

Reconsidering Misinformation in WhatsApp Groups: Informational and Social Predictors of Risk Perceptions and Corrections

OZAN KURU

National University of Singapore, Singapore

SCOTT W. CAMPBELL

University of Michigan, USA

JOSEPH B. BAYER

Ohio State University, USA

LEMI BARUH

Koç University, Turkey

RICHARD S. LING

Nanyang Technological University, Singapore

In a survey study of WhatsApp users across 3 different countries ($N = 3,664$), we tested how misinformation processes on messaging apps are driven by the levels of information shared versus social dynamics within messaging groups. Integrating recent perspectives, we offer a conceptual model that distinguishes (1) the informational activity of users and (2) trust among group members as predictors of misinformation outcomes within WhatsApp groups. Specifically, we focus on how content-sharing practices of users and characteristics of messaging groups (size, type, homogeneity) explain information exposure and group trust, which then predict misinformation risk perceptions and corrections. Structural equation models revealed that contributing content (vs. checking content) positively predicted (mis)information exposure, which then positively predicted risk perceptions and social corrections. Additionally, smaller, closer, and homogeneous groups were associated with greater group trust, which then predicted lower risk

Ozan Kuru: okuru@nus.edu.sg

Scott W. Campbell: swcamp@umich.edu

Joseph B. Bayer: bayer.66@osu.edu

Lemi Baruh: lbaruh@ku.edu.tr

Richard S. Ling: riseling@gmail.com

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perceptions and, concurrently, more social corrections. Overall, the study shows the value of testing informational and social pathways in parallel.

Keywords: messaging applications, WhatsApp, messaging groups, trust, risk perceptions, social corrections, structural equation modeling

Messaging platforms such as WhatsApp, Telegram, and WeChat have faced a great deal of scrutiny for their roles in the spread of misinformation, especially via the unfettered capacity to virally “forward” misinformation. In response, extensive efforts by fact-checking organizations and digital literacy campaigns (Literat, Chang, & Hsu, 2020), as well as key design changes, have been implemented (Singh, 2020). These solutions tend to treat the problem of misinformation as a matter of the technology supporting too much of certain things (e.g., magnitude and velocity of information dissemination) and too little of others (e.g., digital literacy and critical information processing). However, given the central role of messaging apps in daily life, it is also important to account for the social conditions that shape how people perceive, experience, and react to misinformation while using them (Ling, 2018; Marwick, 2018). Examining the informational and social predictors of misinformation—together—thus provides a more comprehensive understanding of misinformation processes on messaging apps.

This study advances a conceptual model to investigate how (1) different levels and types of information activity and (2) social dynamics of messaging groups combine to shape perceptions and practices around misinformation. We focus on messaging groups specifically because groups are a defining component of WhatsApp use and the primary accelerator of misinformation. This study aims to understand how the viral spread of misinformation on messaging applications is supported by both informational activity and social dynamics within messaging groups. We collectively refer to WhatsApp usage patterns and exposure to information as the “informational activity” dimension while characterizing group features and trust in groups as the “social dynamics” dimension in messaging applications. As shown in Figure 1, these two distinct components may operate both independently and simultaneously in shaping misinformation risk perceptions and corrective behavior against misinformation.

The informational dimension captures how much news is being shared, forwarded, and discussed in the messaging group. This dimension includes so-called “active” (share, forward) and “passive” (checking) uses of WhatsApp, as well as exposure to information through these practices. Being mindful of ongoing debates about the distinction between active and passive use (Trifiro & Gerson, 2019), we distinguish between contributing usage, within which respondents share content with the group, and noncontributing use, which primarily involves activities like checking messages that do not contribute content. Yet, informational activities cannot be examined in isolation from social processes. People sometimes share (mis)information to nurture their identities (Marwick, 2018). Hence, the second component of our framework examines the structural features of messaging groups (e.g., size, similarity of members) and their relationships with trust in messaging group members (Ling & Lai, 2016). Altogether, this conceptual model demonstrates how individual practices and structural characteristics of messaging groups function side-by-side to condition how people perceive and react to misinformation.

Misinformation on Messaging Applications

With the increasing regulation of social media platforms to mitigate misinformation in public or semipublic spaces (Funke & Flamini, 2021), the focus has started to broaden to messaging applications, where such regulation is more complicated for both technical and ethical reasons (Banaji, Bhat, Agarwal, Nihal, & Pravin, 2019). While messaging applications are sometimes viewed as a type of social media (Bayer, Triêu, & Ellison, 2020), scholars often treat them as a distinct category of platforms by highlighting their mobile-ness, more robust privacy, and instant-messaging focus (Valeriani & Vaccari, 2018). Research has also documented the prevalence of misinformation on open WhatsApp groups and how it may circulate (Badrinathan & Chauchard, 2022; Garimella & Eckles, 2020). Yet, the end-to-end encryption feature that enhances privacy (WhatsApp, 2021) also makes it difficult for external interventions such as fact checking, particularly in private groups. These distinct features, along with the potential of investigating messaging apps as a distinct category of social platform, make it crucial to understand social and informational processes on platforms such as WhatsApp.

