Received: 6 June 2021 | Revised: 6 March 2022 | Accepted: 3 June 2022

DOI: 10.1111/jpim.12646

ORIGINAL ARTICLE

JOURNAL OF PRODUCT INNOVATION MANAGEMENT pdma

Deflected by the tin foil hat? Word-of-mouth, conspiracy beliefs, and the adoption of innovative public health apps

Tobias Kraemer[1,2] | Welf H. Weiger[3] | Simon Trang[4] | Manuel Trenz[4]

[1]Institute for Management, University of Koblenz-Landau, Koblenz, Germany

[2]Faculty of Economics and Business Studies, Justus Liebig University Giessen, Giessen, Germany

[3]College of Business, Alfaisal University, Riyadh, Kingdom of Saudi Arabia

[4]Faculty of Business and Economics, University of Goettingen, Goettingen, Germany

Correspondence
Tobias Kraemer, Institute for Management, University of Koblenz-Landau, Universitaetsstraße 1, 56070 Koblenz, Germany.
Email: tkraemer@uni-koblenz.de

Associate Editor: Martin Spann

Abstract

Due to rapid technological advances and the increasing diffusion of smart devices, public health applications (apps) have become an integral aspect of public health management. Yet, as governments introduce innovative public health apps (e.g., contact tracing apps, data donation apps, ehealth apps), they have to confront controversial debates that fuel conspiracy theories and face the fact that app adoption rates are often disappointing. This study explores how conspiracy theories affect the adoption of innovative public health apps as well as how policymakers can fight harmful conspiracy beliefs. Acknowledging the importance of word of mouth (WOM) in the context of conspiracy beliefs, the study focuses on the interplay between WOM and conspiracy beliefs and their effects on app adoption. Based on theories of social influence and conspiracy beliefs, substantiated by data derived from a multi-wave field study and confirmed by a controlled experiment, the results show that (1) changes in WOM concerning public health apps change conspiracy beliefs, (2) the effects of WOM on changes in conspiracy beliefs depend on both the sender (peer vs. expert) and the receiver's initial conspiracy beliefs, and (3) increases in conspiracy beliefs reduce public health app adoption and trigger more negative WOM regarding such apps. These results should inform health agencies about how to market innovative public health apps. For consumers with initially low levels of conspiracy beliefs, the distribution of expert WOM supporting the efficacy of public health apps effectively prevents the development of conspiracy beliefs and increases app adoption. However, expert WOM is ineffective in reducing conspiracy beliefs among firm conspiracy believers. These consumers should instead be targeted by campaigns distributing peer WOM that highlights an app's benefits and contradicts conspiracy theories.

KEYWORDS

conspiracy belief, conspiracy theories, contact tracing app, ehealth, public health app, word of mouth

1 | INTRODUCTION

As societies have become increasingly digitized, innovative mobile health applications (apps) have become an integral aspect of public health management (Budd et al., 2020). These public health apps, which are issued by government agencies in an effort to improve public health, can be employed for different purposes, such as tracing the spread of disease, enabling access to health data for scientists, or providing information to disaster responders (CDC, 2022). Although innovative public health apps have immense potential to improve public health and benefit the individual user, their introduction is often met with skepticism, igniting heated debates among experts and consumers (Trang et al., 2020).

The intense debates concerning innovative public health apps, which mainly occur on social media in the form of word of mouth (WOM), are often fueled by conspiracy theories, which link the apps to a hidden and evil purpose. The importance of WOM and conspiracy theories in relation to the adoption of public health apps can be attributed to the apps' central characteristics. Public health apps touch on the sensitive issue of health and so pose potential risks for consumers, which elevates the importance of WOM (Lin & Fang, 2006; Ram & Sheth, 1989). Moreover, public health apps are issued by governments, which results in a rich breeding ground for conspiracy theories (e.g., claims that the apps are used to control the population) (Douglas et al., 2017).

The controversy surrounding public health apps and the related role of conspiracy theories became very apparent during the COVID-19 pandemic when many countries issued tracing apps to identify and warn individuals who may have been in contact with infected persons (Trang et al., 2020). Although public agencies praised the apps as key instruments for limiting the spread of COVID-19 fierce debates involving experts and consumers arose, and adoption rates in countries in which app usage was not mandated were much lower than expected (Seto et al., 2021). Within these debates, conspiracy theories such as the claim that the Gates Foundation and corrupt politicians had orchestrated the pandemic and intended to exploit the tracing apps to control unwitting populations played a central role.

While it is reasonable to assume that conspiracy beliefs impede the diffusion of public health apps, prior research provides few insights into this matter beyond anecdotal evidence and findings showing that conspiracy beliefs hinder other health measures (e.g., vaccination, HIV treatment) (Bogart et al., 2010; Jolley & Douglas, 2014). Moreover, extant studies do not reveal how conspiracy beliefs shape consumer engagement in WOM and consumer reactions to WOM they receive from peers and experts. However, such insights are crucial if policymakers are to successfully market public health apps, especially since intense debates on social media and conspiracy theories flourish during times of crisis, which is when public health apps are most needed (Jolley & Douglas, 2017). We aim to address these research gaps by elucidating (a) how WOM by peers and experts concerning public health apps changes consumers' conspiracy beliefs, (b) how consumers' initial conspiracy beliefs influence these effects, and (c) how consumers' conspiracy beliefs affect the adoption of public health apps and outgoing WOM about the apps.

Practitioner points

- Consumer conspiracy beliefs are a major threat to the success of public health apps.
- Negative WOM about public health apps fosters conspiracy beliefs and sets a negative WOM cycle in motion.
- Consumers with high initial conspiracy beliefs should be targeted with positive WOM by peers but not by experts.

Addressing these issues requires an interdisciplinary approach combining insights from innovation research that provides crucial findings on the effects of WOM and innovation adoption (but little on conspiracy beliefs) with insights from political psychology research that provides important findings on conspiracy beliefs (but little on WOM and adoption). In particular, we merge insights into the influence of WOM on adoption processes and social influence as the underlying mechanism (Abrams & Hogg, 1990; Kawakami et al., 2013) with insights into how conspiracy beliefs emerge and influence information processing (Douglas et al., 2017, 2019). This novel theoretical framework allows us to explore how the interplay between conspiracy beliefs and WOM affects the adoption of public health apps. Accounting for the dynamics of social interaction, we examine changes in both WOM and conspiracy beliefs over time. More specifically, we posit that a change in the extent to which consumers receive negative WOM (NWOM) and positive WOM (PWOM) from peers and experts concerning a public health app will lead to a change in their conspiracy beliefs, which will affect app adoption and consumers' outgoing WOM regarding the apps. We further propose that the influence changes in the different types of WOM exert on change in conspiracy beliefs depends on consumers' initial level of conspiracy beliefs. For instance, based on the idea that consumers with high initial conspiracy beliefs view increasing expert PWOM as an indicator that a growing number of experts are part of the conspiracy, we predict that such consumers will discredit increasing expert PWOM concerning a public health app.

We test our hypotheses within a multi-wave field study focusing on the German COVID-19 tracing app. The data analysis supports our central predictions, showing (a) that change in WOM results in change in conspiracy beliefs, (b) that such effects depend on the WOM sender and the consumer's initial conspiracy beliefs, and (c) that change in conspiracy beliefs affect both app adoption and the consumer's outgoing WOM concerning the app. An experimental study exploring consumer reactions to a fictional public health app validates the results of the field study and increases the generalizability of the findings.

Overall, we make four substantial contributions to the literature. First, we complement the research on technology acceptance in general and public health app adoption in particular (Trang et al., 2020; Walrave et al., 2020) by providing initial empirical evidence that conspiracy beliefs impede public health app adoption above and beyond the established drivers. In addition, we provide detailed insights into the mechanism behind this influence, revealing a twofold process: (1) individuals who exhibit increasing conspiracy beliefs are less likely to adopt public health apps because they are increasingly convinced that the government is pursuing an evil agenda in issuing such apps, and (2) conspiracy beliefs affect how individuals interpret WOM regarding public health apps, which indirectly influences app adoption. While expert WOM praising a public health app reduces conspiracy beliefs and increases app adoption among consumers with low initial conspiracy beliefs, it proves ineffective or even counterproductive among consumers with high initial conspiracy beliefs. This finding complements prior research revealing that conspiracy beliefs can reduce the acceptance of fact-based arguments (Jolley & Douglas, 2017). Beyond the implications for research on public health apps, our findings indicate that innovation research should consider conspiracy beliefs when exploring the adoption of other public and commercial innovations that could be associated with conspiracy theories, such as innovations that concern the sensitive topic of health or collect extensive user data.

Second, aside from showing how conspiracy beliefs affect consumers' public health app adoption decisions, we provide insights into how this effect can spread among consumers. More specifically, consumers who experience increasing conspiracy beliefs tend to voice more NWOM concerning public health apps. This NWOM fosters conspiracy beliefs among their peers, who then also tend to express more NWOM about public health apps. These findings suggest a self-reinforcing loop by which conspiracy beliefs spread and are reinforced in social groups. These insights complement prior research linking conspiracy beliefs to high social media usage (Enders et al., 2021), elucidating the role of peer WOM in the spread of conspiracy beliefs.

Third, we provide important insights into how health agencies can employ WOM marketing to both reduce conspiracy beliefs and increase public health app adoption. In particular, our results reveal the need to consider individuals' initial levels of conspiracy beliefs when employing WOM marketing. Although the dissemination of expert PWOM concerning public health apps is useful in preventing the rise of conspiracy beliefs (i.e., when conspiracy beliefs are still at a low level), it is ineffective or even counterproductive in reducing conspiracy beliefs held by committed conspiracy believers. Among individuals with substantial initial conspiracy beliefs, WOM from peers that contradict conspiracy theories can reduce conspiracy beliefs and increase app adoption. Thus, these consumer segments should be targeted with marketing campaigns encouraging peer-to-peer PWOM (e.g., by providing shareable content).

Fourth, we provide novel insights into factors influencing the effects of WOM in innovation adoption processes, which should inform innovation research beyond the topic of conspiracy beliefs and public health apps. Our findings that initial conspiracy beliefs influence how consumers react to WOM and that this influence differs between the peer and expert WOM show that the effects of WOM can depend on an interplay between the WOM sender's characteristics and the consumer's pre-existing attitudes. The existing innovation research paid substantial attention to the influence of the type of WOM communication (e.g., personal vs. virtual) (e.g., Kawakami & Parry, 2013; Parry et al., 2012), but only a little attention to the WOM sender's characteristics, the consumer's pre-existing attitudes, and the interaction between these factors. Consideration of these factors could provide novel insights into the influence of WOM on innovation adoption processes.

2 | THEORETICAL BACKGROUND

2.1 | WOM and social influence

WOM, which refers to informal communication concerning the assessment of a product or service (Anderson, 1998), substantially influences consumers' innovation adoption decisions, especially when innovations are perceived as risky

(Lin & Fang, 2006; Parry et al., 2012). WOM can be disseminated through different channels (e.g., personal or virtual); however, research emphasizes the crucial impact of WOM delivered via virtual channels (Kawakami et al., 2013). Besides the communication channel, WOM can be differentiated based on criteria such as the WOM message's content or the WOM sender's characteristics (Babić Rosario et al., 2016; Bansal & Voyer, 2000).

