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# Does negative buzz result in social media discontinuation? Investigating the effects of negative word of mouth in the United States, India, and Finland

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ABSTRACT

Negative Word-of-mouth (WOM) significantly influences how users form attitudes toward digital platforms, yet little is known about its role in social media discontinuation. Grounded in Social Cognitive Theory (SCT), this study investigates how two types of negative WOM, online and offline, influence users' perceptions of privacy and social media discontinuation intent among WhatsApp users in the United States (n = 309), India (n = 271), and Finland (n = 205). The research model conceptualizes negative WOM as environmental factors, privacy invasion, and distrust as self-judgment, and discontinuation intention as the behavioral response. The structural equation modeling shows that users do not respond to both types of WOM in the same way in different countries. Online negative WOM significantly increases perception of privacy invasion in the US and India, while offline negative WOM is more influential in shaping distrust in Finland. Distrust consistently predicts discontinuation intention across three countries, with privacy invasion directly affecting discontinuation intention only in Finland. This study contributes to existing literature by examining the impact of environmental factors represented in both offline and online negative WOM, as well as cognitive factors represented in privacy invasion and distrust on discontinuous intention. Further, unlike the mainstream literature that focuses on a single country, we study social media discontinuation across three countries. The research advances SCT-based research by applying it to the underexplored domain of social media discontinuation and provides implications for designing country-specific privacy strategies to mitigate discontinuation risks.

## 1. Introduction

Discontinuation of usage represents a major dynamic force in information systems. Social media discontinuation (SMD) occurs when users abandon all or specific social media platforms. When this behavior takes place *en masse*, social media platforms face the challenge of "negative tipping", where the value created or received by the platform's members is not enough to sustain the platform (Katz & Shapiro, 1985; Salminen et al., 2018). This could happen due to a decline in user engagement, rising operational costs, or a decrease in new revenue opportunities. The platform may no longer sustain itself effectively when reaching this tipping point, leading to potential financial losses and failure. The failure of such platforms is detrimental to individuals as well, who use them for personal and professional interactions, accessing information, and significant sources of community, support, and enjoyment (Yang & Zhang, 2022). Therefore, discontinuation dynamics play a major role in shaping socio-technical systems such as social media platforms.

The existing literature suggests that different factors contribute to the discontinuation of social media, including (1) individual factors such as cognitive (Hong & Oh, 2020), behavioral (Luqman et al., 2018; Turel, 2015) and emotional (Cao et al., 2020; Liu et al., 2021; Maier, 2020; Masood et al., 2021) factors, (2) content-related factors such as information equivocality (Xie & Tsai, 2021), annoying posts (Hong & Oh, 2020), banality of content (Hong & Oh, 2020), and rumors (Xie & Tsai, 2021), and the (3) social media platform's features or even alternative availability (Hong & Oh, 2020). A systematic review of the literature (Farooq et al., 2023a) showed that social pressure, in the form of a

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critical mass, subjective and descriptive norms, also plays a significant role in SMD.

While these studies provide insight into why people discontinue using social media, several gaps remain. First, there is a clear focus on users' cognitive factors as drivers of SMD, with sporadic references to social or platform-related factors (Farooq et al., 2023a). Research shows that users' opinions, referred to as *word of mouth (WOM)*, influence the decision-making processes of other users in terms of both online and offline service adoption (Huang et al., 2014), however, their impact on SMD has not been studied. Second, most studies focus on platforms such as Facebook (Farooq et al., 2023a; Fu et al., 2020; Turel, 2015) and WeChat (Farooq et al., 2023a; Lin et al., 2020), suggesting a future research opportunity to study other platforms, such as WhatsApp. Third, most studies on SMD are conducted in a single country (Farooq et al., 2023a) underscoring the need for cross-country studies.

In response to these research gaps, this study examines the role of the negative valence of WOM in SMD in three countries. This study aims to answer the following research questions: (1) *What is the role of WOM in shaping social media discontinuation intention?* and (2) *How does this relationship differ in culturally different countries, such as the United States (US), Finland, and India?* To answer these questions, we examine how two types of negative WOM, *online negative WOM* and *offline negative WOM*, influence people's privacy attitudes and discontinuation of social media platforms among users from the US, Finland, and India, which differ in their level of digital maturity (Thordsen et al., 2020) (i.e., the measure of a country's ability to create value through digital means), as well as country culture. Our premise is that the level of digital maturity may affect privacy attitudes and discontinuation intent. According to IMD's World Competitiveness Center – World Digital Ranking 2022 Finland's digital ranking is high, it represents a unique context in comparison to the US, with the presence of the most stringent privacy regulation (i.e., GDPR). Moreover, these countries are also culturally different (Hofstede et al., 2010). Information on the three countries in this study is presented in Fig. 1.

In terms of study context, we particularly focus on *WhatsApp*. This popular messaging service enables users to create an account profile, share status updates, photos, and videos, and even transfer money (Matanji, 2019; Oktavianus & Meng, 2024). In March 2021, Meta (then Facebook) acquired WhatsApp and announced plans to expand data sharing between the two services (see Figure A2 in Appendix A). This announcement implied that WhatsApp could access, store, and share some user data with Facebook, including phone numbers, device information, transaction data, and location information; failing to accept the new privacy policy would result in reduced application functionality. This announcement sparked global online protests and offline actions (Griggio et al., 2022), as such data sharing could put users' confidential information at risk, and users have not given sufficient consent to share their data. This opportunity enabled us to collect empirical data through a series of *just-in-time* online surveys, which helped us achieve our study purpose.

This study uses Bandura's *Social Cognitive Theory* (SCT) (Bandura, 1986) as the research framework to study the effect of WOM on SMD intention. SCT is appropriate for this research as it allows the dynamic and reciprocal interaction of the individual, the environment, and behavior. In this study, negative WOM is the environmental factor, whereas the resultant privacy-related attitudes, such as privacy concerns and distrust, are the judgment factors, and behavioral intention has been used as a proxy for SMD behavior. The application of SCT in understanding SMD in a cross-country context is a novel contribution of this research (Farooq et al., 2023a).

The rest of the work is organized as follows. Related literature is discussed in Section 2. The theoretical framework, hypotheses, and the conceptual model are provided in Section 3. Section 4 explains our methodology, while Section 5 reports the results. We then discuss key findings, implications, and limitations in Section 6, followed by the conclusions in Section 7.

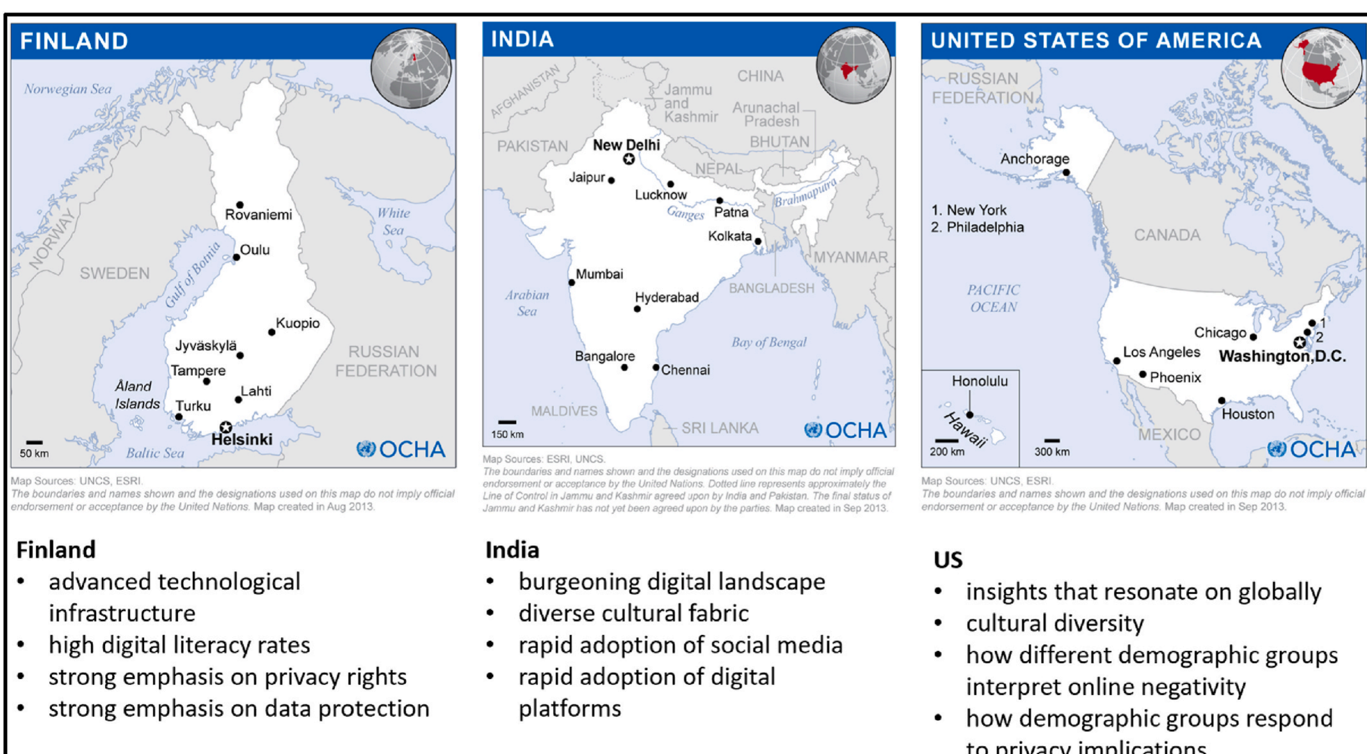



**Fig. 1.** The three countries – Finland, India, and the US – were selected for a study examining the effects of online and offline negative WOM on privacy concerns and social media discontinuation intent.

## 2. Related literature

In this section, we discuss existing research on SMD and introduce the concept of word of mouth.

### 2.1. Social media discontinuation (SMD)

Prior studies on SMD have identified several factors that influence the decision-making process using various theories, as shown in Table 1. Researchers have examined various factors contributing to SMD. Most of the studied factors can broadly be divided into emotional, cognitive, behavioral, relational, and platform-specific drivers (Farooq et al., 2023a). Some of these factors directly influenced discontinuation, whereas the majority were antecedents.