One important area of inquiry is the perceived exposure to misinformation (Wagner & Boczkowski, 2019; Wasserman & Madrid-Morales, 2019). Perceived exposure, or self-assessed risk of exposure, to misinformation on social media is consequential because it may shape trust in media (Stubenvoll, Heiss, & Matthes, 2021). Also, people's beliefs about misinformation can affect intentions and behaviors such as in considerations of vaccine uptake (cf. Compton, van der Linden, Cook, & Basol, 2021). A second key issue, complementing misinformation risk perceptions, concerns the behaviors users engage in when they encounter misinformation (Rossini, Stromer-Galley, Baptista, & Veiga de Oliveira, 2020). Probing the extent to which people may correct others in their group—when they encounter perceived misinformation—could help us identify differences in corrective behaviors that digital literacy training campaigns aim to promote. Recent experimental research has found that simple corrections with hypothetical WhatsApp groups can substantially reduce beliefs in various inaccurate claims (Badrinathan & Chauchard, 2022). Such observations underscore how informational and social factors can both shape corrective user behaviors in messaging apps. Finally, given the challenges brought about by privacy features such as end-to-end encryption, users' self-reports on their WhatsApp use is a key area of interest in studying nonpublic WhatsApp groups.

The current study offers three main contributions. First, it distinguishes informational and social pathways toward misinformation in messaging groups to help advance the literature toward an integrated conceptual model. Second, it provides a dedicated focus on private messaging groups, the study of which has been overshadowed by scholarship on social media that are generally more open and public (Garimella & Eckles, 2020). Third, the current study focuses on predictors of misinformation risk perceptions and corrections. This scope has been neglected in past work, which has focused primarily on the consequences of misinformation—though recent work has started to examine predictors of corrections such as politeness norms or third-person perceptions (Koo, Su, Lee, Ahn, & Rojas, 2021; Malhotra & Pearce, 2022).

Predicting Informational Activity: Contributing Versus Noncontributing Use

Accounting for the ways in which people engage with information is key for understanding misinformation perceptions and practices (Swart, Peters, & Broersma, 2019; Valeriani & Vaccari, 2018). This is indeed reflected in social media companies' attempts to reduce the spread of misinformation by (1) limiting the amount of circulation, such as the capping of forwards on WhatsApp (Singh, 2020) and (2) increasing digital literacy through public service campaigns (Iyengar, 2018). Thus, we suggest that overall tendencies in how people share and consume information are relevant to explaining how they approach misinformation encountered in group-messaging environments. In the context of messaging applications, we posit that this could be studied with a focus on how individual users contribute content and (mis)information to the common shared space in the messaging thread of groups.

We thus make a conceptual distinction between contributing (sharing or forwarding) and noncontributing (checking) uses of these platforms to understand informational activity and exposure differences. This distinction draws from the active versus passive usage paradigm within the literature on the implications of social media use (e.g., Yu, 2016).¹ In conjunction with the active versus passive usage distinction, our approach leverages Muntinga, Moorman, and Smit's (2011) consuming versus contributing categorization as a point of reference. This distinction may be useful given the substantive differences in one's level of involvement in messaging groups, without making assumptions about users' attention (i.e., active vs. passive use). "Passive use" of a messaging app might not necessarily indicate that the user is not paying attention, as recent debates on active versus passive use of social media raised the possibility of "lurking" (Ellison, Triêu, Schoenebeck, Brewer, & Israni, 2020). Hence, we differentiate how some individuals may use messaging applications in noncontributing ways (e.g., by monitoring exchanges through check-ins), while others may use them in more contributing ways by actively bringing in content—which is likely to induce relatively greater activity, interaction, and informational exchanges among members.

¹ Some found active versus passive use as simplistic (Trifiro & Gerson, 2019). Others highlighted that inactivity (e.g., not liking a post) might not be necessarily "passive" (Ellison et al., 2020).

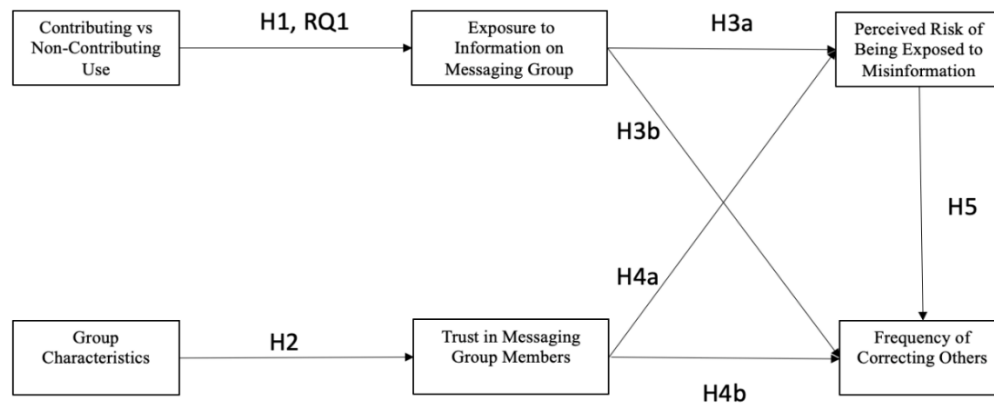


Figure 1. Conceptual model; the (top) paths from contributing versus noncontributing use to exposure to information on messaging group constitute the first major component (informational activity), whereas the (bottom) paths from group characteristics to trust in group members constitute the second major component (social dynamics).

