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Rationally trust, but emotionally? The roles of cognitive and affective trust in laypeople's acceptance of AI for preventive care operations

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Abstract
Artificial intelligence (AI) is transforming healthcare operations. Nevertheless, particularly in the context of preventive care, little is known about how laypeople perceive and accept AI and change their behavior accordingly. Grounded in a solid theoretical framework of trust, this study bridges this gap by exploring individuals' acceptance of AI-based preventive health interventions and following health behavior change, which is critical for preventive care providers' operational and business performance. Through a randomized field experiment with 15,000 users of a mobile health app complemented by a survey, we first show that the use and disclosure of AI in preventive health interventions improve their effectiveness. However, individuals are less likely to accept and achieve the health behavior change suggested by AI than when they receive similar interventions from health experts. We also observe that the effectiveness of AI-based interventions can be improved by combining them with human expert opinions, increasing their algorithmic transparency, or emphasizing their genuine care and warmth. These results collectively suggest that, different from conventional technologies, AI's deficient affective trust, rather than comparable cognitive trust, play a decisive role in the acceptance of AI-based preventive health interventions. This study sheds light on the literature on the role of new-age information technologies in behavioral operations management, consumer marketing, and healthcare as well as the role of trust in technology acceptance. Valuable practical implications for more effective management of AI for preventive care operations and promotion of consumers' health behavior are also provided.

KEYWORDS
Affective and cognitive trust, artificial intelligence, mHealth (mobile health) app, randomized field experiment, technology acceptance

1 | INTRODUCTION

The world is experiencing a serious shortage of human resources for healthcare operations. The shortage of healthcare workers was estimated to be 17.4 million in 2013, and it is projected to decline by only 17% by 2030 (World Health Organization, 2016). With the growing emphasis on and corresponding escalating demand for *preventive care*, in particular, the shortage of its human resources has become especially severe (Stein & Brooks, 2017). Physicians suffer from a lack of time and resources for preventive care, such as prescriptions for diet and exercise (Douglas et al., 2006). As a result, people who could benefit from intensive in-person behavioral counseling often receive inadequate services (Stein & Brooks, 2017). Specifically, while 75% of the U.S. healthcare budget is allocated to preventive care (Beaton, 2017), only 22.4% of Americans receive recommended services (Borsky et al., 2018).

Against this backdrop, by addressing the gap between the high demand for and low supply of preventive care, artificial intelligence (AI) has drawn considerable attention

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as a transformative force in preventive care operations (Guha & Kumar, 2018; Hopp et al., 2018). Specifically, AI is shown to improve preventive care operations by providing more cost-efficient and personalized *preventive health interventions*, including dietary recommendations (Kong & Tan, 2012) and exercise prescriptions (Zhou et al., 2018), which have been offered by health experts. Accordingly, AI is transforming how patients interact with health experts (e.g., physicians) for preventive care.

However, AI-based preventive health interventions (hereafter *AI-interventions*) are facing a critical challenge: users' trust in AI for preventive care operations is significantly lower than their trust in health experts. For example, in one survey of 2048 U.S. adults, only 20% of individuals indicated that they would trust AI which generates healthcare advice (Schierberl, 2019). Given that trust is a key challenge regarding users' acceptance of AI applications (Kumar, 2021), such low trust can hamper the effectiveness of AI-interventions. This creates complexities for preventive care providers regarding whether and how to adopt such a new-age technology to replace their existing preventive health interventions provided by health experts (hereafter *Human-interventions*).

As the performance of AI has been dramatically improved in recent years, firms actively promote that their AI applications provide comparable or even better performance at a lower cost compared to their human counterparts. Given its nature, the media also focuses on such performance comparison, which often includes exaggerated claims about AI's performance (Oscar, 2018). Accordingly, laypeople have heightened their expectations about AI's performance (Brynjolfsson & Mcafee, 2017), and the media hype surrounding several major events where AI beats or outperforms humans (e.g., AlphaGo defeated the world champion of Go) amplify such perception. For example, a recent report showed that more than 66% of patients expect better performance from healthcare AI than from health experts (Collier et al., 2017). Therefore, based on the general rationality-based trust in conventional technologies, which is referred to as cognitive trust (Komiak & Benbasat, 2006), it is surprising that laypeople have such low trust in AI for preventive care operations despite their growing expectations regarding its performance. This is because cognitive trust is established and developed primarily by observing objective performance (Lewis & Weigert, 1985).

To identify the source of this discrepancy, given that AI is one of the new-age technologies with distinct features from conventional technologies (Kumar, 2021), we revisit the extant technology acceptance theories based on an in-depth theoretical discussion about the unique characteristics of AI. In short, different from a general technology of which acceptance is often determined based on its own features or in comparison with those of other comparable *technologies*, individuals tend to first compare an AI application directly to its *human* counterparts (Gursoy et al., 2019). Such a comparison calls for expanding the scope of trust in the previous technology acceptance studies from cognitive trust to affective trust. Affective trust encompasses emotional and somewhat irrational feelings that are not necessarily based on objective performance (Komiak & Benbasat, 2006). In other words, based on their observation of its objective performance, laypeople would have comparable or sometimes even higher cognitive trust in AI than their human counterparts. However, at the same time, they would have inherently lower affective trust in AI compared to their human counterparts. To lend empirical support to the discrepancy between affective and cognitive trust, we conducted a field survey and measured individuals' trust in AI and health experts at a granular level. The survey results also support that individuals exhibit *comparable* cognitive trust in AI and health experts; however, their affective trust in AI is significantly *deficient* compared with that in health experts.

Given that affective trust does not necessarily move together with cognitive trust, a more important practical question would be the relative importance of affective and cognitive trust in laypeople's acceptance of AI for preventive care operations: If affective (cognitive) trust plays a decisive role, individuals' acceptance of AI-interventions will be lower than (comparable to) that of Human-interventions, which would limit (promote) the positive impact of AI on preventive care operations. Thus, the goals of this study are to (1) assess the relative importance of affective and cognitive trust in individuals' acceptance of AI for preventive care operations, (2) thereby examine whether AI can effectively replace health experts in preventive care operations, and (3) provide theory-driven, practically validated strategies to further improve the decisive trust (i.e., affective or cognitive trust) in AI and consequent effectiveness of AI for preventive care operations.

To achieve these goals, we conducted a randomized field experiment with 15,000 unique users of one of the most popular mobile health apps in South Korea. Specifically, we provided two treatment groups with AI- or Human-interventions in which AI or health experts recommended a personalized step goal to users, respectively. A control group was constructed by designing Neutral-interventions that provided the same goals without informing the source of the goal generation (i.e., AI or health experts). We compared the effectiveness of AI-, Human-, and Neutral-interventions in terms of users' acceptance and following actual health behavior change. Our key finding is that, contrary to the recent findings on the negative impact of AI disclosure (e.g., Luo et al., 2019), AI-interventions exhibit significantly higher effectiveness compared with Neutral-interventions. However, they are significantly less effective than Human-interventions. This implies that affective trust in which AI is deficient, rather than comparable cognitive trust, would be particularly important in individuals' acceptance of AI for preventive care operations. Specifically, in the context of preventive care, the ultimate adoption decision is made by laypeople who usually have limited knowledge to make objective assessments of preventive health services. Therefore, it is difficult for them to build knowledge-driven, cognitive trust in healthcare providers. Thus, especially with regard to AI for preventive care operations, this study highlights the important role of affective trust, which has been considered less relevant to the acceptance of general technologies (Gefen et al., 2003).

In addition, we extended our survey and experiment to examine whether the enhancement in deficient affective trust in AI would in turn improve the effectiveness of AI-interventions. To improve affective trust, grounded in the theories of affective trust, we revealed the use of AI in tandem with health experts, disclosed more transparent information about the AI algorithm, or emphasized its genuine care and warmth. The additional survey confirms that such features actually improve individuals' affective trust in AI. In addition, the results of the additional experiments demonstrate that such an improvement in affective trust in AI results in greater effectiveness of AI-interventions. These results provide further support for the decisive role of affective trust in AI for preventive care operations as well as fruitful practical guidance on how to manage AI-based preventive health interventions more effectively by improving their affective trust.

By carefully examining how users perceive and accept AI-interventions, this study contributes to the growing body of literature on the role of new-age information technologies in behavioral operations management (Donohue et al., 2020) and healthcare (Agarwal et al. 2010; Atasoy et al. 2017; Ghose et al. 2021; Yan et al. 2014). Specifically, we focus on the management of AI for preventive care operations, thereby responding to the recent call for research on how AI can be effectively implemented in (Shaw et al. 2019; Goldfarb et al. 2020; Stern et al. 2022) and thereby reshapes and transforms healthcare operations (Guha & Kumar, 2018; M. Johnson et al., 2020). In addition, this study offers novel theoretical insights into the role of affective trust in users' acceptance of AI, thereby making significant contributions to the theories of technology acceptance and trust for more efficient operations management (Ha et al., 2011). Moreover, this study also provides fruitful managerial implications for the design of more effective AI-interventions, which is the key to the success of the preventive care business, thereby contributing to research on the use of AI for consumer marketing in general and the promotion of consumers' health behavior in particular (e.g., Kumar, 2021).

