apply an integrative review (Snyder, 2019), which is recommended when reviewing a diversified body of knowledge and examining the main ideas of broad and intertwined phenomena, to synthesize the research in novel ways (Torraco 2005; Elsbach & van Kippenberg, 2020; Patriotta, 2020).

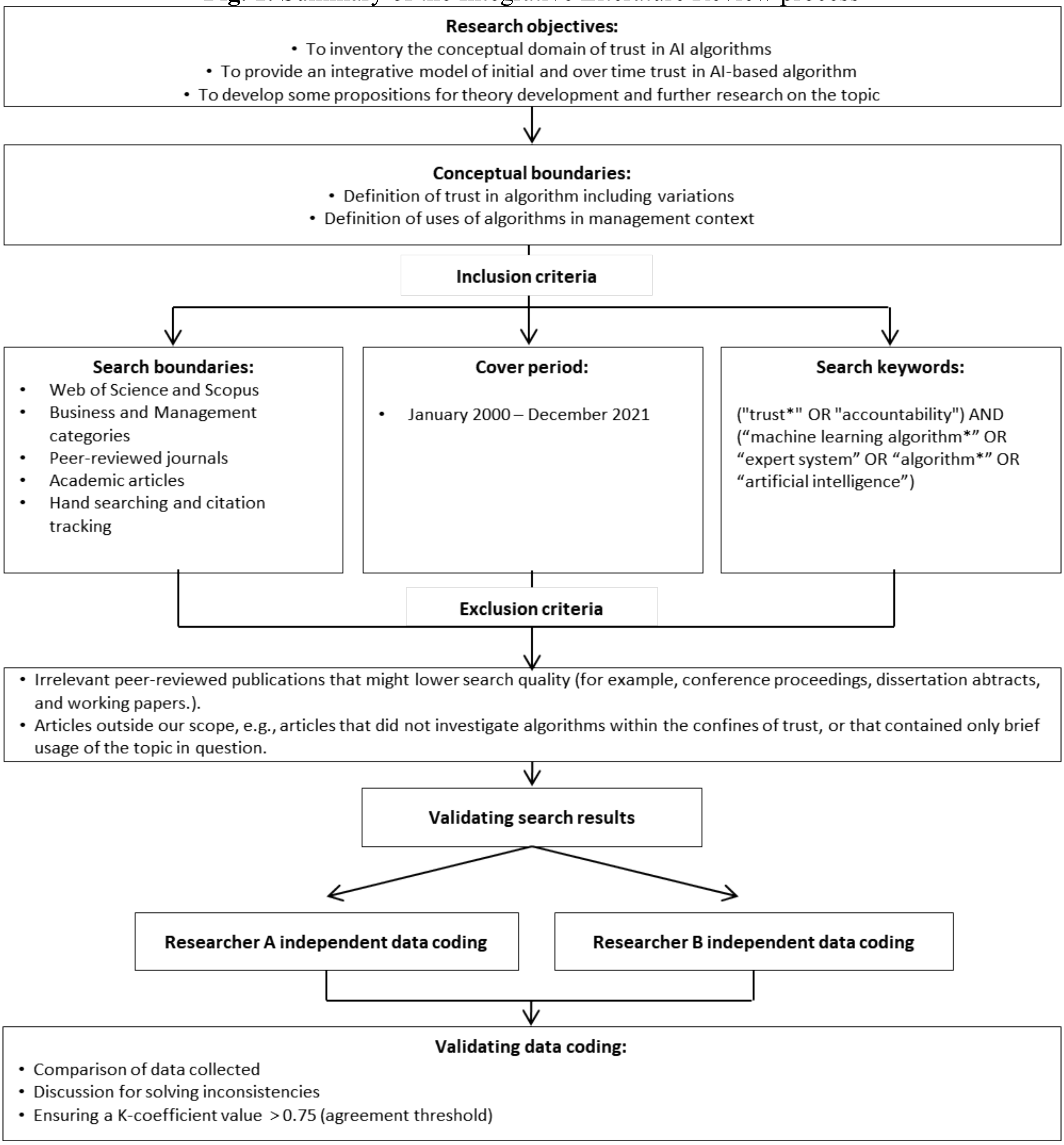
Drawing on the Scopus and Web of Science databases, we used a Boolean search string to retrieve articles that include the terms ("trust*" OR "accountability") AND ("machine learning algorithm*" OR "expert system" OR "algorithm*" OR "artificial intelligence") in their titles, abstracts, or keywords, and restricted our search to business and management areas. This keyword-based search was consistent with our purpose to focus on articles aimed at making a substantial contribution to the field of trust in algorithms. Moreover, in line with previous studies, we limited the search to articles published between January 2000 and December 2021 (the last 20 years) "to address the empirical work concomitant with the recent technological development of AI" (Glikson & Woolley, 2020, p. 4). This procedure resulted in 779 hits. After merging the results from the two databases and cleaning the duplicates from the list of articles, the sample was reduced to 656 papers published across more than 60 different management and business journals.

To preserve search quality and reliability, we focused on peer-reviewed publications. This meant, for example, that we excluded conference proceedings, dissertation abstracts, and unpublished works from our analysis (Calabrò et al., 2019; Nabi et al., 2017; Ramos-Rodríguez et al., 2004; Saggese et al., 2016). In particular, in terms of publication outlets, in order to identify the articles to be included in our analysis, we began with the top journals in the selected areas according to the Journal Citation Reports (with an impact factor of greater than 1.0) (including MIS Quarterly, the Academy of Management Annals, the Academy of Management Reviews, and Information & Management). This broad range allowed us to include studies from several business and management sub-disciplines while also ensuring a certain level of academic rigor. A total of 398 studies were admitted to the next step.

We read all the titles and abstracts carefully to assess whether two basic criteria of relevance had been fulfilled. First, we screened the articles based on their relevance to our purpose (Calabrò et al., 2019). We considered as non-relevant those articles that contained only a brief application of the topic in question or that did not investigate algorithms within the confines of trust (such as articles providing descriptions of algorithm architecture). We also excluded articles that referred to the study of trust in algorithms from a customer perspective but not that of management. Second, to broaden the search and find more articles for consideration, we reviewed the references in all the identified articles. By searching by hand and citation tracking (Nabi et al. 2017; Rashman et al. 2009), we examined the backward and forward citations of the most influential papers. In this way, we ensured that we would be able to extend the initial sample by including those articles "that may have not used verbatim in one of the original search terms and relevant articles in journals in adjacent fields" (Joseph & Gaba, 2020, p. 271). We ended this process when we felt confident that we had included the most representative articles in our analysis. A total of 72 articles were identified (see Table A.1 and B.1 in the Appendix).

We then read and codified each article to develop our categorization scheme (see Table C.1. in the Appendix). Following a thematic analysis (Braun & Clark, 2006), we labeled the underlying theories deployed in each article based on their relevance to initial or over time trust. Two authors carried out the whole review process independently and simultaneously (Furrer et al., 2008; Nabi et al., 2017), cross-referencing their search results (Rashman et al., 2009) and discussing the emerging inconsistencies (Saggese et al., 2016). The articles were recoded where there were disagreements until a Kappa coefficient above 0.75 had been achieved (Bazeley & Jackson, 2013). Figure 1 provides a visual summary of our integrative review process.

Fig. 1. Summary of the Integrative Literature Review process



4. Toward an integrative model of initial trust and over time trust in AI-based algorithms

Trusting beliefs are a trustor's perception that a trustee has attributes that will be beneficial for the trustor (Wang & Benbasat, 2008). Previous research on trust in technology has examined several trusting beliefs that affect both the initial (Wang & Benbasat, 2005) and over time (Lankton et al., 2015) stages of trust development. In the context of algorithms, the notion of trustworthy AI is based on the idea that its full potential can be reached if trust is a distinguishing mark of its development, deployment, and use (Thiebes et al. 2021). In our review, we propose a summarizing framework that integrates and elaborates on the prior management literature to develop a model of human trust in AI-based algorithms in which the identified trusting beliefs, together with their relationship to initial trust versus trust over time, are depicted. Our analysis of this body of work leads us to categorize the main determinants of trust in AI algorithms in terms of users' propensity to trust, IT acceptance levers, the human-like characteristics of the AI-based algorithm, social influence, familiarity, and the system-like characteristics of the AI-based algorithm. Additionally, integrating our review with perspectives on human and system trust leads us to consider the extent to which these drivers of trust are particularly relevant in influencing initial judgements of trust that occur quite early in user interactions with the technology, perhaps even upon first use, and those that operate as users interact with the technology over time (see Figure 2).