Thus, we posit that contributing use should predict greater informational exposure within the groups (H1), although it is unclear how noncontributing use would be associated with informational exposure (RQ1). The reason for this is that sharing more information in a given group signals a user's higher involvement in that group, which is reflected by greater reliance on contributing use as opposed to noncontributing use. Moreover, such (contributing) behaviors are also more likely to elicit responses and sharing from other group members. This would, in turn, be associated with greater information exposure in the group. Overall, then, contributing use, as opposed to noncontributing use, should predict greater informational exposure.² Building on this logic, and in line with the traditional active versus passive use debate, we would expect noncontributing use to be associated with less information exposure; however, this is theoretically less clear, particularly given the possibility of "lurking" and other criticisms on active versus passive use distinction (Ellison et al., 2020). Checking, as a form of noncontributing use, can be associated with greater exposure as well, even when contributing uses such as sharing and forwarding are taken into account. Given these considerations, we leave the association between noncontributing use and information exposure as a research question (RQ1).

Predicting Trust: The Role of Group Characteristics

Messaging groups allow information sharing and discussion within a socially bounded context, which commonly entails fleeting interactions with small collectives of individuals (Ling & Lai, 2016). Prior research has consistently found positive associations between social media use and perceived social resources such as bridging social capital (Ellison, Steinfield, & Lampe, 2007; Williams, 2019). Given the centrality of social relationships to engagement with social media and messaging platforms, misinformation risk may also be

² Reverse directionality in this relationship (individuals joining certain types of groups because there is more activity) is possible, but we view it as less feasible. However, it is beyond the scope of this study to investigate such long-term group formation processes (individuals joining active groups).

attributed to vulnerabilities in the social dynamics of users (Marwick, 2018). A key construct related to social dynamics in messaging applications is trust among group members, which is most proximally explained by the structural features such as the composition of groups (Ma, Cheng, Iyer, & Naaman, 2019; Turner, Hogg, Oakes, Reicher, & Wetherell, 1987). Prior research on group dynamics and trust have focused on a wide set of key group dimensions, including size (number of members), type (family, friends, work, school, etc.), demographic similarity (age, gender, race, education, income), and viewpoint similarity (political like-mindedness; Thomas & Fink, 1963; Turner et al., 1987).

Work on self-categorization theory has documented that perceived group member similarity is positively associated with trust and integration (Turner et al., 1987) and leads to more interpersonal engagement (Earley & Mosakowski, 2000). Relatedly, attitude and value similarity have been associated with less conflict (Oetzel, 2001), with smaller and more homogeneous discussion groups on Facebook eliciting more trust (Ma et al., 2019). A messaging group for family or close friends is likely to differ considerably from a work-based group. Furthermore, trust-sensitive contexts (where privacy is needed) seem also to support the formation of smaller groups (La Macchia, Louis, Hornsey, & Leonardelli, 2016). Hence, we expect that WhatsApp messaging groups that are smaller (H2a), closer-knit (H2b), and more homogenous in terms of age (H2c), gender (H2d), race (H2e), and political views (H2f) will offer fertile ground for the cultivation of group trust.

Predicting Misinformation Risk Perception and Social Corrections

Exposure to information on messaging applications should be associated with greater misinformation risk perceptions (H3a) and corrections (H3b). Prior work shows that those who engage in more political discussions are more likely to believe and share more misinformation (Garrett, 2019). With greater exposure, the possibility of encountering misinformation increases, and individuals will likely perceive greater misinformation risk. Similarly, greater informational activity in messaging groups should predict more corrective behavior, because greater activity will increase opportunities to provide correct information. This is because prior research found that active groups are more cohesive, which may make it easier to correct others (Liu, Chen, & Holley, 2017).

On the other hand, greater trust in messaging group members should predict risk perceptions negatively (H4a) and social corrections positively (H4b). Although this might seem contradictory at first glance, prior research points toward this complicated nature of trust with respect to risk perceptions and correcting others in messaging applications. For one, people may expect less misinformation harm from trusted others. Individuals are more likely to trust news posted by a friend on Facebook than expert-provided information (Snider, 2017). Trust reduces the procedural costs (time and effort) and increases collaboration (Powell, 1990) as people may not feel the need to check on trusted members. Hence, we may expect lower misinformation risk perceptions. On the other hand, when it comes to corrections, some qualitative evidence suggests that although fact checking other WhatsApp group members is not necessarily common, users do feel more comfortable correcting close others (Pasquetto, Jahani, Baranovsky, & Baum, 2020). Thus, WhatsApp may be a safer space for corrections when people trust each other. Moreover, not all risk perceptions will translate to behavioral action in the form of corrections.

Finally, building on expectations from the domain of health risk and protective behavior (Brewer et al., 2007), we expect that higher misinformation risk perceptions should predict greater social corrections (H5). This relationship between risk perceptions and social correction also helps explain the complicated relationship between exposure and trust as key mediators. Although information exposure should predict a higher level of corrections, it can do so both directly and indirectly through heightened misinformation risk perceptions. By contrast, trust as a mediator may operate in a more complicated way: Though heightened trust in group members may directly increase the likelihood of social corrections, it may also indirectly decrease social corrections by hindering misinformation risk perceptions.³

Diverse Informational Ecosystems

The current study also responds to calls for multisite studies to see whether effects of communication processes differ across context (RQ2; cf. Esser, 2019). We provide evidence from Singapore, Turkey, and the United States—three significantly different contexts in terms of their media, regulatory, and information landscapes. For example, the United States has the lowest WhatsApp adoption rate (about 25%), as opposed to Singapore and Turkey (both reportedly higher than 70%; Statista, 2021). These three societies also vary about press freedom (Reporters Without Borders, 2021), an important dimension considering the sensitive nature of messaging applications such as WhatsApp. Singapore and Turkey have stricter laws, whereas the United States has a large body of nongovernmental fact-checking organizations (Funke & Flamini, 2021). Altogether, the three distinctive empirical contexts allow us to test our hypotheses with greater generalizability.