2 | RESEARCH BACKGROUND

AI refers to machines performing *human-like*, *cognitive* functions, such as perceiving, reasoning, learning, problem-solving, and decision-making (Rai et al., 2019). During the past few years, substantial resources have been allocated to a wide range of AI-related products, services, and business operations, including virtual assistants (e.g., Alexa and Siri), cashier-less stores (e.g., Amazon Go), and supply chain and inventory management (Ellis et al., 2018). Accordingly, the global business value of AI is expected to reach $3.9 trillion in 2022 (Gartner, 2018).

Among others, AI is revolutionizing the healthcare operations in particular (Guha & Kumar, 2018; M. Johnson et al., 2020). Healthcare can be generally categorized into two types: diagnostic (i.e., investigating and treating specific health issues) and preventive care (i.e., screening and preventing such health issues). The transformative power of AI is equally promising in both areas. For diagnostic care, due to their powerful predictive performance, AI-based applications assist healthcare providers in making better decisions in various contexts, such as cancer prognosis (M. Johnson et al., 2020) and intensive care monitoring (Zhang & Szolovits, 2008). For preventive care, with the goal to improve users' health behavior, a number of mobile apps are providing AI-based preventive health services and interventions, such as suggesting personalized exercise goals (Okano et al., 2013) and helping people estimate and monitor their calorie consumption in real-time (Pouladzadeh et al., 2014). Extensive studies on healthcare AI have examined how to improve its *technical* performance, including accuracy, cost-efficiency, and scalability (Camerer et al., 2019; M. Johnson et al., 2020). Even if healthcare AI achieves exceptional technical performance, however, it cannot improve healthcare providers' *operational* and *business* performance unless its end-users (e.g., physicians in diagnostic care, patients in preventive care) accept and use it and change their behavior accordingly. Thus, end-users' perceptions and actual behavior regarding healthcare AI are critical. Nevertheless, relatively scant attention has been paid to such areas.

While recent studies in operations management (e.g., Cui et al., 2022; Fan et al., 2020) and marketing (e.g., Castelo et al., 2019; Logg et al., 2019; Longoni et al., 2019; Luo et al., 2019) have investigated how individuals perceive, accept, and use algorithm- (e.g., AI-) based services in diverse industries, this study contributes to five notable research gaps in the literature. First, while several studies have focused on AI for diagnostic care (e.g., Fan et al., 2020; Longoni et al., 2019), this study is among the first to investigate laypeople's perceptions and behavior with respect to AI-based services in the context of preventive care, which accounts for more than 75% of U.S. healthcare spending (Beaton, 2017).

Second, in the context of preventive care, this study provides a novel insight into which theoretical construct drives individuals' acceptance decision and actual behavior change regarding AI-based services. This is particularly important to understand the complexities regarding whether and how to adopt this new-age technology (Kumar et al., 2021). While Longoni et al. (2019) and Fan et al. (2020) provide useful insight into the context of diagnostic care, their results can hardly be generalized into AI for preventive care. Specifically, Fan et al. (2020) focused on the acceptance of AI-based diagnosis support systems by healthcare professionals, who have extensive medical knowledge and might thus behave differently toward AI from laypeople. Similarly, Longoni et al. (2019) identified that uniqueness neglect, a concern that AI is less able than humans to consider consumers' unique characteristics, drives consumers' different willingness to use AI- and human-based services in the context of diagnostic care. However, based on our additional follow-up survey, we identified that uniqueness neglect might not be a significant predictor of individuals' acceptance of AI-based services in our research context of *preventive care* (see Supporting Information Appendix for more details). In this study, different from conventional technologies in which acceptance decision would be governed by cognitive trust, we identified that affective trust is a decisive factor in individuals' acceptance of AI for preventive care operations, contributing significantly to the technology acceptance and trust theories.

Third, given the limited understanding of which theoretical construct drives individuals' acceptance of AI for preventive care operations, it remains relatively silent in terms of developing theory driven, practically validated strategies to improve its effectiveness. Against this backdrop, grounded in the theories of affective trust, we proposed and empirically validated that combining AI-interventions with human expert opinions, increasing their algorithmic transparency, or highlighting their genuine care and warmth improves individuals' affective trust and acceptance behavior toward AI for preventive care operations. Accordingly, we respond to the call for research on the role of trust in behavioral operations (Donohue et al., 2020).

Next, while much insight has been gained into how AI affects individuals' behavioral intention or perception (e.g., Castelo et al., 2019; Fan et al., 2020; Logg et al., 2019; Longoni et al., 2019), relatively scant attention has been paid to whether and how AI consequently influences their actual behavior. This is mainly because of the difficulty in gathering relevant information on actual behavior. Against this backdrop, drawing on advanced mobile technologies (e.g., mobile apps, smartphone pedometers), this study contributes to the literature on behavioral operations management (e.g., Donohue et al., 2020) and consumer marketing (e.g., Kumar, 2021) by examining the impact of AI on individuals' actual behavior in a preventive care context. Specifically, our outcome variables measured in the field, that is, individuals' acceptance of AI and consequent health behavior change, have important implications for public health as well as preventive care providers' operational performance and marketing effectiveness. In particular, this study belongs to the "improve behavior" category (e.g., Choudhary et al., 2021), which has been outlined as a key research goal of behavioral operations management (Donohue et al., 2020), and thereby contributes to the operations management literature that employs behavioral interventions to improve individual behavior and consequent operational performance (e.g., Kim et al., 2020; Song et al., 2018).

Lastly, while most extant studies with surveys and lab experiments (e.g., Castelo et al., 2019; Fan et al., 2020; Logg et al., 2019; Longoni et al., 2019) could mimic actual situations, their results would be vulnerable to observer effects. Thus, they might be affected by a lack of external validity and biased estimates (Aral & Walker, 2011). In this study, a randomized field experiment, which has been recognized as an important method for behavioral operations management research (Ibanez & Staats, 2018; Nguyen & Kim, 2019), allows us to obtain a population of users with the real motivations that drive health behavior (Baek & Shore, 2020) and thereby less biased and more generalizable estimates of causal effects.

3 | HYPOTHESES DEVELOPMENT

With the introduction of the Internet, traditional offline relationships have moved to online platforms where individuals perceive greater risk in their relationships (Reichheld & Sasser, 1990). Accordingly, trust has emerged as a relatively new but important dimension of technology adoption (Gefen et al., 2003). Trust reduces risk perceptions and uncertainty regarding the utility of a technology when the utility is not immediately verifiable, thereby increasing its acceptance (Gefen & Straub, 2004). The existing technology acceptance studies emphasize the rationality of users regarding the adoption of new technology and assume that users make their adoption decision by carefully assessing the expected utility of the technology (Venkatesh et al., 2016). Thus, trust has usually been conceptualized as a deliberate and *rational assessment* of a trustee's characteristics that trustors rely upon (Komiak & Benbasat, 2006). This rationality-based trust is specifically referred to as cognitive trust. Cognitive trust is deeply rooted in the rational expectations that a trustee will bring utility and advantage (Komiak & Benbasat, 2006; Özer et al., 2014). Prior studies have suggested that cognitive trust is accumulated by objective outcomes such as better performance (Lewis & Weigert, 1985; McAllister, 1995). Cognitive trust has been shown to increase acceptance and corresponding use of a technology (Komiak & Benbasat, 2006); a technology with low cognitive trust is less preferred and accepted, even if careful implementation efforts are devoted (Pi et al., 2012).

As technology advances, AI has shown astonishing performance, attested by decades of research showing that statistical models and algorithms generally outperform human intuition in diverse operational situations (e.g., Preil & Krapp, 2021). Healthcare AI research has also shown that AI-based health services and interventions provide more timely results with lower error rates than humans in diagnosing complex diseases (M. Johnson et al., 2020) as well as in generating user-specific goals for daily exercise and food intake (Kong & Tan, 2012; Zhou et al., 2018). In addition, it has been identified that even a simple linear regression model outperforms human experts in diagnosing medical and psychological illnesses (Grove et al., 2000). This outperformance of AI over humans has also been gradually acknowledged by laypeople. An industry report shows that more than 66% of patients agreed that healthcare AI had better performance (e.g., AI could assess greater amounts of data and provide a more accurate prediction for diseases) than human experts (Collier et al., 2017). Accordingly, individuals' cognitive trust in AI would be comparable to or sometimes even higher than their cognitive trust in human counterparts.[1]

Trust can also encompass emotional feelings related to assurance and comfort, such as kindness, caring, bonding, and openness, which is referred to as affective trust (Ha et al., 2011; Komiak & Benbasat, 2006). Affective trust has received relatively little attention in the technology acceptance research, as it was considered "arguably irrelevant to a business transaction" (Gefen et al., 2003, p. 60). Moreover, because affective trust is far less commonly formed with objects than with humans (LaRosa & Danks, 2018), this aspect could have been safely neglected in the previous acceptance research on conventional technologies. A general positive correlation between affective and cognitive trust also contributes to this tendency. Specifically, on the one hand, cognitive trust increases confidence in the utility and usefulness of a technology (Lewis & Weigert, 1985), which provides a base for emotional bonding toward the technology and thereby improves its affective trust (D. Johnson & Grayson, 2005). On the other hand, affective trust in a technology can also heighten its cognitive trust (Punyatoya, 2019) because, to a certain extent, affective trust can act as emotional security that ensures the receipt of expected benefits from the use of the technology (Rempel et al., 1985). This reinforcing positive correlation between cognitive and affective trust has been examined in various contexts, including the adoption of recommendation agents (Nicolaou & McKnight, 2006), online financial services (Pi et al., 2012), and e-commerce platforms (Punyatoya, 2019).