*Emotional factors* refer to the feelings and affections experienced by users. The most widely recognized emotional driver is social media fatigue and exhaustion (Adhikari & Panda, 2020; Fan et al., 2021; Lin et al., 2020; Liu et al., 2021; Xie & Tsai, 2021). Other significant emotional drivers include feelings of guilt (resulting from neglecting other needs, such as hobbies) (Maier, 2020), regret (arising from negative consequences such as anxiety and embarrassment) (Cao & Sun, 2018; Wang, Hu, et al., 2020), dissatisfaction, frustration, distress, strain, negative attitudes towards social media, and stress (Cao et al., 2020; Luqman et al., 2018, 2020; Maier, 2020; Zhou et al., 2018). Another study, environmental factors such as the fear of COVID-19, exacerbated by the abundance of information on social media during the pandemic, have also been identified as a factor increasing SMD (Liu et al., 2021).

*Cognitive factors* relate to thought processes and perceptions. Salient cognitive drivers include the perceived costs and benefits of social media, often framed as a "waste of time" (Hong & Oh, 2020). Privacy concerns have also been consistently reported as a driver for discontinuation (Adhikari & Panda, 2020; Fan et al., 2021). Beyond cognitive factors, *behavioral factors* such as perceived behavioral control (Luqman et al., 2018), and excessive use of social media (Masood et al., 2021) are also considered reasons for discontinuation.

*Relational factors* extend beyond the individual, focusing on the influence of a user's interactions and relationships with others. These factors stem from both close networks (such as family, friends, and colleagues) and broader communities, creating social pressure. For example, social overload is a prominent factor, leading to regret, exhaustion, distress, fatigue, and dissatisfaction (Cao et al., 2020; Cao & Sun, 2018; Wang, Hu, et al., 2020). Other indirect drivers include communication overload (Luqman et al., 2020), cyberbullying (Cao et al., 2020), and friction between family and technology (Luqman et al., 2020). A stronger intrinsic motivation to meet people offline rather than engage with them online can also lead users to abandon social media (Maier, 2020).

Platform-related factors, such as the characteristics of information and features of the social media platforms or their prestige, are also found to be reasons for leaving social media. Among these, information overload is frequently cited as a content-related driver for discontinuation (Cao & Sun, 2018; Liu et al., 2021; Zhou et al., 2018). The dissemination of rumors and an advertisement interface may also drive users away (Xie & Tsai, 2021).

In summary, the most prominent drivers for SMD are predominantly emotional factors and relational factors. Content-related drivers within the platform-specific category rank as the third most significant reason for users to discontinue social media. It is also important to note that these various factors do not operate in isolation, but can be interrelated, with external motivations sometimes triggering internal motivations for discontinuing social media use.

### 2.2. Word of mouth

*Word of Mouth* (WOM) refers to information communication between

**Table 1**
Summary of prior studies on social media discontinuance using theoretical frameworks.

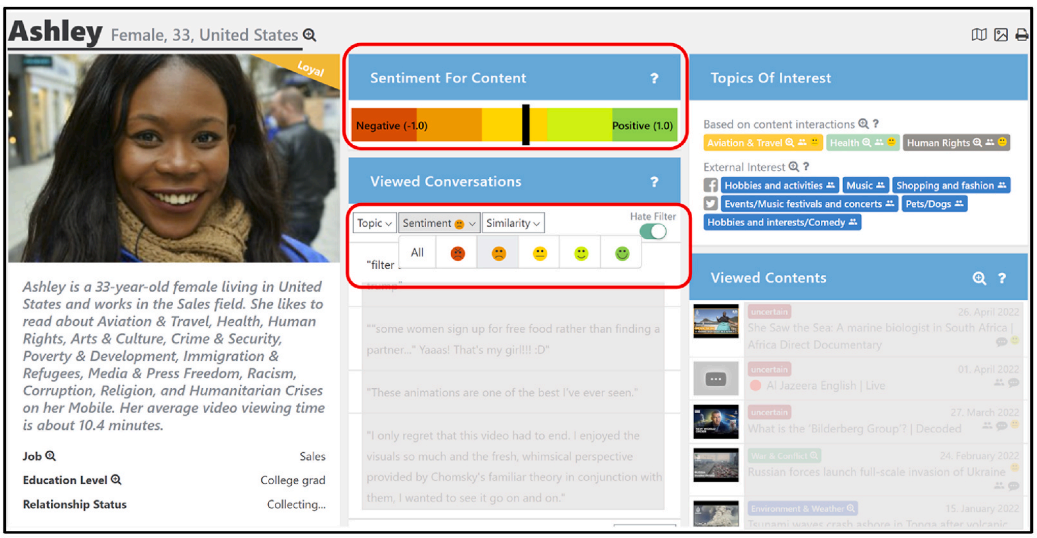
| Reference | Context | Research Method | Theoretical Lense | Country | Key Antecedents/Type | Key Direct Factors/Type |
|---|---|---|---|---|---|---|
| Adhikari and Panda (2020) | Social media in general | Survey | LCM, UTAUT | India | *Cognitive:* Privacy concern, | *Emotional:* Fatigue |
| Cao and Sun (2018) | Social media in general | Survey | Stimulus-Organism-Response (S-O-R) | China | *Relational:* Information overload, communication overload, social overload | *Emotional:* Exhaustion, Regret |
| Cao et al. (2020) | Facebook and WeChat | Survey | SCT | Pakistan | *Relational:* Cyberbullying, social overload | *Emotional:* Social networking sites exhaustion, Distrust |
| Fan et al. (2021) | WeChat | Survey | SCT | China | *Cognitive:* Privacy concerns | *Emotional:* Fatigue |
| Lin et al. (2020) | WeChat | Survey | Stimulus-organism-Response Framework (S-O-R) | China | *Relational:* Information overload, communication overload, social overload | *Emotional:* Fatigue |
| Liu et al. (2021) | Social media in general | Survey | S-O-R | UK | *Relational:* Information overload | *Emotional:* Fatigue<br>*Environmental:* Fear of COVID-19 |
| Luqman et al. (2018) | Chinese social media | Survey | Self-Determination Theory (SDT) and Theory of Planned Behavior (TPB) | China | *Relational:* Autonomous motivation, Controlled motivation | *Relational:* Social Norms<br>*Emotional:* Attitude, *Cognitive:* Behavioral: Perceived behavioral control |
| Maier (2020) | Social media in general | Interview | Cognitive Dissonance Theory | Not specified | *Relational:* Intrinsic motivation, negative feedback, | *Emotional:* Guilt, Stress, Frustration |
| Masood et al. (2021) | Chinese social media | Survey | Stressor-Strain-Outcome Framework, and Ego Depletion Theory | China | *Behavioral:* Excessive use<br>Cognitive: Self-control failure | *Emotional:* Guit Feelings |
| Wang, Zheng, et al. (2020) | WeChat | Survey | Two-Factor model | China | Relational: Social overload | Emotional: Regret |
| Xie and Tsai (2021) | Weibo | Survey | S-O-R | China | *Platform:* Advertising interference, rumors, information equivocality | *Relational:* Information overload<br>Emotional: Fatigue |
| Zhou et al. (2018) | Weibo | Survey | Cognition-Affection-Conation framework | China | *Platform:* system feature overload, information overload, and content characteristics | *Emotional:* Fatigue, Dissatisfaction |

Note: LCM: Limited Capacity Model, UTAUT: Unified Theory of Acceptance and Use of Technology.

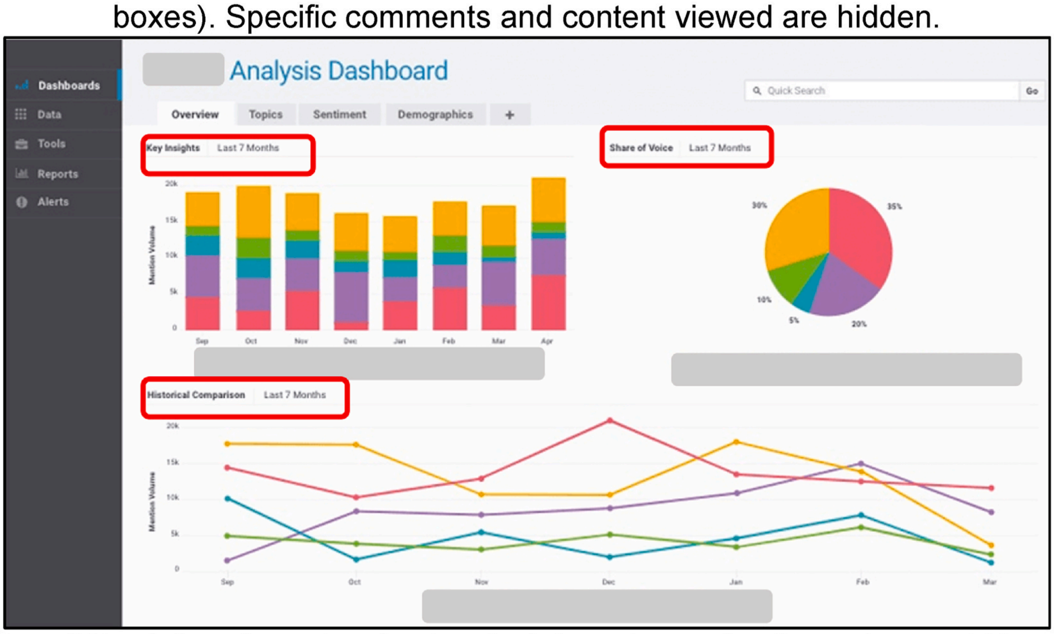
two parties to express their opinions on a range of topical areas, including products, systems, apps, and platforms (Dellarocas, 2003; Jansen et al., 2009). Users share their attitudes, opinions, and reactions regarding platforms with other users in the form of WOM (Huete-Alcocer, 2017). WOM has both boosting, in case of positive WOM, and damping, in case of negative WOM, effects. Academics have conducted in-depth research on the WOM phenomenon, recognizing its significant influence on people's beliefs and actions, especially interactions and intent to use technology. Given an increased relationship between WOM and adoption-related decision-making, research has investigated the factors influencing the generation of WOM (Arndt, 1967; Nam et al., 2020, p. 2). Notably, positive WOM has been proven to boost the chance of product or service uptake, whereas negative WOM reduces such likelihood (Arndt, 1967).

### 2.2.1. Online negative WOM

Social media platforms are 'social' (e.g., people affecting other people) by nature, and the role of peer information, i.e., what others think, naturally affects the user's decision of whether or not to continue using a platform (Farooq et al., 2023b). People use these platforms to voice their views about a product, service, company, or issue, in what is known as *online WOM, also called electronic* WOM (Hennig-Thurau et al., 2004). Existing research has identified why people read (Wang et al., 2013) and write online WOM (Jansen et al., 2009; Nam et al., 2020). Others have studied users' responses to online WOM, mainly in the adoption or selection of services or products (Mladenović et al., 2024; Shankar et al., 2020). This often entails examining aspects such as sentiment (Wang et al., 2023), brand mentions (Agarwal et al., 2024), or the use of pain points (Salminen et al., 2022), with examples in Fig. 2. The several unique characteristics of online WOM, such as diffusion




(a) Automatic Personal Generation (APG) tool interface showing persona's overall sentiment and sentiment for unique social media conversations engaged in (see red boxes). Specific comments and content viewed are hidden.