Methods

Participants and Procedures

The research was reviewed by the Institutional Review Board at the University of Michigan.⁴ The data and code for the study are deposited at the Open Science Framework.⁵ The data from three countries were collected from August 15 to September 1, 2019, by Qualtrics.⁶ The sample comprises WhatsApp users above 18 years of age (Appendix A). Questionnaires were formatted in the most common official languages in the respective countries, English in the United States and Singapore, and Turkish in Turkey. The sample sizes were $N = 1,272$ for United States, $N = 1,193$ for Singapore, and $N = 1,199$ for Turkey. Although these are nonprobability online samples, quotas were used to ensure that

³ We study this conceptual model by accounting for the direct relationships from demographic, informational, and group characteristic variables to misinformation risk and social corrections.

⁴ Funding for the survey data collection came to all authors (PIs Ozan Kuru and Scott Campbell) from the WhatsApp Misinformation Research Awards:

<https://www.whatsapp.com/research/awards/announcement/>. Research and reporting were conducted independently, and the funding organization was not involved in the decision processes.

⁵ OSF link: https://osf.io/7yjgm/?view_only=4384738add924232897b2abfe38965f5

⁶ A pilot study ($N = 420$) was conducted in the United States in April 2019, to validate measures.

the demographic representations, particularly gender, did not deviate substantively from the makeup of the respective populations.⁷

The effective sample sizes for the models were $N = 3,101$ for the combined sample, $N = 1,073$ for Singapore, $N = 1,088$ for Turkey, and $N = 940$ for the United States. This difference between initial sample and the effective analytical sample was largely because of the respondents who were excluded from the analysis because they reported that they had no messaging group on WhatsApp ($n = 70$ for Singapore, $n = 50$ for Turkey, $n = 123$ for the United States). Second, a few missing (at random) responses among predictor variables were dealt with listwise deletion. Demographic descriptions are provided in Appendix A.

Measures

Demographic Variables

We asked respondents' ages, genders, race, income, and education levels. Full details and descriptive summaries for combined sample and for each country are in Appendix A.⁸ Results for demographic analyses are in Appendix C.

WhatsApp Messaging Group Characteristics

To capture group-level characteristics and interactions, we prompted respondents to think of the groups they were most frequently engaged with while responding to the items. If there were multiple such groups, they were asked to focus on the group they deemed the most important.

Group Type

After participants selected which group to report on, they were asked what types of groups they considered those to be, with eight response options (order randomized): family, close friends, work-related, shared hobby, shared interest, acquaintances, news/updates, religious, and other. Given the high frequency of family and friends groups (around 30% in each country), our theoretical interest in predicting group trust and goal to prioritize model parsimony, we instead created a dummy variable (Close Groups) to indicate whether a messaging group is a family/friend group (1) or other (0). This operationalization helps us align this measure with the other group similarity measures detailed below.

⁷ Because of the lower adoption rate of WhatsApp in the United States, the screening left out more individuals there (who were nonusers), but this does not constitute a bias as the population of interest are WhatsApp users.

⁸ Race was not used in the inferential analysis because it was not directly comparable across countries.

Group Size

The size of each WhatsApp messaging group was measured with the following response options: "Less than 3 people, 3 people, 4 to 5 people, 6 to 10 people, 11 to 15 people, 16 to 20 people," or "More than 20 people."⁹

Demographic and Political Similarity

Respondents were asked to evaluate, using a 5-point scale ranging from "not at all similar" to "completely similar," the demographic similarity in their groups in terms of age, sex, ethnicity, race, income, and education (full wording of the instructions are in Appendix A). A few of these demographic similarity measures have not been included in final model (see model specification details below). Perceived similarity of political views was measured using one item with a 5-point scale ranging from "not similar at all in their political views" to "extremely similar in their political views" (cf. Lee, Choi, Kim, & Kim, 2014).

Trust in Group Members

Participants were asked to use a 5-point scale ranging from "Not at all true" to "Extremely true" to evaluate three statements designed to tap trust in group members: (1) "I trust the people in my WhatsApp group," (2) "I feel that the rest of my WhatsApp group accept me," (3) "I feel that the rest of my WhatsApp group care about me" (cf. Ma et al., 2019). The Cronbach's alpha was .91 for Singapore, .88 for Turkey, and .89 for United States. Further details are in Appendix A.

Information Exposure

Participants rated the frequency with which they received information and news from members of their group information in five domains: daily life chatting and organization-related messaging; school- or work-related news or information; political content (policies, economy, elections, and candidates); science-, health-, and medicine-related content (news or advice); and breaking news (cf. Negreira-Rey, López-García, & Lozano-Aguilar, 2017). There were eight response options, ranging from "once a month or less" to "more than 20 times a day." The Cronbach's alpha was .84 for Singapore, .85 for Turkey, and .91 for United States.