Our conceptual development relies on two criteria to distinguish four types of WOM that are expected to impact conspiracy beliefs and public health app-related outcomes differently. First, based on the valence, we differentiate between PWOM (WOM favoring the innovation) and NWOM (WOM criticizing the innovation), as consequences of WOM tend to crucially depend on the valence of the WOM message (Babić Rosario et al., 2016). Second, based on the WOM sender's characteristics, we differentiate between peer WOM (the sender has a social tie to the receiver) and expert WOM (the sender is an expert, who reaches receivers beyond social contacts), as extant research shows that consumers can react very differently to WOM by peers and experts (Keh & Sun, 2018). Next, we will present theoretical insights into social influence, which are crucial to understanding the impact of WOM.

Social influence describes a process by which individuals alter their attitudes, beliefs, or behaviors based on social interaction (Hu et al., 2019). Generally, two types of social influences can be distinguished: normative and informational social influence (Deutsch & Gerard, 1955; Kuan et al., 2014). Normative social influence describes a subjective pressure to comply with the attitudes, beliefs, and behavior of valued individuals or social groups (Abrams & Hogg, 1990). By agreeing with a group's judgment, individuals can increase their identification with the group and enhance their status within it; thus, conformity offers social rewards such as a sense of belonging and social acceptance (Kuan et al., 2014). For instance, if a consumer's peer group voices WOM linking a public health app to a conspiracy, the group consciously or unconsciously puts social pressure on the consumer to conform with the group's beliefs. A failure to conform threatens the consumer's objective or subjective belonging to, and status within, the group.

Informational social influence describes a process by which individuals view the information that social actors provide to be compelling and so alter their attitudes, beliefs, or behaviors based on it (Abrams & Hogg, 1990; Broekhuizen et al., 2011). Individuals who receive ambiguous information and who are uncertain about the correct decision are particularly prone to informational social influence (Hu et al., 2019). The more frequently information is presented, and the more individuals voice the relevant opinion, the more social influence information exerts (Babić Rosario et al., 2016). Moreover, the characteristics of an information source determine its effect, with individuals assigning more weight to information from individuals with whom they share social ties (Hofstetter et al., 2018) or consider to be experts (Abrams & Hogg, 1990). For example, when exposed to increasing WOM from peers or experts who link a public health app to a conspiracy theory (or refute such a link), individuals can be persuaded to adopt the same opinion.

2.2 | Conspiracy beliefs

A conspiracy is a "secret plot by two or more powerful actors" who behave malevolently and illegitimately (Douglas et al., 2019; p. 4). Conspiracy theories blame such secret plots for important events (Douglas et al., 2017). Even though some conspiracy theories have turned out to be true (e.g., the Watergate scandal), they are typically counterfactual or implausible (van Prooijen & Van Vugt, 2018). Despite diverse conceptualizations of conspiracy theories in the literature, most authors agree that conspiracy theories involve the basic beliefs that "(a) nothing happens by chance; (b) nothing is what it seems; (c) everything interconnects with everything" (Orosz et al., 2016; p. 1). Popular conspiracy theories are, for instance, that NASA staged the moon landings, that governments use radiation for mind control and that tin foil hats protect against this control, and that the Gates Foundation developed COVID-19 in cooperation with various governments.

In most conspiracy theories, entire governments or influential units within governments play a critical role, either as the central actor or as the puppet of a secret organization. Conspiracy theories provide alternatives to official explanations (Jolley et al., 2018). We use the term "conspiracy belief" to describe the belief in a set of conspiracy theories (Douglas et al., 2019). Most individuals who believe in one conspiracy theory also embrace multiple other (even unrelated or possibly contradictory) conspiracy theories (Goertzel, 1994).

Although prior research has linked conspiracy beliefs to a variety of sociodemographic factors (e.g., low education, unemployment) (Freeman & Bentall, 2017), such beliefs can be found across the entire population (Uscinski & Parent, 2014), as they promise to satisfy salient psychological needs (Douglas et al., 2017). Three types of needs from system justification theory explain the attraction of conspiracy beliefs: *epistemic*, *existential*, and *social needs* (Douglas et al., 2017; Jost & Andrews, 2011). These needs also explain why individuals tend to maintain conspiracy beliefs even when confronted with contradictory information.

Epistemic needs are based on the human tendency to believe that significant events must have been planned by someone (Orosz et al., 2016). Thus, individuals seek causal explanations for salient events to maintain an internally consistent understanding of the environment (Douglas et al., 2017). When individuals face uncertainty, conspiracy theories help them to make sense of their environment (Sunstein & Vermeule, 2009). Therefore, conspiracy beliefs flourish during times of unforeseeable change or when evidence-based explanations of large-scale events are perceived as unsatisfactory (Douglas et al., 2019). Conspiracy theories differ from other causal explanations in two major ways. First, conspiracy theories are speculative, claiming without substantial evidence that there are extensive actions by powerful actors hidden from the public (Jolley et al., 2018). Second, conspiracy theories are very resistant to falsification, as the information refuting them is often discredited by the belief that the individuals providing such information are part of the conspiracy (Douglas et al., 2017). This self-sealing quality of conspiracy beliefs is built on the assumption that actors who have the power to plan a conspiracy also have the means to disseminate information that allegedly debunks it (Sunstein & Vermeule, 2009).

Causal explanations of salient events based on conspiracy theories also contribute to the satisfaction of *existential needs* for security, safety, and control (Douglas et al., 2017). Thus, during times when individuals are anxious and their existential needs are subjectively threatened, conspiracy beliefs provide a certain and conclusive narrative that satisfies such needs (Grzesiak-Feldman, 2013). Although conspiracy beliefs typically involve the idea that society is controlled by untrustworthy and malicious individuals (implying an existential threat), knowledge of these plots and an understanding of how the world works provide a sense of control (Douglas et al., 2019). As a consequence, information that challenges conspiracy beliefs is likely to be perceived as an existential threat. Therefore, existential needs tend to uphold conspiracy beliefs.

Individuals exhibit inherent *social needs* in terms of fostering a positive self-identity and a positive social identity (Ashforth & Mael, 1989; Douglas et al., 2019). Conspiracy beliefs can satisfy these needs by shifting the blame for negative events away from the self or an in-group toward external groups such as the government or other alleged conspirators (Douglas et al., 2017). Furthermore, communally held conspiracy beliefs can both strengthen social bonds and improve social status by fostering a feeling of belonging to an exclusive group that possesses important knowledge (Douglas et al., 2019). Social needs also tend to maintain conspiracy beliefs, as rejecting these beliefs would substantially impair an individual's self and social identity.

3 | HYPOTHESIS DEVELOPMENT

3.1 | Overview of the conceptual model

Building on the theoretical background, we will now present our hypotheses, which rest on the basic proposition that individuals associate WOM concerning a public health app with the likelihood of a conspiracy. Given that public health apps are issued by governments, individuals are likely to connect an app's design and functionality to the government's motives and abilities. As most conspiracy theories claim that influential people within governments are engaged in an evil plot to harm the majority of the population (van Prooijen & Van Vugt, 2018), information about a public health app is directly associated with conspiracy beliefs. If an app is presumed to work well, a conspiracy seems less likely, as the government is apparently pursuing its official goals. By contrast, the perception that a public health app does not provide its advertised function increases the possibility that the government is involved in a conspiracy. For instance, if a tracing app is presumed to be unable to limit the spread of the disease, it could indicate that the government has ulterior motives and is using the app for other purposes (e.g., controlling users).

In accordance with these arguments, we predict that changes in peer and expert WOM (i.e., change in the perceived extent peers and experts engage in NWOM and PWOM) cause change in individuals' conspiracy beliefs. However, we also posit that individuals' initial levels of conspiracy beliefs influence their appraisal of peer and expert NWOM and PWOM, meaning that initial conspiracy beliefs moderate the effects that peer and expert NWOM and PWOM have on change in conspiracy beliefs. Finally, we predict that changes in individuals' conspiracy beliefs affect public health app adoption and change the valence of individuals' WOM regarding such apps. Figure 1 summarizes our conceptual model.

3.2 | How change in perceived peer WOM affects change in conspiracy beliefs

Based on insights concerning social influence and the proposition that individuals associate WOM regarding a public health app with the likelihood of a conspiracy, we predict that a change in peer WOM causes a change in an individual's conspiracy beliefs through normative and

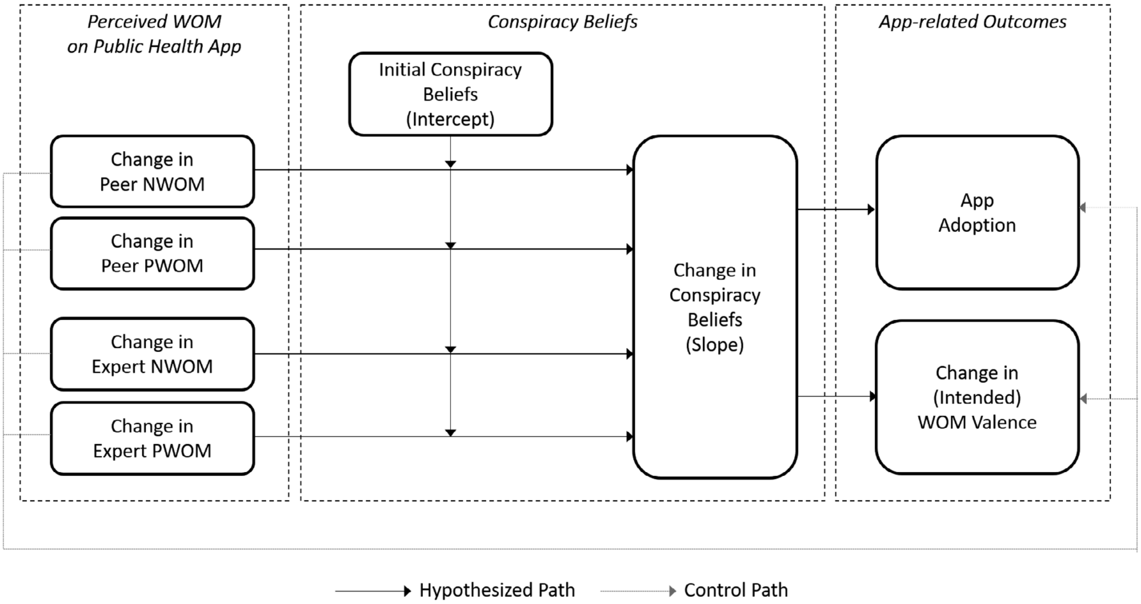

FIGURE 1 Overview of the conceptual model.

informational social influence. In terms of normative social influence, peer WOM exerts social pressure on the recipient to conform to the peer group's beliefs so as to maintain a sense of belonging and social status within the group (Kuan et al., 2014). Informational social influence occurs when arguments provided in WOM persuade the receiver to adopt the sender's opinion (Abrams & Hogg, 1990).

Individuals pay a great deal of attention to information voiced by people within their social environment (Hofstetter et al., 2018). Thus, when peers increasingly voice NWOM concerning a public health app, individuals may feel pressured to agree with such an evaluation (normative influence) and these arguments could convince them (informational influence). If individuals believe the increasing peer NWOM concerning the public health app, a conspiracy is subjectively more likely, meaning that their conspiracy beliefs increase. For example, WOM that questions a tracing app's ability to effectively trace contacts could lead an individual to seek an alternative causal explanation (other than contact tracing) for the existence of the app. Conspiracy theories can provide such an alternative explanation. When peers increasingly voice PWOM concerning a public health app, social influence may lead an individual to adopt the increasingly positive group opinion. In that case, a conspiracy becomes less likely, causing conspiracy beliefs to decrease.