4.1. Initial trust in AI-based algorithm

Based on the previous literature on trust in technology (Söllner et. al., 2016), our study assumes that initial trust is formed during a user's early experiences and interactions with an AI algorithm. This is a very critical moment. At this stage, users often lack previous knowledge, and may perceive certain risks or uncertainties (Gao & Waechter, 2017) that might prevent them from using algorithms or lead them to attempt to circumvent algorithmic recommendations. Additionally, the evolution of trust over time is in part a function of initial trust judgments.

4.1.1. User propensity to trust

Prior research on trust in IT has highlighted the fact that ***user propensity*** is a factor in the initial formation of trust in technology. A propensity to trust in technology suggests that a person is willing to depend on a technology across situations and technologies (McKnight et al. 2011). Our review confirms that user propensity to trust also applies in the AI algorithm context (Kordzadeh & Ghasemaghaei, 2021). Users in this context include business analysts, managers, and other organizational decision-makers.

Individual differences of users (e.g., gender, culture, age, and personality) are closely related to the propensity for or tendency toward technology users may manifest or develop (Gefen et al., 2008; McKnight et al. 2011). For example, some authors suggest that people of different ages, genders, and cultural backgrounds may employ different strategies when analyzing the trustworthiness of automated systems (Hoff & Bashir, 2015). Pre-existing attitudes, knowledge and expectations are also unconscious mechanisms that form a user's disposition to trust a particular technology (positive dispositional tendency); hence, a lower level of trust may be attributed to a user's dispositional unwillingness to trust the technology (negative dispositional tendency) (Hoff & Bashir, 2015; Kim et al., 2009; Wang & Benbasat, 2008). In the AI-based algorithm context, user trust results in greater confidence in algorithmic outputs. It also leads to increased fairness perceptions (Shin & Park, 2019) and willingness to accept an algorithmic recommendation or adopt a system, even where the algorithm's outputs are biased (Glikson & Woolley, 2020).

Despite the differences between AI algorithms and IT, we propose that the user propensity that influences initial trust formation in technology also operates in the context of AI-based algorithms. Thus, we formulate the following proposition:

Proposition P1. *Initial trust in an AI-based algorithm will be a function of* user propensity to trust.

4.1.2. The characteristics of human-like AI-based algorithms

We found that the characteristics of the human-like algorithms incorporated in a technology contribute toward forging a user's initial trust in AI algorithms in several ways (De Cicco et al., 2020; Kaplan & Haenlein, 2020; Lanktlon et al., 2015; Majchrzak et al., 2013; Nowak & Rauh, 2005). In the algorithm domain, this anthropomorphism, or human-likeness perception, can be driven by the human-like form of the interface that embeds the AI-based algorithm (tangibility) (Glikson & Woolley, 2020), such as those of a robot, or by behavioral features, such as immediacy, that "refer to socially-oriented gestures intended to increase interpersonal closeness, such as proactivity, active listening, and responsiveness" (Glikson & Woolley, 2020, p. 632). When AI-based algorithm behavior turns out to be human-like, users tend to trust and follow it, regardless of the exact task (and level of reliability) (Castelo et al., 2019). However, there is also evidence for a negative effect of an algorithm's human-like characteristics. Some researchers who have investigated anthropomorphic robots have built on the uncanny valley theory (Mori, 1970), which argues that interacting with an artificial agent that has human-like features will be perceived as more agreeable up to a point, after which it becomes so human that people find its non-human imperfections unsettling (Ho & MacDorman, 2010). Taken together, these findings suggest that increasing the humanness of systems may have a positive impact on initial user trust, but this relationship may be curvilinear (Hoff & Bashir, 2015).

Generally, when users are dealing with algorithms that share **human-like** characteristics, their trust beliefs are triggered by features of interpersonal trust: **benevolence, competence and ability**, and **integrity** (Mayer et al., 1995; Lankton et al. 2015; Gefen et al., 2003).

"**Benevolence** beliefs" (Mayer et al., 1995) refer to a user's confidence that algorithms have a positive orientation toward their users beyond an egocentric profit motive, and that they will consider their wellbeing and act in their interests (Thiebes et al. 2021). If users encounter some problems during the first interaction with AI-based algorithms (for example, slow responses), they may doubt whether these technologies have enough benevolence to help them achieve their objectives (Gao & Waechter, 2017). **Ability** corresponds to "that group of skills, competencies, and characteristics that enable a party to have influence within some specific domain" (Mayer et al., 1995, p. 717). AI-based algorithms that exhibit features of ability augment humans' capacity to achieve certain goals (e.g., prevent diseases, optimize logistics) (Floridi et al., 2018), but if the quality of information provided by these technologies is perceived as low by users, this may negatively impact their initial trust (Gao & Waechter, 2017). Therefore, we propose as follows:

Proposition P2a. *The greater the* benevolence *an algorithm demonstrates, the higher the probability of building initial trust in AI-based algorithms.*

Proposition P2b. *The greater the* ability and competence *an algorithm demonstrates, the higher the probability of building initial trust in AI-based algorithms.*

Integrity beliefs reflect "the trustor's perception that the trustee adheres to a set of principles that the trustor finds acceptable" (Mayer et al., 1995, p. 719). In the context of an algorithm, integrity can be explained in terms of fairness, transparency, and accountability (Shin and Park, 2019; Shin et al., 2020). **Fairness**, which is also referred to as justice (Thiebes et al. 2021), refers to the extent to which an algorithm is perceived to be fair (Lee, 2018). AI-based algorithms should be characterized by procedural, substantive, and interactional fairness in order to address these issues. Procedural or distributive fairness "requires that all decisions relating to the same or comparable facts are taken according to the same automated procedure" (Brkan, 2019, p. 94), by which it shows that it is reliable and consistent in the performance of its functions (see, for example, Beer, 2017; Glikson & Woolley, 2020; Hoff & Bashir, 2015; McKnight et al., 2011; Kordzadeh & Ghasemaghaei, 2021). Substantive fairness means that decisions "should not be discriminatory in any way" (Brkan, 2019, p. 94). Finally, fair interaction refers to the presentation by AI-based algorithms of complete and accurate information during interactions with users (Robert et al., 2020). For example, AI-based algorithms can be unfair in their interactions with minorities if they fail to respond to users based on their skin color (Daugherty et al. 2019). Fairness in algorithms is related to algorithmic bias, which occurs when the outcomes of algorithms are influenced by the implicit values of the humans involved in coding, programming, and training them. Accordingly, algorithmic bias is defined as "a systematic deviation from equality that emerges in the outputs of an algorithm" (Kordzadeh and Ghasemaghaei, 2021, p. 8). Moreover, previous research has shown that perceived fairness may change depending on the different nature of the algorithm's task (Lee, 2018; Castelo et al. 2019). Algorithmic decisions are usually more trusted when tasks require mechanical skills, but they are less trusted when they need human skills (subjective judgment and emotion) (Lee, 2018; Castelo et al. 2019). We, therefore, propose as follows:

Proposition P2c *The greater the integrity in terms of* fairness *an algorithm demonstrates, the higher the probability of building initial trust in AI-based algorithms.*

Transparency is "the disclosure of certain key pieces of information, including aggregate results, practice, and benchmarks" (Diakopoulos, 2016, pp. 58-59). Transparency is more problematic for AI than it is for other technologies because of the black box nature of algorithms, meaning that their internal operations are not known by their users because this information is proprietary and sufficiently complex not to be understood (Glikson & Woolley, 2020; Lindebaum et al., 2020). An important aspect of transparency is explicability relating to "the creation of explainable AI by producing (more) interpretable AI models whilst maintaining high levels of performance and accuracy" (Thiebes et al. 2021, p. 455). Some authors have shown, for example, that explaining the reasons behind possible mistakes made by an AI algorithm to users may have a significant positive effect on trust (Dzindolet et al., 2003). For this reason, transparency is particularly important as a means of fostering users' trust in algorithms, especially in the early stages, when users are still not familiar with using technologies (Hoff & Bashir, 2015; Orlikowski & Scott, 2014; Shin, 2021; Wang & Benbasat, 2008). Therefore, we propose as follows:

Proposition P2d. *The greater the integrity in terms of* transparency *an algorithm demonstrates, the higher the probability of building initial trust in AI-based algorithms.*