Contributing Versus Noncontributing Use

We asked participants to report their frequency of checking WhatsApp (noncontributing), sharing content on WhatsApp (contributing), and forwarding content on WhatsApp (contributing). All three questions had the same nine response options ranging from "once a month or less" to "more than 40 times a day." We asked sharing and forwarding separately given the differences in the original source of message (one forwards a message that is shared with or forwarded to them by others) and because of the centrality of

⁹ Few respondents who stated "less than three people" were not included in this analysis since a group should have at least three people.

forwarding in viral dissemination across groups. We measured these behaviors not on the particular group level but in terms of overall WhatsApp use. This is primarily because we wanted to focus on overall WhatsApp use specifically, which makes usage levels more comparable across participants.¹⁰ Second, some of these questions do not make sense to be measured at the group level (for a particular messaging group; e.g., users will usually not “check” their groups unless there is a notification).

Misinformation Exposure Risk Perceptions

Participants were asked to use a 5-point scale ranging from “not risky at all” to “extremely risky” to “evaluate the overall level of risk that you will be exposed to false, misleading, or suspicious information in this WhatsApp group” (cf. Wasserman & Madrid-Morales, 2019).

Respondent (Social) Corrections

Respondents were asked to indicate, using a 5-point scale ranging from “never” to “always” the frequency with which “you correct others in your group when they share or forward inaccurate/false news?”

Analytical Strategy

Model Description

Structural equation modeling (SEM) with latent factor loadings was conducted with the lavaan package in R (Rossee, 2012) to examine the proposed model in Figure 2. We implemented SEM as it allowed us to look at the relationship between multiple predictors and predicted variables simultaneously while probing the mediating role of trust and information exposure.¹¹ Both trust and information exposure are latent factors. As seen in Figure 2, these two key latent factors, controlling for the exogenous variables on the leftmost side, predict the perceived risk of misinformation and the frequency of correcting others. Additionally, risk perceptions are also set to predict the frequency of correcting others. For statistical control and descriptive purposes and to induce less causal assumptions, we included (1) a covariance between the two mediating factors of trust and information exposure, (2) paths for the cross-cutting relationships between informational and social variables (the relationship between group characteristics and information exposure as well as the relationship between contributing/noncontributing use and trust); hence, there is no hypothesis on the relationship for these associations. More background and literature discussion on these decisions are provided in Appendix C. Although they are not shown in Figure 2, there are also direct paths from the exogenous variables to risk perception and correcting others, allowing for the testing of direct effects. This approach avoids imposing additional causal assumptions (see Appendix B for correlations).¹² Finally, we also tested the indirect effects from exogenous variables to the predicted latent factors and indicators, all of which are reported in Appendix C.

¹⁰ If we relied only on group-specific measures, then we could not distinguish between a user who uses WhatsApp more intensely/frequently (e.g., having 10 messaging groups) versus a user who has only one group.

¹¹ SEM allows us to test these multiple mediator models at once and reduce error.

¹² Not including direct associations between exogenous variables and predicted indicators would need to assume full mediation. Hence, our approach has fewer causal assumptions.

Estimating and Model Specification

Given the few missing responses at random for some questions and the continuous nature of predicted variables, we used maximum likelihood estimation with robust (Huber-White) standard errors (MLR estimation in lavaan package in R). Following Kline (2016), we reported four model fit indices (the chi-square goodness of fit test, RMSEA, CFI, SRMR).

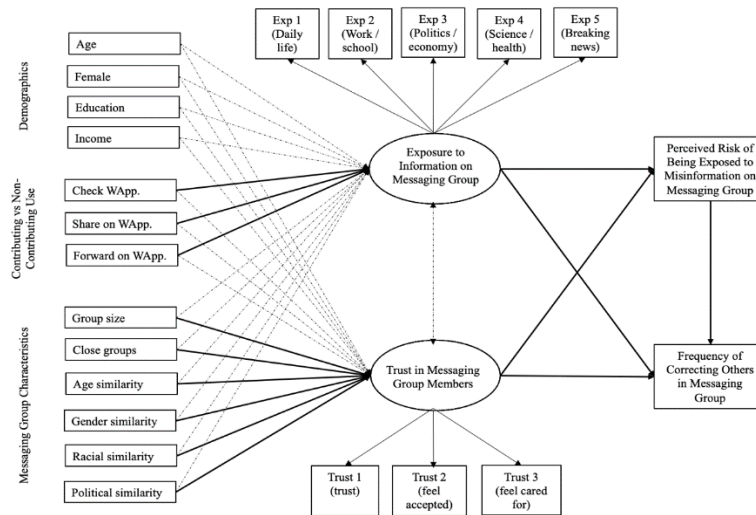


Figure 2. Structural equation model for predicting misinformation risk perceptions and frequency of social corrections; the solid lines represent theoretical associations of interest (hypothesis testing), whereas dashed lines represent connections included for statistical control. The direct paths from exogenous variables to risk perceptions and correcting others are not shown; error terms are not shown. The model is identical across the countries.

A few adjustments were made after our initial model specification to improve the model fit of our final model. First, we initially included different types of demographic similarities and set them as indicators of latent variable. Ultimately, three of them (age similarity, gender similarity, and race similarity) were included as separate variables in the final model.¹³ Second, we initially conceptualized sharing and forwarding as indicators of latent factor of contributing use of WhatsApp. However, model fits did not meet acceptable cut-off points, so these two variables were entered as separate variables in the final model.

