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Antecedents of Members' Trust Propensity and Its Impact on Self-Disclosure Intention in Mobile-Based Online Dating Apps

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Cover Page Footnote

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INTRODUCTION

According to Madigan (2020), 15% of adults in the United States have used online dating services, that means an estimated 50 million Americans have or continue to use dating services. Approximately 26.6 million U.S. adults used smartphone dating apps in 2020. Moreover, the dating services industry has a growing revenue stream, which is estimated to increase annually at a rate of 7.6% and reach $4 billion by 2023. One of the reasons why people are using mobile-based dating apps is because of hectic work schedules that limit alternative ways of meeting potential romantic partners (Madigan, 2020). The online dating service industry is very competitive, with more than 1,500 online dating service companies in operation. Therefore, the increasing competition requires service providers to invest their efforts and strategies in retaining consumers (Madigan, 2020).

This study focuses on the experiential factors that influence Mobile-Based Online Dating Apps (MBODAs) users' self-disclosure intention. There are two major mobile app categories: informational and hedonic experiential (Bellman, Potter, Treleaven-Hassard, Robinson, and Varan, 2011). MBODAs are categorized as experiential hedonic mobile apps since users become more socially engaged in in-app hedonic activities, include visiting more users' profiles, sending more messages, and achieving more matches (Jung, Bapna, Ramaprasad, and Umyarov, 2019). The ubiquity and impulsivity mechanisms of mobile apps have strengthened engagement and provided evidence of the impact of the channel shift from traditional web to mobile in the context of online dating.

Scholars in information systems (IS) employed experimental studies to find users' usage levels and to understand users' behaviors in MBODAs (Bapna, Ramaprasad, Shmueli, and Umyarov, 2016; Jung et al., 2019). However, the potential risk of exposure for MBODA users suggests that the level of usage will depend on consumers' comfort level with their vulnerability to a service provider, which is anchored in users' trust in other members of the mobile dating community. Thus, this study aims to understand how perceived members' trust propensity is affected and the consequences for users' self-disclosure intention on MBODAs. The theoretical framework of Privacy Calculus Theory (PCT) was adopted. Furthermore, members' trust propensity was posited as a central factor in exchange relationships between PCT factors (risks, benefits, and disclosure) that influence users' behavior intention and that involve highly unknown risks, such as those created by self-disclosure (Barth and De Jong, 2017; Li, Cho, and Goh, 2019).

Although there are undeniable benefits of MBODAs, several apprehensions often arise; in particular, users who are unaware of potential scams and crimes may expose themselves as attractive victims. Online dating scams are an unfortunate and severe part of dating technology's growth. They are one of the most expensive types of fraud: damages were estimated at roughly $201 million in 2019 (Fair, 2020). Therefore, dating service providers and MBODAs developers need to understand the benefits and risks for end-users and develop security strategies to protect and create a safe environment, while improving the matching algorithms to strengthen the ability to identify compatible matches. Our study attempts to understand the beneficial and risky factors associated with the MBODAs environment.

This study's thesis is that the degree to which a consumer is willing to be vulnerable to the service provider is a function of their trust propensity in other users of the platform. We conceptualized perceived risk and perceived benefit as multidimensional constructs: tech risk and social risk, as well as tech benefit and social benefit, are antecedents of perceived members' trust propensity. Furthermore, we consider user experiences and other members' electronic word of mouth (eWOM) commentary about MBODAs as antecedents of perceived trust propensity. This research has both practical and theoretical contributions because it assesses the bright and dark sides of MBODAs in the relationship between perceived members' trust propensity and their self-disclosure intention. This study provides insights for MBODAs providers to understand factors that can reinforce members' trust propensity. The findings provide clues for MBODAs companies to develop policies that create a safe dating environment and an enhanced user experience.