However, we further predict that an individual's initial conspiracy beliefs substantially moderate the impact that a change in peer WOM has on the change in their conspiracy beliefs. This proposition is based on findings of prior studies indicating that individuals who hold firm conspiracy beliefs tend to maintain them due to salient psychological needs (Jolley & Douglas, 2017). Conspiracy theories promise to fulfill psychological needs by providing individuals with causal explanations for important developments that appear to make the world more predictable and secure, in addition to fostering feelings of social belonging and status (Douglas et al., 2017). Thus, relinquishing conspiracy beliefs potentially leads to undesirable feelings of disorientation and fear, and threatens social needs, whereas intensifying conspiracy beliefs promises control, safety, social belonging, and status (Douglas et al., 2019; Jolley et al., 2018).

The greater individuals' conspiracy beliefs, the greater their unconscious motivation to maintain and foster such beliefs. Therefore, individuals with high levels of conspiracy beliefs tend to overestimate the credibility of information supporting those beliefs and to devalue information contradicting them in order to maintain their psychological well-being (Jolley & Douglas, 2017). We predict that individuals with high initial conspiracy beliefs place a high value on increasing peer NWOM regarding public health apps, as such information supports their beliefs. Conversely, individuals with lower initial conspiracy beliefs are less likely to give credence to increasing peer NWOM concerning public health apps. Accordingly, we hypothesize that an individual's initial conspiracy beliefs positively moderate the positive effect that change in peer NWOM exerts on change in conspiracy beliefs.

Similarly, we suggest that individuals with high initial conspiracy beliefs tend to devalue increasing peer PWOM regarding public health apps, as such information contradicts their conspiracy beliefs and so endangers their psychological well-being. Thus, the negative effects of increasing peer PWOM on change in conspiracy beliefs should be limited among such individuals. By contrast, individuals with lower initial conspiracy beliefs tend to find increasing peer PWOM concerning public health apps more credible, meaning that change in peer PWOM has greater effects on change in conspiracy beliefs among these individuals. In summary, we hypothesize:

> **Hypothesis 1a.** Change in peer NWOM positively affects change in conspiracy beliefs: an increase (decline) in peer NWOM causes an increase (decline) in conspiracy beliefs.

> **Hypothesis 1b.** The positive effect of change in peer NWOM on change in conspiracy beliefs is enhanced by initial conspiracy beliefs, such that the positive effect is greater at higher levels of initial conspiracy beliefs.

> **Hypothesis 2a.** Change in peer PWOM negatively affects change in conspiracy beliefs: an increase (decline) in peer PWOM causes a decline (increase) in conspiracy beliefs.

> **Hypothesis 2b.** The negative effect of change in peer PWOM on change in conspiracy beliefs is mitigated by initial conspiracy beliefs, such that the negative effect is smaller at higher levels of initial conspiracy beliefs.

3.3 | How change in perceived expert WOM affects change in conspiracy beliefs

We posit that WOM by experts also causes change in conspiracy beliefs through normative and informational social influence. However, we further propose that the effect of change in expert WOM on change in conspiracy beliefs varies substantially depending on both the initial level of conspiracy beliefs and the type of expert WOM (NWOM vs. PWOM).

3.3.1 | Change in expert NWOM and change in conspiracy beliefs

The status of an expert signifies a certain reputation (Brown et al., 2007). Thus, individuals could view experts as a desirable social group, which would enable the experts to exert normative social influence. When an individual has a high regard for experts, adopting the experts' opinion will establish social identification with them and improve the individual's subjective social status (Kuan et al., 2014). In addition, individuals tend to believe that experts have access to privileged information and so are susceptible to experts' informational social influence (Abrams & Hogg, 1990). We propose that when individuals perceive an increase in NWOM by experts concerning public health apps, they perceive a conspiracy to be more likely, which enhances their conspiracy beliefs. Yet, similar to peer NWOM, we propose that the extent to which change in expert NWOM causes change in conspiracy beliefs depends on the individual's initial conspiracy beliefs. Thus, we posit that individuals with higher conspiracy beliefs are more likely to embrace expert NWOM, as such information supports their beliefs, and experts are regarded more favorably (Jolley & Douglas, 2017), which enhances their social influence and the effect of change in expert NWOM on change in conspiracy beliefs. Individuals with lower initial conspiracy beliefs will be more critical of expert NWOM, which limits their social influence and the effect of change in conspiracy beliefs. We hypothesize:

> **Hypothesis 3a.** Change in expert NWOM positively affects change in conspiracy beliefs: an increase (decline) in expert NWOM causes an increase (decline) in conspiracy beliefs.

> **Hypothesis 3b.** The positive effect of change in expert NWOM on change in conspiracy beliefs is enhanced by initial conspiracy beliefs, such that the positive effect is greater at higher levels of initial conspiracy beliefs.

3.3.2 | Change in expert PWOM and change in conspiracy beliefs

We propose that change in expert PWOM also affects change in conspiracy beliefs. Yet, we expect that the effect essentially depends on an individual's initial conspiracy beliefs. Individuals with lower levels of initial conspiracy beliefs may view experts voicing PWOM as a desirable social group, and positive expert WOM will have some credibility. Thus, we propose that increasing expert PWOM concerning public health apps will exert normative and informational social influences on these individuals, who will consider a governmental conspiracy increasingly unlikely.

However, we expect divergent effects with regard to individuals with higher initial conspiracy beliefs. Epistemic needs draw individuals to conspiracy theories and also tend to reinforce them (Douglas et al., 2017). Thus, when individuals who hold strong conspiracy beliefs are confronted by increasingly contradictory information, they tend to reinterpret such information so as to maintain a coherent system of cause and effect (Jolley & Douglas, 2017). The most effective way to discredit information that contradicts conspiracy beliefs is to claim that the information source is part of the conspiracy (Douglas et al., 2019). This self-sealing quality is amplified by the characteristics that conspiracy believers tend to attribute to alleged conspirators (Sunstein & Vermeule, 2009). Thus, most conspiracy theories imply that the conspirators are treacherous and wield immense power. For instance, the conspiracy theory that the Gates Foundation and the "deep state" orchestrated the COVID-19 pandemic depends on the belief that the alleged conspirators are extremely evil and powerful to carry out a plot of this magnitude. Accordingly, if individuals believe in conspiracy theories, it seems reasonable for them to assume that conspirators are willing and able to spread information that contradicts the conspiracy theory.

While individuals can reinterpret peer WOM to some extent in an effort to uphold their conspiracy beliefs (see Hypothesis 2b), it appears unlikely that even individuals with firm conspiracy beliefs consider their peers to be part of a conspiracy. Individuals typically possess private information about their peers, which makes it unlikely that those peers are part of an evil conspiracy. Moreover, peers typically have only very limited influence on public opinion, which would make them a poor mouthpiece for conspirators. By contrast, experts have a high media presence, and so exert great influence on public opinion. In addition, experts often interact with governments and may be seen as part of the societal elite. Thus, individuals with strong conspiracy beliefs could infer that experts are an effective tool used by conspirators to manipulate public opinion or are part of the conspiracy.

In light of this, we propose that individuals with strong conspiracy beliefs who are confronted with increasing expert PWOM concerning public health apps (i.e., WOM opposing their conspiracy beliefs) not only discredit such information but also conclude that the conspiracy is even bigger than initially thought. The perception that growing numbers of experts are part of the conspiracy or that conspirators are increasingly able to control expert opinion is likely to strengthen conspiracy beliefs. Thus, we posit that among individuals with firm conspiracy beliefs, increasing expert PWOM strengthens conspiracy beliefs. We hypothesize:

> **Hypothesis 4.** Change in expert PWOM affects change in conspiracy beliefs: when the initial conspiracy beliefs are low, an increase (decline) in expert PWOM causes a decline (increase) in conspiracy beliefs; when the initial conspiracy beliefs are high, an increase (decline) in expert PWOM causes an increase (decline) in conspiracy beliefs.

3.4 | Behavioral consequences of change in conspiracy beliefs

Most conspiracy theories are grounded in the notion that powerful people within governments conceal their true motives and act against the public's interests (Sunstein & Vermeule, 2009). Thus, individuals who hold conspiracy beliefs tend to have little trust in government agencies and are often skeptical of government actions. This skepticism is more pronounced when government actions involve sensitive or high-risk issues, such as privacy or personal health. This is evident in prior research showing that conspiracy beliefs counteract government initiatives intended to increase vaccination rates (Jolley & Douglas, 2017). Public health apps are issued by governments and are typically associated with significant privacy and health concerns (Trang et al., 2020). It is reasonable to assume, therefore, that conspiracy beliefs involving governments influence the adoption of such apps. Accordingly, we predict that an increase in conspiracy beliefs will raise doubts about government actions and so decrease the likelihood of an individual adopting a public health app. Conversely, as conspiracy beliefs decrease, an individual places more trust in the government and so has a higher probability of adopting a public health app.

Furthermore, we expect that change in an individual's conspiracy beliefs also influence how that individual intends to communicate with peers about the app. With increasing conspiracy beliefs, individuals are increasingly skeptical about the purpose and benefits of public health apps and, therefore, feel an increasing need to warn their peers and discourage app adoption. Thus, we propose that with increasing conspiracy beliefs, individuals intend to voice more negatively valenced WOM to peers about public health apps. By contrast, with decreasing conspiracy beliefs, individuals find it increasingly likely that an app's advertised purpose is credible and so are likely to voice more positively valenced WOM to peers regarding it. In summary, we hypothesize:

> **Hypothesis 5.** Change in conspiracy beliefs negatively affects public health app adoption: an increase (decline) in conspiracy beliefs causes a declining (increasing) likelihood of public health app adoption.

Hypothesis 6. Change in conspiracy beliefs affects change in the WOM valence on the public health app: an increase (decline) in conspiracy beliefs causes increasingly negatively (positively) valenced WOM on the public health app.

4 | FIELD STUDY

4.1 | Research context and data collection

To test the proposed model, we rely on a unique longitudinal data set collected via a multi-wave panel study conducted in Germany during the COVID-19 pandemic, both before and after the official voluntary tracing app was released in 2020. We deem this setting particularly suitable for investigating the interplay between WOM, conspiracy beliefs, and public health app adoption for three key reasons. First, tracing apps exemplify innovative public health apps that attract attention and provoke debate. On the one hand, tracing apps invade the privacy of individuals because they require access to sensitive information regarding their social interactions (e.g., tracing social contacts), health status (e.g., COVID-19 test results), and other personal data (e.g., contact information). On the other hand, they have the potential to effectively contain COVID-19 and help society to more quickly return to normal. This tension between potential societal benefits and possible serious risks to the individual has sparked heated debates in which advocates voice PWOM and critics voice NWOM in both private and public settings. Second, individuals are likely to be receptive to WOM during pandemics. Most individuals have no experience with tracing apps and lack the technological knowledge required to assess whether using an app puts them at risk. Thus, evaluations of the app that are communicated via WOM will strongly affect individuals' views on the matter. Third, COVID-19-related conspiracy theories flourished in 2020 and substantially influenced debates regarding the tracing app.

We recruited our study participants via Clickworker, a large Western European crowdsourcing platform, and collected data from 565 individuals. To enhance the effort invested and avoid potential biases associated with using professional survey takers recruited through crowdsourcing platforms (e.g., lack of attentiveness, lack of skills, non-independence of participants), we applied various procedural remedies: including attention and comprehension checks, offering a moderate monetary incentive as well as a warning that participants would not be paid if they were inattentive, emphasizing the importance of the study, and choosing neutral wording (Hulland & Miller, 2018). After the data collection, we matched the responses from the different waves and screened them for exclusion criteria such as click-through patterns. The final sample comprised 347 participants (40% female, $M_{\text{age}} = 32.46$) who completed the surveys during all waves and fulfilled all the conditions, leading to an effective response rate of 61.4% across the three survey waves. After the initial survey in April (t_0), in which we asked the respondents about time-invariant and basic personality traits, sociodemographic characteristics, and first impressions of the tracing app, the first survey wave (t_1) commenced at the end of May, when the app was officially announced by the government but prior to its release. The second wave (t_2) began at the end of June (two weeks after the app's release) and the third wave (t_3) at the end of August (two and half months after the app's release).