Our final SEM model was replicated across the three countries separately as well as in the combined data set for all countries. Given overwhelmingly consistent results across countries, only combined data set results are reported in the study while country-by-country results are provided in Appendix C. Reverse ordering of directional relationships between the latent factors and misinformation outcomes did not produce an acceptable model fit. Despite this, we caution against causal inference given the cross-sectional data.

¹³ These three demographic similarity measures emerged as key factors with high factor loadings in the three countries studied.

Results

Model Fitting

Acceptable cutoffs for RMSEA and SRMR are below .08 and for CFI above .95. The p -value for a chi-square test that is insignificant also indicates a good fit but is not a prerequisite with large sample size (Kline, 2016). SEM solutions had an acceptable model fit (Table 1; Table C4 in Appendix C). As is usual with large samples, the chi-square indexes were significant (Schermele-Engel, Moosbrugger, & Müller, 2003). By contrast, the RMSEA, CFI, and the SRMR exhibited good fit. Both latent factors (trust in group members and exposure to information) had moderate to strong factor loadings, with most standardized coefficients ranging from .61 to .89 (Table C2 in Appendix C) and all were significant. Explained variances for items and latent factors were moderately strong (Appendix C).

Table 1. Model Fit Indices.

Model Fit Type	Countries Combined
Chi-square	$\chi^2 (109) = 946.331, p < .001$
RMSEA	.050 [.047-.053]
CFI	.95
SRMR	.028

Predicting Information Exposure and Trust

First, we examine how contributing use predicts information exposure and group characteristics predict trust. SEM path coefficients (Table 2) showed that contributing behaviors of sharing (row 11) and forwarding (row 12) predicted information exposure positively (H1 supported). On the other hand, checking WhatsApp (i.e., noncontributing use) predicted information exposure negatively (row 10, RQ1).

Participants' perceptions of WhatsApp group characteristics played an important role in predicting trust in group members. Controlling for demographics and informational activity patterns, being in a close group (row 5), being in a group that is more similar with respect to age (row 6), gender (row 7), race (row 8), and political views (row 9) predicted stronger levels of trust in group members. In contrast, being in a larger group was negatively associated with trust in group members (row 4). Overall, H2 is fully supported (H2a-f).

Predicting Perceived Risk and Corrections

Next, we examined paths from information exposure and trust to perceived risk and correcting others, probing the mediating role of these two key variables. Exposure to information predicted both misinformation risk perceptions (row 29) and frequency of correcting others (row 40) positively (H3a and H3b supported). Trust predicted misinformation risk perceptions within the messaging groups negatively (row 28) and predicted frequency of correcting others against misinformation within the messaging groups positively (row 39; H4a and H4b supported). We also found that misinformation risk perception predicted the frequency of correcting others positively (row 41; H5 supported). Collectively,

trust has a direct positive association with corrections while an indirect negative association through the mediating role of risk perceptions.

Societal Comparisons

Overall, we found that the substantive results were largely similar across the countries (RQ2; Appendix C). Respondent ages and genders were exceptions. For example, being female (vs. male) in Turkey was associated with greater levels of information exposure, as opposed to Singapore and the United States (Table C2). The rest of the country differences were driven by small changes in the strength of coefficients. Specifically, age similarity, political similarity, and being in a closed group predicted higher risk significantly only in Singapore.

Further Analysis

We examined the association between the two latent factors (mediator variables) and found a weak positive correlation at $r = .07$ (row 42). We also examined the cross-cutting associations between informational and social components (i.e., association between contributing use and trust; association between group characteristics and information exposure). Larger group sizes (row 13), higher similarities in terms of ages (row 15), genders (row 16), and political orientations (row 18) predicted higher levels of exposure to information in messaging groups. However, though checking WhatsApp did not predict trust, contributing behaviors of sharing (row 2) and forwarding (row 3) did predict trust positively. Similarly, we also reported the direct associations between the exogenous variables (demographics, informational activity and group characteristics) and the criterion variables (risk perceptions and corrections) in Table 2. Finally, we examined the role of users' demographic characteristics and all indirect effects in Appendix C.

Table 2. Path Coefficients and Covariances.

#	Path Coefficients	Countries Combined Coef. (se)
1	Check WhatsApp->Trust in Group	-.01 (.01)
2	Share on WhatsApp->Trust in Group	.03** (.01)
3	Forward on WhatsApp->Trust in Group	.03** (.01)
4	Group Size->Trust in Group	-.02** (.01)
5	Close Group->Trust in Group	.33*** (.03)
6	Age similarity->Trust in Group	.05*** (.01)
7	Gender similarity->Trust in Group	.03* (.01)
8	Racial similarity->Trust in Group	.14*** (.01)
9	Political similarity->Trust in Group	.13*** (.01)
10	Check WhatsApp->Exposure to Info.	-.06*** (.01)
11	Share on WhatsApp->Exposure to Info.	.12*** (.01)
12	Forward on WhatsApp->Exposure to Info.	.22*** (.01)
13	Group Size->Exposure to Info.	.10*** (.01)