However, such emotional affective trust is not necessarily positively correlated with cognitive trust (McAllister, 1995) and can even be perceived as irrational on *some* occasions (Gefen et al., 2003). Compared with general technologies, AI is unique in several ways, and the most notable difference is that it imitates *human* intelligence. In other words, most AI applications are developed to replace existing human tasks. Thus, individuals tend first to compare AI with their human counterparts when determining whether to accept and use it (Gursoy et al., 2019). Such a comparison between technology and its human counterpart makes individuals consider not only cognitive trust but also affective aspects of the technology.

The human–machine interaction literature has demonstrated that while machines, including AI, often outperform humans in terms of their cognitive capabilities, they usually lag far behind humans in terms of affective characteristics (Haslam et al., 2008). This is because individuals deem machines incapable of experiencing emotion and sensation, given that they are designed to perform cognitive tasks in a standardized and rote manner (Haslam et al., 2008; Turkle, 2005). Therefore, while AI might gain comparable or sometimes greater cognitive trust from individuals than its human counterpart, it would be deficient in affective trust: individuals' affective trust in AI would be lower than their affective trust in health experts.[1] Such low affective trust in AI in preventive care settings has been demonstrated in the literature. For example, a study about disease screening, in a representative preventive setting (U.S. Preventive Services Task Force, 1996), found that users generally perceive less affective trust toward AI compared with a human expert (Ongena et al., 2020). Specifically, users generally agreed that AI does not take their feelings into account and that humans are more responsible compared to AI. Another study on individuals' usage intention and perceived risks regarding AI-based skin cancer screening found that increased patient anxiety was its most commonly perceived risk compared to clinician-based procedures (Nelson et al., 2020). In addition, Yokotani et al. (2018) compared individuals' trust in AI and human experts proceeding to mental health interviews, a common procedure for depression screening. Their findings show that participants are less likely to perceive trust and emotional rapport with respect to AI than human experts.

Particularly in a healthcare context, compared to cognitive trust, the role of affective trust in individuals' acceptance decision would be more salient, mainly because the relationship between healthcare providers and consumers is governed by significant information asymmetry. In other words, individuals often lack the ability to make objective assessments of the healthcare services they receive (Alford & Sherrell, 1996). This information asymmetry makes it difficult for them to build knowledge-driven, cognitive trust in healthcare providers. Accordingly, instead of cognitive trust which requires objective observations and evidence, affective trust usually works as a major indicator of service quality in healthcare. That is, rather than logically and rationally assessing available observations and evidence, individuals tend to use affective information, such as healthcare providers' human aspects, soft skills, and social and cultural backgrounds, as a determinant of their acceptance decision (Halpern, 2003). Such a tendency would become even more prominent in the context of preventive care (compared to diagnostic care) where the effectiveness of preventive treatments can hardly be measured accurately due to a number of confounders, and available rough measures of its effectiveness also require a longer time.

In sum, the crucial role of affective trust particularly in a preventive care context, together with individuals' lower affective trust in AI than health experts in general, would result in their lower acceptance of AI-interventions than Human-interventions. Hence, we posit the following hypothesis:

Hypothesis 1: *Individuals will exhibit lower acceptance of AI-interventions compared with Human-interventions.*

The acceptance of products or services directly reflects a *positive behavioral intention* to use them or readiness to perform a given behavior (Schifter & Ajzen, 1985). Behavioral intention represents "instructions that people give to themselves to behave in certain way" (Triandis, 1979). Specifically, intentions encompass both the direction (e.g., to do or not to do) and the intensity (e.g., how much time and effort a person is prepared to expend in order to do) of a decision (Sheeran, 2002). Thus, a positive or negative intention of an individual indicates that she already determined the direction and intensity of her decision and is likely to actually behave in that way. In other words, if an individual has a positive intention (e.g., the acceptance of products or services), this implies that she is ready to spend time and effort to perform and engage in a given behavior (Schifter & Ajzen, 1985). Accordingly, positive intentions have been used to predict a wide range of actual behavior changes, including diet (e.g., McCoy et al., 2017), physical activity (e.g., Sheeran &

Orbell, 1999), weight loss (e.g., Kreuzfeld et al., 2013), and smoking cessation (e.g., Norman et al., 1999). Particularly for technology (e.g., AI), the positive link between behavioral intention to use it and its actual usage has been established in the extensive literature (see Davis, 1989; Venkatesh et al., 2003).

Indeed, previous studies have shown that the acceptance of health interventions or recommendations lead to actual health behavior change. For example, Hurling et al. (2007) identified that individuals who accepted a physical activity program were more likely to lose weight than those who did not accept it. McCoy et al. (2017) provided more direct evidence for the positive link between individuals' acceptance of interventions and their actual behavior change in the context of preventive care. In this study, participants who accepted preventive health interventions spent more time walking and running compared with those who did not accept the interventions. Similarly, Kreuzfeld et al. (2013) showed that people who accepted a voluntary physical activity program for six months reduced body fat significantly more than those who did not accept the program. Thus, we expect that individuals exhibit consistent behavior toward their acceptance of different interventions and actual health behavior change after accepting the interventions:

Hypothesis 2: *AI-interventions induce less health behavior change compared with Human-interventions.*

Hypotheses 1 and 2 predict the lower effectiveness (i.e., acceptance and health behavior change) of AI-interventions than Human-interventions. If the lower effectiveness of AI-interventions is attributable to the lack of affective trust, enhancing deficient aspects of affective trust in AI-interventions would significantly improve their effectiveness. The affective trust consists of two theoretical dimensions, that is, benevolence and integrity (Doney & Cannon, 1997; Morgan & Hunt, 1994), which refers to individuals' perception about how much the other party cares about them or personal attachment to other agents and that about the other party's good faith and honesty, respectively. On the one hand, previous studies suggest a positive relationship between benevolence of a service and its human aspects. This association is deeply rooted in the nature of benevolence; benevolence is formed by *personal* traits such as a warm, kind, and caring attitude as well as their delivery to another agent (Hoejmose et al., 2012; Mayer et al., 1995). Machines are thus generally considered agents lacking in benevolence (Martelaro et al., 2016). Therefore, enhancing human aspects of a machine can improve its benevolence (e.g., Tapus et al., 2007). In this regard, AI-interventions used in tandem with human experts will improve their effectiveness, as the presence of health experts would compensate for the lack of human aspects and corresponding benevolence of AI-interventions.

On the other hand, integrity is positively linked with the transparency of a service (Mayer et al., 1995). Providing transparent information on the process, criteria, and constraints of an agent's decision-making creates the perception that the agent takes responsibility for its decisions, thereby conveying trust in general (Buell et al., 2021, Özer et al., 2014) and honesty and integrity in particular (Mayer et al., 1995) toward the agent. For example, Gatling et al. (2017) show that transparent communication by a healthcare provider increases the perception that the provider will behave with high integrity. This is because transparent communications make it easier to understand how a service will be provided, thereby improving word-deed alignment perception. Thus, with improvement in integrity, AI-interventions will show greater effectiveness if more transparent information on how AI generates AI-interventions is provided. Hence, we expect that AI-interventions would be more effective when complemented by human expert opinions or algorithmic transparency:

Hypothesis 3: *AI-interventions will be more effective if they are used in tandem with human experts.*

Hypothesis 4: *AI-interventions will be more effective if transparent information on their generating mechanism is provided.*

4 | HYPOTHESES VALIDATION

4.1 | Relative effectiveness of AI-interventions and human-interventions

We provided the theoretical arguments and a series of anecdotal evidence that average individuals have comparable (or higher) cognitive trust and lower affective trust in AI than human experts. Given this discrepancy between cognitive and affective trust, together with the crucial role of affective trust in preventive care, we hypothesized lower effectiveness (i.e., acceptance and health behavior change) of AI-interventions than Human-interventions (i.e., Hypotheses 1 and 2, respectively). To validate the hypotheses and provide empirical support for its underlying mechanism, we conducted both a survey and a randomized field experiment.