4.2 | Measures

Unless otherwise noted, we measured all the variables using validated multi-item scales, which were adapted to the context of this study where necessary. Web Appendix A.1 provides an overview of all the items and the construct reliabilities. We measured WOM valence (i.e., the valence of the intended outgoing WOM) with three items adapted from Maxham and Netemeyer (2002) using a seven-point semantic differential. We measured app adoption with a single item capturing self-reported behavior regarding app installation. For all the remaining multi-item variables, we used seven-point Likert scales anchored by 1 = "do not agree" and 7 = "fully agree." We used six items from Imhoff and Bruder (2014) to measure conspiracy beliefs. To measure perceived peer PWOM (PPWOM), peer NWOM (PNWOM), expert PWOM (EPWOM), and expert NWOM (ENWOM), we created three items, each based on a scale by Trenz et al. (2018).

As the control variables for app adoption and WOM valence, we used the established drivers of user behavior in a technology acceptance context, namely perceived ease of use, perceived usefulness (both Davis, 1989), and subjective norms (Venkatesh et al., 2003), in addition to the sociodemographic variables of age, gender, and education. For all the multi-item constructs, the Cronbach's alphas were greater than 0.80 (lowest: 0.88) and the composite reliability statistics were greater than the recommended cut-off of 0.70 (lowest: 0.93), indicating measurement reliability.

4.2.1 | Measurement model

We conducted a confirmatory factor analysis based on all the latent variables to examine our measurement model. The model showed an acceptable model fit: $\chi^2(369) = 788.87$, comparative fit index = 0.963, Tucker-Lewis index = 0.957, root mean square error of approximation = 0.058 (90% lower-level confidence interval = 0.052; upper-level confidence interval = 0.063), and standardized root mean square residual = 0.043. The descriptive statistics and the correlation matrix are available in Web Appendix A.2.

4.2.2 | Construct validity

To examine the construct validity, we first relied on Fornell and Larcker (1981) approach to obtain the convergent validity. The average variance extracted for each multiple-item construct exceeded 0.50, suggesting adequate convergent validity. We then employed the heterotrait-monotrait (HTMT) method to assess the discriminant validity (Voorhees et al., 2016). Estimation of the HTMT ratio for all the latent constructs yielded values ranging from 0.02 to 0.69, which were below the threshold of 0.85. The largest upper limit of the 95% bias-corrected confidence intervals for all the constructs was 0.75, further indicating the discriminant validity.

4.3 | Estimating changes in variables

In accordance with recent literature (Kraemer et al., 2020), we employed mixed-effects growth-curve modeling to capture the temporal changes in our focal variables as slopes, rather than computing the difference score. This allowed us to estimate the individual-specific variable changes over time, and it also accounted for inter-individual differences in these changes. This led to less biased and more precise estimates. Web Appendices A.3 and A.4 explain how we considered potential common-method variance and obtained the change scores used as indicators of change in the variables in our analysis, respectively.

4.4 | Hypothesis testing

4.4.1 | Model specification

Testing the equation system resulting from our framework (Figure 1) needed consideration of two key characteristics of the data. First, we considered the potential correlation of the error terms across the resulting set of theoretically linked equations (Kashyap et al., 2012). Second, as we combined continuous (change in conspiracy beliefs and WOM valence) and binary (app adoption) dependent variables in the equation system, we made different assumptions regarding their respective distributions and specified the normal distribution for the former and the logistic distribution for the latter. Our equation system consisted of three equations with app adoption, WOM valence, and conspiracy beliefs as the dependent variables. In each equation with a change score as the dependent variable (i.e., change in conspiracy beliefs and WOM valence), we controlled for the scores of the respective dependent variables at t_1 to consider the starting point of each slope. We simultaneously estimated the following equation system:

$$\begin{aligned}\text{APP ADOPTION}_{i,t3} = {} & \beta_{10} + \beta_{11}\text{CB CHANGE}_{i,t1-t3} \\ & + \beta_{12}\text{EOU}_{i,t0} + \beta_{13}\text{PEU}_{i,t3} \\ & + \beta_{14}\text{SUN}_{i,t3} + \beta_{15}\text{ICB}_{i,t1} \\ & + \beta_{16}\text{PNWOM}_{i} + \beta_{17}\text{PPWOM}_{i,t3} \\ & + \beta_{18}\text{ENWOM}_{i,t3} + \beta_{19}\text{EPWOM}_{i,t3} \\ & + \beta_{110}\text{AGE}_{i} + \beta_{111}\text{FEM}_{i} + \beta_{112}\text{ACA}_{i} \\ & + \varepsilon_{1i}\end{aligned} \tag{1}$$

$$\begin{aligned}&\text{WOM VALENCE CHANGE}_{i,t1-t3} \\ &\quad = \beta_{20} + \beta_{21}\text{CB CHANGE}_{i,t1-t3} + \beta_{22}\text{EOU}_{i,t0} + \beta_{23}\text{PEU}_{i,t3} \\ &\qquad + \beta_{24}\text{SUN}_{i,t3} + \beta_{25}\text{ICB}_{i,t1} + \beta_{26}\text{WOI}_{i,t1} + \beta_{27}\text{AGE}_{i} \\ &\qquad + \beta_{28}\text{FEM}_{i} + \beta_{29}\text{ACA}_{i} + \varepsilon_{2i}\end{aligned} \tag{2}$$

$$\begin{aligned}&\text{CONSPIRACY BELIEFS CHANGE}_{i,t1-t3} \\ &\quad = \beta_{30} + \beta_{31}\text{PNWOM CHANGE}_{i,t1-t3} \\ &\qquad + \beta_{32}\text{PPWOM CHANGE}_{i,t1-t3} \\ &\qquad + \beta_{33}\text{ENWOM CHANGE}_{i,t1-t3} \\ &\qquad + \beta_{34}\text{EPWOM CHANGE}_{i,t1-t3} \\ &\qquad + \beta_{35}\text{PNWOM CHANGE}_{i,t1-t3} \times \text{ICB}_{i,t1} \\ &\qquad + \beta_{36}\text{PPWOM CHANGE}_{i,t1-t3} \times \text{ICB}_{i,t1} \\ &\qquad + \beta_{37}\text{ENWOM CHANGE}_{i,t1-t3} \times \text{ICB}_{i,t1} \\ &\qquad + \beta_{38}\text{EPWOM CHANGE}_{i,t1-t3} \times \text{ICB}_{i,t1} + \beta_{39}\text{ICB}_{i,t1} \\ &\qquad + \beta_{310}\text{PNWOM}_{i,t1} + \beta_{311}\text{PPWOM}_{i,t1} + \beta_{312}\text{ENWOM}_{i,t1} \\ &\qquad + \beta_{313}\text{EPWOM}_{i,t1} + \beta_{314}\text{AGE}_{i} + \beta_{315}\text{FEM}_{i} + \beta_{316}\text{ACA}_{i} \\ &\qquad + \varepsilon_{3i}\end{aligned} \tag{3}$$

where CB $\text{CHANGE}_{i,t1–t3}$ refers to the empirical Bayes estimates of the change in conspiracy beliefs; $\text{EOU}_{i,t0}$ refers to the perceived ease of use at t_0; $\text{PEU}_{i,t3}$ refers to the perceived usefulness at t_3; $\text{SUN}_{i,t3}$ refers to the subjective norms at t_3; $\text{ICB}_{i,t1}$ refers to the initial scores for conspiracy beliefs at t_1; PNWOM_i, PPWOM_i, ENWOM_i, and EPWOM_i refer to the absolute values of the perceived

WOM types at t_1 and t_3, respectively; PNWOM $CHANGE_{i,t1-t3}$, PPWOM $CHANGE_{i,t1-t3}$, ENWOM $CHANGE_{i,t1-t3}$, and EPWOM $CHANGE_{i,t1-t3}$ refer to the empirical Bayes estimates of the changes in the perceived WOM types; AGE_i refers to a subject's age; FEM_i indicates whether the subject is female; ACA_i refers to subjects who have a degree in higher education (i.e., academics); and ε_{1i}, ε_{2i}, and ε_{3i} refer to the respective error terms of subject i.

4.4.2 | Endogeneity and attrition bias

To correct potential endogeneity resulting from simultaneity in the conspiracy belief change model (Ebbes et al., 2017), we computed Gaussian copulas associated with the different WOM types and included them in our model estimation of Equation 1 (see Web Appendix A.5 for details). We also control for potential attrition bias across the three survey waves by computing the inverse Mills ratio (Heckman correction factor) and including it in Equations (1)–(3) (see Web Appendix A.6 for details). Prior to the model estimation, we orthogonalized all the interacting covariates (i.e., perceived WOM changes per type and initial conspiracy beliefs) and the copula terms to address any multicollinearity concerns (Sine et al., 2003).

4.4.3 | Results

To test our hypotheses, we simultaneously estimated Equations (1)–(3) (Gruner et al., 2019). The choice of model was supported by a significant Breusch-Pagan test, which indicated that the regression equations were significantly correlated ($\chi^2(3) = 10.832$; $p < 0.05$).

Table 1 displays the results, which indicate the positive and significant effect of PNWOM change on conspiracy belief change ($\beta = 0.133$, $p < 0.01$), thereby providing support for Hypothesis 1a. We do not find support for Hypothesis 1b, as initial conspiracy beliefs do not positively moderate the relationship between PNWOM change and conspiracy belief change ($\beta = -0.061$, $p > 0.10$). The results do not support Hypothesis 2a either, as PPWOM change has no significant effect on conspiracy belief change ($\beta = 0.033$, $p > 0.10$). We must also reject Hypothesis 2b, as the interaction effect between PPWOM change and initial conspiracy beliefs on change in conspiracy beliefs is negative and significant ($\beta = -0.087$, $p < 0.05$), whereas our hypothesis suggested it to be positive. As this represents a particularly noteworthy result, the negative interplay is illustrated in Figure 2 (Panel A), which depicts the predicted marginal effect of PPWOM change on change in conspiracy beliefs alongside the observed range of initial conspiracy beliefs. For lower initial conspiracy beliefs, increasing PPWOM leads to positive changes in conspiracy beliefs, while it leads to negative changes for higher initial conspiracy beliefs. This is surprising, as individuals with higher initial conspiracy beliefs do not seem to discredit increasing PPWOM; rather, they give more credence to peer support for the tracing app as "social proof" that there is no conspiracy, thereby overturning their prior conspiracy beliefs (leading to a negative change). By contrast, individuals with lower initial conspiracy beliefs appear to begin deliberating conspiracy beliefs when confronted with peaks in PPWOM. Thus, while some individuals with low conspiracy beliefs seem to show increasing conspiracy beliefs as a consequence, others have little room to reduce their conspiracy beliefs further (as their initial conspiracy beliefs are already close to the baseline level).

The results support Hypothesis 3a, showing that the effect of ENWOM change on change in conspiracy beliefs is positive and significant ($\beta = 0.267$, $p < 0.001$). However, this positive effect is not enhanced by initial conspiracy beliefs ($\beta = -0.034$, $p > 0.10$), meaning that we reject Hypothesis 3b.