14	Close Group->Exposure to Info.	-.06 (.04)
15	Age similarity->Exposure to Info.	.08*** (.02)
16	Gender similarity->Exposure to Info.	.03* (.01)
17	Racial similarity->Exposure to Info.	.00 (.01)
18	Political similarity->Exposure to Info.	.14*** (.02)
19	Check WhatsApp->Exposure Risk	-.07*** (.01)
20	Share on WhatsApp->Exposure Risk	.02 (.02)
21	Forward on WhatsApp->Exposure Risk	.04** (.02)
22	Group Size->Exposure Risk	.02† (.01)
23	Close Group->Exposure Risk	.09† (.05)
24	Age similarity->Exposure Risk	.00 (.02)
25	Gender similarity->Exposure Risk	.06*** (.02)
26	Racial similarity->Exposure Risk	-.01 (.02)
27	Political similarity->Exposure Risk	.04* (.02)
28	Trust in Group->Exposure Risk	-.24*** (.03)
29	Exposure to Info.->Exposure Risk	.31*** (.03)
30	Check WhatsApp->Corrections	.05** (.01)
31	Share on WhatsApp->Corrections	.04* (.02)
32	Forward on WhatsApp->Corrections	.00 (.02)
33	Group Size->Corrections	-.03* (.01)
34	Close Group->Corrections	.04 (.05)
35	Age similarity->Corrections	.00 (.02)
36	Gender similarity->Corrections	.02 (.02)
37	Racial similarity->Corrections	-.03† (.02)
38	Political similarity->Corrections	.07** (.02)
39	Trust in Group->Corrections	.26*** (.03)
40	Exposure to Info.->Corrections	.10*** (.03)
41	MisInfo. Exposure Risk->Corrections	.12*** (.02)
42	Trust in Group <-> Exposure to Info.	.07*** (.01)

† $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$. Unstandardized coefficients are reported. Standardized coefficients (STDYX) are in Appendix C.

Discussion

Messaging applications such as WhatsApp comprise a key channel type where misinformation can spread unencumbered (Avelar, 2019; Rahman, 2018). This study made progress toward a conceptual model that helps identify countervailing forces that may shape beliefs and behaviors related to misinformation (Ling & Lai, 2016; Marwick, 2018). We conducted national surveys in three countries to understand the ways informational tendencies and social characteristics function in explaining how and why people respond to misinformation in WhatsApp groups. Our findings unveil how key aspects of the WhatsApp messaging

context, including individual practices and group characteristics, condition the ways people feel and act toward misinformation.

The current study addresses the problem of misinformation on messaging apps by proposing and testing an integrative model. About informational activity, we found contributing users to be positively associated with overall information exposure, while the reverse was true for noncontributing users. This result illustrates that differences in individuals' informational activity tendencies matter in efforts to explain or curb the spread misinformation on WhatsApp. Specifically, this means that users with a higher tendency to engage in contributing uses of WhatsApp (by sharing and forwarding) are more involved in news consumption and exposure; and given that greater exposure predicted greater risk perceptions and corrections, these individuals were more aware of their vulnerabilities to misinformation (cf. Valeriani & Vaccari, 2018). On the other hand, noncontributing users who check for new messages without sharing or forwarding content may be underestimating their risk. That greater exposure to information predicts both higher risk perceptions and social corrections, while risk perceptions predict more corrections, gives more weight to the possibility that more contributing users are likely to be critical and attentive to informational exchanges (Brewer et al., 2007). Though we cannot definitively infer about the role of "real" misinformation exposure, we can speculate that more contributing use and critical attentiveness may explain higher overall information exposure and activity (cf. Yu, 2016).

On the other hand, it is harder to make clear inferences about the potential mechanism behind why noncontributing use was negatively associated with information exposure in our data. This finding is more in line with active versus passive use distinction as opposed to possibility of "lurking" or other mechanisms through which checking WhatsApp can bolster information exposure (cf. Ellison et al., 2020). Alternatively, it may be because potential information overload in the context of group messages (when users check in too frequently), such that they might be overwhelmed and less attentive to various information (Nonnecke & Preece, 2001). It may also be because of specific model specification in this study. Future research can further probe this relationship by measuring privacy concerns and information overload.

Our second set of findings showed the importance of group characteristics and trust in efforts to explain misinformation encounters on WhatsApp. Respondents were more likely to trust groups that were smaller, closer (family and close friends), and both demographically and politically similar. Some of these results are in line with recent findings, reporting that similar groups elicit more trust on Facebook messenger groups (Ma et al., 2019), as well as classic sociological research (Turner et al., 1987). This gives us insights about how trust arises on private messaging groups on major platforms such as WhatsApp. Yet, these results do not mean that more homogeneous groups are always more trustworthy. Organizational research shows that members of diverse groups also have the capacity to rapidly build trust (Meyerson, Weick, & Kramer, 1996; Pinjani & Palvia, 2013). More research is needed to examine the conditions under which group similarity leads to greater trust. Also, previous research suggests that trust is less easily developed in larger collectives, particularly when membership entails formal or professional engagements. These group features (size, type, and composition of messaging groups) may condition the effects of perceived norms, which are associated with the tendency to correct others (Koo et al., 2021). It would be useful for future research to examine the role of perceived norms.