(b) BrandWatch interface showing key insights, share of online voice, and historical timeline (see red boxes). Company names are hidden.

**Fig. 2.** Two services that scan the publicly available web and generate electronic word of mouth insights are (a) APG https://persona.qcri.org and (b) BrandWatch https://www.brandwatch.com.

speed, persistence, accessibility, and measurability, make it an interesting topic for human-computer interaction (HCI) and information systems research (Nam et al., 2020). While the importance of online WOM in determining users' opinions, pain points, and behaviors has long been realized in the literature on consumer behavior (Nam et al., 2020), marketing (Ismagilova et al., 2017), and technology adoption (Shankar et al., 2020), its application in SMD has not been investigated yet.

Literature in the social media context shows that online negative WOM can result from privacy concerns on social media. For instance, qualitative and quantitative studies on Facebook users showed that users' concerns for self-presentation and privacy concerns/behavior are major antecedents of online negative WOM (Pasternak et al., 2017). Similarly, perceived security and privacy in social networking sites negatively impacts online WOM (Park & Kim, 2020). Additionally, online WOM has improved social media information privacy/security awareness (Sari & Prasetio, 2017, pp. 113–117). Despite research on the privacy concern as an antecedent for online negative WOM, little is known about how the online negative WOM impacts the privacy concerns of others. We add to this literature by studying the impact of online negative WOM on privacy concerns and SMD.

#### 2.2.2. *Offline negative WOM*

Offline WOM is face-to-face communication between the information disseminators and receivers. Such conversations do not occur in social isolation but between two parties that may share social ties (Chawdhary & Weber, 2025). Offline WOM constitutes the bulk of our social conversations, and like online WOM, the offline WOM has both dimensions of WOM valence: positive and negative (East et al., 2007). While online WOM has elements of speed, accessibility, persistence, and measurability, the offline WOM has characteristics such as interpersonal factors (tie-strength, homophily), personal factors (expertise and experience), and message characteristics (content and strength of delivery), making them equally important and interesting in decision making (East et al., 2007). Offline WOM has been found to affect decision-making in addition to online WOM significantly (Qi & Kuik, 2022). Some discussed the importance of offline WOM as a moderator in the relationship between online WOM and product diffusion (Huang et al., 2014), and as one of the drivers for online WOM (Zhang et al., 2017). In certain cases, offline WOM was found to be more influential than online WOM (Bayraktar & Erdogan, 2015).

Additionally, offline WOM can influence digital decision-making through trust transfer, social proof, and reinforcement mechanisms that operate independently of, but also in synergy with, online interactions (Bayraktar & Erdogan, 2015; Huete-Alcocer, 2017). Offline conversations often carry higher perceived credibility due to the relational closeness and contextual richness of face-to-face communication (Bayraktar & Erdogan, 2015). Furthermore, in highly mobile and internet-penetrated societies, offline WOM can act as a trigger for subsequent online engagement, shaping platform adoption, content sharing, and brand evaluations (Huete-Alcocer, 2017). Thus, a holistic approach to measuring WOM, which includes both offline and online WOM, is suggested.

In existing research on technology adoption, security, and privacy, the opinions of peers and significant others have been studied in terms of norm, mainly *subjective norms* and *descriptive norms* (Park & Smith, 2007). distinguished subjective norms, reflecting perceived societal expectations, from perceived descriptive norms, which capture individuals' perceptions of the dominance of a behavior. Subjective (and descriptive) norms have been shown to serve as precursors to privacy concerns (Masur et al., 2021; Nov & Wattal, 2009) and to privacy behaviors (Barth & de Jong, 2017). However, both these norms are "perceived expectations" rather than information or general discussions, as in the case of online WOM. Individuals are free to decide when expectations are not attached to them. Accordingly, this study investigates offline WOM as one of the antecedents to privacy concerns among social media users, further affecting SMD.

## 3. Theoretical framework, hypotheses, and research model

In this section, we describe the theoretical framework used, along with hypotheses and the research model of the study.

### 3.1. *Social cognitive theory*

The *SCT* describes human behavior as a dynamic and reciprocal interaction of environment, personal, and behavioral factors (Bandura, 1986). SCT regards learning as an information-processing activity that governs future behaviors (Bandura, 1986). SCT posits that individuals learn about changes in their environment – social or physical – and initiate an evaluation process to gauge the situation, adjusting their actions accordingly to address it. SCT offers substantial benefits for the research community, as it provides a lens through which human behavior in a technology interaction context can be understood and analyzed. The SCT provides a foundation that aligns well with the intricate and dynamic nature of user interactions with digital environments. SCT enables researchers to investigate how users respond to changes in their digital environment and how these responses shape their subsequent behaviors. Such insights are crucial for an extended understanding of the symbiotic relationship between users and technology.

SCT has proven its suitability in understanding social media user behavior (Gan et al., 2023). In contrast, a handful of studies have used SCT as a lens to understand SMD (see Table 2). So, the application of SCT in this context is both warranted and novel. In Table 2, we also highlight the differences between our study and existing studies that utilize SCT in the context of SMD.

### 3.2. *Model and hypotheses*

We used SCT to explain *discontinuation intention* (DI), where online negative WOM and offline negative WOM have been considered as environmental factors that create a sense of privacy invasion and distrust, which is regarded as an individual's evaluation and judgment of environmental factors. Once someone experiences privacy invasion and develops a distrust in the service provider, DI is the most common outcome, depicting a behavioral change in social media use (Gan et al., 2023). Fig. 3 depicts the research model, and the hypotheses are discussed thereafter. In the context of our research, the key concepts are defined and exemplified in Table 3.

#### 3.2.1. *Environmental factors*

According to SCT, individuals are active agents who are influenced by their environment, but in a proactive way (Bandura, 1986). That is,

**Table 2**
Studies applying SCT in SMD.

| Reference | Context | Environmental Factors | Personal Factors |
|---|---|---|---|
| Cao et al. (2020) | Facebook, WeChat | Cyberbullying, social overload | Distress, Exhaustion |
| Fan et al. (2021) | WeChat | Role conflict | Privacy concerns, fatigue |
| Fu et al. (2020) | Facebook | Technology overload, information overload, social overload | Fatigue, dissatisfaction |
| Gan et al. (2023) | WeChat | None | Habit, excessive use, exhaustion, regret |
| Turel (2015) | Facebook | None | Guilt, self-efficacy to discontinue, use addiction |
| The current study | WhatsApp | Online negative word of mouth, offline negative word of mouth | Privacy concerns, distrust |

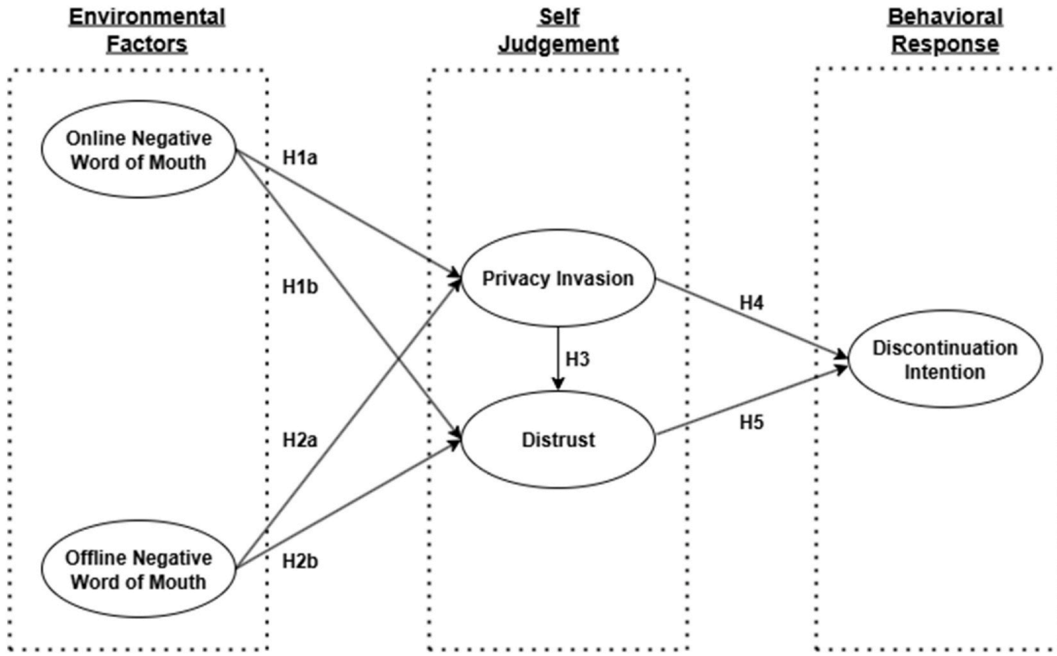



**Fig. 3.** Research model showing the relationship of online negative WOM and offline negative WOM with privacy concerns and SMD intent.

**Table 3**
Key concepts and their definitions.

| Construct | Definition |
|---|---|
| Online Negative WOM | Online negative WOM describes any adverse assertion published online concerning a product or a service (Farooq et al., 2023b). |
| Offline Negative WOM | Offline WOM is face-to-face communication between the information disseminators and receivers. |
| Privacy Invasion | The unease and concern arising from the apprehension of potential misuse of personal data and surveillance of social media activities (Wang, Hu, et al., 2020), also called privacy concerns. |
| Distrust | An individual's lack of confidence or skepticism towards a particular entity, service, or platform |
| Discontinuance Intention | The inclination or intention of users to discontinue or cease using a particular product, service, or platform. |

individuals not only perceive the information from the environment but also evaluate and process it to better understand it and then take the appropriate course of action. In the context of our study, negative online and offline WOM are two sources of information available to social media users and are considered the environmental factors in our model.

Social media platforms enable users to discuss both their positive and negative experiences publicly. It has been observed that businesses have started to respond to users' experiences quickly online (Prasad et al., 2017). Online negative WOM describes any adverse assertion published online concerning a product or a service (Farooq et al., 2023b). For example, negative product reviews or negative experiences shared on X (formerly Twitter), and experts critiquing a service or a product through blog posts. It has been observed that among online WOM, the negative WOM has a broader reach and quicker travel time than the positive WOM. Online negative WOM has been shown to have a larger impact on behavior than other methods of spreading negative messages (King et al., 2014).