Explicability is also a factor in creating accountable AI-based algorithms (Thiebes et al. 2021) The concept of algorithmic **accountability** states that companies should be held accountable for the consequences or impacts of an algorithmic system on stakeholders and society (Diakopoulos, 2016; Shin et al., 2020). Normally, users are unaware of the business risks inherent in the decisions taken by algorithms because of the degree of uncertainty on which AI-based algorithms' predictions are based (Lindebaum et al., 2020; Thiebes et al., 2021). Using and designing accountable AI-based algorithms is critical to developing initial trust in them. Since humans rely on AI algorithms to perform several tasks, it is important to ensure that they do not commit errors or harms when doing certain functions. Therefore, AI-based algorithms that fulfill accountability are capable of doing what needs to be done when humans delegate important decisions to such autonomous systems (Floridi et al., 2018). Therefore, we propose as follows:

Proposition P2e. *The greater the integrity in terms of* accountability *an algorithm demonstrates, the higher the probability of building initial trust in AI-based algorithms.*

Among the human-like features that affect initial trust in algorithms, **agency** or **autonomy** also describe whether an algorithm advises users or performs tasks autonomously (Brkan, 2019; Curchod et al., 2020; Kellogg et al., 2020; Leonardi & Contractor, 2018). This is a peculiar process by which users who feel they have a certain autonomy when it comes to taking a final decision and some control over an algorithm's judgment trust it (Burton et al., 2020). Otherwise, individuals who do not believe that they have some level of control over decision-making systems may perceive themselves as mere "recipients" of decisions, without the opportunity to demonstrate their expertise. When dealing with algorithms, situations like this can lead to algorithm aversion on the part of users (Burton et al., 2020; Langer et al., 2020). In the context of AI-based algorithms, therefore, in order to promote initial trust in algorithms it is important to strike a balance between the decisional power users retain for themselves and the power they delegate to algorithms (Burton et al. 2020; Floridi et al., 2018; Shrestha et al., 2019; Thiebes et al. 2021). Therefore, we propose as follows:

Proposition P2f. *The greater the* agency or autonomy *an algorithm demonstrates, the lower the probability of building initial trust in AI-based algorithms.*

4.1.3. IT acceptance levers

The "technology acceptance model (TAM)" (Davis, 1989) is generally considered to be one of the theoretical models most commonly used to analyze the adoption of ITs by users. According to this theory, two personal beliefs (perceived usefulness and perceived ease of use) predict attitudes toward using a technology. According to TAM, perceived ease of use indicates the cognitive effort needed to learn and use new IT. Perceived ease of use is the extent to which users believe that learning how to use an IT or using it will be relatively free of effort (Bhattacherjee, 2001; Bhattacherjee & Lin, 2014; Davis, 1989; Gefen et al. 2003). **Perceived usefulness** measures an individual's subjective assessment of new IT's usefulness in a specific task-related context. The more useful the technology is in enabling the users to accomplish their tasks, the more it will be used (Gefen et al. 2003). More recent approaches have added the concept of trust as a predictor of technology acceptance (Hoff & Bashir, 2015; Lee & See, 2004). In particular, in the context of AI-based algorithms, they must first prove themselves to be useful to users in order for trust to be at stake. Despite their technical sophistication, algorithms do not have the affordance that would allow users to understand how best to utilize them in order to achieve their goals and to be explainable (Shin & Park, 2019; Wolker &

Powell, 2020). Users will perceive AI-based algorithms as useful and tend to trust them if they expect that they will perform in a manner that people can perceive as fair, transparent, and accountable (Shin & Park, 2019).

We assume that the IT acceptance lever of perceived usefulness also operates in the context of AI algorithms. Because usefulness is focused directly on the AI algorithm and related to concepts like the competence and accountability of the algorithm, whereas ease of use is more about the system incorporating the algorithm, our review leads us to propose that perceived usefulness is the more relevant construct for developing initial trust. Therefore, we advance the following proposition:

Proposition 3. *The greater the* perceived usefulness*, the higher the probability of building initial trust in AI-based algorithms.*

4.2. Trust over time in algorithms

Our integrative model also outlines the key elements that explain how and why users trust AI algorithms over time after more significantly experiencing one. Notably, the identified trusting beliefs relating to initial trust are likely to influence a user's intention to continue using a specific technology in the post-adoption stage. Of course, the constructs identified as contributing to initial trust vary in the extent to which they will tend to remain relatively stable (e.g. user propensity to trust) and the extent to which they will likely continue to evolve with additional experiences (e.g. perceived usefulness). While it will ultimately be an empirical question as to when some constructs are more or less influential, our review leads us to propose that the following constructs are likely to play their most important role over time as users gain significantly more experience with a particular AI algorithm.

4.2.1. Social influence

Users' continued intention to use is often incentivized by information provided by other people about the use of technology (**social influence**) (Alexander et al., 2018; Venkatesh & Morris, 2000). This information can also be termed "normative influences" from peers, colleagues, or other close key referents who may shape an individual's intentions toward a given behavior (Bhattacherjee & Lin, 2014). Closeness makes it possible to receive the appropriate information and knowledge to reach a decision based on a recommendation. Recommendations from people close to a user are trusted more than recommendations from less close contacts (Filieri, 2015; Matook et al., 2015).

The information provided directly by algorithms could also trigger social influence. AI-based algorithms may be characterized by the use of recommender systems (for example, recommendation agents (RAs). In discussions about technology, these mechanisms make recommendations to users based on their characteristics, preferences, and profiles, in order to offer better support for online decision-making (Wang & Benbasat, 2007; Tahmasbi et al., 2020; Yu, 2012). These recommendations offer customized searches, and make it easier for users to find the desired products or services, thus providing a more emotionally and cognitively trustworthy view of queries (Belém et al., 2020; Ding et al., 2019; Komiak & Benbasat, 2006; Marchand & Marx, 2020; Yu et al., 2019). They are used if users perceive them as being useful, and reduce information asymmetry (Pedeliento et al., 2017). Highly personalized, useful, and humanized online RAs significantly influence users' trusting beliefs and ultimately their intention to use the agent as an aid to decision-making (Dabholkar & Sheng, 2012; He et al., 2020; Qiu & Benbasat, 2009). Accordingly, we state as follows:

Proposition 4. *The greater the positive* social influence *a user perceives over algorithms, the higher the probability of building trust in AI algorithms over time.*

4.2.2. Familiarity

Familiarity represents the general level of knowledge about technologies: that users may have. The literature highlights that trust develops over time with the accumulation of trust relevant knowledge resulting from experience with other technologies (Gefen et al. 2003).

Indeed, users' interactive experiences with technology develop trust over time (Wang & Benbasat, 2008). For example, consumers continue to trust recommendation systems (RAs) that provide familiar recommendations than RAs that provide novel recommendations (Xiao & Benbasat, 2007. Therefore, users who have more training in how a technology works (and thus have knowledge of how to interact with a particular tool) develop expertise and a high level of competence that will powerfully affect their perceptions and expectations about the utility of decision aids and the trustworthiness of technology (Burton et al., 2020; Xiao & Benbasat, 2007). In other words, it has been found that if people have had previous experience with outcomes from using technology (for example, from the work of recommendation agents) (Xiao & Benbasat, 2007), this previous experience is positively related to their use (Hoff & Bashir, 2015; Montazemi, 1991; Whitecotton, 1996). Accordingly, we state as follows:

Proposition 5. *The greater the* familiarity *a user demonstrates with algorithms, the higher the probability of building trust in AI algorithms over time.*

4.2.3. The characteristics of system-like AI-based algorithms

We discovered that the early work on acceptance and use of new technology in organizations focused prevalently on technological or system-like characteristics such as the perceived usefulness considered in the TAM model (Davis, 1989). System-like trust constructs such as perceived usefulness (Talwar et al., 2020), reliability, predictability (McKnight et al., 2011), performance, purpose, and process (Lee & See, 2004) are also used in the context of algorithms for evaluating trust over time because they have a more powerful influence on outcomes (Lankton et al. 2015).