We first conducted the survey to validate (1) individuals' greater acceptance of AI-interventions than Human-interventions (i.e., Hypothesis 1) and to support its underlying mechanism, that is, (2) individuals have comparable (or greater) cognitive trust in AI than health experts, (3) while exhibiting lower affective trust in AI than health experts. To this end, we designed AI- and Human-interventions that recommend individuals to walk more than a specific number of steps in the next 7 days. In other words, our interventions were designed to promote individuals' physical activity, which has been considered a representative preventive care context in national guidelines for preventive care (e.g., U.S. Preventive Services Task Force, 1996) as well as in the literature on preventive care (e.g., Sallis, 2015). Each of AI- and Human-interventions disclosed whether the step goal was generated by AI or health experts, respectively. The participants were randomly assigned to AI- or Human-interventions. The survey started with providing each participant with a mobile screenshot of her assigned

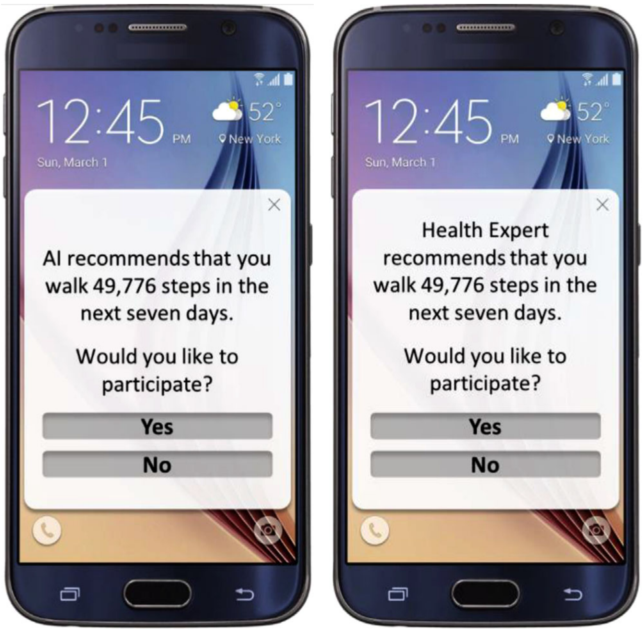

FIGURE 1 Description of intervention messages for AI- and Human-Interventions group [Color figure can be viewed at wileyonlinelibrary.com]

intervention. Specifically, Figure 1 shows the two screenshots shown to participants who were assigned to the AI- (i.e., the left side of Figure 1) and Human-interventions (i.e., the right side of Figure 1) group.[2] We then measured users' acceptance of AI- and Human-interventions by asking them which button they would tap into the provided intervention: Yes or No. Next, we measured their cognitive and affective trust toward an intervention provider (i.e., AI and human experts). Trust is measured using the scale developed by Gefen (2002) in three dimensions, that is, ability, benevolence, and integrity. Ability, which indicates individual perceptions about an agent's knowledge and competence in providing higher quality health recommendations, belongs to the cognitive trust. On the other hand, benevolence and integrity are considered to constitute affective trust (Doney & Cannon, 1997; Morgan & Hunt, 1994). These three dimensions of trust allow us to identify which type of trust (i.e., cognitive or affective trust) is critical for individuals' acceptance of AI-interventions. All items were rated using a five-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*).[3] The survey questionnaires were distributed at five offline community health centers in South Korea. We collected 95 valid responses while discarding three low-quality samples.[4]

Using the survey, we first examined the acceptance rates of each intervention group. As can be seen in the third column of Table 1, the Human-intervention group shows a significantly greater acceptance rate than the AI-interventions group (t-test, $p < 0.05$), which supports Hypothesis 1. We then compared the mean values of the three dimensions of trust (i.e., ability, benevolence, and integrity) between the AI- and Human-interventions groups (see the last three columns of Table 1). The results indicate that the AI-interventions group shows statistically similar cognitive trust (i.e., ability) in the intervention provider compared to the Human-interventions group (t-test, $p > 0.1$). However, survey participants showed significantly low perceived benevolence and integrity (i.e., affective trust) regarding AI than health experts (t-test, $p < 0.01$). This implies that, consistent with our theoretical arguments, individuals' lower acceptance of AI-interventions than Human-interventions can be attributed to their lower affective trust, rather than comparable cognitive trust, in AI. In other words, affective trust plays a decisive role in individuals' acceptance decision of AI-interventions.

In addition to the survey, a randomized field experiment was conducted to confirm the validity of the greater acceptance of AI-interventions than Human-interventions (i.e., Hypothesis 1) in practice. Moreover, it allows us to further investigate whether individuals exhibit consistent behavior regarding AI- and Human-interventions in terms of their actual health behavior change after accepting the interventions (i.e., Hypothesis 2). To this end, we collaborated with one of the largest mHealth app providers in South Korea. The focal app is a free app with an average of 120,000 weekly active users and has been downloaded more than 500,000 times (as of January 2021). The app runs in the background to track each user's real-time walking activity using sensors in the smartphone unless users force-stop the background function.

For the experiment, we designed similar AI- and Human-interventions to encourage users to walk more than an *individual-specific* number of steps over 7 days (i.e., 1 week). Each intervention reveals whether the step goal is generated by AI or health experts. We also designed Neutral-interventions that do not disclose the use of AI or health experts in generating the step goals. Table 2 presents the specific messages used for the three main interventions. We randomly assigned users into three groups (AI-, Human-, and Neutral-interventions) and sent a corresponding intervention message to each group.

An intervention message contains an individual-specific step goal which is generated by a behavior prediction algorithm (see Aswani et al., 2019, and Zhou et al., 2018, for more details about the algorithm). Based on individuals' historical daily step data in the prior month, this AI algorithm leverages reinforcement learning to generate a challenging yet attainable step goal for the following 7-day period, which is predicted to maximize each user's expected step count in that period. We found that the step goals were generated in a reasonable manner; users with less (more) step count in the prior month were suggested to make a greater (smaller) percentage increase in their number of steps in the next week. It should be noted that step goals for the three intervention groups were generated by the same AI algorithm. This is to ensure that we focus on users' different *perceptions* (i.e., cognitive and affective trust) toward AI and health experts while controlling for the *actual performance* of AI and health experts.

We conducted our experiment during a one-week period in South Korea. For the experiment, we first randomly selected

TABLE 1 Main survey results

Group	Observations	Acceptance (%)	Ability (Cognitive trust)	(Affective trust)	
				Benevolence	Integrity
AI-interventions	49	34.7	2.673	2.484	2.479
Human-interventions	46	52.2	2.695	3.722	3.233
Difference (Human − AI)		17.5	0.022	1.238	0.754
p-value of t-test		$p < 0.05$	$p > 0.1$	$p < 0.01$	$p < 0.01$

TABLE 2 Main intervention messages

Group	Intervention message
Neutral-interventions (Baseline)	Would you walk [*personalized step goal*] in the next seven days? Would you like to participate?
AI-interventions	AI recommends that you walk [*personalized step goal*] in the next seven days. Would you like to participate?
Human-interventions	Health expert recommends that you walk [*personalized step goal*] in the next seven days. Would you like to participate?

3000 unique users, who had used the focal app for more than 1 month, for each of the three intervention groups, resulting in a total of 9000 unique users. Next, we calculated the step goal for each user using the AI algorithm. We then sent the interventions to the users through pop-up notifications of the app (e.g., see Figure 1). If a user tapped the "Yes" button in the pop-up notification, the app counted the user's number of steps for the next 7 days. Our interventions did not involve any financial, social, or reputational incentives, and the focal app had never provided any interventions with personalized step goals for users before this experiment.

To test Hypothesis 1, users' acceptance of interventions is measured by the outcome variable $Acceptance_i$, that is, a binary variable indicating whether user i tapped the "Yes" button in the pop-up notification. To test Hypothesis 2, users' actual health behavior change after accepting interventions, or whether they made a sufficient effort and commitment to accomplish the recommended step goals, is measured by another outcome variable $Achievement_i$, that is, a binary variable indicating whether user i walked more than her recommended step goal within 7 days. By comparing the two outcome variables between the three intervention groups, we can identify the extent to which AI improves the focal firm's operational and business performance (i.e., how effectively AI replaces the extant human-based operations and promotes users' health behavior, respectively) in the context of preventive care.

After the experiment, we obtained additional information on users' gender, age, height, weight, previous walking activity, mobile app usage, and location. Information on gender, age, height, and weight was collected by in-app surveys before the experimental period, while that on previous walking activity, mobile app usage, and location was collected at the time of each user's receipt of an intervention. Accordingly, we could generate variables *Gender* (a binary variable where a value of one indicates female gender), *Age* (in years), *Height* (in centimeters), and *Weight* (in kilograms). In addition, *Previous Steps* indicates the number of steps walked in the past 7 days, and *App Proficiency* represents how many times each user launched the focal app in the past 7 days. Finally, *Location* indicates a series of dummy variables representing the 15 geographical areas in which each user received the intervention. Table 3 provides descriptive statistics.