As users encounter negative WOM during their online or offline social experiences, they may observe that others perceive WhatsApp's privacy policy updates as an invasion of personal privacy, making them lose their trust in WhatsApp. Users, therefore, learn the possible consequences of the updated privacy policy through online negative WOM and offline negative WOM communicated by others, which drives them to think about the impact of these changes on them. While online negative WOM receives more attention and thinking from a user, the penetration rate and power of online negative WOM make it a faster medium to spread information. Online negative WOM can make consumers more unsure since unfavorable remarks raise users' doubts about technology. Whereas, owing to strong ties, negative offline WOM, the words one hears from family, friends, and peers during daily routine conversations, such as those on WhatsApp, and the change in its privacy policy and the resulting privacy issues can create both a sense of privacy invasion and distrust in WhatsApp. Thus, we hypothesize that.

**H1a**. Online negative WOM positively impacts the sense of privacy invasion.

**H1b**. Online negative WOM positively impacts distrust.

**H2a**. Offline negative WOM positively impacts the sense of privacy invasion.

**H2b**. Offline negative WOM positively impacts distrust.

### 3.2.2. *Self-judgment factors*

The agency of individuals in SCT is manifested in the self-judgment factors. Through these factors, individuals assess their capabilities, feelings, and beliefs in light of the environment's information to regulate their behavior (Bandura, 1986). In the context of our study, as mentioned above, users observe online and offline negative WOM about WhatsApp's updated privacy policy and then critically evaluate the invasion of privacy and distrust, which regulates their behavior regarding whether to continue or discontinue using WhatsApp. Accordingly, we consider privacy invasion and distrust as self-judgment factors.

*Privacy invasion* depicts the unease and concern that arise from the apprehension of potential misuse of personal data and surveillance of social media activities (Wang, Hu, et al., 2020). The role of privacy invasion (also sometimes referred to as privacy concerns) has been acknowledged in several online contexts, including e-commerce (Dinev et al., 2006), health (Xu, 2019), and social media (Yang & Zhang, 2022). As part of their business models, social media platforms collect users' data, share it with third parties, process it, and then use it to attract businesses. This was also highlighted in WhatsApp's updated privacy policy. Users, lacking control or knowledge about the data collected, how it is used, and with whom it is shared, begin to feel that their privacy is being infringed upon and invaded (Dinev et al., 2006). The utilization of personal information by social media platforms can be perceived as a breach of privacy, undermining trust in them. Accordingly, we hypothesize that.

**H3**. Privacy invasion positively impacts distrust.

Social media platforms that gather excessive personal data prompt individuals to adopt protective measures, including disclosing less information (Zlatolas et al., 2015) and seeking alternative applications (Farooq et al., 2023b). Privacy invasion or concerns are found to affect online services negatively (Yang & Zhang, 2022). Accordingly, we hypothesize that.

**H4**. Privacy invasion positively impacts discontinuation intention.

*Distrust (DT) results from prior encounters* or observations that indicate the individual's inability to perform a task or dishonesty in a communication (McKnight et al., 2017). Distrust can significantly impact discontinuation intention by fostering negative perceptions and attitudes towards a product, service, or relationship. Distrust may also lead to a reduced perceived value, increased perceived risks, and heightened feelings of vulnerability (Hermesh et al., 2020). Consequently, the presence of DT leads users to adopt a more cautious and vigilant approach (Benamati et al., 2010), even resulting in leaving or reducing service use (Farooq, Dahabiyeh, & Maier, 2023). Therefore, we hypothesize that.

**H5**. Distrust positively impacts discontinuation intention.

SCT provides a comprehensive framework through which to examine the theoretical relationships posited in the above hypotheses, as SCT underscores the reciprocal nature of human cognition, behavior, and environmental influences. Our study uses SCT to investigate the potential mechanisms that link WOM, privacy concerns, distrust, and discontinuation intentions. Specifically, H1a and H1b propose that online negative WOM positively influences the sense of privacy invasion and distrust. SCT's emphasis on observational learning and cognitive evaluation aligns with these hypotheses, suggesting that exposure to online negative WOM shapes users' perceptions of their privacy being compromised and eroding their trust. H2a and H2b, suggesting the impact of offline negative WOM on the sense of privacy invasion and distrust, align with SCT's emphasis on the role of social cues and cognitive processes. H3, which posits that privacy invasion contributes to increased distrust, resonates with SCT's idea of cognitive processing in response to environmental changes. Moreover, H4 and H5, which propose that privacy invasion and distrust have a positive impact on discontinuation intention, respectively, fit with SCT's model of behavioral adaptation based on cognitive evaluations and perceived outcomes. As such, SCT offers a suitable lens for understanding the interplay of cognitive processes, social influences, and behavioral responses that underscore the relationships investigated in impactful studies in the information systems and HCI domains.

## 4. Methodology

We conducted just-in-time surveys to determine how WhatsApp users responded to changes in privacy policy notices. The "just-in-time" surveys are run soon after an event "to balance the 'freshness' of an event in participants' minds while still allowing enough time for an event to propagate to a broad audience." (Das et al., 2018, p. 18). The procedure adopted for data collection and the measures used in the questionnaire are presented next.

### 4.1. Country selection

The selection of the US, India, and Finland as the focal countries for this study is rooted in the intention to encompass a diverse range of cultural, social, and technological contexts, differing in their level of digital maturity (Thordsen et al., 2020). Each of these countries represents a distinct socio-cultural backdrop that contributes to varying user behaviors and perceptions in online interactions, as well as privacy concerns. Analyzing how users in the US can offer insights that resonate on a global scale, as the cultural diversity within the US population allows for examining how different demographic groups interpret and respond to online negativity and privacy implications. India, a country with a burgeoning digital landscape, a diverse cultural fabric, and a rapid adoption of social media, introduces a unique perspective. Finland, renowned for its advanced technological infrastructure and high digital literacy rates, presents an intriguing context for investigation. With a strong emphasis on privacy rights and data protection, Finnish responses can offer valuable insights into how societies with a robust privacy framework perceive and address privacy invasion issues. By selecting the US, India, and Finland as the study's focal countries, we aim to capture a comprehensive spectrum of cultural, technological, and societal dimensions, thereby contributing valuable insights into technology adoption. Moreover, the three countries also differ culturally, as shown in Fig. 4. We will focus only on power distance, individualism-collectivism, and uncertainty avoidance dimensions, given their proven relationships with privacy behaviors and management (Merhi et al., 2019; Paupini et al., 2022).

### 4.2. Procedure and questionnaire design

Participants from the US and India were engaged through Amazon Mechanical Turk (MTurk), a popular crowdsourcing platform (Paolacci et al., 2010). Finnish participants were recruited through social media announcements and email invitations to mailing lists. We followed the recommended qualification criteria for online participant recruitment (Paolacci et al., 2010).

The participants were recruited in two steps from MTurk. In the first step, participants were asked to identify their most frequently used social media platforms over the past six months. Only those who listed WhatsApp among their top three choices were deemed eligible for the study. In this way, we tackle self-selection bias (Berinsky et al., 2012). The eligible participants were then introduced to survey questions in the second step. Here, we did not disclose that we are studying SMD, but portrayed the study as general social media usage. This approach ensured external validity, minimizing the chance of guessing the actual hypotheses (Chandler et al., 2015). We inquired about their WhatsApp usage patterns, specifically in terms of frequency and duration of use. Following the disclosure of usage patterns, participants were provided with a news article discussing WhatsApp's updated privacy policy and terms, with a screenshot of WhatsApp's official message to the users (see Appendix A). The participants then responded to items measuring environmental factors, self-judgment factors, and discontinuation intention (see the next section for details of the measures). To ensure the data quality, three attention checks were randomly inserted in the survey. This step was taken to mitigate the motivational bias that occurs when workers complete surveys for financial gain. In this way, we did our best to design a study mitigating biases related to MTurk sampling.

Like other researchers, for example, (Difallah et al., 2018, pp. 135–143), we were unable to recruit Finnish WhatsApp users through MTurk. Thus, we recruited Finnish participants via social media announcements and mailing list invitations. The data collection was conducted in March 2021, immediately following WhatsApp's announcement of the change in terms of use, ensuring that all participants received the same level of stimuli across three countries.

Three experts, including two assistant professors and one postdoctoral researcher, examined the questionnaire before its deployment. These experts possessed expertise in information sciences and useable security, as well as experience in conducting such studies. A pretest of the questionnaire was conducted on 15 Finnish university students.

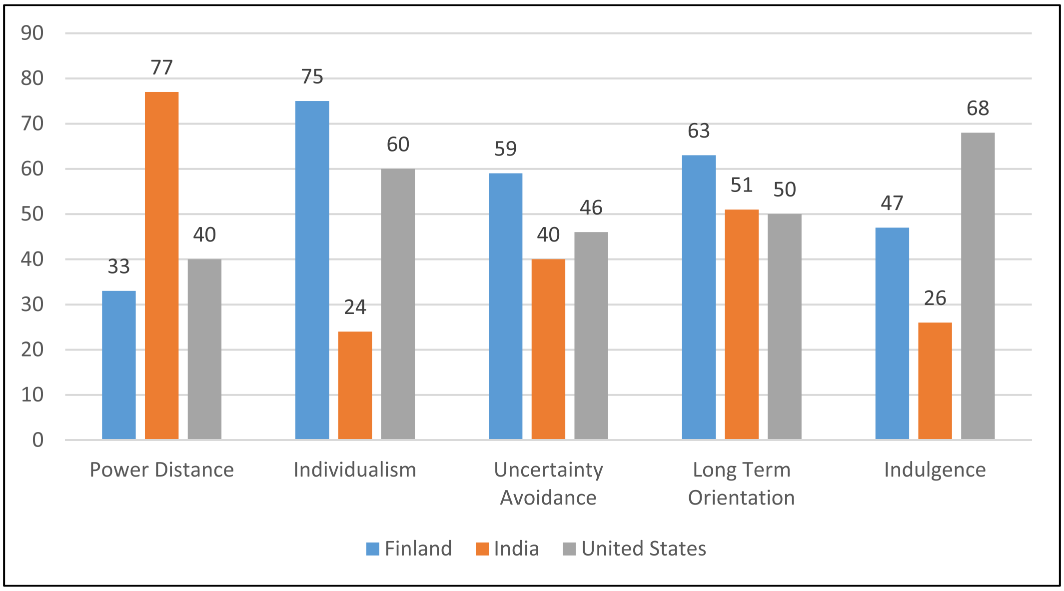



**Fig. 4.** Cultural differences among Finland, India, and the US, based on Hofstedt's cultural dimension scores (source: theculturefactor.com).