In the post-adoption stage of technology, users will even develop trust based on their learned **usefulness**. Users are unlikely to continue to use IT unless it benefits them in their future work (Bhattacherjee, 2001; Bhattacherjee & Lin, 2014; Cho et al., 2019; Lin et al., 2005; Talwar et al., 2020). For instance, users may have low initial usefulness perceptions of AI-based algorithms because they are unsure of how the technology will help them perform a task. Nonetheless, they may begin using the algorithm with the intention of forming more concrete perceptions of the algorithm's performance (Bhattacherjee, 2001, Glikson & Woolley, 2020). This means that in the context of algorithm systems, trust over time will be related to confirmation of initial expectations in terms of perceived usefulness (Shin & Park, 2019; Wolker & Powell, 2020). If experience leads users to think that algorithms are getting more and more useful than that builds trust, but if it fails to meet user initial usefulness expectations than that reduces trust. We, therefore, assume as follows:

Proposition 6a. *The greater the* learned usefulness *an algorithm demonstrates, the higher the probability of building trust in AI algorithms over time.*

The **performance** of an AI algorithm indicates the skill or expertise demonstrated by the algorithm's ability to achieve a user's goals is also relevant to the user's trust over time (Efendić et al., 2020; Thiebes et al. 2021; Wang et al., 2019). An high performance proves that AI-based algorithms own that capacity and functionality to perform certain tasks, and users will be more willing to keep on trusting them if they seem capable of reaching their goals (Thiebes et al. 2021).

Performance includes characteristics such as **reliability** and **predictability**. Algorithm reliability is defined as the belief that a specific technology will consistently operate properly (see, for example, Fraile et al., 2018; Glikson & Woolley, 2020; Hoff & Bashir, 2015; Jøsang et al., 2007; McKnight et al., 2011). Numerous studies have shown that providing users with accurate feedback about the reliability of how algorithms operate can better facilitate the appropriate trust (Hoff & Bashir, 2015). Additionally, once users have experienced algorithms, they develop trust according to the capacity of the technology to perform the intended tasks (**purpose** or **process**) (Lee & See, 2004; Thibes et al 2021), in a manner consistent with their expectations or forecasts (predictability) (De Baets & Harvey, 2020; Hoff & Bashir, 2015; McKnight & Chervany, 2002). A mismatch between expectations and performance (better, same, or worse) can lead users to a disconfirmation process with regard to their initial expectations (Bhattacherjee & Premkumar, 2004; Lankton & McKnight, 2012).

Proposition 6b. *The greater the* reliability *an algorithm demonstrates, the higher the probability of building trust in AI algorithms over time.*

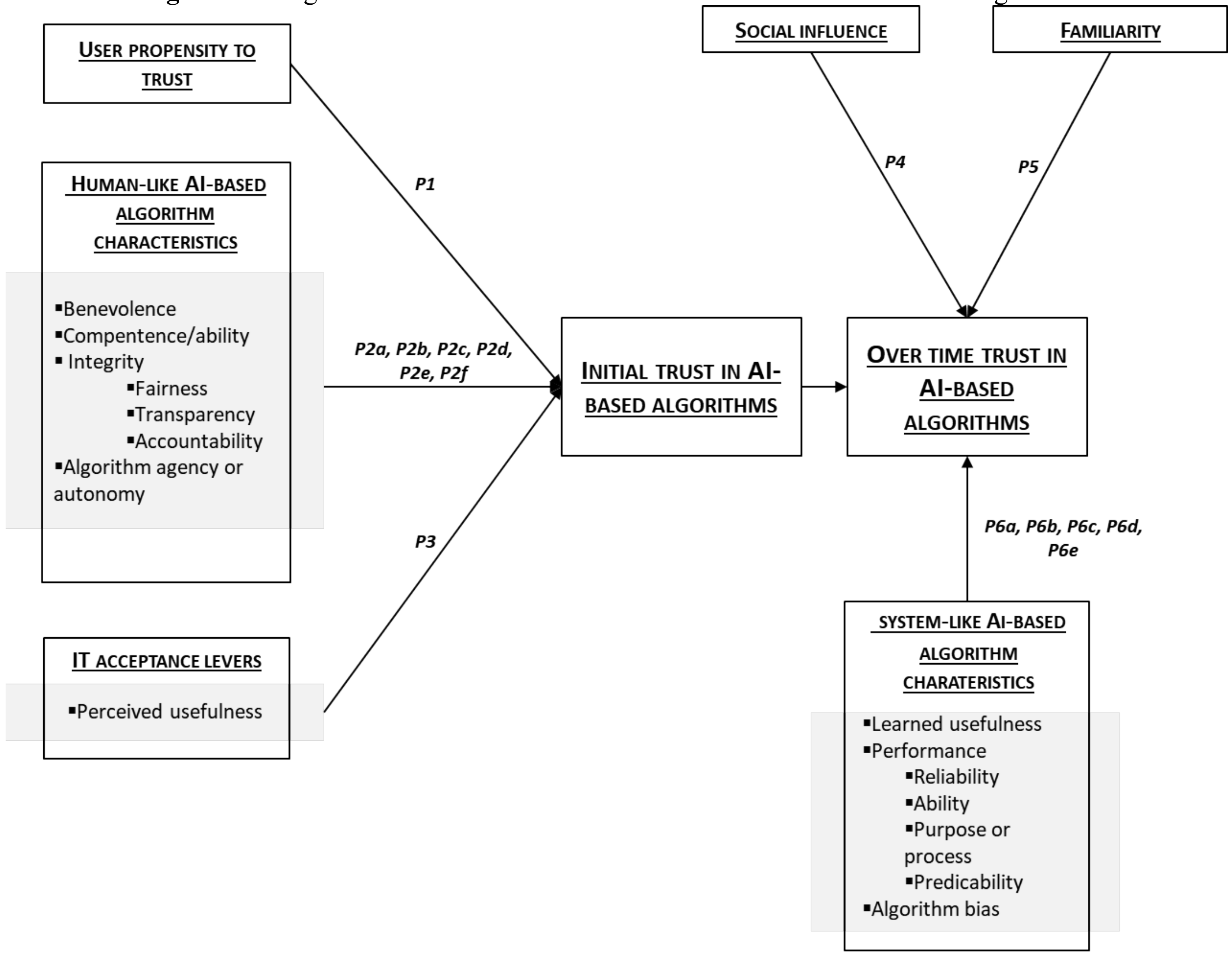
Proposition 6c. *The greater the* ability *of an algorithm to perform its intended task (purpose or process), the higher the probability of building trust in AI algorithms over time.*

Proposition 6d. *The greater the ability of an algorithm to perform its intended task* (purpose or process) *in a manner consistent with user expectations* (predictability)*, the higher the probability of building trust in AI algorithms over time.*

Another parameter to evaluate algorithm performance is **algorithmic bias**, which "occurs when the outputs of an algorithm benefit or disadvantage certain individuals or groups more than others without a justified reason for such unequal impacts" (Kordzadeh & Ghasemaghaei, 2021, p. 7). Indeed, algorithms used to take organizational decisions may contain errors, thereby producing biased or discriminatory "answers". This situation may reduce value and the users' trust in the long term, thus affecting their intention to continue to use them. Errors can derive from pre-existing cultural, social, or institutional expectations or from technical design limitations, or because the algorithm is used by an audience that was not taken into consideration in the initial software design (Lambrecht & Tucker, 2019; Martin, 2019a). Mistakes of this nature may destroy value or lead to poor decisions. Algorithmic decision mistakes can present as category mistakes (for example, the incorrect assignment of a label) or process mistakes (that is, an error in the way the decision was reached, regardless of the outcome) (Martin, 2019b).

Proposition 6e. *The greater the* algorithm bias*, the lower the probability of building trust in AI algorithms over time.*

Fig. 2. An integrative model of initial trust and over time trust in AI-based algorithms



5. Discussion

This article aims to summarize the existing research on trust in AI-based algorithms, with a particular focus on the key determinants of initial trust and trust over time. Users generally experience different trust-building moments when they interact with an algorithm for the first time compared to the post-adoption stage of these systems (Bhattacherjee, 2001; Bhattacherjee & Lin, 2014; Gao & Waechter, 2017). The previous literature has investigated initial trust (Wang & Benbasat, 2005) and trust over time (Lankton et al., 2015) as constructs that do not share the same determinants. However, this literature has not explicitly described the factors that affect users' trust in AI-based algorithms at the various stages of adoption (Burton et al., 2020). Starting from the traditional definition of initial trust and trust over time in technology (Bhattacherjee, 2001; Bhattacherjee & Lin, 2014; Söllner et.al. 2016), our work provides a basis for theoretical extensions and future research by proposing a model of initial trust and over time trust in AI-based algorithms framework that contributes toward advancing the current literature on trust in technology in several important ways.

First, our study extends the literature on trust in technology by distinguishing between the formation of initial trust and trust over time in AI-based algorithms and specifying the determinants of trust in each phase. Specifically, based on past research, we identify three main dimensions as factors that influence initial trust in AI algorithms: a user's propensity to trust, the human-like characteristics of AI-based algorithms, and IT acceptance levers. We also identify three dimensions that affect trust over time in AI-based algorithms: social influence, familiarity, and the system-like characteristics of AI-based algorithms.