Hypothesis 4 postulated that change in EPWOM affects change in conspiracy beliefs, where it is expected that for lower initial conspiracy beliefs, an increase in EPWOM will cause *a decrease* in conspiracy belief change, whereas, for higher initial conspiracy beliefs, an increase in EPWOM will cause *an increase* in conspiracy belief change. The results provide initial evidence in support of this hypothesis, as the interaction effect between EPWOM change and initial conspiracy beliefs on conspiracy belief change is positive and significant ($\beta = 0.084$, $p < 0.05$), whereas the main effect of EPWOM change is insignificant ($\beta = -0.017$, $p > 0.10$). To determine whether we find full support for Hypothesis 4, we illustrate the effect in Figure 2 (Panel B), which shows that when individuals with lower initial conspiracy beliefs are confronted with increasing EPWOM, they reduce their conspiracy beliefs even further. Yet, the predicted change effects also show that individuals with higher initial conspiracy beliefs tend to retain their current conspiracy beliefs, as the predicted change scores approach zero for higher initial conspiracy belief values. As we postulated in Hypothesis 4 that such individuals would likely conclude that the conspiracy is even bigger than initially thought, thereby resulting in a positive change in conspiracy beliefs (rather than zero), we only find partial support for Hypothesis 4.

TABLE 1 Results of field study

Variable	Conspiracy belief change$_{t1\text{-}t3}$ Coef.[a]	SE[a]
Constant	0.555	0.498
WOM change effects		
PNWOM change$_{t1–t3}$	0.133**	0.050
PPWOM change$_{t1–t3}$	0.033	0.059
ENWOM change$_{t1–t3}$	0.267***	0.060
EPWOM change$_{t1–t3}$	−0.017	0.061
Interactions with initial conspiracy beliefs		
PNWOM change × conspiracy beliefs$_{t1}$	−0.061	0.044
PPWOM change × conspiracy beliefs$_{t1}$	−0.087*	0.042
ENWOM change × conspiracy beliefs$_{t1}$	−0.034	0.048
EPWOM change × conspiracy beliefs$_{t1}$	0.084*	0.041
Controls		
Conspiracy beliefs$_{t1}$	−0.300***	0.053
PNWOM$_{t1}$	−0.016	0.039
PPWOM$_{t1}$	0.029	0.040
ENWOM$_{t1}$	−0.106*	0.043
EPWOM$_{t1}$	−0.071	0.044
Age	0.019	0.019
Female	−0.153†	0.089
Academics	−0.087	0.099
Inverse Mills ratio	−0.588	0.631
PNWOM change$_{Copula}$	0.000	0.043
PPWOM change$_{Copula}$	−0.013	0.039
ENWOM change$_{Copula}$	0.041	0.046
EPWOM change$_{Copula}$	0.057	0.045
R^2	0.274	

Variable	App adoption$_{t3}$ Coef.	SE	WOM valence change Coef.	SE
Constant	−2.731†	1.613	0.303†	0.167
Conspiracy belief change effect				
Conspiracy belief change$_{t1\text{-}t3}$	−3.704*	1.766	−0.518*	0.260
Technology acceptance controls				
Perceived ease of use	0.250†	0.142	0.071***	0.017
Perceived usefulness	0.247*	0.099	0.066***	0.016
Subjective norms	0.448***	0.109	0.061***	0.014
Other controls				
Conspiracy beliefs$_{t1}$	−0.332**	0.111	−0.080***	0.013
PNWOM$_{t3}$	−0.020	0.135		
PPWOM$_{t3}$	0.101	0.107		
ENWOM$_{t3}$	0.075	0.127		
EPWOM$_{t3}$	0.026	0.110		
WOM valence$_{t1}$			−0.144***	0.016
Age	0.003	0.062	0.010	0.008
Female	−0.280	0.277	0.045	0.037
Academics	−0.407	0.302	−0.016	0.041
Inverse mills ratio	−2.097	2.095	−0.653**	0.249
R^2	0.244		0.310	

Note: $N = 347$. All coefficients are unstandardized. The highest variance inflation factor is 2.63, which is within the acceptable range (O'Brien 2007).

[a]Multiplied by 10 for better interpretability.

†$p \leq 0.10$.

*$p \leq 0.05$.

**$p \leq 0.01$.

***$p \leq 0.001$.

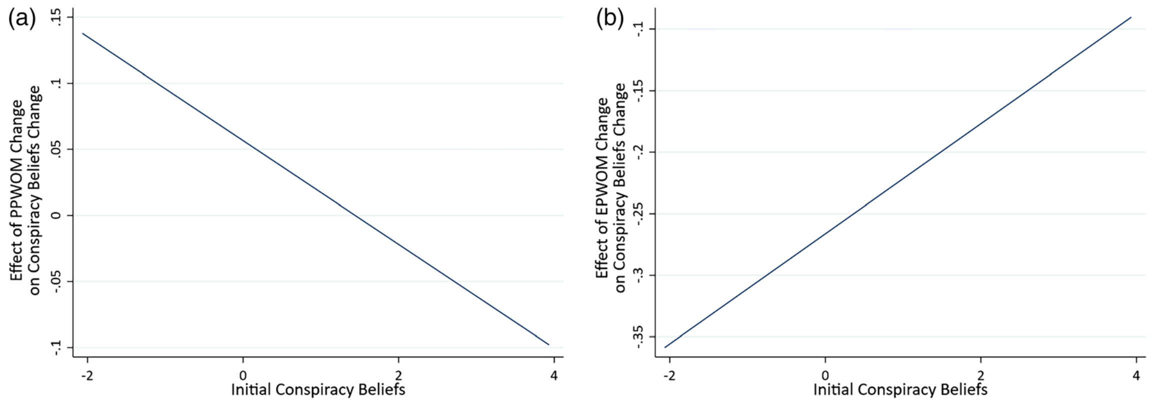

FIGURE 2 Analysis of the interaction effects, field study. (a) Marginal effect of PPWOM change on conspiracy belief change for different levels of initial conspiracy beliefs. (b) Marginal effect of EPWOM change on conspiracy belief change for different levels of initial conspiracy beliefs. Slopes are based on raw, untransformed variables.

Finally, the results support Hypothesis 5 and Hypothesis 6, as change in conspiracy beliefs has significant and negative effects on both app adoption ($\beta = -3.704$, $p < 0.05$) and change in WOM valence ($\beta = -0.518$, $p < 0.05$). That is, individuals who exhibit increasing conspiracy beliefs over time are less likely to adopt public health apps and more likely to spread more negative WOM about such apps.

5 | EXPERIMENTAL VALIDATION STUDY

5.1 | Study goal

The field study on the German COVID-19-tracing app, as a prime example of an innovative public health app, allowed us to observe the evolution of real conspiracy beliefs and actual app usage over an extended period. To increase confidence in our findings, we conducted a controlled scenario experiment that complements the field study in multiple ways. We employed (1) a different type of public health app to generalize beyond tracing apps, (2) a fictitious app to avoid any past experience effects, (3) a context unrelated to the COVID-19 pandemic to extend beyond the boundaries of this crisis, (4) systematic WOM manipulations in an experimental setting to achieve high internal validity, (5) a different measure for capturing conspiracy belief outcomes to demonstrate the robustness of the observed effects (i.e., change in conspiracy beliefs in the context of a real app over time vs. emerging conspiracy beliefs regarding a described app), and (6) another cultural context to expand our investigation beyond a single cultural context.

5.2 | Design and participants

We conducted a scenario experiment using a 2 (WOM source: peer vs. expert) × 2 (WOM valence: negative vs. positive) between-subjects design. We focused on the health monitoring and data donation context and used a *fictitious* public health app introduced by the *actual* Centers for Disease Control and Prevention (CDC; the US national public health agency). In this way, we aimed to balance minimizing past experience effects with maintaining a sufficient level of realism regarding the governmental entity issuing the app. The app is designed to help users monitor their health and collects data for research on cardiovascular diseases. We recruited 173 US participants[i] (57% female, $M_{age} = 43$) through Prolific Academic (Peer et al., 2017), a major international crowdsourcing platform.

5.3 | Materials

The utilized materials are described in Web Appendices B.1 (app description), B.2 (experimental treatments), and B.3 (Twitter Tweets). The app description page mimicked a typical consumer-focused presentation and outlined how the app allows users to monitor their health and collects data for cardiovascular disease research while maintaining users' data privacy. This description was the same for all the conditions so that participants could perceive the app in isolation from any experimental manipulation.

To manipulate the WOM, we relied on Tweets with an authentic design to ensure realistic appeal. Based on the WOM scenario descriptions and the Tweets, we employed four different scenarios: PNWOM, PPWOM, ENWOM, and EPWOM. The WOM scenario descriptions manipulated the source (peer vs. expert) of the WOM. The peer source was described as a close and trusted friend, whereas the expert source was described as a distinguished tech expert. We adjusted the text of the Tweets to manipulate the sentiment behind the WOM message (negative vs. positive). The negative WOM contained only unfavorable statements (e.g., "New CDC app for a dubious cause!") concerning the health app's functionality, data security, and benefits, whereas the positive WOM contained only favorable statements (e.g., "New CDC app for a good cause!"). Manipulation checks indicated the four WOM manipulations to work well (Web Appendix B.4).

5.4 | Procedure

The experiment was embedded within a two-wave online questionnaire. We purposefully separated the initial measurement of conspiracy beliefs at t_1 from the experimental treatment at t_2 and the measurement of the dependent variables to reduce common-method variance. In the first questionnaire, the participants were presented with an instructive text on the CDC and a description of the recently released public health app ("CDC Health Monitoring & Data Donation Service"). The participants then answered items measuring general conspiracy beliefs and control variables driving technology acceptance based on their initial perception of the app. The second data collection wave started at least four weeks later. After reminding the participants of the public health app, we randomly assigned them to one of five conditions (i.e., four WOM treatments vs. control). The participants answered questions on app-specific conspiracy beliefs, app installation intention, WOM valence, and manipulation checks. To complement the multi-wave and repeated-measure design adopted in the field study, we measured app-specific conspiracy beliefs instead of measuring general conspiracy beliefs again in the second wave, to alleviate concerns about repeated measures. Web Appendix B.6 presents the items and reliability measures, while Web Appendix B.7 provides the descriptive statistics and correlation matrix.

5.5 | Results

As in the field study, we used seemingly unrelated regressions to estimate three equations. In the first equation, we regressed app-specific conspiracy beliefs on the four treatment dummy variables representing peer and expert WOM with negative and positive sentiments, initial conspiracy beliefs, and their interactions. That is, the reference groups for each of the four treatment dummies were the control group and the other WOM treatment groups. In the other two equations, we regressed installation intention and WOM valence on app-specific conspiracy beliefs, perceived ease of use, perceived usefulness, subjective norms, and initial conspiracy beliefs, replicating the right-hand side of our conceptual model (i.e., the app adoption and WOM valence models).

The results of the experimental study support the hypothesized findings of the field study. The results of the conspiracy beliefs model suggest a positive and significant effect of the PNWOM treatment on app-specific conspiracy beliefs ($\beta = 0.672$, $p < 0.05$), providing further support for Hypothesis 1a. In contrast to the unexpected finding from the field study, we find no negative interaction effect between the PPWOM treatment and initial conspiracy beliefs on app-specific conspiracy beliefs ($\beta = -0.178$, $p > 0.10$). In accordance with the field study and Hypothesis 3a, we find a positive and significant effect of ENWOM on app-specific conspiracy beliefs ($\beta = 0.556$, $p < 0.05$).