THEORETICAL FRAMEWORK AND HYPOTHESES DEVELOPMENT

Theoretical framework

The literature on IS is abundant with studies on the risks associated with social networking services (SNS) (Benson, Saridakis, and Tennakoon 2015b; Silic and Back, 2016). MBODAs are computer-mediated platforms for forming social relationships; specifically, they are SNS that focus mainly on romantic relationships. Several theoretical frameworks, such as Social Cognitive Theory (Shih, Hsu, Yen and Lin, 2012), Communication Privacy Management (Zlatolas, Welzer, Heričko, and Hölbl, 2015), Protection Motivation Theory (Bansal, Zahedi, and Gefen, 2015), and the Theory of Planned Behavior (Alashoor, Han, and Joseph, 2017), were applied to explain SNS usage. They mainly contribute to the SNS literature by examining the relationships between awareness and privacy concerns on the one hand and self-disclosure on the other. These studies considered various factors of individual perception, such as attitude, awareness, and self-efficacy.

Our study complements prior research by simultaneously considering risks and benefits from a broader perspective using PCT (Klopfer and Rubenstein, 1977) to examine risks and benefits within the MBODA context. PCT explains that users evaluate risks and benefits associated with specific online services within individual prior decisions, influencing their information disclosure behavior (Dinev and Hart, 2006; Li et al., 2019; Xu, Teo, Tan, and Agarwal, 2009). We examine the role of perceived trust propensity as a central factor that links risk/benefit perceptions and users' information disclosure intention. Specifically, tech risk and social risk are considered dimensions of risks, and tech benefit and social benefit are the dimensions of benefits. The risks and benefits are associated with SNS that are embedded in mobile technology applications.

An intriguing distinction between MBODAs and other SNS is that satisfied MBODAs users who found a match subsequently left the platform, while SNS users continue logging in. Furthermore, MBODAs request that users sign up with a location-based service and create a profile that contains their personal information to find a potential partner who has matching preferences within a specific geographic location (Ekström, 2020). Furthermore, online dating facilitates in-person meetings between strangers, while SNS enhances activities among people who already know each other; hence, users' behavior on MBODAs is temporal. Perceived members' trust propensity is a critical factor that captures the trust that an individual user has in other members. Therefore, the stronger the perceived trust propensity, the greater the intention to participate in MBODAs.

This study traces the roots of members' trust propensity as a function of the perceived benefit and the perceived risk of using MBODAs. In prior research, privacy benefits and privacy risks were identified to drive users' privacy-related decision-making (Dinev and Hart, 2006; Li et al., 2019; Xu et al., 2009). The present study postulates that perceived risk and perceived benefit include granular components: tech risk and social risk; tech benefit and social benefit. We included the usage experience, which is defined as users' knowledge about and familiarity with MBODAs, because experience acts as a reinforcing mechanism for online services' usage (Khalifa and Liu, 2007). Besides, eWOM—which is defined as the extent of users' observation of online reviews and comments—messages comprise positive and negative information that may help users evaluate and make informed decisions about purchase intentions on SNS (See-To and Ho, 2014). These factors may influence members' trust propensity. Finally, the dependent variable—self-disclosure intention—refers to a user's intention to disclose private information on MBODAs.

Trust comprises complex beliefs that reflect a party's willingness to be vulnerable to another party's actions, including trust propensity, cognitive perceptions of trustworthiness, and willingness to be vulnerable to another (Mayer, Davis, and Schoorman, 1995). Among these central beliefs, trust propensity is an individual characteristic of trusting others in specific contexts (Mayer et al., 1995), and it reflects stable tendencies to believe and trust others (Colquitt, Scott, and LePine, 2007). Users who have high trust propensity tend to have strong faith, even in unfamiliar environments (Colquitt et al., 2007; McKnight, Choudhury, and Kacmar, 2002). Perceived members' trust propensity is defined as a stable individual difference that influences the probability that they will believe others across various situations in a new environment (Colquitt et al., 2007). Arguments in social exchange have shown that trust propensity has direct effects on behavioral outcomes. Individuals who have stronger trust propensity tend to show more trustworthy actions (Rotter, 1980), strengthening their prosocial and moral manner (Webb and Worchel, 1986). Through meta-analytic study, Colquitt et al. (2007) further supported trust propensity's role as a central factor which has incremental effects on both positive and negative behavioral outcomes across different contexts.