Second, and relatedly, our review suggests that different representations of the technology mark the transition between initial trust and trust over time in AI-based algorithms. AI-based algorithms are equivocal technologies (Weick, 1990), and as such constitute important triggers of sensemaking. Our analysis suggests that algorithms are initially anthropomorphized and conceptualized in terms of human attributes. The technology is therefore perceived as a human counterpart, and trust will depend on the integrity of the algorithm in terms of fairness, transparency, autonomy, and accountability. Conversely, over time, algorithms tend to be increasingly represented as systems and treated as tools. This is because users become familiar with the technology and gradually embed AI-based algorithms into their work practices. Previous studies have distinguished between algorithms' human-like and system-like characteristics, explaining how users develop trust in an algorithm differently depending on whether they perceive it as more or less human-like (Lankton et al, 2015). Our analysis suggests that these perceptions are likely to evolve with continued use and experience. The human-like attributes of AI-based algorithms affect trust because they make the technology conspicuous and intrusive, and as such they are likely to pose a threat to users' autonomy, discretion, and professional jurisdiction. Over time, as users familiarize themselves with algorithm-based work, they are more likely to emphasize the system-like qualities of algorithms. Algorithms become tools that complement and support human expertise. They then tend to become taken for granted and integrated into existing work practices.

Third, our findings complement previous literature indicating the determinants that influence the transition from initial trust to over time trust are not only the human-like and system-like characteristics of AI-based algorithms but also other determinants that may have different implications for the different phases. One important factor for initial trust is the user's propensity to trust, which, being tacit, bestows a positive impact on this starting phase and tends to remain stable over time (McKnight et al. 2011). Therefore, higher trust in an AI-based algorithm can be attributed to an individual propensity to trust a technology whereas lower trust can be attributed to a dispositional unwillingness to trust the technology. Since user's propensity varies with culture, age, gender, and other personality traits (Hoff & Bashir, 2015), these factors may influence algorithm adoption Another important determinant that has different implications for initial trust and trust over time is perceived usefulness. Our review suggests that initial perceived usefulness has a positive but low impact on trust in AI-based algorithms. This may increase over time due to a positive experience that confirms the initially perceived usefulness. Previous studies have viewed perceived usefulness as a post-adoption users' belief (Bhattacherjee, 2001), or as an initial belief related to the degree to which a potential user believes that technology will perform, so that people can develop perceptions of fairness, transparency, and accountability (Shin & Park, 2019). Other important determinants that enable the shift from initial trust to trust over time include social influence and familiarity with AI algorithm. Our review suggests that both social influence and familiarity will positively impact trust in AI algorithms over time because users are incentivized by information from other people about the use of technology and by users' interactive experiences. Social influence and familiarity are critical to understanding user trust in AI-based Algorithms since they could play an important role in determining how users decide to adopt and use algorithms. In fact, there is a significant body of evidence outside the domain of AI-based Algorithms supporting the view that social influence and familiarity play a critical role in influencing behaviors in a wide variety of domains (Venkatesh & Morris, 2000). Moreover, social influence and familiarity have been considered in relation to trust in general technologies (Wang & Benbasat, 2008) and occasionally extended to the context of AI-based technologies (Alexander et al., 2018). What has not been considered, however, is their role in an integrated framework in which they acquire importance if they are associated with other determinants, such as the system-like characteristics of AI-based algorithms. For example, prior literature showed that familiarity with an AI-Based algorithm is acquired through one's prior and direct experiential exchanges with the algorithm. Our study underlines how familiarity may increase either trust or distrust, depending not only on whether the trustor's experience with the trustee is positive or negative but also on the influence of other factors such as system-like or human-like characteristics of the AI-based algorithm.

6. Directions for future research

As a body of literature in its early phase, research on AI-based algorithms appears to be rather theoretically and empirically fragmented. While research on algorithms has only emerged recently, their pervasive role in contemporary organizations makes it a compelling line of future study. Therefore, the field offers substantial opportunities for theoretical integration and novel extensions of organizational research and practice. Our review has only started to cover some theoretical ground by synthesizing extant knowledge on how trust in AI-based algorithms evolves over time. However, further research is needed to advance our understanding of this important field of studies. Our framework provides several avenues for future research.

First, organizational research has a longstanding desire to increase theoretical integration without suppressing the alternative approaches critical to a young, applied field. Future empirical studies should validate our framework through longitudinal research in different organizational settings. In particular, future studies could look at how the nature of the task, the organizational context, and users' professional identity shape perceptions of trust. Second, while this research has primarily looked at the antecedents of AI-based trust, future studies could explore the impact of trust on organizational practices and performance. For example, how does trust in algorithms affect motivation at work? How does it impact interpersonal relationships and team dynamics? And what are the consequences for organizational performance and for the development and deployment of AI algorithms in the workplace? Relatedly, future researchers could also identify important moderators and mediators in the relationship between initial trust and trust over time in validating the proposed framework. Third, our review provides a platform for considering competing views of technology use. For example, various streams of research on IT use have assumed that the expectation-confirmation model (ECM) (Bhattacherjee, 2001) can predict intentions to continue using technology better than other models based on well-established behavior frameworks such as the technology acceptance model (TAM) (Davis et al., 1989). Future research could use our initial framework of AI-based algorithm trust to explore which of these two models can better explain a decision to continue using algorithms, or if other models are needed. Finally, we have analyzed the main features that impact initial trust and trust over time in AI algorithms, but we have not investigated how the organizational contexts into which AI-based algorithms are embedded affect perceptions of trust. In other words, we have focused on the characteristics of the technology – and the perceptions they trigger – rather than considering the wider organizational contexts in which AI-based technologies are embedded. These contexts are defined, for example, by the mass of material, cognitive, cultural, and institutional elements within which AI-based algorithms are used. Future research could investigate how selected aspects of organizational contexts – cultural values, organizational artifacts, social relations, structures and procedures - affect perceptions of trust in relation to AI-based algorithms.

7. Conclusion

Our framework, which is derived from an integrative review of the existing literature, offers a view of AI-based algorithms as intelligent technologies pervaded by a tension between human- and system-like perceptions. The core of our approach to AI-based algorithms is that their meaning in the workplace evolves over time and is primarily derived from the distinction between human and system: users of these technologies induce meaning from constructions that characterize technology as either human-like or system-like. Our study contributes toward increasing the level of attention organizations should devote to the determinants that constitute initial and over time trust in AI algorithms. It could therefore help managers orient their behavior, thereby improving the effectiveness of their performance in business contexts in which persuading people may be a challenge. For example, by distinguishing between ways of building trust in relation to different phases of technology adoption, managers may use the identified dimensions of our integrative model to guide their assessments of the actions needed to encourage initial trust and then foster over time trust. Initial trust might be built by either demystifying the human character of the technology or recognizing the technology as a social actor endowed with agency creating perceptions of the fairness, transparency, and accountability of algorithms. Later stages of adoption might be aimed at blending the technology into the cultural fabric of the organization.

.

References

Alexander, V., Blinder, C., & Zak, P. J. (2018). Why trust an algorithm? Performance, cognition, and neurophysiology. *Computers in Human Behavior, 89*, 279–288. https://doi.org/10.1016/j.chb.2018.07.026.

Bazeley, P., & Jackson, K. (2013). *Qualitative data analysis with NVivo*. Sage Publications Limited.

Beer, D. (2017). The social power of algorithms. Information. *Communication & Society, 20*(1), 1-13. https://doi.org/10.1080/1369118X.2016.1216147

Belém, F. M., Silva, R. M., de Andrade, C. M., Person, G., Mingote, F., Ballet, R., Alponti, H., de Oliveira, H. P., Almeida, J. M., & Gonçalves, M. A. (2020). "Fixing the curse of the bad product descriptions"–Search-boosted tag recommendation for E-commerce products. *Information Processing & Management*, *57*(5), 102289. https://doi.org/10.1016/j.ipm.2020.102289.

Bhattacherjee, A. (2001). Understanding Information Systems Continuance: An Expectation-Confirmation Model. *MIS Quarterly, 25*(3), 351-370. https://doi.org/10.2307/3250921.

Bhattacherjee, A., & Lin, C. P. (2014). A Unified Model of IT Continuance: Three Complementary Perspectives and Crossover Effects. *European Journal of Information Systems*, *24*(4), 364–373. https://doi.org/10.1057/ejis.2013.36.