### *4.3. Measures*

To ensure the construct's reliability and validity, we utilized items from existing work that measured constructs relevant to the study. All constructs were measured using a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). The constructs, Online WOM (Prasad et al., 2017) and distrust (McKnight et al., 2017), were measured using four items each, whereas offline WOM (Chen et al., 2018), privacy invasion (Ayyagari et al., 2011), and discontinuation intention (Tang & Chen, 2020) were measured using three items each. For items' descriptions, see Table B1 in Appendix B.

## **5. Analysis and results**

Before analysis, we removed responses from participants who could not pass the attention checks or completed the survey too quickly (a completion time of 10–15 min was estimated during pilot testing). Ultimately, we had 785 respondents from three countries (n = 309 for US, n = 271 for India, and n = 205 for Finland). Table 4 shows the sample characteristics and WhatsApp usage patterns of the respondents.

To validate the model and test the hypotheses, the current study used partial least squares structural equation modeling (PLS-SEM) in SmartPLS 3.3 software (Hair et al., 2016). Partial least squares–structural equation modelling (PLS-SEM) is widely used for assessing complex pathway models involving latent variables (Hair et al., 2016). In assessing the complex pathways, first, the reliability and validity of the constructs are assessed. This step is referred to as measurement model testing. Once the reliability and validity of the constructs are established, the relationship is evaluated using the PLS algorithm, while the significance is tested through bootstrapping (Hair et al., 2016). This step is referred to as structural model testing. We tested both measurement and structural models individually for each country, Finland, India, and the US, to determine if a single model could explain and forecast SMD intent.

Since we aimed to compare and contrast social media users from Finland, India, and the US, we employed *PLS-multi-group analysis* (PLS-MGA), a procedure suggested by Henseler et al. (2009). In this approach, group-specific bootstrap estimates for each group/sample are compared, and the significance (p-value for a two-tailed test) of path coefficients is assessed, along with the difference between them. If the *p*-values (at 5 % level) are below 0.05 or above 0.95, the difference is considered significant. This group comparison approach is suitable when there are unequal sample sizes, as in our case (Hair Jr et al., 2017). Several researchers have used this approach to understand group differences while studying technology adoption and cybersecurity behaviors, for example, (Ameen et al., 2021; Zefreh et al., 2023). We assessed the group differences in pairs (Finland vs. India, Finland vs. the US, and India vs. the US) as SmartPLS does not allow multi-group comparison among three groups. In addition, we also ran a permutation-based measurement invariance (MICOM) analysis to ensure our groups (Finland, India, USA) are comparable (Henseler et al., 2016). MICOM is a three-step process that checks for configural invariance, compositional invariance, and equality of composite mean values and variances. Configural Invariance (*Step 1)* was confirmed as we used the same indicators across three countries to measure constructs, and the data were analyzed using the same algorithms (see Table B1 and Table 5). *In Step 2*, the original permutation correlation was compared with the 5 % quantile and found to be equal or greater (See Appendix C). Thus, compositional invariance was achieved. Finally, *Step 3* was performed to check the equality of composite means (Step 3a) and equality of composite variances (Step 3b). The results are in Appendix C. In some cases, we had partial invariance; however, as noted in (Henseler et al., 2016), it is permissible to run MGA with some caution where full invariance is not established.

**Table 4**
Sample characteristics and WhatsApp usage patterns.

| Variable | Finland (n = 205) | India (n = 271) | US (n = 309) |
|---|---|---|---|
| *Gender* | | | |
| Male | 53.2 % | 67.9 % | 63.4 % |
| Female | 43.4 % | 31.7 % | 36.6 % |
| I prefer not to tell | 3.4 % | 0.4 % | 0 % |
| *Age* | | | |
| Min - Max | 18–71 | 21–63 | 18–65 |
| Mean (SD) | 32.11 (10.30) | 31.73 (6.29) | 38.12 (10.03) |
| *Usage Frequency per day* | | | |
| Never | 0 % | 2.6 % | 1.3 % |
| Seldom | 10.7 % | 9.6 % | 13.6 % |
| Sometimes | 24.4 % | 25.1 % | 35 % |
| Often | 64.9 % | 62.7 % | 50.2 % |
| *Usage Experience* | | | |
| <1 year | 0 % | 0 % | 3.2 % |
| 1–2 years | 4.4 % | 4.1 % | 11.3 % |
| 2–3 years | 4.4 % | 20.3 % | 13.6 % |
| 3–4 years | 4.9 % | 20.3 % | 18.1 % |
| 4–5 years | 17.1 % | 23.2 % | 17.2 % |
| >5 years | 69.3 % | 32.1 % | 36.6 % |

**Table 5**
Composite reliability (CR) and average variance extracted (AVE) show the constructs' reliability and convergent validity.

| Constructs | India | | Finland | | US | |
|---|---|---|---|---|---|---|
| | CR | AVE | CR | AVE | CR | AVE |
| Discontinuation Intention (DI) | 0.92 | 0.85 | 0.95 | 0.91 | 0.91 | 0.83 |
| Distrust (DT) | 0.88 | 0.64 | 0.91 | 0.73 | 0.88 | 0.65 |
| Online negative WOM | 0.86 | 0.62 | 0.91 | 0.72 | 0.90 | 0.69 |
| Offline negative WOM | 0.88 | 0.79 | 0.89 | 0.81 | 0.90 | 0.82 |
| Privacy Invasion (PI) | 0.84 | 0.64 | 0.92 | 0.81 | 0.86 | 0.67 |

Note that partial invariance, due to the lack of equality of means and variances, is sufficient to compare the coefficients of the structural model across groups [120].

### 5.1. Measurement model testing results

Before testing the measurement model, we tested the data for all three countries for multicollinearity and common method bias (CMB) issues (Kock, 2015). All external and internal variance inflation factor (VIF) values were lower than 5 and 3.3, respectively, indicating the absence of multicollinearity and CMB, except for one item of DI in the Finnish sample, which had a VIF higher than 5. This item was removed from all three samples for further analysis.

The convergent validity in three groups was tested by examining the Item loadings and average variance extracted (AVE). In all three groups, item loadings were 0.7, except for one item (NO1) from offline negative WOM in the Finnish sample. This item was dropped from all samples during further analysis. The AVE for all constructs in the three groups was above 0.5. Internal consistency was assessed with composite reliability (CR), which was 0.7 or higher in all three groups. Table 5 shows the CR and AV for all the samples. Discriminant validity was assessed using the Fornell-Larker criterion and found to be at an acceptable level for all three groups (Hair et al., 2016). Detailed measurement model statistics are provided in Appendix B.

### 5.2. Structural model testing results

We tested the model in each country to determine whether a single model can be used to explain discontinuation intention across the three countries. The results are shown in Table 6 and Fig. 5 and are summarized below for all three samples.

For the US sample, four out of seven hypotheses were supported: H1a: online negative WOM - > PI ($\beta = 0.45$, $p < 0.001$), H1b: online negative WOM - > DT ($\beta = 0.29$, $p < 0.001$), H3: PI - > DT ($\beta = 0.77$, $p < 0.001$), H5: DT - > DI ($\beta = 0.38$, $p < 0.001$).

In the Indian sample, three out of seven hypotheses were supported: H1a: negative online WOM - > PI ($\beta = 0.48$, $p < 0.001$), H3: PI - > DT ($\beta = 0.72$, $p < 0.001$), and H5: DT - > DI ($\beta = 0.29$, $p = 0.002$).

For the Finnish sample, out of seven hypotheses, four are supported: H2b: offline negative WOM - > DT ($\beta = 0.13$, $p = 0.004$), H3: PI - > DT ($\beta = 0.79$, $p < 0.001$), H4: PI - > DI ($\beta = 0.40$, $p < 0.001$) and H5: DT - > DI ($\beta = 0.30$, $p = 0.001$). The other three were not supported because the p-values were higher than 0.05.

Two relationships- Privacy invasion impacting distrust and distrust impacting discontinuation intent- were found significant in all three samples.

In terms of variance, the results indicate that the combined model can explain 18 % ($R^2 = 0.18$) of the variance in discontinuation intention, 21 % ($R^2 = 0.21$) in privacy invasion, and 67 % ($R^2 = 0.67$) in distrust. In the US sample, the model explains 16 % of the variance ($R^2 = 0.16$) in discontinuation intention, 32 % ($R^2 = 0.32$) in privacy invasion, and 66 % ($R^2 = 0.66$) in distrust. In the Indian sample, the model explains 15 % of the variance ($R^2 = 0.15$) in discontinuation intention, 32 % ($R^2 = 0.32$) in privacy invasion, and 68 % ($R^2 = 0.68$) in distrust. In the Finnish sample, the model explains 48 % of the variance ($R^2 = 0.48$) in discontinuation intention, 6 % ($R^2 = 0.05$) in privacy invasion, and 70 % ($R^2 = 0.70$) in distrust. Our model explains considerable portions of the constructs investigated, most notably Distrust, Privacy invasion, and Discontinuation intention, to a lesser extent.

### 5.3. Multi-group analysis results

The PLS-MGA shows differences in the path significance across the US, Indian, and Finnish samples (Table 7). For the hypothesis explaining the relationship between online negative WOM and privacy invasion ($H_{1a}$), significant differences were found between Finland and India ($p < 0.01$) and between Finland and the US ($p = 0.01$).

For $H_{1b}$ (relationship between online negative WOM and distrust), no significant difference was found between Finland and India ($p = 0.75$); however, significant differences were found between Finland and the US ($p < 0.01$), India and the US ($p = 0.02$).

No significant differences between differences of path coefficients were found across three samples for the effect of offline negative WOM on privacy invasions ($H_{2b}$).

However, like $H_{1b}$, no significant difference was found between Finland and India ($p = 0.47$); however, significant differences were found between Finland and the US ($p < 0.01$), India and the US ($p = 0.04$).

For $H_3$ (the relationship between privacy invasion and distrust), the path coefficient did not differ significantly between Finland and India ($p = 0.24$) or India and the US ($p = 0.42$); however, significant differences were found in the path coefficients of Finland and the US ($p < 0.01$).

For $H_4$ (the relationship between privacy invasion and discontinuation intention), significant differences in path coefficients were found between Finland and India ($p < 0.01$) and between Finland and the US ($p > 0.01$). Still, no such difference was found between India and the US ($p = 0.94$).

Lastly, for the relationship between distrust and discontinuation intention ($H_5$), no significant differences in path coefficients were found across the three countries.