Previous studies have suggested that members' trust propensity is a crucial component of virtual online relationships (Cheung and To, 2017; Robert, Denis, and Hung, 2009). Perceived trust propensity is a user's subjective belief toward other members within the SNS community (Chen, Sharma, and Rao, 2016) that involves acting in an appropriate manner consistent with their presumption. However, little attention has been paid to perceived members' trust propensity toward MBODAs and their effects on self-disclosure intention. In fact, the literature review shows that self-disclosure and privacy issues were mainly investigated in two research streams: the SNS context (Alashoor et al., 2017; Benson, Saridakis, and Tennakoon, 2015a; Posey, Lowry, Roberts and Ellis 2010; Zhang, Kwok, Lowry and Liu, 2019; Zlatolas et al., 2015) and self-disclosure technologies (i.e., instant messages, location-based technologies, etc.; Hsieh and Lee, 2020; Keith et al. 2013; Keith, Thompson, Hale, Lowry and Greer 2013; Lowry, Cao and Everard 2011; Shih et al.

2012). However, self-disclosure in the context of MBODAs has not been explored. Table 1 presents a definition and sources of the key variables of this study.

Variable name	Definition of variable	Measurement (adapted from)
Perceived risk (PR)	User's discomfort about using online dating platforms considering the likely exposure to cybercrimes.	Chakraborty, Lee, Bagchi-Sen, Upadhyaya, & Rao (2016)
Perceived benefit (PB)	User's belief about the extent they will become better off from the online dating platform.	Kim, Ferrin and Rao (2008)
Perceived members' trust propensity	User's willingness to trust other members in the online dating platform.	Chen et al. (2016)
Experience (EXP)	User's knowledge and familiarity with online dating platform.	Khalifa and Liu (2007)
eWOM (EWM)	The degree to which the word-of-mouth system on the online dating platform is deemed relevant and useful.	Awad and Ragowsky (2008)
Self-disclosure (DISC)	Amount of disclosure of private information, such as identity, state, and disposition, into online dating platform.	Chen and Sharma (2015)

Table 1. Variables for the research model

Hypotheses

The major difference between online dating platforms and other traditional SNS (e.g., Facebook, Twitter, Instagram) is that online dating platforms are set up to meet new people who share emotions in their communications to form a romantic relationship. Online dating platforms are based on person-to-person communication; therefore, it is crucial to form trust in the initial interaction. In the MBODA context, the stronger the perceived members' trust propensity, the less wary members will be. For example, users of Tinder (an MBODA) were able to correctly estimate the home locations of other members within the application without the target's awareness (Veytsman, 2014). Therefore, we posit that perceived members' trust propensity is the most important factor when discussing disclosure behavior on MBODAs.

MBODAs are prone to privacy and security vulnerabilities (Buchanan and Whitty, 2014; Shetty, Grispos, and Cho, 2017). Therefore, we posit that risks, such as security, privacy, and service quality, can arise in the context of MBODAs. Jacoby and Kaplan (1972) suggested perceived risk may comprise different components depending on the different environments in which one operates. Consumers will assess and perceive risk components embedded in a specific environment. Previous studies of MBODAs proposed two major risk factors: tech risk (Farnden, Martini, and Choo, 2015; Shetty et al., 2017) and social risk (Buchanan and Whitty, 2014). Therefore, we focus on tech risks and social risks

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associated with MBODAs. We suggest that tech risks may result from technology failures, such as data breaches, and social risks result from other users deceiving and manipulating people within the apps, such as through scams, frauds, and harassment.

Perceived risk has been defined as the degree to which a user believes that a high potential for loss is associated with releasing personal information to a platform (Benson et al., 2015b; Choi and Lee, 2017). Studies of the risks associated with MBODAs platforms include Farnden et al. (2015), who conducted an experiment across five MBODAs and found that several data breaches from these apps raised users' concerns about technological privacy risks. Moreover, MBODAs encourage users to share more personal information than do conventional social media apps (e.g., location data and connected personal information, and information from connected SNS, like Facebook or LinkedIn; Albury, Burgess, Light, Race and Wilken, 2017). Inevitably, this enforced disclosure makes MBODA users vulnerable to hacking and scams. Therefore, a user's perceived members' trust propensity will be low if they sense that there is a high level of risk in using the MBODAs platform. Thus, we propose that:

H1: Perceived risk is negatively associated with perceived members' trust propensity.