Bhattacherjee, A., & Premkumar, G. (2004). Understanding changes in belief and attitude toward information technology usage: A theoretical model and longitudinal test. *MIS Quarterly*, *28*(2), 229-254. https://doi.org/10.2307/25148634.

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative research in psychology, 3*(2), 77-101. https://doi.org/10.1191/1478088706qp063oa.

Brkan, M. (2019). Do algorithms rule the world? Algorithmic decision-making and data protection in the framework of the GDPR and beyond. *International journal of law and information technology*, *27*, 91–121. https://doi.org/10.1093/ijlit/eay017.

Burton, J. W., Stein, M.-K., & Jensen, T. B. (2020). A systematic review of algorithm aversion in augmented decision making. *Journal of Behavioral Decision Making*, *33*(2), 220– 239. https://doi.org/10.1002/bdm.2155.

Calabrò, A., Vecchiarini, M., Gast, J., Campopiano, G., De Massis, A., & Kraus, S. (2019). Innovation in family firms: A systematic literature review and guidance for future research. *International journal of management reviews, 21*(3), 317-355. https://doi.org/10.1111/ijmr.12192.

Castelo, N., Maarten W.B., & Donald R. L. (2019). Task-Dependent Algorithm Aversion. *Journal of Marketing Research*, *56*(5), 809–25. https://doi.org/10.1177/0022243719851788.

Cho, M.H., Bonn, M.A., & Li, J. (2019). Differences in perceptions about food delivery apps between single-person and multi-person households. *International Journal of Hospitality Management*, *77*, 108–116. https://doi.org/10.1016/j.ijhm.2018.06.019.

Copeland, R., & Hope, B. (2016). *The world's largest hedge fund is building an algorithmic model from its employees' brains*. Retrieved from https:// www.wsj.com/articles/the-worlds-largest-hedge-fund-isbuilding-an-algorithmic-model-of-its-founders-brain1482423694. Accessed March 20, 2021.

Curchod, C., Patriotta, G., Cohen, L., & Neysen, N. (2020). Working for an algorithm: Power asymmetries and agency in online work settings. *Administrative Science Quarterly, 65*(3), 644-676. https://doi.org/10.1177/0001839219867024.

Dabholkar, P.A., & Sheng, X. (2012). Consumer participation in using online recommendation agents: effects on satisfaction, trust, and purchase intentions. *Service Industries Journal*, *32*(9), 1433-1449. https://doi.org/10.1080/02642069.2011.624596.

Daugherty, P.R., Wilson, H.J. & Chowdhury, R. (2019). "Using Artificial Intelligence to Promote Diversity". *MIT Sloan Management Review, 60*(2), 59-63.
Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, *48*, 24–42. https://doi.org/10.1007/s11747-019-00696-0.
Davis, F.D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008.
Davis, M.S. (1971). That's Interesting! Toward a Phenomenology of Sociology and a Sociology of Phenomenology. *Philosophy of the Social Sciences, 1*(4), 309-344. https://doi.org/10.1177/004839317100100211.
De Baets, S., & Harvey, N. (2020). Using judgment to select and adjust forecasts from statistical models. *European Journal of Operational Research, 284*(3), 882-895. https://doi.org/10.1016/j.ejor.2020.01.028.
De Cicco, R., Silva, S. C., & Alparone, F. R. (2020). Millennials' attitude toward chatbots: An experimental study in a social relationship perspective. *International Journal of Retail & Distribution Management*, *48*(11), 1213-1233. https://doi.org/10.1108/IJRDM-12-2019-0406.
Diakopoulos, N. (2016). Accountability in algorithmic decision making. *Communications of the ACM*, *59*(2), 56–62. https://doi.org/10.1145/2844110.
Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General*, *144*, 114-126. https://doi.org/10.1037/xge0000033.
Ding, S., Yue, Z., Yang, S., Niu, F., & Zhang, Y. (2019). A Novel Trust Model based Overlapping Community Detection Algorithm for Social Networks. *IEEE Transactions on Knowledge and Data Engineering, 32*(11), 2101-2114. https://10.1109/TKDE.2019.2914201.
Dzindolet, M. T., Peterson, S. A., Pomranky, R. A., Pierce, L. G., & Beck, H. P. (2003). The role of trust in automation reliance. *International Journal of Human-Computer Studies, 58*(6), 697–718. https://doi.org/10.1016/S1071-5819(03)00038-7.
Efendić, E., Van de Calseyde, P. P., & Evans, A. M. (2020). Slow response times undermine trust in algorithmic (but not human) predictions. *Organizational Behavior and Human Decision Processes*, *157*, 103-114. https://doi.org/10.1016/j.obhdp.2020.01.008.
Elsbach, K. and van Knippenberg, D. (2020). 'Creating high-impact literature reviews: An argument for integrative reviews'. *Journal of Management Studies*, 57, 1277-1289. https://doi.org/10.1111/joms.12581.
Filieri, R. (2015). Why Do Travelers Trust TripAdvisor? Antecedents of Trust towards Consumer-Generated Media and Its Influence on Recommendation Adoption and Word of Mouth. *Tourism Management*, *51*, 174–85. https://doi.org/10.1016/j.tourman.2015.05.007.
Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., et al. (2018). AI4People—An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. Minds and Machines, 28(4), 689–707. https://doi.org/10.1007/s11023-018-9482-5.
Fraile, F., Tagawa, T., Poler, R., & Ortiz, A. (2018). Trustworthy industrial IoT gateways for interoperability platforms and ecosystems. *IEEE Internet Things Journal*, *5*(6), 4506–4514. https://doi.org/10.1109/JIOT.2018.2832041.
Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological forecasting and social change, 114*, 254-280. https://doi.org/10.1016/j.techfore.2016.08.019.

Friedman, B., Khan, P. H., Jr., & Howe, D. C. (2000). Trust online. *Communications of the ACM, 43*(12), 34-40. https://doi.org/10.1145/355112.355120.

Furrer, O., Thomas, H., & Goussevskaia, A. (2008). The structure and evolution of the strategic management field: A content analysis of 26 years of strategic management research. *International Journal of Management Reviews, 10*(1), 1-23. https://doi.org/10.1111/j.1468-2370.2007.00217.x.

Gao, L., & Waechter, K. (2017). Examining the role of initial trust in user adoption of mobile payment services: an empirical investigation. *Information Systems Frontiers*, *19*, 525-548. https://doi.org/10.1007/s10796-015-9611-0.

Gefen, D., Benbasat, I., & Pavlou, P. A. 2008. A research agenda for trust in online environments. *Journal of Management Information Systems*, *24*, 275–286. https://doi.org/10.2753/MIS0742-1222240411.

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly*, *27*, 51–90. https://doi.org/10.2307/30036519.

Gibson, J. J. (1977). *The theory of affordances*. In R. E. Shaw & J. Bransford (Eds.), Perceiving, acting and knowing, Hillsdale: Lawrence Erlbaum Associates.

Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals, 14*(2), 627-660. https://doi.org/10.5465/annals.2018.0057.

He, J., Wang, X., Vandenbosch, M. B., & Nault, B. R. (2020). Revealed preference in online reviews: Purchase verification in the tablet market. *Decision Support Systems*, *132,* 113281. https://doi.org/10.1016/j.dss.2020.113281.

Helbing, D., Frey, B. S., Gigerenzer, G., et al. (2019). Will Democracy Survive Big Data and Artificial Intelligence?, in Helbing D. (ed.) *Towards Digital Enlightenment. Essays on the Dark and Light Sides of the Digital Revolution*, pp. 73–98. Cham: Springer.

Ho, C.-C., & MacDorman, K.F. (2010). Revisiting the uncanny valley theory: Developing and validating an alternative to the Godspeed indices. *Computers in Human Behavior*, 26(6), 1508–18. https://doi.org/10.1016/j.chb.2010.05.015.

Hoff, K. A., & Bashir, M. (2015). Trust in automation: Integrating empirical evidence on factors that influence trust. *Human Factors*, *57*, 407–434. https://doi.org/10.1177/0018720814547570.

Jones, G.R., & George, J.M. (1998). The experience and evolution of trust: implications for cooperation and teamwork. *Academy of Management Review, 23*(3), 531–546. https://doi.org/10.5465/amr.1998.926625.

Jøsang, A., Ismail, R., & Boyd, C. (2007). A survey of trust and reputation systems for online service provision. *Decision Support Systems, 43*(2), 618 –644. https://doi.org/10.1016/j.dss.2005.05.019.