This study provides further insights concerning Hypothesis 4, which postulated that EPWOM decreases conspiracy beliefs among individuals with lower initial conspiracy beliefs and increases conspiracy beliefs among individuals with higher initial conspiracy beliefs. As in the field study, we find evidence of the significant positive interaction effect between EPWOM and initial conspiracy beliefs on app-specific conspiracy beliefs ($\beta = 0.350$, $p < 0.05$) and a not significant main effect of EPWOM ($\beta = 0.305$, $p > 0.10$). Depicting the interaction effect between EPWOM and initial conspiracy beliefs on app-specific conspiracy beliefs (Figure 3) lends full support for Hypothesis 4. Among individuals with *lower* initial conspiracy beliefs, exposure to EPWOM *negatively* influences app-specific conspiracy beliefs. By contrast, among individuals with *higher* initial conspiracy beliefs, EPWOM exposure *positively* affects app-specific conspiracy beliefs. All the other effects in the conspiracy beliefs model were insignificant and, therefore, consistent with the findings of the field study.

Finally, in line with the app adoption and WOM valence models from the field study, the results of the experiment support Hypothesis 5 and Hypothesis 6, as - app-specific conspiracy beliefs have negative and significant effects on both installation intention ($\beta = -0.326$, $p < 0.001$) and WOM valence ($\beta = -0.287$, $p < 0.01$). The effects of the control variables concerning the established drivers of technology acceptance exhibit consistent directions and significance levels, as in the field study. Web Appendix B.8 displays all the results.

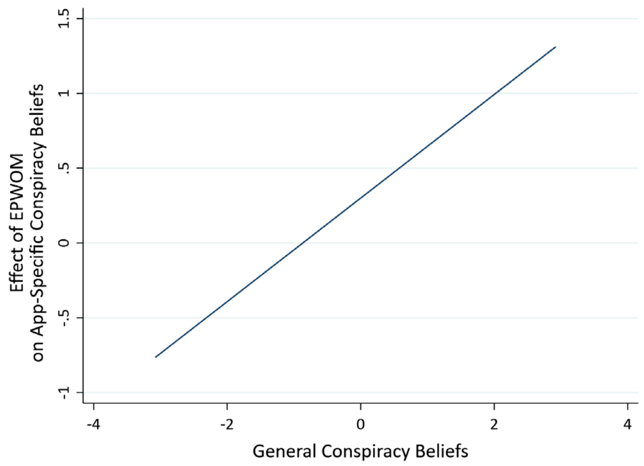

FIGURE 3 Analysis of the interaction effects, experimental study. The marginal effect of EPWOM on app-specific conspiracy beliefs for different levels of general conspiracy beliefs.

6 | GENERAL DISCUSSION

6.1 | Overview of the findings

Across a field study and a controlled experiment, we provide empirical evidence in support of our central proposition that conspiracy beliefs impede the adoption of innovative public health apps. Table 2 provides a comparison of the two studies that highlight their complementarity in terms of their design and methodology. Next, we will summarize and discuss the two studies' key findings.

The two studies confirm that the behavioral consequences of increased conspiracy beliefs are twofold: (1) increasing conspiracy beliefs essentially reduce consumers' willingness to adopt public health apps, and (2) increasing conspiracy beliefs trigger consumers' increasingly negatively valenced WOM concerning public health apps. Moreover, the results provide substantial insights into how WOM can change individuals' conspiracy beliefs as well as how the level of initial conspiracy beliefs affects this relationship. Increases in peer NWOM and expert NWOM enhance an individual's conspiracy beliefs substantially. In contrast to our expectations, initial conspiracy beliefs do not moderate these effects. Accordingly, increasing peer NWOM and expert NWOM increase conspiracy beliefs and lower adoption intentions among consumers (whether they have high or low initial conspiracy beliefs prior to receiving the WOM).

However, initial conspiracy beliefs affect how consumers process PWOM concerning public health apps. Consistent across both studies, we find that increasing expert PWOM has no significant main effect on conspiracy belief change, but initial conspiracy beliefs exert a significant positive moderating influence on this effect. This indicates that the effect of expert PWOM change on conspiracy belief change depends entirely on the initial level of consumers' conspiracy beliefs. Further analysis reveals that at low levels of initial conspiracy beliefs, expert PWOM consistently reduces conspiracy beliefs, whereas at high levels, increasing expert PWOM has no effect (field study) or even a positive effect (experimental validation study). In pointing to the context sensitivity of the magnitude of the observed effect, these results indicate that in certain circumstances, an expert's WOM intended to encourage public health app usage and contradict conspiracy theories can have the opposite effect.

A discrepancy between the two studies' results that is worth noting concerns the fact that we could not replicate the counterintuitive negative interaction effect between peer PWOM and initial conspiracy beliefs on app-specific conspiracy beliefs. In other words, while the main study indicates that peer PWOM can reduce conspiracy beliefs (and encourage app adoption) among firm conspiracy believers, the experimental study finds an effect that points in the same direction but remains insignificant. We conclude that peer PWOM concerning public health apps can mitigate conspiracy beliefs among firm conspiracy believers, although this effect may depend on the volume of the peer WOM and the personal connection to the peer. Thus, in the experimental study, peer WOM was only manipulated through a single message, and the instruction to imagine that the message came from a close and trusted friend may have been insufficient to simulate a personal bond. Moreover, the discrepancy may be attributed to the different empirical settings of the studies. The field study was set in the agitated echoverse surrounding the COVID-19 pandemic, whereas the experiment focused on a setting (i.e., health monitoring and data donation app issued by the CDC) in which the adoption of the focal app was associated with less heated debates. Thus, in line with our previous argument, the experimental variation in the WOM message might not have been strong enough to impact app-specific conspiracy beliefs in a calmer setting.

6.2 | Theoretical implications

6.2.1 | Conspiracy beliefs and the adoption of innovative public health apps

Our findings offer novel insights into how individuals process information about innovative public health apps and the determinants of app adoption. Prior research has uncovered factors that influence the adoption of public health apps, such as app benefits and privacy designs (e.g., Trang et al., 2020; Walrave et al., 2020). Our research

TABLE 2 Study comparison

Comparison standard	Field study	Experimental validation study
Setting	COVID-19 tracing app	Health monitoring and data donation app
Study type	Three-wave field study (establishing external validity)	Two-wave scenario experiment (establishing internal validity)
WOM measures	Perceptions (surveyed)	Manipulated treatments (scenario-based)
Conspiracy beliefs measure	DV: Change scores for conspiracy beliefs from t_1–t_3 estimated via mixed-effects growth-curve modeling MV: Initial conspiracy beliefs at t_1	DV: App-specific conspiracy beliefs at t_2 MV: Initial conspiracy beliefs at t_1
Behavioral consequences measures	App adoption: Actual installation decision (self-reported) WOM valence (surveyed)	App adoption: Installation intention (surveyed) WOM valence (surveyed)
Primary goal	Examine the overall framework	Validate the findings from the field
Most important findings	• Change in conspiracy beliefs negatively affects public health app adoption and WOM valence • Change in peer and expert NWOM positively affects change in conspiracy beliefs • When initial conspiracy beliefs are low, an increase in expert PWOM causes a decline in conspiracy beliefs	• Replication of hypothesized field study findings in a controlled setting • When initial conspiracy beliefs are low, an increase in expert PWOM causes a decline in app-specific conspiracy beliefs; when initial conspiracy beliefs are high, an increase in expert PWOM causes an increase in app-specific conspiracy beliefs

Abbreviations: DV, dependent variable; MV, moderating variable; NWOM, negative words of mouth; PWOM, positive word of mouth; WOM, word of mouth.

complements these findings by showing that conspiracy beliefs—a factor neglected in the extant research—play a crucial role in public health app adoption.

Our findings highlight how conspiracy beliefs influence public health app adoption in two ways. First, as conspiracy beliefs imply that governments pursue secret and evil plans, individuals who hold conspiracy beliefs tend to believe that public health apps do not perform their advertised functions, instead being used to control the population or for some other malicious purpose. Prior studies have identified similar effects in other areas of public health, showing that conspiracy beliefs reduce adherence to advice about vaccination (Jolley & Douglas, 2017) or HIV treatment (Bogart et al., 2010). However, we not only highlight similar effects for public health apps, which are not related to medical treatment in a narrow sense but also demonstrate the inhibitory effects of general conspiracy beliefs. In our main study, conspiracy beliefs not related to COVID-19 or tracing apps (but to a general belief about powerful groups operating in secrecy) inhibited app usage, whereas previous studies (as our experimental study) analyzed the influence of conspiracy beliefs related to specific health measures. These results highlight the dangers of a "conspiracy mindset" (Sutton & Douglas, 2020), which likely affects not only the specific public health apps examined in this study but also the entire range of public health apps.

Second, a more indirect influence on public health app adoption can be ascribed to the effect that conspiracy beliefs have on individuals' interpretation of information concerning such apps. Our findings outline how individuals with firm conspiracy beliefs tend to discredit expert WOM that contradicts their conspiracy beliefs (i.e., expert PWOM on public health apps). This finding supports the notion that conspiracy beliefs have a self-sealing quality, as "the very arguments that give rise to them, and account for their plausibility, make it more difficult for outsiders to rebut or even to question them" (Sunstein & Vermeule, 2009, 207). Thus, when consumers believe that public health apps play a role in a conspiracy, they also likely believe that experts are part of the conspiracy or serve as mouthpieces of the conspirators. This finding is supported by prior studies showing that initial conspiracy beliefs can reduce or prevent acceptance of fact-based arguments that contradict conspiracy beliefs (Jolley & Douglas, 2017). However, our findings extend these results, showing that this effect depends on the source of the information (i.e., whether it originates from a peer or an expert) and that expert information contradicting conspiracy beliefs can enhance conspiracy beliefs, thereby having the opposite outcome than intended.

These insights are crucial in terms of developing a deeper understanding of public health app adoption. Conspiracy beliefs are not merely another factor that influences public health app adoption; they also shape the processing of information about the apps. Thus, it is reasonable to assume that conspiracy beliefs influence how consumers evaluate the app-related benefits and privacy designs shown to be important factors in relation to public health app adoption (e.g., Trang et al., 2020, Walrave et al., 2020). For instance, individuals who hold strong conspiracy beliefs and, therefore, distrust government authorities are likely to be very critical of the collection of sensitive user data (e.g., geo-locations) and to have greater privacy concerns.

6.2.2 | How conspiracy beliefs spread and are reinforced

Aside from the previously described influences of conspiracy beliefs on individual consumers, our findings reveal how conspiracy beliefs can spread, exerting effects on other consumers' public health app adoption decisions. We show that NWOM about public health apps increases conspiracy beliefs, which not only reduces the likelihood of app adoption but also motivates consumers to spread more negative WOM about the apps. Accordingly, a consumer who receives NWOM about public health apps is more likely to spread NWOM about such apps, thereby influencing other consumers not to adopt them and, in turn, to further disseminate the NWOM. This indicates that due to their infectious nature, conspiracy beliefs are more dangerous to the success of public health apps than a purely individual-focused analysis would suggest. By spreading NWOM about public health apps, a few influential individuals can set in motion a chain of WOM that spreads conspiracy beliefs among different groups and leads them to resist government advice to adopt public health apps.