To ensure the quality of the randomization procedure, we conducted an analysis of variance (ANOVA) and compared the means of the covariates (i.e., *Age*, *Gender*, *Height*, *Weight*, *Previous Steps*, *App Proficiency*, and *Location*) among the three groups. The results indicate that all the covariates other than *Previous Steps* are balanced and statistically similar across the three groups ($p > 0.1$). While *Previous Steps* is not balanced across the groups ($p < 0.1$), we obtained consistent results for the matched sample generated by using the propensity score matching method (Rosenbaum & Rubin, 1983).[5]

For the empirical analyses, we employed the Neutral-interventions group as the baseline group and model the probability or likelihood of whether each user accepted an assigned intervention and achieved an assigned goal [i.e., $Pr(Acceptance_i \ or \ Achievement_i = 1)$, respectively] as a logistic function of whether a user received AI- or Human-interventions as well as other control variables:

$$Pr(Acceptance_i \ or \ Achievement_i = 1 | AI_i, Human_i, X_i)$$
$$= \frac{\exp(U_i)}{1 + \exp(U_i)},$$
$$U_i = \alpha + \beta_1 * AI_i + \beta_2 * Human_i + \tau * X_i + \varepsilon_i, \quad (1)$$

where i represent each user and U_i denotes the latent utility of the intervention that user i received. AI_i and $Human_i$ are binary variables indicating which intervention user i received, that is, AI- or Human-interventions. X_i is a vector of control variables regarding user characteristics, and ε_i comprises idiosyncratic error terms. To obtain less-biased estimates of users' different acceptance of AI- and Human-interventions, we controlled for the potential confounding effects of various user characteristics. Specifically, we incorporated *Age*

TABLE 3 Descriptive statistics for the main interventions

Group	Observations	Acceptance (%)	Achievement (%)	Female (%)	Average (SD)				
					Age	Height	Weight	Previous steps	Appproficiency
Neutral-interventions	3000	11.33	5.86	54.05 (0.49)	51.05 (13.90)	164.67 (10.15)	64.52 (17.15)	49,359.24 (31,688.17)	3.373 (9.3527)
AI-interventions	3000	18.70	10.30	53.53 (0.49)	50.97 (13.74)	164.51 (10.95)	65.59 (17.27)	49,758.91 (31,989.82)	3.585 (9.321)
Human-interventions	3000	22.36	13.23	54.03 (0.49)	51.04 (13.89)	164.08 (10.94)	64.54 (17.61)	50,177.93 (37,317.04)	3.507 (9.239)

TABLE 4 Results of the main interventions

Variables	(1) Acceptance	(2) Achievement
AI	0.589***	0.609***
	(0.0743)	(0.0985)
Human	0.819***	0.896***
	(0.0724)	(0.0946)
Constant	–2.753***	–3.662***
	(0.569)	(0.856)
Controls	Y	Y
Observations	9000	9000
Log-likelihood	–4089.02	–2822.92

Note: The baseline group is the *Neutral-interventions* group. Controls include demographic (i.e., *Age*, *Gender*), physical (i.e., *Height*, *Weight*), behavioral (i.e., *Previous Steps*), technical (i.e., *App Proficiency*), and geographical (i.e., *Location*) variables. Robust standard errors are in parentheses.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

and *Gender* to alleviate concern about the different effects of AI- and Human-interventions across people with different demographic characteristics. We also included *Height* and *Weight* to account for each user's physical characteristics, which could explain different perceptions of the preventive health interventions provided by AI and health experts. To account for each user's previous health behavior as well as her usual activity level, we included *Previous Steps* in our model. Given that higher proficiency in utilizing mobile health apps could lead to a higher propensity to accept a mobile intervention, we also incorporated *App Proficiency* in the model. In addition, we incorporated 14 *Location* dummies in the model to address the potential effect of geographical differences between users as well as contextual variations across different locations (e.g., weather).

Table 4 shows the results.[6] First, compared to the baseline Neutral-interventions group, the effects of AI-interventions are significantly positive regarding both outcome measures (i.e., $Acceptance_i$ and $Achievement_i$) ($p < 0.01$). This implies that the use and disclose of AI significantly improves the acceptance of preventive health interventions and individuals' health behavior, even after controlling for the potential effects of demographic (i.e., *Age*, *Gender*), physical (i.e., *Height*, *Weight*), behavioral (i.e., *Previous Steps*), technical (i.e., *App Proficiency*), and geographical characteristics (i.e., *Location*). This deviates from the previous findings on the negative impact of AI disclosure (e.g., Luo et al., 2019). Second, however, we find that the acceptance of AI-interventions is significantly lower than that of Human-interventions (i.e., for $Acceptance_i$, reject the null hypothesis: $\beta_{\mathrm{Human}} - \beta_{\mathrm{AI}} = 0$ at $p < 0.01$), thereby providing further support for Hypothesis 1. In addition, we identify consistent results regarding individuals' actual health behavior change. In other words, the effect of AI-interventions on $Achievement_i$ is significantly smaller than that of Human-interventions ($\beta_{\mathrm{Human}} - \beta_{\mathrm{AI}} = 0$ at $p < 0.01$), which supports Hypothesis 2. Specifically, compared to Neutral-interventions, AI-interventions (Human-interventions) increase the odds of *Acceptance* and *Achievement* by a factor of 1.80 (i.e., $e^{0.589}$) and 1.84 (2.27

TABLE 5 Additional intervention messages

Group	Intervention message
AI-interventions (Baseline)	AI recommends that you walk [*personalized step goal*][a] in the next seven days. Would you like to participate?
AI-Human interventions	By using AI, a health expert recommends that you walk [*personalized step goal*] in the next seven days. Would you like to participate?
AI-Transparency interventions	AI recommends that you walk [*personalized step goal*] in the next seven days. AI has predicted how many steps you will walk in the next seven days based on your previous walking activity. Given that prediction, AI has selected a challenging yet attainable step goal that would maximize your physical activity. Would you like to participate?

[a]For survey participants, the identical step goal (i.e., 49,776 steps) was provided.

and 2.45), respectively. The results align well with our theoretical arguments and survey results that lower affective trust in AI than health experts dominates its comparable cognitive trust and thereby results in lower acceptance of AI-interventions than Human-interventions. This corroborates the decisive role of affective trust in the acceptance of AI-interventions.

4.2 | How to improve the effectiveness of AI-interventions

To test Hypotheses 3 and 4 regarding the roles of affective trust and thereby provide managerial implications for how to improve the effectiveness of AI-interventions, we extended our main survey and experiment with additional interventions. Specifically, we designed two additional interventions, each of which discloses the use of AI in tandem with health experts (i.e., AI-Human interventions) and provides a detailed explanation of how AI generated the interventions (i.e., AI-Transparency interventions). In other words, AI-Human and AI-Transparency interventions were designed to build different dimensions of affective trust in AI-interventions (i.e., benevolence and integrity, respectively) and thereby test Hypotheses 3 and 4, respectively. Thus, the AI-interventions group served as the baseline group in the following analyses. The specific messages used for the additional interventions are provided in Table 5.

First, using a survey, we investigated whether and to what extent AI-Human and AI-Transparency interventions improve affective trust in AI and consequent acceptance of AI-interventions. To this end, the survey questionnaires regarding AI-Human and AI-Transparency interventions were distributed together with the main interventions (i.e., AI- and Human-interventions). We collected 118 valid responses while discarding four low-quality samples.[7]

Table 6 shows the survey results of the additional interventions. As can be seen in the table, compared to AI-interventions, AI-Human interventions improve benevolence by 1.350 (t-test, $p < 0.01$) while integrity is improved by 1.016 (t-test, $p < 0.01$). On the other hand, AI-Transparency interventions show 1.311 greater integrity compared with AI-interventions (t-test, $p < 0.01$), while their improvement in benevolence is 1.212 (t-test, $p < 0.01$). Thus, consistent with our theoretical arguments, the use of AI in tandem with human experts (providing transparent information on AI) is most helpful in improving benevolence (integrity) of AI, validating our experimental design. In addition, the results demonstrate that the AI-Human and AI-Transparency interventions groups show a significantly greater acceptance rate compared with the AI-interventions group (t-test, $p < 0.01$ and $p < 0.1$, respectively), lending support for Hypotheses 3 and 4, respectively. In other words, the inclusion of the additional features (i.e., human aspects, transparent information) into AI-interventions and the resulting increased affective trust in AI enhance the acceptance of AI-interventions.

To further identify whether the improved acceptance of AI-Human and AI-Transparency interventions holds true in practice and whether these additional interventions are also more effective for actual health behavior change, we also extended the main experiment; each additional intervention was randomly sent to 3000 unique users of the collaborating app without overlapping with the users who receive the main interventions. This results in a total of 6000 additional unique users. Note that the additional interventions were sent on the same day in the same manner as the main interventions (i.e., AI-, Human-, Neutral-interventions). Table 7 shows descriptive statistics for the additional interventions. To ensure the quality of the randomization procedure, we conducted an ANOVA test and compared the means of the covariates among the three groups (i.e., AI-, AI-Human, and AI-Transparency interventions). The results indicate that all the observed attributes are statistically similar across the groups ($p > 0.1$).

We replicated the main analysis (i.e., Equation 1) for the users with AI-Human, AI-Transparency, and AI-interventions, utilizing the AI-interventions group as the baseline group. Table 8 shows the results.[8] Given that the AI-interventions group was used as the baseline group, a significant and positive coefficient of each of the additional interventions (e.g., AI-Human, AI-Transparency) implies its greater effectiveness than AI-interventions. As can be seen in the first column of Table 8, users' acceptance of AI-Human interventions is significantly greater than that of AI-interventions ($p < 0.01$). AI-Transparency interventions also exhibit a significantly greater acceptance compared with AI-interventions ($p < 0.01$). The results are also consistent with users' actual health behavior change (i.e., *Achievement*; see the second column of Table 8). Specifically, compared to AI-interventions, AI-Human (AI-Transparency) interventions increase the odds of *Acceptance* and *Achievement* by a factor of 1.65 (i.e., $e^{0.498}$) and 2.05 (1.24 and 1.30), respectively. The results collectively support Hypotheses 3 and 4.