Joseph, J., & Gaba, V. (2020). Organizational structure, information processing, and decision-making: a retrospective and road map for research. *Academy of Management Annals, 14*(1), 267-302. https://doi.org/10.5465/annals.2017.0103.

Kaplan, A., & Haenlein, M. (2018). Siri, Siri, in My Hand: Who's the Fairest in the Land? On the Interpretations, Illustrations, and Implications of Artificial Intelligence. *Business Horizons*, *62* (1), 15-25. https://doi.org/10.1016/j.bushor.2018.08.004.

Kaplan, A., & Haenlein, M. (2020). Rulers of the world, unite! The challenges and opportunities of artificial intelligence. *Business Horizons, 63*(1), 37-50. https://doi.org/10.1016/j.bushor.2019.09.003.

Karahanna, E., Straub, D.W., & Chervany, N.L. (1999). Information technology adoption across time: a cross-sectional comparison of preadoption and post-adoption beliefs. *MIS Quarterly, 23* (2), 183–213. https://doi.org/10.2307/249751.

Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals, 14*(1), 366-410. https://doi.org/10.5465/annals.2018.0174.

Kim, D.J., Ferrin, D.L., & Rao, H.R. (2009). Trust and satisfaction, two stepping stones for successful e-commerce relationships: A longitudinal exploration. *Information Systems Research*, *20*(2), 237–257. https://doi.org/10.1287/isre.1080.0188.

Komiak, S., & Benbasat, I. (2006). The effects of personalization and familiarity on trust and adoption of recommendation agents. *MIS Quarterly*, *30*(4), 941–960. https://doi.org/10.2307/25148760.

Komiak, S.Y.X., Wang, W., & Benbasat, I. (2005). Trust building in virtual salespersons versus in human salespersons: Similarities and differences. *e-Service Journal, 3*(3), 49–63. https://doi.org/10.2979/esj.2004.3.3.49.

Kordzadeh, N., & Ghasemaghaei, M. (2021). Algorithmic bias: review, synthesis, and future research directions. *European Journal of Information Systems*, 1-22. https://doi.org/10.1080/0960085X.2021.1927212.

Lambrecht, A., & Tucker, C. (2019). Algorithmic bias? An empirical study of apparent gender-based discrimination in the display of STEM career ads. *Management Science*, *65*(7), 2966–2981. https://doi.org/10.1287/mnsc.2018.3093.

Langer, M., König, C. J., & Busch, V. (2020). Changing the means of managerial work: Effects of automated decision support systems on personnel selection tasks. *Journal of Business and Psychology*, 1–19. https://doi.org/10.1007/s10869-020-09711-6.

Lankton, N. K. & McKnight, H. D. (2012). Examining two expectation disconfirmation theory models: assimilation and asymmetry effects. *Journal of the Association for Information Systems*, *13*, 88–115. https://doi.org/10.17705/1jais.00285.

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*, 880–918. https://doi.org/10.17705/1jais.00411.

Lee, M. (2018). Understanding perception of algorithmic decisions: Fairness, trust, and emotion in response to algorithmic management. *Big Data & Society, 5*(1), 1-16. https://doi.org/10.1177/2053951718756684.

Lee, J. D., & See, K. A. (2004). Trust in automation: Designing for appropriate reliance. *Human factors, 46*(1), 50-80. https://doi.org/10.1518/hfes.46.1.50_30392.

Leonardi, P., & Contractor, N. (2018). Better people analytics. *Harvard Business Review, 96*(6), 70-81.

Lepri, B., Staiano, J., Sangokoya, D., Letouzé, E., & Oliver, N. (2017). *The tyranny of data? The bright and dark sides of data-driven decision-making for social good*. In Transparent data mining for big and small data (pp. 3–24). Springer.

Lin, C. S., Wu, S. & Tsai, R. J. (2005). Integrating perceived playfulness into expectation confirmation model for web portal context. *Information & Management*, *42*(5), 683–693. https://doi.org/10.1016/j.im.2004.04.003.

Lindebaum, D., Vesa, M., & Den Hond, F. (2020). Insights from "the machine stops" to better understand rational assumptions in algorithmic decision making and its implications for organizations. *Academy of Management Review, 45*(1), 247-263. https://doi.org/10.5465/amr.2018.0181.

Majchrzak, A., Faraj, S., Kane, G. C., & Azad, B. (2013). The contradictory influence of social media affordances on online communal knowledge sharing. *Journal of Computer-Mediated Communication, 19*(1), 38-55. https://doi.org/10.1111/jcc4.12030.

Marchand, A., & Marx, P. (2020). Automated Product Recommendations with Preference-Based Explanations. *Journal of Retailing*, *96*, 328-343. https://doi.org/10.1016/j.jretai.2020.01.001.
Martin, K. (2019a). Ethical Implications and Accountability of Algorithms. *Journal of Business Ethics*, *160*, 835-850. https://doi.org/10.1007/s10551-018-3921-3.
Martin, K. (2019b). Designing ethical algorithms. *MIS Quarterly Executive*, *18*(2), 129–142. http://dx.doi.org/10.2139/ssrn.3056692.
Matook, S., Brown, S.A., & Rolf, J. (2015). Forming an intention to act on recommendations given via online social networks. *European Journal of Information Systems*, *24*(1), 76–92. https://doi.org/10.1057/ejis.2013.28.
Mayer, R. C., Davis, J. H., & Schoorman, D. (1995). An integrative model of organizational trust. *Academy of Management Review*, *20*, 709-734. https://doi.org/10.5465/amr.1995.9508080335.
McKnight D.H., Liu P., & Pentland B.T. (2020). Trust Change in Information Technology Products. *Journal of Management Information Systems, 37*(4), 1015-1046. https://doi.org/10.1080/07421222.2020.1831772.
McKnight, D. H., & Chervany, L. C. (2002). What trust means in ecommerce customer relationships: An interdisciplinary conceptual typology. *International Journal of Electronic Commerce*, *6*(2), 35–59. https://doi.org/10.1080/10864415.2001.11044235.
McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). Developing and validating trust measures for e-commerce: An integrative typology. *Information systems research, 13*(3), 334-359. https://doi.org/10.1287/isre.13.3.334.81.
McKnight, D. H., Cummings, L. L., & Chervany, N. L. (1998). Initial Trust Formation in New Organizational Relationships. *Academy of Management Review*, *23*, 473-490. https://doi.org/10.5465/amr.1998.926622.
Mcknight, D., Carter, M., Thatcher, J., et al. (2011). Trust in a specific technology: An investigation in its components and measures. *ACM Transactions on Management Information Systems*, *2*, 1–12. https://doi.org/10.1145/1985347.1985353.
Michelman, P. (2017). When People Don't Trust Algorithms. *MIT Sloan Management Review*, 59.
Montazemi, A. R. (1991). The impact of experience on the design of user interface. *International Journal of Man-Machine Studies*, *34*, 731–749. https://doi.org/10.1016/0020-7373(91)90022-Y.
Mori, M. (1970). Bukimi no tani (the uncanny valley). *Energy, 7*(4), 33–35.
Nabi, G., Liñán, F., Fayolle, A., Krueger, N., & Walmsley, A. (2017). The impact of entrepreneurship education in higher education: A systematic review and research agenda. *Academy of Management Learning & Education, 16*(2), 277-299. https://doi.org/10.5465/amle.2015.0026.
Nass, C., Steuer, J. S., & Tauber, E. (1994). *Computers are social actors*. In Proceedings of the CHI Conference (pp. 72-77). Boston, MA: Springer-Verlag.
Nowak, K. L., & Rauh, C. (2005). The influence of the avatar on online perceptions of anthropomorphism, androgyny, credibility, homophily, and attraction. *Journal of ComputerMediated Communication*, *11*, 153-178. https://doi.org/10.1111/j.1083-6101.2006.tb00308.x.
OECD (2020). *Using artificial intelligence to help combat COVID-19*. Retrieved from: https://read.oecd-ilibrary.org/view/?ref=130_130771-3jtyra9uoh&title=Using-artificial-intelligence-to-help-combat-COVID-19. Accessed March 20, 2021.
Orlikowski, W. J., & Scott, S. V. (2014). What happens when evaluation goes online? Exploring apparatuses of valuation in the travel sector. *Organization Science, 25*(3), 868-891. https://doi.org/10.1287/orsc.2013.0877.
Paravastu, N., Gefen, D., & Creason, S. (2014). Understanding Trust in IT Artifacts -An Evaluation of the impact of Trustworthiness and Trust on Satisfaction with Antiviral Software. *The DATA*