**Table 6**
Structural model results across three samples. Significant results are bolded.

| Relationship | Finland | | | India | | | United States | | |
|---|---|---|---|---|---|---|---|---|---|
| | β | t | p | β | t | p | β | t | p |
| H1a: Online Negative WOM - > PI | 0.12 | 1.251 | 0.21 | **0.48** | **5.814** | **<0.001** | **0.45** | **5.031** | **<0.001** |
| H1b: Online Negative WOM - > DT | 0.04 | 0.983 | 0.32 | 0.07 | 1.047 | 0.29 | **0.29** | **4.128** | **<0.001** |
| H2a: Offline Negative WOM - > PI | 0.15 | 1.858 | 0.06 | 0.12 | 1.427 | 0.15 | 0.14 | 1.594 | 0.11 |
| H2b: Offline Negative WOM - > DT | **0.13** | **2.891** | **0.004** | 0.08 | 1.455 | 0.14 | −0.09 | 1.434 | 0.15 |
| H3: PI - > DT | **0.79** | **23.13** | **<0.001** | **0.72** | **16.34** | **<0.001** | **0.67** | **13.78** | **<0.001** |
| H4: PI - > DI | **0.40** | **4.116** | **<0.001** | 0.01 | 0.158 | 0.87 | 0.02 | 0.243 | 0.81 |
| H5: DT - > DI | **0.30** | **3.304** | **0.001** | **0.29** | **3.118** | **0.002** | **0.38** | **4.375** | **<0.001** |

Note: PI: Privacy invasion, DT: Distrust, DI = Discontinuation Intention.

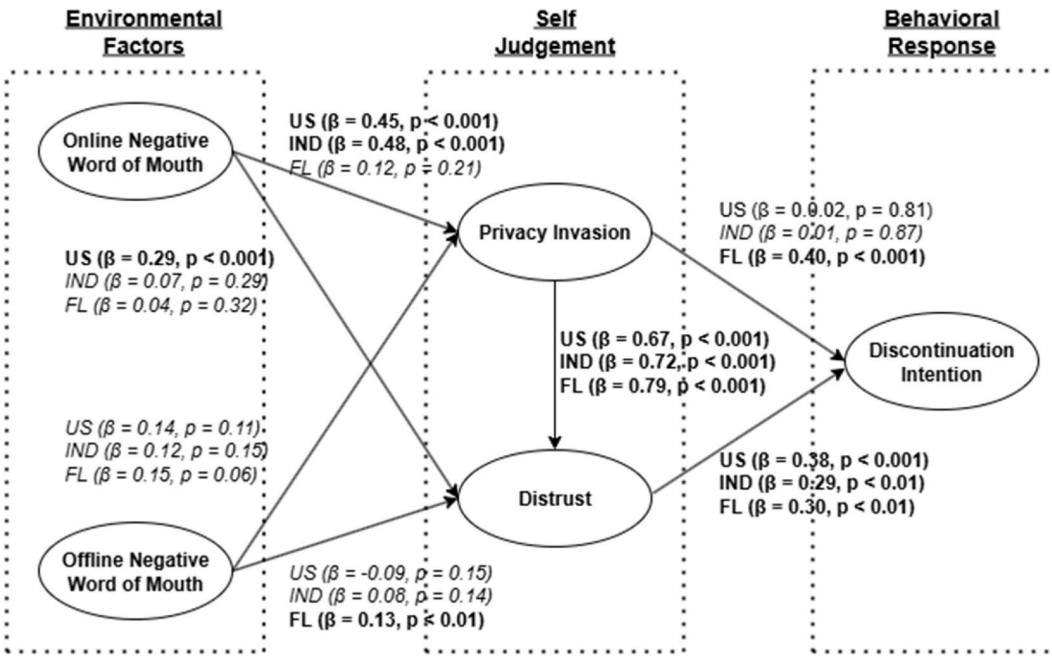



**Fig. 5.** The structural model results. Significant relationships are shown in bold whereas non-significant relationships are shown in italic.

**Table 7**
Multi-group analysis highlighting differences across three countries. Significant differences are bolded.

| Relationships | Finland vs. India | | Finland vs. US | | India vs. US | |
|---|---|---|---|---|---|---|
| | b | p | b | p | b | p |
| H1a: Online Negative WOM - > PI | **−0.36** | **<0.01** | **−0.33** | **0.01** | 0.03 | 0.78 |
| H1b: Online Negative WOM - > DT | −0.02 | 0.75 | **−0.24** | **<0.01** | **−0.22** | **0.02** |
| H2a: Offline Negative WOM - > PI | 0.02 | 0.83 | 0.01 | 0.97 | −0.02 | 0.87 |
| H2b: Offline Negative WOM - > DT | 0.05 | 0.47 | **0.22** | **<0.01** | **0.17** | **0.04** |
| H3: PI - > DT | 0.06 | 0.24 | **0.11** | **<0.05** | 0.05 | 0.42 |
| H4: PI - > DI | **0.38** | **<0.01** | **0.37** | **<0.01** | −0.01 | 0.94 |
| H5: DT - > DI | 0.01 | 0.90 | −0.07 | 0.561 | −0.09 | 0.48 |

Note: PI = Privacy Invasion, DT = Distrust, DI = Discontinuation Intention.

## 6. Discussion

The findings of this study provide insights into how online and offline negative WOM, privacy invasion, distrust, and SMD intention interact across three culturally distinct countries: the US, India, and Finland. Our results reveal that users from the three examined countries do not react to online and offline WOM in the same manner and that there are differences in social media users' discontinuation intention in the US, India, and Finland.

### 6.1. Key findings

The research examination of three culturally diverse countries enriches the community's understanding of how interactions online and offline, negative WOM, privacy invasion, distrust, and SMD intentions manifest across different societies. The results show both commonalities and differences in how negative WOM impacts privacy and trust perceptions, and the discontinuation intention across three countries.

*First*, the consistent support of H3 and H5 across all three countries suggests that privacy invasion universally fosters distrust, which in turn raises users' intention to discontinue social media use. This is consistent with existing literature (Farooq et al., 2023a). Our results contribute to this literature by demonstrating that, regardless of the location of social media users, privacy concerns are real and a persistent issue in users' eyes, and that privacy invasion erodes trust in institutions (Smith et al., 2011). Furthermore, the significant relationship of distrust and discontinuation intention highlights distrust as an important antecedent of discontinuation intention, corroborating previous studies in the social media context (Farooq et al., 2023a). This insight resonates deeply within the HCI community, emphasizing the importance of designing user-centered platforms that prioritize privacy and security to mitigate distrust and foster positive user experiences.

*Second,* the differential support for hypotheses related to negative WOM reflects cultural nuances, technology maturity, and regulatory protection perceptions. Online negative WOM about a social media platform significantly impacted distrust in the US rather than in Finland and India. However, this factor significantly impacted privacy invasion in the US and India, but not in Finland. This suggests that Finnish users were not swayed by the negative feedback and opinions others are sharing online regarding the privacy policies of social media platforms. In other words, the negative remarks about WhatsApp's updated privacy policy did not create distrust in Finnish WhatsApp users or even cause them to consider the changes as an invasion of their privacy. On the contrary, users from the US and India were more influenced by what was being disseminated online. The change in the privacy policy made them unhappy, and they perceived it as an invasion of their privacy. These differences may be because of several reasons. For example, the presence of the *General Data Privacy Regulation* (GDPR) in Europe empowers social media users in Europe to opt out of the updated policy without compromising their use of the application, reducing privacy concerns. However, any privacy-violating action by service providers still creates distrust among the users. The absence of a GDPR-like regulatory mechanism for US or Indian users, who must accept the updated policy to continue using the application, would likely exacerbate their concerns about privacy invasion. Furthermore, the cultural differences between the countries, as outlined by Hofstede's dimensions (Hofstede et al., 2010), can help explain these results. Finland, scoring the highest (across the three countries) in individualism (TheCultureFactor, 2025), reflects a society with loosely knit social ties. Individuals are expected to make their decisions autonomously and not rely much on others' opinions. Unlike collectivistic countries, people in individualist societies do not feel the need to belong to a larger community. Therefore, their decisions are influenced more by the 'self' rather than what others are saying. Accordingly, users in Finland might not have felt influenced by the online negative WOM of WhatsApp's updated privacy policy. While this matter requires further investigation in future research, it highlights the potential for regulatory policies and culture to influence user behavior at both the individual and system levels.

Interestingly, offline negative WOM did not significantly impact distrust or privacy invasion in all three countries, although offline negative WOM significantly influenced distrust in Finland. The negative feedback from friends and family delivered through offline channels (e.g., face-to-face, over the phone) did not matter for Indian and American WhatsApp users, nor did it create privacy concerns or distrust. Prior literature has revealed that one's close network has a strong influence on one's attitude and decisions (Dahabiyeh et al., 2020; Shen et al., 2013). Our findings do not necessarily contradict those of previous studies; however, a plausible reason for this finding is that in our digital society, offline communication has been significantly reduced. Therefore, the low frequency of offline communication may be the reason behind the lack of impact of offline negative WOM. In addition, unlike online negative WOM, which is persistent and has a digital trace, offline negative WOM is transient and susceptible to forgetfulness. Still, the significant impact of offline negative WOM on distrust in Finland reveals the influence of one's close network (e.g., family, friends) (Arpaci, 2016; Dahabiyeh et al., 2020; Shen et al., 2013). In high individualistic societies, such as Finland, people may not have a large social network; however, they tend to invest in a few strong relationships. Accordingly, the credibility of these sources and the strong bond with them lead Finnish users to take their negative opinions seriously, resulting in the formation of distrust.

Accordingly, changes in the privacy policies that grant more control to application providers than users can make users unhappy with the application and increase their dissatisfaction. This is alarming because our results further reveal that the impact of distrust on discontinuous intention is significant across the three countries. While previous studies (see (Farooq et al., 2023a) identified several individual drivers for SMD, our study identifies distrust as another individual factor that could result in discontinuation. Our findings reveal that when considering the US, India, and Finland, distrust has a universal impact and hence can be seen as a strong driving factor for discontinuing social media use. While distrust has a similar impact on discontinuation across the three countries, privacy invasion did not have the same influence on discontinuation intentions.