These findings of the additional interventions demonstrate that improving human aspects or transparency of AI-interventions significantly enhances deficient aspects of

TABLE 6 Additional survey results

Group	Observations	Acceptance (%)	(Affective trust) Benevolence	Integrity
AI-interventions	49	34.70	2.484	2.479
AI-Human	62	59.68	3.834	3.495
AI-Transparency	56	48.21	3.696	3.790
Difference (AI-Human – AI)		24.98	1.350	1.016
p-value of t-test		$p < 0.01$	$p < 0.01$	$p < 0.01$
Difference (AI-Transparency – AI)		13.51	1.212	1.311
p-value of t-test		$p < 0.1$	$p < 0.01$	$p < 0.01$

affective trust (e.g., benevolence, integrity) in AI and in turn increases the effectiveness of AI-interventions. Thus, the results of the additional interventions further corroborate that affective trust plays a decisive role in the acceptance of AI-interventions.

5 | ADDITIONAL ANALYSES

5.1 | Causality between affective trust and acceptance of AI-interventions

To provide more direct evidence for the causal relationship between affective trust in AI and acceptance of AI-interventions, we conducted an additional experiment.[9] To this end, we collaborated with Macromill Embrain, a market research company that specializes in consumer research and surveys with 6.4 million panels worldwide. In the additional experiment, participants were randomly assigned to a treatment or control group. For the control group, we provided a simple description of the focal app and its AI-based preventive health intervention. On the other hand, the treatment group was offered additional descriptions designed to improve affective trust in AI. Specifically, the two sets of additional descriptions were provided to improve benevolence and integrity of AI by emphasizing its genuine care and warmth as well as transparency, respectively. Table 9 shows the specific descriptions given to the control and treatment groups. After providing the different descriptions to the control and treatment groups, we measured their affective trust in AI. We then showed the identical AI-interventions to both groups (see the left side of Figure 1) and measured their acceptance.

For the experiment, we recruited 85 and 86 participants for the control and treatment groups, respectively. Among 171 participants, 49.7% were female, and their average age was 39.4. We conducted t-tests and found that the treatment and control groups were statistically similar in age ($p > 0.1$) and gender ($p > 0.1$). To identify whether the additional information given only to the treatment group actually improves their affective trust in AI, we compared the mean values of each dimension of affective trust (i.e., benevolence and integrity) between the treatment and control groups. The result shows that the treatment group exhibits higher mean benevolence and integrity than the control group (t-test: $p < 0.01$). Such higher mean affective trust validates our experimental design. We then examined whether this increased affective trust in AI actually results in greater acceptance of AI-interventions. To this end, we compared the acceptance rates of AI-interventions between the treatment and control groups. The result demonstrates that the treatment group shows a significantly higher acceptance rate than the control group (t-test: $p < 0.1$). The results further confirm that an increase in affective trust in AI causes greater acceptance of AI-interventions.

5.2 | Actual health behavior change

To investigate individuals' health behavior change caused by interventions, we focused on *whether* users achieved recommended step goals or not (i.e., *Achievement*) in the main analyses. However, another important outcome regarding AI for preventive care operations is *to what extent* it improves users' actual health behavior. Though we have shown the significant differences in the achievement rate of the different interventions, the practical implications would diminish if the difference disappeared in terms of the *amount* of health behavior change. To investigate the amount of users' actual health behavior change driven by the different interventions, we introduce an additional continuous outcome variable, that is, $Average\ Steps_{i,t}$, which indicates user i's average daily number of steps walked in week t. Given the strict data protection policy of the firm, we could obtain each user's $Average\ Steps_{i,t}$ only in the week before the treatments (i.e., $t = -1$) as well as the first, second, third, and sixth weeks after the treatments (i.e., t = 1, 2, 3, and 6). We applied the log-transformation to $Average\ Steps_{i,t}$ to improve its normality. We constituted the panel data consisting of users' weekly number of steps walked before and after the interventions. Accordingly, the panel dataset includes 45,000 observations: 3 groups (i.e., Neutral-, AI-, and Human-interventions) × 3,000 users × 5 weeks (i.e., one pretreatment and four posttreatment weeks). We then applied the DID method with individual- and week-fixed effects to the Neutral-, AI-, and Human-interventions groups, while

TABLE 7 Descriptive statistics for the additional interventions

Group	Observations	Acceptance (%)	Achievement (%)	Female (%)	Average (SD) Age	Height	Weight	Previous steps	App proficiency
AI-interventions	3000	18.70	10.30	53.53	50.97	164.51	65.59	49,758.91	3.585
				(0.49)	(13.74)	(10.95)	(17.27)	(31,989.82)	(9.321)
AI-Human	3000	27.33	18.93	52.86	50.97	164.28	64.85	50,486.01	3.386
				(0.49)	(14.08)	(10.48)	(16.61)	(31,411.84)	(9.126)
AI-Transparency	3000	21.09	12.83	54.20	51.26	164.37	64.92	50,102.94	3.427
				(0.49)	(13.63)	(10.58)	(16.75)	(33,861.77)	(8.876)

TABLE 8 Results of the additional interventions

Variables	(1) Acceptance	(2) Achievement
AI-Human	0.498***	0.718***
	(0.0625)	(0.0764)
AI-Transparency	0.212***	0.259***
	(0.0644)	(0.0816)
Constant	−1.514***	−1.678***
	(0.573)	(0.611)
Controls	Y	Y
Observations	9000	9000
Log-likelihood	−3582.874	−4779.8793

Note: The baseline group is the AI-interventions group. Controls include demographic (i.e., *Age*, *Gender*), physical (i.e., *Height*, *Weight*), behavioral (i.e., *Previous Steps*), technical (i.e., *App Proficiency*), and geographical (i.e., *Location*) variables. Robust standard errors are in parentheses.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 9 Descriptions given to different experimental groups

Group	Description
Control	Suppose that you are using a mobile healthcare application, wherein its AI (artificial intelligence) provides you with a personalized health recommendation about the number of walking steps for the next week based on your number of steps in the last month.
Treatment	Suppose that you are using a mobile healthcare application, wherein its AI (artificial intelligence) provides you with a personalized health recommendation about the number of walking steps for the next week based on your number of steps in the last month. In this context, our AI, named AIden, is taking good care of you and trying very hard to provide just the right recommendation to you. AIden is always ready to answer any questions you might have about suggested recommendations and their impact on your health. In addition, AIden is genuine and believable as it provides a detailed and easy explanation of how recommended goals are generated. For example, AIden has predicted how many steps you will walk in the next seven days based on your previous walking activity. Given that prediction, AIden has selected a challenging yet attainable step goal that would maximize your physical activity.

considering the Neutral-interventions group as the control and the AI- and Human-interventions groups as the two different treatments:

$$\begin{aligned} \mathit{Average\ Steps}_{i,t} = \beta_0 &+ \beta_1 * \mathit{AfterIntervention}_t \\ &+ \beta_2 * \mathit{AI}_i * \mathit{AfterIntervention}_t \\ &+ \beta_3 * \mathit{Human}_i * \mathit{AfterIntervention}_t \\ &+ \alpha_i + \mu_t + \varepsilon_{i,t}, \end{aligned} \tag{2}$$

where i indicates each user and t denotes each week (i.e., −1, 1, 2, 3, 6). $\mathit{AfterIntervention}_t$ is a dummy variable indicating whether t is before (i.e., $t = -1$) or after the interventions (i.e., $t = 1, 2, 3$, or 6). The individual-fixed effect, α_i, allows us

TABLE 10 Results of DID analyses

(1) Main interventions		(2) Additional interventions	
Variables	**Average steps**	**Variables**	**Average steps**
AfterIntervention (β_1)	0.108***	AfterIntervention (β_1)	0.729***
	(0.0257)		(0.0361)
AI * AfterIntervention (β_2)	0.118***	AI-Human *AfterIntervention (β_2)	0.326***
	(0.0309)		(0.0579)
Human * AfterIntervention (β_3)	0.284***	AI-Transparancy * AfterIntervention (β_3)	0.150***
	(0.0202)		(0.0513)
Constant	8.597***	Constant	8.599***
	(0.00926)		(0.0182)
Individual and week fixed effects	Y	Individual and week fixed effects	Y
Observations	45,000	Observations	45,000
R^2	0.0083	R^2	0.0021

Note: Robust standard errors are in parentheses.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

to account for the unobserved time-invariant individual heterogeneity. μ_t is the week-fixed effect which controls weekly variation in the average daily number of steps. The parameters of interest are the coefficients of the interaction terms, that is, β_2 and β_3. Specifically, β_2 (β_3) indicates the difference between the effects of Neutral- and AI-interventions (Human-interventions) on average daily walking steps.

The results are provided in the first panel of Table 10. The significant positive values of $\hat{\beta}_2$ and $\hat{\beta}_3$ ($p < 0.01$) indicate that AI- and Human-interventions lead to more health behavior change than Neutral-interventions, respectively. In addition, a significantly smaller estimated value of β_2 than β_3 ($p < 0.01$) shows that AI-interventions induce less health behavior change than Human-interventions, further supporting Hypothesis 2. Specifically, compared to Neutral-interventions, AI- and Human-interventions increase *Average Steps* by 12.5% and 32.8% (i.e., $e^{0.118} - 1$ and $e^{0.284} - 1$), respectively.