Perceived benefit refers to an individual's perceptual belief that the use of specific online services will result in positive outcomes (Hsieh and Lee, 2020; Kim et al., 2008). Users may evaluate their performance based on the perceived benefit of MBODAs. Previous studies suggested MBODAs offer two central benefits: social interaction with others and matching engagement (Bellman et al., 2011; Jung et al., 2019). Jung et al. (2019) showed that MBODAs users become more socially engaged in in-app activities, including visiting more users' profiles, sending more messages, and achieving more matches. In our study, we employ the net valence framework, theoretically grounded in PCT, to integrate the benefits and risks of MBODA disclosure intention. We argue that tech benefit offers useful features for online interaction (Albury et al., 2017), while social benefit enhances extensive communication and allows users to access a larger pool of members (Heino et al., 2010). Tech benefits are algorithmic matching, personalization, and geo-location searches for users with GPS functionality on their smartphones allow users to search for prospective dates near their current location, while social benefits include providing alternative ways of meeting romantic partners (Albury et al., 2017). In contrast to perceived risk, users' perceived benefit provides an incentive for users to participate in MBODA services. Besides, by using MBODAs, users may obtain benefits, such as personalization (Chellappa and Sin, 2005) or find potential romantic partners effectively (Ellison et al., 2006). Hence, the perceived benefit may impact users' perceived members' trust propensity. When the perceived benefit is relatively high, users tend to increase their trusting beliefs toward members within the MBODA environment. Hence, we formulated the below hypothesis:

H2: Perceived benefit is positively associated with perceived members' trust propensity.

Experience refers to the personal knowledge or skills derived from actual usage behavior (Khalifa and Liu, 2007; Li et al., 2019). Although the experience has received a lot of research attention in diverse contexts, few studies have explored the effects of experience in the MBODA context. In the context of online services, the online experience is a crucial factor in building trust in a website's brand (Gefen, Karahanna, and Straub, 2003; Khalifa and Liu, 2007). Users are more likely to be satisfied with their experience when they perceive better performance. However, we know less about how frequent users' experiences influence (i.e., strengthen or weaken) their perceived members' trust propensity given the unknown risks in the MBODA environment. Generally, online users visit a platform frequently when their prior experience is positive. Prior positive experience acts as a reinforcing mechanism for online services' usage (Khalifa and Liu, 2007), which is a critical internal factor of frequent online platform usage. Users' experience in the online dating platform encourages perceived members' trust propensity in MBODAs. Therefore, we propose the following:

H3: Users' experience with MBODAs is positively associated with perceived members' trust propensity.

Following this is the effect of user observations in the form of eWOM. eWOM is online feedback offered to build trust and shape customers' expectations (Dellarocas, 2003). Features allow online daters to rate and provide feedback about an app and online dating services. This eWOM, in turn, can reinforce users' expectations, influence trust beliefs, and affect participation and continuance decisions (Bulut and Karabulut, 2018; Dellarocas 2003; Ladhari and Michaud, 2015). eWOM messages may contain both positive and negative information that influences users' attitudinal beliefs and helps them make informed decisions about purchase intentions (See-To and Ho, 2014). Therefore, we posit that eWOM is a crucial external factor in reinforcing perceived members' trust propensity in the context of MBODAs. More importantly, information from eWOM reflects members' perceptions of the platform. Therefore, we hypothesize:

H4: eWOM positively influences perceived members' trust propensity.

Perceived members' trust propensity is defined as a stable individual difference that influences the probability that a user will trust a new organization (Mayer et al., 1995; Colquitt et al., 2007), electronic commerce (Kim et al., 2008), or SNS (Chen et al. 2016) in various situations, with the riskier and more suspicious activities being found on MBODAs (Fair, 2020). Perceived members' trust propensity refers to individual users' willingness to trust other members on the online dating platform, and it serves as a central source that induces one's perceptions of other members. It may have a critical impact on a user's self-disclosure, especially in response to manipulative activities that may happen on the MBODA (Doffman, 2020). This is essential when unknown risks are involved (Dinev and Hart, 2006; Shetty et al., 2017). Information disclosure is vital to assess the experience of the online service, especially in computer-mediated interactions. Therefore, users who perceive that other members in the shared environment can be trusted tend to disclose more information in their interactions. Thus, we expect:

H5: Perceived members' trust propensity is positively associated with self-disclosure intention.