In accordance with the previously described mechanism, our findings provide insights into how conspiracy beliefs are reinforced in individuals and groups. When entire social groups share conspiracy beliefs, individuals are likely to receive less WOM contradicting conspiracy beliefs and more WOM supporting them. Thus, group interaction and social pressure uphold or even reinforce conspiracy beliefs. In groups in which members show substantial increases in conspiracy beliefs (e.g., as the result of an acute crisis), conspiracy beliefs may spiral into a self-reinforcing feedback loop (or vicious cycle) fueled by social interaction between group members (Kraemer et al., 2020; Sunstein & Vermeule, 2009). Accordingly, our findings indicate that social interaction that reinforces conspiracy beliefs also contributes to the previously described self-sealing quality of conspiracy beliefs. In other words, the social reinforcement of conspiracy beliefs makes it even more difficult to convince individuals who identify with social groups whose members share conspiracy beliefs that a conspiracy theory represents a false and dangerous belief.

6.2.3 | How WOM sources and pre-existing consumer attitudes affect WOM influence

Our findings extend innovation research on the role of WOM in adoption processes beyond the subject of conspiracy beliefs and public health apps. Our findings suggest that simultaneously considering the WOM source and pre-existing consumer attitudes is crucial to understanding the influence of WOM on consumers' adoption decisions. Prior studies that considered only WOM sender characteristics suggest that the sender's expertise promotes the influence of WOM on receivers (Bansal & Voyer, 2000; Bone, 1995). However, we provide a more comprehensive perspective, showing that expert PWOM does not encourage app adoption among individuals with high initial conspiracy beliefs and can even have the opposite effect. A consumer's baseline attitude at a given time (initial conspiracy beliefs) can nullify or even reverse the effect of expert WOM, whereas such an influence was not found in the case of peer WOM. By considering the interplay between WOM sender characteristics (e.g., expertise, social ties) and pre-existing attitudes that can relate to factors other than conspiracy beliefs (e.g., brand or risk attitudes), innovation research could gain deeper insights into adoption processes. This would complement prior innovation studies highlighting the influence that different communication channels (e.g., personal vs. virtual) have on the impact of WOM (e.g., Kawakami & Parry, 2013; Parry et al., 2012).

6.3 | Practical implications

6.3.1 | Marketing innovative public health apps

This study provides novel insights into factors that determine public health app adoption, enabling us to provide valuable guidance for those marketing these innovative apps. Our findings highlight how conspiracy beliefs can substantially inhibit public health app adoption. Consequently, when launching novel public health apps, health agencies should take into account the possibility that conspiracy theories could limit an app's diffusion. As the effectiveness of a public health app largely depends on its widespread adoption, popular conspiracy theories could substantially limit an app's prospects of success.

However, public health agencies can engage in targeted marketing campaigns to increase app adoption. Marketers should analyze how widespread conspiracy theories are in specific consumer segments and then adapt their marketing campaigns accordingly. Thus, the interpretation of WOM regarding public health apps depends on the level of conspiracy beliefs. Consumer segments with low levels of conspiracy beliefs could be targeted by employing expert WOM to promote the benefits of public health apps. Prior research indicates that WOM by well-known and reputable experts is particularly successful in influencing opinion (Bone, 1995; Jolley & Douglas, 2017). These marketing activities should help to repress emerging conspiracy beliefs and increase public health app adoption in these segments.

In consumer segments in which conspiracy beliefs are widespread, expert WOM proves ineffective at mitigating such beliefs and may even reinforce them. Thus, targeting these segments with expert WOM promoting the public health app represents a waste of resources at best and a counterproductive measure at worst. However, peer WOM supporting public health apps can reduce conspiracy beliefs and encourage app adoption among firm conspiracy believers. Thus, when targeting these segments, government agencies should focus on promoting and disseminating peer PWOM. Reaching potential users with peer WOM supporting public health apps could be achieved by providing shareable content (e.g., user experiences, appeals for societal responsibility), integrating recommendation functionality into the apps, or targeting key influencers. Yet, health agencies must ensure that the solicited peer WOM is credible. Moreover, they should avoid giving the impression that the message originates from the government, as conspiracy believers may then view it as an effort to conceal a conspiracy, which may reinforce their conspiracy beliefs.

Although peer WOM can help to reduce conspiracy beliefs and market public health apps in groups with widespread conspiracy beliefs, it is important to recognize that this is a difficult task for government agencies. Social interaction upholds and reinforces conspiracy beliefs in these groups, which limits information diversity and makes it difficult to attract peer WOM that contradicts conspiracy beliefs and promotes public health apps. Our results regarding the (lack of) effectiveness of peer PWOM in the context of high initial conspiracy beliefs also indicate that prevention is likely to prove substantially more effective than intervention in certain situations (Jolley & Douglas, 2017). Existing approaches such as flagging misinformation on social media appear to be promising in this regard (Kreko, 2020), and they could be complemented by expert WOM contradicting conspiracy beliefs as discussed above.

6.3.2 | Implications for commercial actors

Although our conceptual development and empirical analysis focus on public health apps and, therefore, on implications for public agencies, the findings also have valuable implications for commercial actors. First, it must be recognized that companies and their innovations can also become the targets of conspiracy theories. For example, a wide array of conspiracy theories surrounds pharmaceutical companies, claiming that they conceal damages caused by vaccinations or make up diseases to generate profits (Jolley & Douglas, 2017). In addition, various conspiracy theories focus on technology companies, for example, stating that the Google algorithm only searched out unfavorable news about former US president Donald Trump in order to sway the electorate. Insights into conspiracy theories suggest that media products and products addressing sensitive topics such as health or collecting sensitive user data are particularly susceptible to conspiracy theories (Douglas et al., 2019; Uscinski & Parent, 2014). Our results indicate that such firms need to be cautious when actively opposing conspiracy theories. Targeting consumers who exhibit high levels of conspiracy beliefs with fact-based expert opinions in an effort to debunk conspiracy theories is likely to prove ineffective or may even backfire by reinforcing conspiracy beliefs and situating the firm increasingly in the focus of conspiracy believers. Instead, firms should fight existing conspiracy beliefs by encouraging the dissemination of peer WOM that contradicts such theories and preventing the emergence of new conspiracy theories by adopting response strategies for mitigating blistering WOM firestorms (Herhausen et al., 2019).

6.4 | Limitations and future research directions

This study has limitations that should be taken into account, which, however, also offer promising directions for future research. First, when analyzing the effects of WOM, we differentiated between two sources: peers and experts. Yet, within these broad categories, specific WOM senders are likely to be perceived differently, which may influence the effects of their WOM on conspiracy beliefs. For instance, WOM from peers with whom an individual is very close (e.g., family members) is likely to have a greater effect than WOM from more distant peers (e.g., online acquaintances) (Brown & Reingen, 1987; Hofstetter et al., 2018). The characteristics of experts, such as their ties to the government, could also influence the effects of expert WOM. Similarly, a WOM sender's network position could influence the effects of WOM on the receivers. For example, it is reasonable to assume that opinion leaders on social media exert greater effects than individuals who occupy less central network positions. Thus, future studies should complement our aggregated perspective with an individual-level analysis that examines the effects of specific WOM sender characteristics.

Second, when analyzing the effects of WOM, we relied on perceived WOM (i.e., the extent to which individuals noticed PWOM and NWOM by peers and experts) to determine how WOM from different sources is processed by individual receivers. However, it is possible that conspiracy beliefs not only affect how individuals interpret WOM, but also the extent to which they notice different types of WOM. For example, individuals who hold firm conspiracy beliefs might be able to recall WOM supporting their conspiracy beliefs better than WOM contradicting their beliefs. Therefore, future studies should analyze whether conspiracy beliefs promote a selective perception of WOM and, if so, how it influences public health app adoption.

Third, when testing the relationships in our model, we relied on samples of German and US consumers, which suggests that our results hold for different cultural settings. Yet, we only looked at consumers from two different countries and did not account for the influence of specific cultural factors. It is likely that the central variables in our model, such as WOM activities, reactions to WOM, and conspiracy beliefs, and the relationships between them are affected by cultural factors (e.g., Broekhuizen et al., 2011). Thus, future studies should test our model in other cultural contexts and explicitly analyze the influence of culture.

Finally, while we analyzed how conspiracy beliefs develop from a certain starting point, we cannot provide insights into the factors that explain this starting point. However, such insights are crucial to fighting conspiracy beliefs and increasing public health app adoption. Although prior studies have identified general factors that contribute to the long-term development of conspiracy beliefs (e.g., education, social status) (Freeman & Bentall, 2017), further research is required to support public agencies in their efforts to reduce conspiracy beliefs and improve public health.

ACKNOWLEDGMENT

Open Access funding enabled and organized by Projekt DEAL.

CONFLICT OF INTEREST

The authors have declared no conflict of interest.

ORCID

Tobias Kraemer https://orcid.org/0000-0001-6134-6636
Welf H. Weiger https://orcid.org/0000-0003-4346-3681
Simon Trang https://orcid.org/0000-0002-4784-4038
Manuel Trenz https://orcid.org/0000-0002-8970-958X

ENDNOTE

[i] We excluded 92 participants who participated in the first wave of the survey, but not in the second wave.

REFERENCES

Abrams, D., and M. A. Hogg. 1990. "Social Identification, Self-Categorization and Social Influence." *European Review of Social Psychology* 1(1): 195–228.

Anderson, E. W. 1998. "Customer Satisfaction and Word of Mouth." *Journal of Service Research* 1(1): 5–17.

Ashforth, B. E., and F. Mael. 1989. "Social Identity Theory and the Organization." *The Academy of Management Review* 14(1): 20–39.

Babić Rosario, A., F. Sotgiu, K. De Valck, and T. H. Bijmolt. 2016. "The Effect of Electronic Word of Mouth on Sales: A Meta-Analytic Review of Platform, Product, and Metric Factors." *Journal of Marketing Research* 53(3): 297–318.

Bansal, H. S., and P. A. Voyer. 2000. "Word-of-Mouth Processes within a Services Purchase Decision Context." *Journal of Service Research* 3(2): 166–77.

Bogart, L. M., G. Wagner, F. H. Galvan, and D. Banks. 2010. "Conspiracy Beliefs about HIV Are Related to Antiretroviral Treatment Nonadherence among African American Men with HIV." *Journal of Acquired Immune Deficiency Syndromes* 53(5): 648–55.

Bone, P. F. 1995. "Word-of-Mouth Effects on Short-Term and Long-Term Product Judgments." *Journal of Business Research* 32(3): 213–23.

Broekhuizen, T. L., S. A. Delre, and A. Torres. 2011. "Simulating the Cinema Market: How Cross-Cultural Differences in Social Influence Explain Box Office Distributions." *Journal of Product Innovation Management* 28(2): 204–17.

Brown, J., A. J. Broderick, and N. Lee. 2007. "Word of Mouth Communication within Online Communities: Conceptualizing the Online Social Network." *Journal of Interactive Marketing* 21(3): 2–20.

Brown, J. J., and P. H. Reingen. 1987. "Social Ties and Word-of-Mouth Referral Behavior." *Journal of Consumer Research* 14(3): 350–62.

Budd, J., B. S. Miller, E. M. Manning, V. Lampos, M. Zhuang, M. Edelstein, G. Rees, V. C. Emery, M. M. Stevens, and N. Keegan. 2020. "Digital Technologies in the Public-Health Response to COVID-19." *Nature Medicine* 26(8): 1183–92.

CDC (2022). Centers for Disease Control and Prevention: Mobile Apps. https://www.cdc.gov/mobile/mobileapp.html.

Davis, F. D. 1989. "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology." *MIS Quarterly* 13(3): 319–40.

Deutsch, M., and H. B. Gerard. 1955. "A Study of Normative and Informational Social Influences upon Individual Judgment." *The Journal of Abnormal and Social Psychology* 51(3): 629–36.