We also replicated the same analyses for the additional interventions. Specifically, we applied the same DID specification with individual- and week-fixed effects to the AI-, AI-Human, and AI-Transparency interventions groups. Therefore, users with AI-interventions are considered the control group, while those with AI-Human and AI-Transparency interventions represent the two different treatment groups. The second panel of Table 10 shows the results, which are consistent with the main results. AI-Human and AI-Transparency interventions lead to more health behavior change than AI-interventions ($p <$ 0.01), further supporting Hypotheses 3 and 4, respectively. Specifically, compared to AI-interventions, AI-Human, and AI-Transparency interventions increase *Average Steps* by 38.5% and 16.2%, respectively. Thus, the results of DID analyses collectively show that our findings remain valid for the amount of health behavior change and are robust against the unobserved time-invariant individual heterogeneity and time-specific peculiarities.

TABLE 11 Results of the additional interventions with Human-Interventions as the alternative baseline group

Variables	(1) Acceptance	(2) Achievement
AI-Transparency	0.0165	0.0337
	(0.0622)	(0.0772)
AI-Human	0.283***	0.361***
	(0.0604)	(0.0722)
Constant	–1.507***	−2.364***
	(0.579)	(0.647)
Controls	Y	Y
Observations	9000	9000
Log-likelihood	–4,928.15	−3758.0585

Note: The baseline group is the Human-interventions group. Controls include demographic (i.e., *Age*, *Gender*), physical (i.e., *Height*, *Weight*), behavioral (i.e., *Previous Steps*), technical (i.e., *App Proficiency*), and geographical (i.e., *Location*) variables. Robust standard errors are in parentheses.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.3 | Comparison with Human-interventions

To further examine whether properly designed AI-based interventions can be even more effective than Human-interventions, we compared AI-Transparency and AI-Human interventions, which showed greater acceptance than AI-interventions, to another control group, that is, Human-interventions. Specifically, we replicated the main analyses for the users with AI-Human, AI-Transparency, and Human-interventions, while utilizing the Human-interventions group as the baseline group (see Table 11 for the results). We observe that the difference in the effectiveness between AI-Transparency and Human-interventions is statistically insignificant ($p > 0.1$). This result stresses that improving the transparency of AI-interventions helps compensate for the affective deficiency in AI, making the effectiveness of AI-Transparency interventions comparable to that of human-based interventions. Moreover, the use of AI

TABLE 12 Summary of robustness checks

Potential concerns	Additional analyses	Supporting Information Appendix location
Previous Steps of the Human-interventions group was slightly higher than that of the AI- and Neutral-interventions groups	Replicated the main analysis by adopting the propensity score matching method	Tables A2–A4
Achievement could be captured only if *Acceptance* = 1	Replicated the analysis of *Achievement* only for users whose *Acceptance* = 1 Adopted Heckman (1976)'s selection model	Table A5 Tables A6–A7
The difference between the previous number of steps and the suggested step goal could affect the effectiveness of different interventions	Replicated the main analyses with an additional control variable which indicates the gap between the previous number of steps and the suggested step goal	Tables A8–A9
Given that the term *experts* could be related to authority or social obligation, the results could be different if a softer message was used in Human-interventions	Conducted an additional experiment to identify whether the use of softer message results in lower acceptance of Human-interventions	Table A10
The use of an additional question mark only in Neutral-interventions would affect individuals' responsiveness to Neutral-interventions	Replicated the main analysis while using an alternative control group of users who did not receive any interventions	Table A11
The results could be biased by users who did not read the intervention messages	Replicated the main analyses for users who can be considered to read the intervention messages	Tables A12–A14
The results could not be generalizable to people in different age groups	Replicated the main analyses for users in three different age groups (i.e., Under 30, 30 – 59, and Over 60)	Tables A15–A18
The results could be biased by people who already walked enough before the experiments	Replicated the main analyses for users whose *Previous Steps* are less than a certain level	Tables A19 and A20
The results could be explained by greater "uniqueness neglect" of AI than humans, which is identified as a critical factor of AI acceptance in a diagnostic care context	Conducted a survey to measure individuals' perceived "uniqueness neglect" toward AI- and Human-interventions	Table A21

in tandem with human experts (i.e., AI-Human interventions) makes AI-interventions even more effective than Human-interventions ($p < 0.01$). This result implies that supplementing Human-intervention with AI can be an attractive strategy to derive the greatest effectiveness. This additional comparison provides further implications for how to make AI-based interventions comparable to or even more effective than Human-interventions.

5.4 | Robustness checks

We conducted a series of additional analyses to address potential concerns regarding the results. A summary of potential threats to our results and corresponding additional analyses are provided in Table 12. The main findings are robust against all the different factors that we considered. The details of the robustness checks are provided in the Supporting Information Appendix.

6 | DISCUSSION

6.1 | Theoretical contributions

The specific theoretical contributions of this study are twofold. First, this study contributes to the literature on the role of new-age information technologies in behavioral operations management (e.g., Donohue et al., 2020), consumer marketing (e.g., Kumar, 2021), and healthcare (e.g., Agarwal et al. 2010; Atasoy et al. 2017; Ghose et al. 2021; Yan et al. 2014) in general and the implementation of AI in healthcare (e.g., Goldfarb et al. 2020; Shaw et al. 2019; Stern et al. 2022) in particular. The development of healthcare AI has concentrated mainly on the context of diagnostic care, where healthcare providers directly drive its adoption. Accordingly, considerable research has been devoted to how healthcare providers perceive and adopt AI-based services in the diagnostic care context (e.g., AI-based disease diagnosis and treatment) (Krittanawong, 2018; Palanica et al., 2019). In preventive care, however, laypeople are empowered to interact directly with AI-based preventive health services and make acceptance decisions without being much influenced by healthcare providers (Kwon et al., 2022; Yu et al., 2018). Thus, lay consumers' high receptivity to AI-based preventive health services is critical for preventive care providers to achieve their enhanced operational performance, business outcomes, and public health. Nevertheless, while a number of AI-based preventive health services are readily available in the market and draw considerable attention from preventive care providers who seek to improve their operational performance and consumer behavior, little is known about how the general public perceives and accepts AI-based preventive health services as well as how they change their actual health behavior accordingly. Drawing on a randomized field experiment complemented by a survey, this study responds to this call.

While we examined the acceptance of AI-based services in a specific context, that is, preventive care, our results can be extended to other contexts where affective trust plays a significant role, such as travel, education, legal, and insurance services (Alford & Sherrell, 1996; Patti & Chen, 2009). Similar to preventive care, these industries are often considered a credence-based field, where consumers find it difficult to evaluate the exact performance of a service after consumption due to the lack of objective evidence and necessary knowledge to evaluate the performance as well as the long-time gap until outcomes are realized (Alford & Sherrell, 1996; Darby & Karni, 1973). As a result, in a credence-based field, consumers rely heavily on providers' affective signals (Darby & Karni, 1973). Thus, as we theorized, such a significant role of affective trust in a credence-based field, together with the low affective trust in AI in general, would result in the low acceptance of AI-based services compared with their human counterparts.

Second, this study contributes to the technology acceptance and trust literature by directly comparing the effectiveness of AI- and Human-interventions as well as assessing the roles of cognitive and affective trust in the acceptance of AI-interventions. As AI is expected to replace the tasks that have been typically conducted by humans, it is increasingly critical to understand what factors drive users to accept AI-based services *over* human-based ones, or vice versa. However, while trust has been suggested as a key challenge regarding users' acceptance of AI (Kumar, 2021), prior technology acceptance studies did not provide comprehensive insights into this issue. This is because these studies exclusively considered technology applications and examined the role of different features in their acceptance, without much consideration of the comparable tasks conducted by humans. Accordingly, the previous studies emphasized the rational aspect of trust, which cannot explain the current lower overall trust in AI-interventions than Human-interventions even though AI-interventions often show comparable performance with or even outperform Human-interventions. Thus, this makes it difficult to theoretically explain or predict the relative acceptance of AI- and Human-interventions. By broadening the scope of trust to include the affective aspect, which could be divorced from objective performance, this study revises the extant theoretical perspective to explain the lower acceptance of AI-interventions, particularly in a context where affective trust plays a decisive role (e.g., credence-based fields). Based on this theoretical perspective, this study also provides theory-driven, practically validated strategies to enhance the extent to which AI-interventions improve operational and business performance in the preventive care context. Specifically, we identified that including human-like features, providing an explicit explanation of how AI generates intervention, and highlighting its genuine care and warmth, results in greater acceptance of AI-interventions by improving affective trust in AI.