*Third,* we demonstrate that privacy invasion has a significant impact on discontinuation intention in Finland only. This might be due to differing privacy requirements and regulations in each country, where the presence of privacy legislation can make individuals more information sensitive and hence place more value on their information (Markos et al., 2017). The enactment of a comprehensive and strict privacy regulation in Europe (GDPR) reflects the importance the EU gives to privacy. A prior study revealed that Europeans value their privacy more than Americans (Prince & Wallsten, 2022). Another report showed that EU countries are ranked the best in data privacy protection. At the same time, India, which lacks a comprehensive dedicated data privacy regulation, ranked at the bottom of the list (Mash, 2022). Moreover, nearly 75 % of Finns are aware of data access rights guaranteed by the GDPR (Petrosyan, 2024). Therefore, the strength of privacy laws in Europe, combined with knowledge of these laws, led Finnish users to perceive incidents of privacy invasion negatively, which could lead them to abandon the application.

### 6.2. *Practical implications*

Our research offers practical implications with a direct impact on researchers and practitioners.

**Country-Specific Discontinuation Intentions**: It is apparent that there are different pathways to SMD intentions across countries. Accordingly, a universal one-size-fits-all strategy to discourage discontinuation is likely to be ineffective. Social media platforms must adjust their strategy to align with each country's most influential factors, implying nuanced country-specific approaches. For example, the presence of a strong regulatory framework in Finland seems to reduce the impact of negative WOM. Accordingly, social media providers should be mindful of this and recognize that complaints and negative feedback will have a stronger negative impact on the use of their services in countries with less mature regulations, such as the US and India, in our context. Swift measures should be taken to rectify any bad news in such countries.

**Country-Specific Platform Design Recommendations**: Our findings suggest several user interface adaptations as well as localized transparency policies aligned with each country's regulatory and cultural context. For instance, in the United States, WhatsApp offers fine-grained privacy controls that allow users to selectively manage visibility, content sharing, and data usage. Similarly, consent transparency dashboards can be implemented, showing, in plain language, how and where data is being used, with real-time options to opt in or opt out. Additionally, there should be regulatory alignment to ensure compliance with sector-specific U.S. privacy laws while using design cues (e.g., color-coded alerts) to prompt informed user decisions. For India, WhatsApp can offer multilingual onboarding to support major regional languages, along with localized terminology, to enhance inclusivity and comprehension. Additionally, localized awareness nudges can be used with culturally relevant examples in prompts and reminders to encourage informed privacy choices. For Finland, WhatsApp can adopt minimalist, non-intrusive notification patterns in line with user preferences for unobtrusive digital experiences. Similarly, privacy defaults can be employed, such as pre-set high-privacy configurations, which allow users to adjust settings as desired, reflecting local expectations for strong data protection. Additionally, building on Finland's high trust in institutions, concise and user-friendly explanations of content recommendations and personalization logic can be provided.

**Online Negative WOM ≫ Offline Negative WOM**: Notably, users are more influenced by online negative WOM than offline negative WOM (Goodrich & De Mooij, 2014) in this context, aligning with prior research in other areas. The online environment facilitates the spread of information; social media platforms must contain negative feedback and experiences shared online before they cause damage. However, this finding may be biased because we focus on social media. So, this would need to be investigated further.

**Distrust drives Discontinuation**: Distrust is a salient driver of discontinuation intention in all three countries, indicating a commonality. Social media providers should, therefore, be cautious of any policy change that could result in inciting distrust and instead strive to consistently meet users' privacy expectations. Users' perception of whether social media platforms' privacy policies invade their privacy varies across countries and is influenced by the country's data protection regulations. Users in countries with strict privacy requirements place a high value on their privacy; therefore, violating their privacy expectations can result in discontinuation of the application's use. This does not mean that users in countries with minimal privacy regulations do not care about their privacy. Instead, privacy invasion can lead to distrust in the provider, which can translate into discontinuation. Accordingly, social media platforms must be aware of each country's privacy regulations and their implications, pointing to the need for country-specific policies.

Overall, the multi-country analysis presented in this study provides a comprehensive view of the nuanced relationships among negative WOM, privacy concerns, and SMD intention. The divergent effects of online negative WOM and offline negative WOM on privacy invasion and distrust emphasize the need for culturally sensitive design approaches in this area of technology adoption. Results suggest that a one-size-fits-all approach to addressing user concerns may not be effective. Instead, tailoring design interventions to each country's unique user attitudes, cultural norms, and privacy regulations is imperative. The observed variations in users' discontinuation intentions among the three countries highlight the complex factors influencing user decisions to remain or disengage from social media platforms.

However, as distrust emerged as a consistent outcome of privacy invasions across all examined countries, it becomes a pivotal target for interventions aimed at retaining social media users. This research offers valuable insights for social media providers, highlighting the importance of establishing user trust and strengthening privacy safeguards.

### *6.3. Limitations*

Despite the comprehensiveness of the study, several limitations should be considered when interpreting the findings. *First,* the study relied on self-reported data, which may have been influenced by social desirability bias, potentially affecting responses. *Second,* the cross-sectional design did not account for the actual discontinuation of the respondent. *Third,* the treatment of WOM was largely quantitative and restricted by design. Future qualitative studies may investigate the impact of WOM through qualitative inquiry to see its impact on affective or emotional state (Saleem et al., 2021). *Fourth,* we only considered WhatsApp, an instant messaging service, in this study. Facebook or Instagram contains much more information than just messages. It may thus induce a higher level of perceived privacy invasion and distrust under the scenario in which this study was conducted. Therefore, the findings of this study may be prudently applied beyond instant messaging applications. Nonetheless, we reiterate that using WhatsApp as a case study provided us with a rare opportunity to study privacy concerns and their implications in the wild, rather than in a laboratory setting. *Fifth,* although we have tried to justify the findings of the study, future studies may consider employing the cultural typology developed by (Triandis & Gelfand, 1998) to better understand differences within individualistic and collective societies. *Sixth,* we operationalized discontinuation intention in terms of abandonment without considering specific discontinuation type, as suggested by (Altrichter & Benoit, 2025). Future studies may consider discontinuation type while operationalizing the outcome variable.

## 7. Conclusion

This study examined the effect of negative online and offline word of mouth on privacy attitudes and SMD intentions among WhatsApp users from three geographically and culturally distinct countries. Our research model was based on the social cognitive theory, where word of mouth was an environmental factor, privacy invasion and distrust were individual judgment factors, and WhatsApp discontinuation intention was the behavioral response. The perception of privacy invasion increased only due to negative electronic word of mouth in India and the US, without affecting the distrust. On the other hand, negative offline word of mouth only increased distrust in Finland, with no effect on feelings of privacy invasion in any of the three countries. The relationship linking privacy invasion and discontinuation intent was mediated by distrust in all three countries. This research highlights distrust as a driver of SMD. Findings from this research advance the technology adoption field by unraveling the intricate relationships between negative word of mouth, privacy concerns, distrust, and discontinuation intent within a cross-cultural framework, ultimately guiding the way toward more user-centric and culturally aware privacy design strategies for social media platforms.

## CRediT authorship contribution statement

**Ali Farooq:** Writing – review & editing, Writing – original draft, Visualization, Project administration, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Joni Salminen:** Writing – review & editing, Writing – original draft. **Laila Dahabiyeh:** Writing – review & editing, Writing – original draft, Resources, Investigation. **Yousra Javed:** Writing – review & editing, Writing – original draft, Resources, Data curation. **Bernard J. Jansen:** Writing – review & editing, Writing – original draft, Visualization, Supervision.

## Declaration of generative AI and AI-assisted technologies in the Writing process

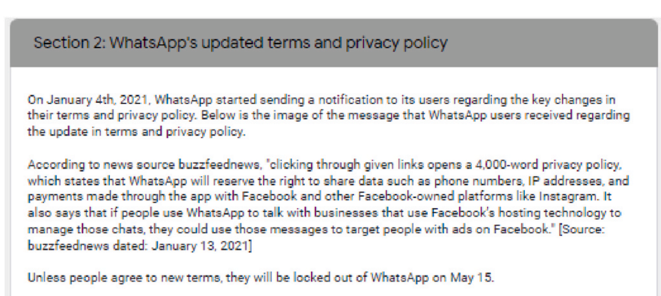
During the preparation of this work, the author(s) used Grammarly to check language-related issues. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## APPENDIX

*Appendix A: Screenshot of a media news item and WhatsApp's notification about key changes in its updated terms and privacy policy*



Section 2: WhatsApp's updated terms and privacy policy

On January 4th, 2021, WhatsApp started sending a notification to its users regarding the key changes in their terms and privacy policy. Below is the image of the message that WhatsApp users received regarding the update in terms and privacy policy.

According to news source buzzfeednews, "clicking through given links opens a 4,000-word privacy policy, which states that WhatsApp will reserve the right to share data such as phone numbers, IP addresses, and payments made through the app with Facebook and other Facebook-owned platforms like Instagram. It also says that if people use WhatsApp to talk with businesses that use Facebook's hosting technology to manage those chats, they could use those messages to target people with ads on Facebook." [Source: buzzfeednews dated: January 13, 2021]

Unless people agree to new terms, they will be locked out of WhatsApp on May 15.