Douglas, K. M., R. M. Sutton, and A. Cichocka. 2017. "The Psychology of Conspiracy Theories." *Current Directions in Psychological Science* 26(6): 538–42.

Douglas, K. M., J. E. Uscinski, R. M. Sutton, A. Cichocka, T. Nefes, C. S. Ang, and F. Deravi. 2019. "Understanding Conspiracy Theories." *Political Psychology* 40: 3–35.

Ebbes, P., D. Papies, and H. J. van Heerde. 2017. "Dealing with Endogeneity: A Nontechnical Guide for Marketing Researchers." In *Handbook of Market Research* 1–37. Basel & Cham: Springer International Publishing.

Enders, A. M., J. E. Uscinski, M. I. Seelig, C. A. Klofstad, S. Wuchty, J. R. Funchion, M. N. Murthi, K. Premaratne, and J. Stoler. 2021. "The Relationship between Social Media Use and Beliefs in Conspiracy Theories and Misinformation." *Political Behavior*: 1–24. [advance online publication].

Fornell, C., and D. F. Larcker. 1981. "Structural Equation Models with Unobservable Variables and Measurement Error: Algebra and Statistics." *Journal of Marketing Research* 18(3): 382–8.

Freeman, D., and R. P. Bentall. 2017. "The Concomitants of Conspiracy Concerns." *Social Psychiatry and Psychiatric Epidemiology* 52(5): 595–604.

Goertzel, T. 1994. "Belief in Conspiracy Theories." *Political Psychology* 15: 731–42.

Gruner, R. L., A. Vomberg, C. Homburg, and B. A. Lukas. 2019. "Supporting New Product Launches with Social Media Communication and Online Advertising: Sales Volume and Profit Implications." *Journal of Product Innovation Management* 36(2): 172–95.

Grzesiak-Feldman, M. 2013. "The Effect of High-Anxiety Situations on Conspiracy Thinking." *Current Psychology* 32(1): 100–18.

Herhausen, D., S. Ludwig, D. Grewal, J. Wulf, and M. Schoegel. 2019. "Detecting, Preventing, and Mitigating Online Firestorms in Brand Communities." *Journal of Marketing* 83(3): 1–21.

Hofstetter, R., S. Aryobsei, and A. Herrmann. 2018. "Should you Really Produce What Consumers like Online? Empirical Evidence for Reciprocal Voting in Open Innovation Contests." *Journal of Product Innovation Management* 35(2): 209–29.

Hu, X., X. Chen, and R. M. Davison. 2019. "Social Support, Source Credibility, Social Influence, and Impulsive Purchase Behavior in Social Commerce." *International Journal of Electronic Commerce* 23(3): 297–327.

Hulland, J., and J. Miller. 2018. ""Keep on Turkin"?" *Journal of the Academy of Marketing Science* 46(5): 789–94.

Imhoff, R., and M. Bruder. 2014. "Speaking (Un-)Truth to Power: Conspiracy Mentality as a Generalised Political Attitude." *European Journal of Personality* 28(1): 25–43.

Jolley, D., and K. M. Douglas. 2014. "The Effects of Anti-Vaccine Conspiracy Theories on Vaccination Intentions." *PLoS One* 9(2): e89177.

Jolley, D., and K. M. Douglas. 2017. "Prevention Is Better than Cure: Addressing Anti-Vaccine Conspiracy Theories." *Journal of Applied Social Psychology* 47(8): 459–69.

Jolley, D., K. M. Douglas, and R. M. Sutton. 2018. "Blaming a Few Bad Apples to Save a Threatened Barrel: The System-Justifying Function of Conspiracy Theories." *Political Psychology* 39(2): 465–78.

Jost, J. T., and R. Andrews. 2011. "System justification theory." In *The Encyclopedia of Peace Psychology*. New York, NY: John Wiley & Sons.

Kashyap, V., K. D. Antia, and G. L. Frazier. 2012. "Contracts, Extra-contractual Incentives, and ex Post Behavior in Franchise Channel Relationships." *Journal of Marketing Research* 49(2): 260–76.

Kawakami, T., K. Kishiya, and M. E. Parry. 2013. "Personal Word of Mouth, Virtual Word of Mouth, and Innovation Use." *Journal of Product Innovation Management* 30(1): 17–30.

Kawakami, T., and M. E. Parry. 2013. "The Impact of Word of Mouth Sources on the Perceived Usefulness of an Innovation." *Journal of Product Innovation Management* 30(6): 1112–27.

Keh, H. T., and J. Sun. 2018. "The Differential Effects of Online Peer Review and Expert Review on Service Evaluations: The Roles of Confidence and Information Convergence." *Journal of Service Research* 21(4): 474–89.

Kraemer, T., W. Weiger, M. Gouthier, and M. Hammerschmidt. 2020. "Toward a Theory of Spirals: The Dynamic Relationship between Organizational Pride and Customer-Oriented Behavior." *Journal of the Academy of Marketing Science* 48(6): 1095–115.

Kreko, P. 2020. "Countering conspiracy theories and misinformation." In *Routledge Handbook of Conspiracy Theories* 242–56. Milton Park: Routledge.

Kuan, K. K., Y. Zhong, and P. Y. Chau. 2014. "Informational and Normative Social Influence in Group-Buying: Evidence from Self-Reported and EEG Data." *Journal of Management Information Systems* 30(4): 151–78.

Lin, T. M., and C.-H. Fang. 2006. "The Effects of Perceived Risk on the Word-of-Mouth Communication Dyad." *Social Behavior and Personality: An International Journal* 34(10): 1207–16.

Maxham, J. G., and R. G. Netemeyer. 2002. "A Longitudinal Study of Complaining customers' Evaluations of Multiple Service Failures and Recovery Efforts." *Journal of Marketing* 66(4): 57–71.

O'Brien, R. M. 2007. "A Caution Regarding Rules of Thumb for Variance Inflation Factors." *Quality and Quantity* 41(5): 673–690.

Orosz, G., P. Krekó, B. Paskuj, I. Tóth-Király, B. Bőthe, and C. Roland-Lévy. 2016. "Changing Conspiracy Beliefs through Rationality and Ridiculing." *Frontiers in Psychology* 7: 1525.

Parry, M. E., T. Kawakami, and K. Kishiya. 2012. "The Effect of Personal and Virtual Word-of-Mouth on Technology Acceptance." *Journal of Product Innovation Management* 29(6): 952–66.

Peer, E., L. Brandimarte, S. Samat, and A. Acquisti. 2017. "Beyond the Turk: Alternative Platforms for Crowdsourcing Behavioral Research." *Journal of Experimental Social Psychology* 70: 153–63.

Ram, S., and J. N. Sheth. 1989. "Consumer Resistance to Innovations: The Marketing Problem and its Solutions." *Journal of Consumer Marketing* 6(2): 5–14.

Seto, E., P. Challa, and P. Ware. 2021. "Adoption of COVID-19 Contact Tracing Apps: A Balance between Privacy and Effectiveness." *Journal of Medical Internet Research* 23(3): e25726.

Sine, W. D., S. Shane, and D. D. Gregorio. 2003. "The Halo Effect and Technology Licensing: The Influence of Institutional Prestige on the Licensing of University Inventions." *Management Science* 49(4): 478–96.

Sunstein, C. R., and A. Vermeule. 2009. "Conspiracy Theories: Causes and Cures." *Journal of Political Philosophy* 17(2): 202–27.

Sutton, R. M., and K. M. Douglas. 2020. "Conspiracy Theories and the Conspiracy Mindset: Implications for Political Ideology." *Current Opinion in Behavioral Sciences* 34: 118–22.

Trang, S., M. Trenz, W. H. Weiger, M. Tarafdar, and C. M. Cheung. 2020. "One App to Trace them all? Examining App Specifications for Mass Acceptance of Contact-Tracing Apps." *European Journal of Information Systems* 29(4): 415–28.

Trenz, M., J. Huntgeburth, and D. Veit. 2018. "Uncertainty in Cloud Service Relationships: Uncovering the Differential Effect of Three Social Influence Processes on Potential and Current Users." *Information & Management* 55(8): 971–83.

Uscinski, J. E., and J. M. Parent. 2014. *American Conspiracy Theories*. Oxford: Oxford University Press.

van Prooijen, J.-W., and M. Van Vugt. 2018. "Conspiracy Theories: Evolved Functions and Psychological Mechanisms." *Perspectives on Psychological Science* 13(6): 770–88.

Venkatesh, V., M. G. Morris, G. B. Davis, and F. D. Davis. 2003. "User Acceptance of Information Technology: Toward a Unified View." *MIS Quarterly* 27(3): 425–78.

Voorhees, C. M., M. K. Brady, R. Calantone, and E. Ramirez. 2016. "Discriminant Validity Testing in Marketing: An Analysis, Causes for Concern, and Proposed Remedies." *Journal of the Academy of Marketing Science* 44(1): 119–34.

Walrave, M., C. Waeterloos, and K. Ponnet. 2020. "Ready or Not for Contact Tracing? Investigating the Adoption Intention of COVID-19 Contact-Tracing Technology Using an Extended Unified Theory of Acceptance and Use of Technology Model." *Cyberpsychology, Behavior and Social Networking* 24(6): 377–83.

AUTHOR BIOGRAPHIES

Tobias Kraemer, Ph.D. is an Assistant Professor for Service Management at the Institute for Management at the University of Koblenz-Landau in Germany and a Visiting Professor at the Justus-Liebig-University in Giessen, Germany. He received his Ph.D. from EBS University, Germany. His research focuses on consumer innovation resistance, online customer engagement, digital co-creation, and AI in services. His research on these topics has been published in journals such as Journal of the Academy of Marketing Science, Journal of Service Research, Journal of Service Management, and Journal of Business Research.

Welf H. Weiger, Ph.D. is an Assistant Professor of Marketing and the Chair of the Marketing Department at the Alfaisal University, Kingdom of Saudi Arabia. He earned his Ph.D. at the University of Goettingen, Germany. His research interests lie primarily in social media marketing, customer engagement, gamification, and artificial intelligence in the service frontline. His work has been published in outlets such as the Journal of the Academy of Marketing Science, International Journal of Research in Marketing, European Journal of Information Systems, Journal of Business Research, Journal of Service Management, and Journal of the Association for Consumer Research.

Simon Trang, Ph.D. is an Assistant Professor at the University of Goettingen and holds the Chair of Information Security and Compliance at the Department of Business Administration. He received his Ph.D. in management science, specializing in management information systems, from the University of Goettingen. His work focuses on information security management, health IS, and sustainable IS. His research has been published in outlets such as the Journal of the Association for Information Systems, European Journal of Information Systems, Information Systems Frontiers, and others.

Manuel Trenz, Ph.D. is Professor of Interorganizational Information Systems at the University of Goettingen, Germany. He holds a Ph.D. from the Business School of the University of Mannheim, Germany. His research is dedicated to the study and advancement of data-driven innovation and digital platforms. He is particularly interested in how people interact in data-intensive contexts and how data can be used in prudent ways for innovation and algorithmic decision-making. His work has appeared in journals such as MIS Quarterly, Journal of Management Information Systems, European Journal of Information Systems, Information Systems Journal, Internet Research, and others.

SUPPORTING INFORMATION

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

How to cite this article: Kraemer, Tobias, Welf H. Weiger, Simon Trang, and Manuel Trenz. 2022. "Deflected by the Tin Foil Hat? Word-of-Mouth, Conspiracy Beliefs, and the Adoption of Innovative Public Health Apps." *Journal of Product Innovation Management* 1–21. https://doi.org/10.1111/jpim.12646