6.2 | Managerial implications

This study also provides valuable practical implications for how firms should design and exploit their AI applications regarding preventive care operations. First, the higher effectiveness of AI-interventions compared with Neutral-interventions underscores the positive effect of highlighting the use of AI on encouraging more intervention acceptance and health behavior change. While various AI algorithms are being used to provide personalized services and interventions for preventive care operations, the use of AI is rarely explicitly revealed because such information is often considered irrelevant. Previous findings on the negative effect of AI disclosure (e.g., Luo et al., 2019) also contribute to this trend. However, our results suggest that such practices miss the opportunity to further improve the operational performance and ultimately enhance public health. Thus, we recommend that the use of AI in preventive health interventions should be clearly disclosed. Nevertheless, the replacement of existing Human-interventions with AI-interventions should be approached carefully. This is because our results indicate that users receiving AI-interventions show less acceptance and health behavior change compared with those receiving Human-interventions even though both interventions were generated by the same AI algorithm.

This study also calls for managerial efforts to reduce users' resistance to AI through active customer communication and to make AI applications more trustworthy. Specifically, the results collectively illustrate the role of trust in the acceptance of AI-interventions. Thus, firms should be cautious to avoid the common pitfall of believing that improving the objective performance of their technology is sufficient to convince consumers to use the technology and thus neglecting efforts to build consumer trust through effective communications and personalized attention (Slater & Mohr, 2006). According to our results, budgets should be allocated appropriately to strike a balance between the technological advancements of and users' receptivity to AI.

Moreover, our theoretical arguments and survey results consistently demonstrate that such low trust in AI is rooted in its low affective trust rather than cognitive trust. Despite the recent debate on the importance of affective aspects (e.g., warmth, kindness, and humanism) in users' trust and positive responses to AI, we do not see many practitioners tapping affective aspects directly into their AI-based services. Having the causal understanding that the affective aspects of AI drive the effectiveness of AI-interventions, preventive care providers should consider facilitating affective trust in their AI-based preventive health interventions in general and physical activity promotion in particular. Specifically, the results demonstrate that designing AI in a way to highlight its genuine care and warmth would improve its acceptance by enhancing affective trust. More generally, given that affective trust consists of benevolence and integrity, providers could improve the effectiveness of AI-based preventive health interventions by cultivating their image that they carefully consider consumers, have good intentions toward consumers, put consumers' interests before their own (i.e., benevolent), and are reliable and honest (i.e., integrity).

Our results also provide more specific implications for how AI-based preventive health interventions can be designed in a more affectively trustworthy and effective way. First, the finding that AI-Human interventions are more effective than AI- and Human-interventions strongly recommends exploiting AI-interventions together with human experts. For example, an ideal scenario would be letting existing health experts use AI to generate more effective preventive health interventions with greater scalability, while explicitly emphasizing the involvement and opinions of human experts as well as the use of AI. An increasing number of preventive care service providers, including the popular weight loss app Noom Coach, have implemented such an approach. This further substantiates the perspective that AI would have the most significant effect when it augments humans rather than replacing them (Wilson & Daugherty, 2018).

The results also stress the important role of transparency in building trust in AI and improving its consequent acceptance, a recommendation that is consistent with the growing emphasis on the notion of explainable AI (Anjomshoae et al., 2019). This is also well aligned with the literature on operational transparency (e.g., Buell et al., 2021; Lee et al., 2021). Given that the acceptance of AI-interventions in our study was improved when information about the underlying mechanisms behind the recommended personalized goals was provided, AI-based preventive health interventions should be offered with an explicit explanation of how AI generates their services or interventions (e.g., AI-Transparency interventions). Providers offering human-based preventive health interventions (e.g., Human-interventions) can also consider adopting transparent AI-based interventions (e.g., AI-Transparency interventions) given that Human- and AI-Transparency interventions have statistically similar effectiveness. Moreover, governments and regulatory agencies need to establish a legal framework for transparent AI, especially in the preventive care sector, in order to improve the effects of AI-based preventive health services on public health as well as consumers' right to receive an explanation for an algorithm-based decision. For example, the European Union's new General Data Protection Regulation (GDPR) requires businesses to provide information on the logic of AI-based decision-making processes (Wallace & Castro, 2018).

6.3 | Limitations and future research

Several limitations of the study are noteworthy and pave the way for future research. First, the sample in our experiments is a set of users who voluntarily downloaded and installed the focal healthcare app. Thus, while we believe our sample represents users with the real motivations that drive health behavior (Baek & Shore, 2020), at the same time, it is also possible that our sample represents people with a specific characteristic. Though we endeavored to address this concern by controlling for their proficiency with mobile healthcare apps, we acknowledge that this deficiency may not have been fully resolved. Second, unobserved time-variant individual heterogeneity might threaten our identification strategy. While we conducted various robustness checks to address individual heterogeneity, the cross-sectional nature of this study does not allow us to completely rule out the potential confounding effect of unobserved individual heterogeneity. Another caveat is related to the recommended step goals. While our AI algorithm considered users' previous health behavior (i.e., step records) to generate step goals, more sophisticated health recommendations would take account of their diverse health characteristics. We call for future studies that would address these concerns and extend the validity of our findings. In addition, future research could conduct additional experiments with the full 2×2×2 factorial design to investigate how additional features designed to improve *either* affective or cognitive trust affect individuals' acceptance of AI- and Human-interventions differently, which can provide a more comprehensive understanding of trust in and acceptance of AI for preventive care. Lastly, this study focused on a specific preventive care context where interventions are designed to promote physical activity. While we provided the theoretical arguments and a series of anecdotal evidence of low affective trust in AI in general preventive care contexts, our findings might not be generalizable to a particular preventive care context where individuals have higher affective trust in AI than their human counterparts. Future studies can explore such contexts and investigate the boundary conditions for our findings.

7 | CONCLUSIONS

Our results from a randomized field experiment with 15,000 unique users of a mobile healthcare app show that disclosing the use of AI in preventive health interventions (i.e., AI-interventions) induces more acceptance and health behavior change than providing the interventions without disclosure (i.e., Neutral-interventions). However, the effectiveness of AI-interventions is consistently lower than that of Human-interventions across the different analyses. The survey results show that the lower acceptance of AI-interventions is attributable to individuals' lower affective trust in AI than health experts. In addition, the effectiveness of AI-interventions is improved when the affective trust features (i.e., human collaboration, transparency, genuine care, and warmth) are successfully added. These results collectively substantiate the perspective that affective trust, rather than typical cognitive trust, plays a decisive role in the acceptance of AI-interventions.

Given the escalating demand for and constrained supply of manpower for preventive care operations, AI has the potential to address this gap and improve the operational and business performance of preventive care providers by offering more effective preventive health interventions in place of health experts at a lower cost. Given that the general public is the ultimate consumer of AI for preventive care operations, understanding how they perceive and accept it is crucial for its effective utilization. However, users' reluctance to trust AI for preventive care operations despite its rapid technological development warns that the unconditional replacement of health experts with AI would undermine firms' performance. This becomes a more serious issue as firms are increasingly required by consumers and regulations to reveal whether and how they use AI in their services and products.[10] Nevertheless, due to the clear distinction between AI and conventional technologies, little is known about the unique aspects of individuals' acceptance of AI for preventive care operations. Motivated by this gap, this study aims to identify how and why people accept AI- and Human-interventions differently, thereby providing a solid theoretical framework to explain the unique aspects of the acceptance of AI for preventive care operations, which deviate from the acceptance of conventional technologies, as well as managerial implications for more effective use of AI for preventive care operations. We hope this research motivates additional inquiries into how we could extend and revise our accumulated knowledge in order to manage threats and opportunities of this new-age technology.

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ENDNOTES

[1] Our field survey also provides empirical support for the arguments regarding individuals' relative trust in AI and health experts. Specifically, the survey results demonstrate that individuals have statistically similar cognitive trust toward AI and health experts. On the other hand, individuals exhibit significantly lower affective trust in AI than health experts. The details of the survey are provided in Section 4.

[2] The step goal used in the survey (i.e., 49,776 steps) is the average value of step goals generated by an AI algorithm adopted for our field experiment. The details of the algorithm and the experiment are provided later in the paper.

[3] The survey items for the three theoretical constructs, that is, ability, benevolence, and integrity, with the supporting literature are provided in Table A1 in the Supporting Information Appendix.

[4] The quality of the survey is described in detail in the Supporting Information Appendix.

[5] The results for the matched sample are provided in the Supporting Information Appendix (see Tables A2–A4). We also adopted the difference-in-differences (DID) design to take account of the unobserved individual heterogeneity and found consistent results (see Section 5.2).

[6] The full results with the coefficient estimates for the control variables are provided in the Supporting Information Appendix (see Table A22).

[7] The quality of the survey is described in detail in the Supporting Information Appendix.

[8] The full results with the coefficient estimates for the control variables are provided in the Supporting Information Appendix (see Table A23).

[9] We thank the anonymous reviewer for this valuable suggestion.

[10] Given that health-related decisions are often associated with substantial risk (Epstein & Peters, 2009), consumers become more likely to establish a clear-cut line of responsibility for the use of AI in healthcare services or products. In response to such consumer needs, regulations and policies increasingly compel businesses to reveal and explain the use of AI in their services or products. For example, the European Union's new GDPR requires businesses to provide information on the logic of AI-based decision-making processes (Wallace & Castro, 2018). Such regulatory pressure is more pronounced in industries where more sensitive personal data is utilized, such as healthcare.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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