**Fig. A1.** Media news item

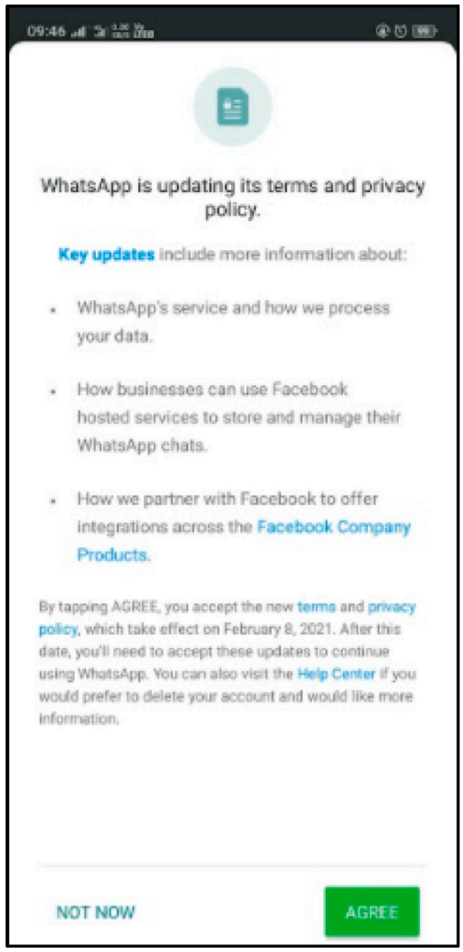



**Fig. A2.** WhatsApp explanation sent to every WhatsApp user through the App

## Appendix B. Measurement items, additional statistics related to measurement model testing

**Table B1**
Constructs, item descriptions and their loadings showing internal reliability

| Constructs and Items | Item loadings | | | |
|---|---|---|---|---|
| | Combined | India | Finland | USA |
| **Discontinuation Intention** (Tang & Chen, 2020) | | | | |
| *DI1-I will discontinue using WhatsApp* | *0.91* | *0.88* | *0.96* | *0.89* |
| DI2-I would stop using WhatsApp | 0.93 | 0.92 | 0.93 | 0.89 |
| DI3-I plan to stop using WhatsApp | 0.91 | 0.91 | 0.95 | 0.89 |
| **Distrust** (McKnight et al., 2017) | | | | |
| DT1-I am not sure if WhatsApp would act in my best interest after a change in the privacy policy | 0.80 | 0.79 | 0.86 | 0.76 |
| DT2-I suspect that WhatsApp is just interested in its own benefit and not in my well-being | 0.81 | 0.77 | 0.84 | 0.83 |
| DT3-I am worried about whether WhatsApp would be truthful in dealing with my data after the implementation of the new policy | 0.84 | 0.83 | 0.88 | 0.82 |
| DT4-It is uncertain whether WhatsApp/Facebook would keep its commitment of safeguarding my privacy | 0.83 | 0.82 | 0.84 | 0.81 |
| **Online Negative Word of Mouth** (Prasad et al., 2017) | | | | |
| NE1-Many people are talking badly about the new WhatsApp privacy policy online | 0.84 | 0.77 | 0.89 | 0.84 |
| NE2-On social media, there is unrest among WhatsApp users due to changes in their privacy policy | 0.81 | 0.74 | 0.84 | 0.81 |
| NE3-People are giving negative remarks online regarding WhatsApp new privacy policy | 0.83 | 0.82 | 0.80 | 0.84 |
| NE4-People online are critical of WhatsApp's new privacy policy | 0.83 | 0.81 | 0.84 | 0.83 |
| **Offline Negative Word of Mouth** (Chen et al., 2018) | | | | |
| *NO1-My friends and/or relatives warn me not to use WhatsApp due to the change in their terms and privacy policy* | *0.80* | *0.86* | *0.50* | *0.85* |
| NO2-My friends and/or relatives complain about the privacy implications of using WhatsApp | 0.87 | 0.85 | 0.85 | 0.87 |
| NO3-My friends and/or relatives are talking negatively about the new WhatsApp policy | 0.88 | 0.87 | 0.92 | 0.87 |
| **Privacy Invasion** (Ayyagari et al., 2011) | | | | |
| PI1-I feel uncomfortable that my use of WhatsApp can be easily monitored | 0.84 | 0.80 | 0.89 | 0.83 |
| PI2-I feel my privacy can be compromised because of sharing my WhatsApp data with Facebook | 0.81 | 0.76 | 0.91 | 0.76 |
| PI3-I feel that my communication and other personal information from WhatsApp can be misused by Facebook | 0.86 | 0.84 | 0.89 | 0.86 |

**Note:** NO1 was removed due to <0.7 loadings in Finnish sample.

**Table B2**
Discriminant validity using Fornell-Larcker criteria

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| ***Country: India*** | | | | | |
| 1. Discontinuation Intention | **0.90** | | | | |
| 2. Distrust | 0.31 | **0.80** | | | |
| 3. Online Negative Word of Mouth | 0.20 | 0.54 | **0.79** | | |
| 4. Offline Negative Word of Mouth | 0.31 | 0.49 | 0.74 | **0.89** | |
| 5. Privacy Invasion | 0.23 | 0.75 | 0.58 | 0.49 | **0.80** |
| ***Country: Finland*** | | | | | |
| 1. Discontinuation Intention | **0.96** | | | | |
| 2. Distrust | 0.63 | **0.86** | | | |
| 3. Online Negative Word of Mouth | 0.32 | 0.28 | **0.84** | | |
| 4. Offline Negative Word of Mouth | 0.45 | 0.32 | 0.57 | **0.90** | |
| 5. Privacy Invasion | 0.65 | 0.80 | 0.20 | 0.21 | **0.90** |
| ***Country: USA*** | | | | | |
| 1. Discontinuation Intention | **0.91** | | | | |
| 2. Distrust | 0.39 | **0.81** | | | |
| 3. Online Negative Word of Mouth | 0.30 | 0.60 | **0.83** | | |
| 4. Offline Negative Word of Mouth | 0.28 | 0.47 | 0.77 | **0.90** | |
| 5. Privacy Invasion | 0.31 | 0.78 | 0.56 | 0.49 | **0.82** |

Note: The bold values in the diagonal show the square root of AVEs of the given construct.

**Table B3**
Variance inflation factor (VIF) for combined and individual samples showing lack of multicollinearity and common method bias

| Constructs and Items | Variance Inflation Factor | | | | Constructs & Items | Variance Inflation Factor | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Combined | India | Finland | USA | | Combined | India | Finland | USA |
| Discontinuation Intention | | | | | Offline Negative Word of Mouth | | | | |
| DI1 | 2.562 | 2.068 | 5.240 | 2.289 | NO1 | 1.645 | 1.883 | 1.185 | 1.823 |
| DI2 | 2.635 | 2.068 | 3.245 | 2.183 | NO2 | 1.996 | 1.845 | 1.868 | 1.967 |
| DI3 | 2.823 | 2.786 | 3.170 | 2.365 | NO3 | 1.832 | 1.820 | 1.692 | 1.960 |
| Distrust | | | | | Privacy Invasion | | | | |
| DT1 | 1.737 | 1.629 | 2.483 | 1.601 | PI1 | 1.662 | 1.426 | 2.496 | 1.551 |
| DT2 | 1.787 | 1.577 | 2.280 | 1.896 | PI2 | 1.617 | 1.369 | 2.880 | 1.416 |
| DT3 | 1.930 | 1.786 | 2.568 | 1.808 | PI3 | 1.758 | 1.503 | 2.368 | 1.712 |
| DT4 | 1.905 | 1.879 | 2.311 | 1.817 | | | | | |
| Online Negative Word of Mouth | | | | | | | | | |
| NE1 | 2.132 | 1.648 | 2.813 | 2.134 | | | | | |
| NE2 | 1.798 | 1.531 | 1.908 | 1.866 | | | | | |
| NE3 | 2.023 | 1.755 | 2.025 | 2.084 | | | | | |
| NE4 | 1.851 | 1.736 | 2.119 | 1.921 | | | | | |

Note: DI3 was removed due to >5 VIF in Finland.

## Appendix C

Findings of Permutation-Based Invariance Testing

| Finland VS. India | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Construct | Step 1 | Step 2 | | | Step 3a | | | Step 3b | | | Invariance |
| | Configural Invariance | Original Correlation | 5 % quantile | Compositional Invariance | Mean Diff. | Confidence Intervals (Mean) | Equal Mean | Variance Difference | Confidence Intervals (Variance) | Equal Variance | |
| DI | Yes | 1 | 0.999 | Yes | 0.031 | [-0.183, 0.183] | Yes | −0.338 | [-0.172, 0.172] | No | Partial |
| DT | Yes | 1 | 0.999 | Yes | 0.099 | [-0.184, 0.187] | Yes | 0.276 | [-0.311, 0.281] | Yes | Full |
| Online NWM | Yes | 0.996 | 0.995 | Yes | −0.600 | [-0.182, 0.184] | No | 0.337 | [-0.300, 0.301] | No | Partial |
| Offline NWM | Yes | 0.999 | 0.994 | Yes | −0.630 | [-0.185, 0.183] | No | 0.102 | [-0.252, 0.237] | Yes | Partial |
| PI | Yes | 0.999 | 0.997 | Yes | −0.006 | [-0.182, 0.181] | Yes | 0.495 | [-0.289, 0.268] | No | Partial |
| Finland VS. USA | | | | | | | | | | | |
| Construct | Step 1 | Step 2 | | | Step 3a | | | Step 3b | | | Invariance |
| | Configural Invariance | Original Correlation | 5 % quantile | Compositional Invariance | Mean Diff. | Confidence Intervals (Mean) | Equal Mean | Variance Difference | Confidence Intervals (Variance) | Equal Variance | |

(continued on next page)

**Appendix C** (*continued*)

| Finland VS. USA | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Construct | Step 1 | Step 2 | | | Step 3a | | | Step 3b | | | Invariance |
| | Configural Invariance | Original Correlation | 5 % quantile | Compositional Invariance | Mean Diff. | Confidence Intervals (Mean) | Equal Mean | Variance Difference | Confidence Intervals (Variance) | Equal Variance | |
| DI | Yes | 1 | 0.999 | Yes | −0.057 | [-0.174,0.176] | Yes | −0.181 | [-0.185,0.178] | Yes | Partial |
| DT | Yes | 0.999 | 0.999 | Yes | 0.279 | [-0.179,0.173] | No | 0.054 | [-0.292,0.278] | Yes | Full |
| Online NWM | Yes | 0.998 | 0.998 | Yes | −0.158 | [-0.173,0.179] | Yes | −0.186 | [-0.287,0.269] | Yes | Full |
| Offline NWM | Yes | 0.996 | 0.996 | Yes | −0.316 | [-0.181,0.179] | No | −0.062 | [-0.228,0.223] | Yes | Partial |
| PI | Yes | 0.999 | 0.999 | Yes | 0.17 | [-0.181,0.177] | Yes | 0.338 | [-0.28,0.26] | No | Partial |

| India VS. USA | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Construct | Step 1 | Step 2 | | | Step 3a | | | Step 3b | | | Invariance |
| | Configural Invariance | Original Correlation | 5 % quantile | Compositional Invariance | Mean Diff. | Confidence Intervals (Mean) | Equal Mean | Variance Difference | Confidence Intervals (Variance) | Equal Variance | |
| DI | Yes | 1 | 0.997 | Yes | −0.082 | [-0.166,0.161] | Yes | 0.155 | [-0.144,0.14] | No | Partial |
| DT | Yes | 0.999 | 0.999 | Yes | 0.2 | [-0.163,0.157] | No | −0.22 | [-0.262,0.253] | Yes | Partial |
| Online NWM | Yes | 1 | 0.999 | Yes | 0.407 | [-0.165,0.163] | No | −0.527 | [-0.282,0.283] | No | Partial |
| Offline NWM | Yes | 0.999 | 0.998 | Yes | 0.31 | [-0.168,0.166] | No | −0.333 | [-0.263,0.251] | No | Partial |
| PI | Yes | 1 | 0.998 | Yes | 0.196 | [-0.162,0.161] | No | −0.153 | [-0.278,0.254] | Yes | Partial |

Note: DI: Discontinuation Intention, DT: Distrust, NWM: Negative Word of Mouth, PI: Privacy Invasion.

## Data availability

Data will be made available on request.

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