BASE for Advances in Information Systems, *45*, 30–50. https://doi.org/10.1145/2691517.2691520.
Patriotta, G. (2020). Writing impactful review articles. *Journal of Management Studies, 57*, 6, 1272-1276. https://doi.org/10.1111/joms.12608.
Pedeliento, G., Andreini, D., Bergamaschi, M., & Klobas, J.E. (2017). Trust, information asymmetry and professional service online referral agents. *Journal of Service Theory and Practice*, *27*(6), 1081-1104. https://doi.org/10.1108/JSTP-10-2016-0185.
Prahl, A., & Van Swol, L. (2017). Understanding algorithm aversion: When is advice from automation discounted? *Journal of Forecasting*, *36*, 691–702. https://doi.org/10.1002/for.2464.
Qiu, L., & Benbasat, I. (2009) Evaluating Anthropomorphic Product Recommendation Agents: A Social Relationship Perspective to Designing Information Systems. *Journal of Management Information Systems*, *25*(4), 145-182. https://doi.org/10.2753/MIS0742-1222250405.
Ramos-Rodríguez, A. R., & Ruíz-Navarro, J. (2004). Changes in the intellectual structure of strategic management research: A bibliometric study of the Strategic Management Journal, 1980–2000. *Strategic management journal, 25(*10), 981-1004. https://doi.org/10.1002/smj.397.
Rashman, L., Withers, E., & Hartley, J. (2009). Organizational learning and knowledge in public service organizations: A systematic review of the literature. *International journal of management reviews, 11*(4), 463-494. https://doi.org/10.1111/j.1468-2370.2009.00257.x.
Reeves, B., & Nass, C. (1996). *How people treat computers, television, and new media like real people and places*. Cambridge: Cambridge University Press.
Robert, L. P., Pierce, C., Marquis, E., Kim, S., Alahmad, R. (2020). Designing Fair AI for Managing Employees in Organizations: A Review, Critique, and Design Agenda, *Human -Computer Interaction*, 35(5-6), 545-575. https://doi.org/10.1080/07370024.2020.1735391.
Rotter, J. B. (1967). A new scale for the measurement of interpersonal trust. *Journal of Person- ality, 35*, 651-665. https://doi.org/10.1111/j.1467-6494.1967.tb01454.x.
Rousseau, D.M., Sitkin, S.B., Burt, R.S., et al. (1998). Not so Different after All: A Cross-Discipline View of Trust. *Academy of Management Review*, *23*, 393–404. https://doi.org/10.5465/amr.1998.926617.
Saggese, S., Sarto, F., & Cuccurullo, C. (2016). Evolution of the debate on control enhancing mechanisms: A systematic review and bibliometric analysis. *International Journal of Management Reviews, 18*(4), 417-439. https://doi.org/10.1111/ijmr.12072.
Schwab, K. (2017). *The fourth industrial revolution*. Currency, Geneva Switzerland, World Economic Forum.

Shin, D. (2021). The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI *International Journal of Human-Computer Studies, 146*, 102551. https://doi.org/10.1016/j.ijhcs.2020.102551.
Shin, D., & Park, Y. J. (2019). Role of fairness, accountability, and transparency in algorithmic affordance. *Computers in Human Behavior*, 98, 277-284. https://doi.org/10.1016/j.chb.2019.04.019.
Shin, D., Zhong, B., & Biocca, F. A. (2020). Beyond user experience: What constitutes algorithmic experiences? *International Journal of Information Management, 52*, 102061. https://doi.org/10.1016/j.ijinfomgt.2019.102061.
Short, J., Williams, E., & Christie, B. (1976). *The social psychology of telecommunications*. London, UK: John Wiley.

Shrestha, Y.R., Ben-Menahem, S.M., & von Krogh, G. (2019). Organizational decision-making structures in the age of artificial intelligence. *California Management Review, 61*(4), 66–83. https://doi.org/10.1177/0008125619862257.

Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. *Journal of Business Research*, *104*, 333-339. https://doi.org/10.1016/j.jbusres.2019.07.039.

Söllner, M., Hoffmann, A., & Leimeister, J.M. (2016). Why different trust relationships matter for information systems users. *European Journal of Information Systems*, *25*, 274–287. https://doi.org/10.1057/ejis.2015.17.

Susskind, R., & Susskind, D. (2015). *The future of professions. How technology will transform the work of human experts*. Oxford: Oxford University Press.

Tahmasbi, H., Jalali, M., & Shakeri, H. (2021). TSCMF: Temporal and social collective matrix factorization model for recommender systems. *Journal of Intelligent Information Systems*, *56*, 169-187. https://doi.org/10.1007/s10844-020-00613-w.

Talwar, S., Dhir, A., Khalil, A., Mohan, G., & Islam, A. N. (2020). Point of adoption and beyond. Initial trust and mobile-payment continuation intention. *Journal of Retailing and Consumer Services*, *55*, 102086. https://doi.org/10.1016/j.jretconser.2020.102086.

Teo, T.S.H., Srivastava, S.C., & Jiang, L. (2009). Trust and electronic government success: an empirical study. *Journal of Management Information Systems, 25*, 103-137. https://doi.org/10.2753/MIS0742-1222250303.

Thiebes, S., Lins, S., & Sunyaev, A. (2021). Trustworthy artificial intelligence. *Electronic Markets, 31*(2), 447-464. https://doi.org/10.1007/s12525-020-00441-4.

Torraco, R. J. (2005). Writing integrative literature reviews: Guidelines and examples. *Human Resource Development Review*, *4*(3), 356-367. https://doi.org/10.1177/1534484305278283.

Vance, A., Elie-Dit-Cosaque, C., & Straub, D.W. (2008). Examining Trust in Information Technology Artifacts: The Effects of System Quality and Culture. *Journal of Management Information Systems*, *24*, 73–100. https://doi.org/10.2753/MIS0742-1222240403.

Venkatesh, V., & Morris, M. G. (2000). Why don't men ever stop to ask for directions? Gender, social influence, and their role in technology acceptance and usage behavior. *MIS quarterly*, *24*(1), 115-139. https://doi.org/10.2307/3250981.

Wang W., & Benbasat, I. (2008). Attributions of Trust in Decision Support Technologies: A Study of Recommendation Agents for E-Commerce. *Journal of Management Information Systems*, *24*(4), 249-273. https://doi.org/10.2753/MIS0742-1222240410.

Wang, W. Q., & Benbasat, I. (2007). Recommendation Agents for Electronic Commerce: Effects of Explanation Facilities on Trusting Beliefs. *Journal of Management Information Systems*, *23*, 217-246. https://doi.org/10.2753/MIS0742-1222230410.

Wang, W., & Benbasat, I. (2005). Trust in and adoption of online recommendation agents. *Journal of the Association for Information Systems*, *6* (3), 72–101. https://doi.org/10.17705/1jais.00065.

Wang, X., Lin, X., & Liu, Z. (2019). Understanding consumers' post-adoption behavior in sharing economy services. *Journal of Computer Information Systems*, 1–10. https://doi.org/10.1080/08874417.2019.1631132.

Weick, K. E. (1990). *Technology as equivoque: sensemaking in new technologies*. In Goodman, P. S., Sproull, L. S. et al. (Eds), Technology and Organizations. San Francisco: Jossey-Bass.

Whitecotton, S. M. (1996). The effects of experience and confidence on decision aid reliance: A causal model. *Behavioral Research in Accounting*, *8*, 194–216. https://doi.org/10.1006/obhd.1996.0042.

Wolker, A. & Powell, TE. (2018). Algorithms in the Newsroom? News Readers' Perceived Credibility and Selection of Automated Journalism." *Journalism*, 22 (1), 86-103. https://doi.org/10.1177/1464884918757072.
Xiao, B., & Benbasat, I. (2007). E-commerce product recommendation agents: Use, characteristics, and impact. *MIS quarterly*, *31*(1), 137–209. https://doi.org/10.2307/25148784.
Yu, C., Zhang, Z., Lin, C., & Wu, Y. (2019). Can data-driven precision marketing promote user AD clicks? Evidence from advertising in WeChat moments. *Industrial Marketing Management*, *90*, 481-492. https://doi.org/10.1016/j.indmarman.2019.05.001.
Yu, S. J. (2012). The dynamic competitive recommendation algorithm in social network services. *Information Sciences*, *187*, 1–14. https://doi.org/10.1016/j.ins.2011.10.020.