Group trust predicted risk perceptions negatively and social corrections positively. These findings suggest that there may be at least an implicit standard within messaging groups and that trust plays a crucial role in steering whether and how that standard is upheld. This could also mean that individuals lower their guard in a trusted group as they do not expect harm (i.e., misinformation) from group members. It may be that trust reduces the perceived risks of misinformation by causing individuals to underestimate or overlook their friends and families as potential spreaders. These findings may be used to help advance and test new hypotheses about the role of group trust in the handling of misinformation. Future research should examine the conditions under which trust can be both an asset and a liability. The positive relationship between trust and social corrections points to another possible explanation of the negative relationship between trust and risk perceptions: it is possible that risk perceptions are lower because people see that corrections are taking place (and hence the trust is higher). Other factors predicting corrections such as politeness norms (e.g., comfort with which a younger member can correct an older member) could interact with these trust mechanisms too (Koo et al., 2021; Malhotra & Pearce, 2022). Since our study did not focus on the actual risk levels in closer groups, future research, utilizing longitudinal and logged data, could be fruitful for more definitive answers.

The results related to group trust also speak to the potentially detrimental role of echo chambers exacerbating misinformation risk on social media (Törnberg, 2018). Although much of the related research focuses on cross-cutting interactions that take place on more public social media platforms (Guess, Nyhan, Lyons, & Reifler, 2018), messaging-centered platforms like WhatsApp may differ in the size and nature of the groups. These structural differences, when coupled with the ability to carry out immediate and ongoing chat sessions, may be more conducive to such information cocoons. Yet, we should be careful about the possibility that echo-chamber dynamics may operate differently for subjective risk perceptions as opposed to real vulnerabilities. The finding that trust predicted perceived misinformation risk negatively—while political similarities emerged as a positive predictor of both trust and risk—shows that political similarities explain risk perceptions above and beyond the mediating role of trust. It may mean that people have a lay understanding of the potential pitfalls of filter bubbles to some extent (Levendusky & Malhotra, 2016).

Our findings also suggest that research and theory on group-messaging platforms should be careful not to place too much focus on the sheer amount of user-generated content. It is essential to pay attention to how certain social dynamics shape misinformation perceptions and practices, while simultaneously accounting for the informational dynamics. For example, members of highly trusted homogenous groups may feel more motivated to take action to protect others against misinformation than those in larger and more diverse groups (cf. Marwick, 2018). Hence, aggregate and interactive effects may be overlooked if informational or social pathways are viewed in isolation. Hence, our conceptual model helps both unmask theoretical relationships and suggest targeted interventions that address both informational and social pathways in messaging platforms (Campbell, 2020; Ling, 2018). Notably, we found that cross-cutting paths linking WhatsApp uses to group trust and group characteristics to information exposure to be positively associated, and that exposure to information in a group is also positively associated with trust. These results are important in showing how informational and social dynamics are not isolated factors (Evans & Dion, 2012; Mullen & Copper, 1994).

Although WhatsApp users' perceptions offer important insights into (mis)informational practices on the platform (Wasserman & Madrid-Morales, 2019), it is important to note that these views may be skewed.

Indeed, past work suggests that audience perceptions of “fake news” are driven by many factors, including poor journalism, unfavorable information, or hidden advertisements (Nielsen & Graves, 2017). It is particularly worrisome if people engage in motivated reasoning while they label information as fake news (Tsang, 2020). For these reasons, more research is needed to understand what misinformation risk means for users of messaging applications.

Finally, our key observed relationships were consistent across countries, while inconsistencies were largely because of differences in effect sizes. This pattern is noteworthy given that the three countries studied differ in important ways, and it points toward greater generalizability of the findings. Yet, our study design does not allow for making inferences about the nature of the comparisons. Future work should include more countries and/or select countries based on specific theoretical expectations.

Limitations

Several aspects of our design offer room for improvement in follow-up work on misinformation on messaging platforms. The operationalization of misinformation risk perceptions involves a notable level of subjective judgment. Future research should find more ways to cross-validate self-reported perceptions and behaviors. Although the alternative models we tested with reverse ordering of variables were not as empirically feasible (based on model fit statistics), we cannot make conclusive statements about causality given the cross-sectional data; designs that allow for more causal inference, such as field experiments, would be a helpful next step, keeping in mind the practical and ethical considerations. Also, our items for contributing and noncontributing practices were asked in the context of one’s overall WhatsApp usage rather than the specific group they reported on elsewhere. More targeted and nuanced WhatsApp usage measures would provide more specificity and benefit from drawing on recent measures that identify distinct informational behaviors (e.g., Gerson, Plagnol, & Corr, 2017). This should include clarification of how checking one’s app might be interpreted differently across respondents as well as integrating an overall WhatsApp use measure and group-specific use measure simultaneously.

Other drawbacks include single-item measures for some concepts and a lack of consideration for the varied types of behaviors enacted on WhatsApp (e.g., discussion; Kuru & Pasek, 2016). Additionally, as our focus is not one-to-one chats on WhatsApp, our results will not be relevant for messaging users who do not use groups chats at all (Rossini et al., 2020). The different messaging groups one engages with could differ from each other in (unmeasured) substantive ways, so we must be careful about extrapolating results from a single WhatsApp group to overall WhatsApp activity. Future research should also (1) investigate potential differences in messaging group types (work, school, religious groups) beyond the friends/family (vs. other) distinction, (2) compare WhatsApp use with other platforms and information seeking behaviors of users to disentangle interactions among multiple platforms use, (3) examine the role of personality in the relationship between trust and corrections. We hope our conceptual model offers the groundwork to inform future theorizing of misinformation dynamics in messaging-centered spaces.

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