Our research model is shown in Figure 1 below.

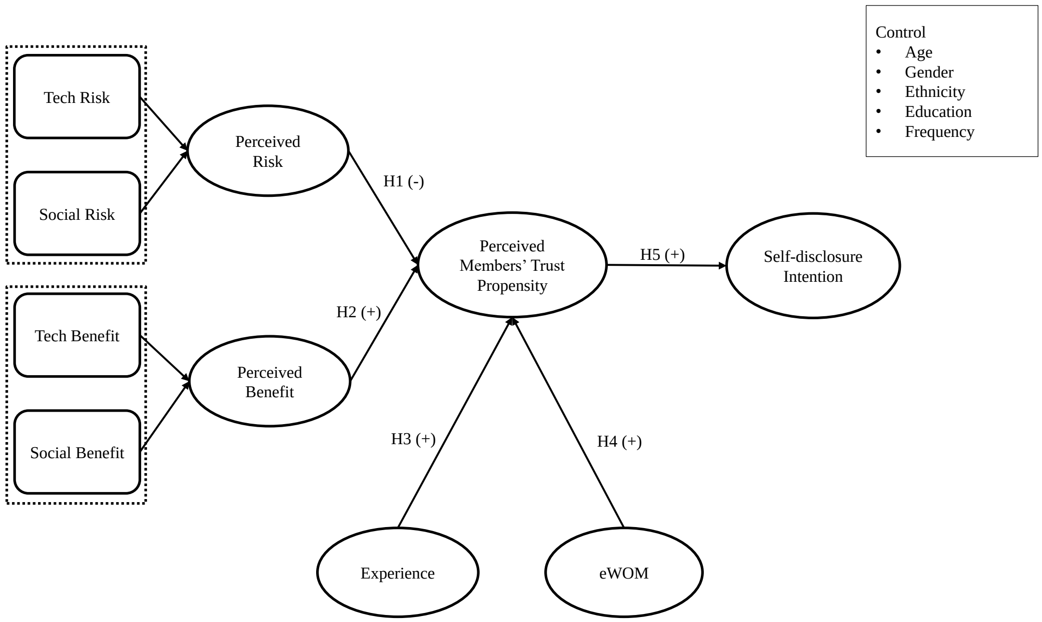

Figure 1. The research model

METHODOLOGY

Data collection procedures

We recruited respondents from the Amazon Mechanical Turk (MTurk) online crowdsourcing platform. Respondents were MBODA users residing in the United States. Any potential participants who did not satisfy the MBODA usage requirement were not allowed to participate.

There are dozens of MBODA applications with over 50 million subscribers in the United States alone (Madigan, 2020). Therefore, we did not designate a specific MBODA in the survey but asked participants to provide the name of the MBODA they use most frequently to gain sufficient variance for our research model's variables. Since participants may prefer different MBODAs, their response on risk and benefit perceptions, member trust belief, and self-disclosure intention may vary based on the MBODA they use the most. This approach allows us to achieve generalizability and to capture their impacts more accurately (Zhao, Lu, and Gupta, 2012). Furthermore, age, gender, ethnicity, and education were added as control variables to reduce bias created by service preference. A total of 344 usable responses out of 348 were received and used in our data analysis. Table 2 presents the demographic information of the participants.

Variable	Labels	Percentage
Gender	Males Females Others	59.50% 39.50% 1.00%

Ethnicity	White Black/African American Hispanic Asian Mixed Race	65.90% 11.10% 7.00% 12.8% 3.20%
Education	Less than 12th grade High school/GED Bachelor's degree Graduate degree	0.90% 34.50% 49.40% 15.20%
Frequency	Less than 1 month 1 to 3 months 6 months More than 6 months	8.10% 18.30% 14.20% 59.30%

Table 2. Descriptive statistics

Measures

All the measures were adapted from previous studies and have been proven to be reliable and valid. Five-point Likert scales ranging from "strongly disagree" to "strongly agree" were used for multiple items of all latent constructs. Based on previous studies (Featherman and Pavlou, 2003; Jacoby and Kaplan, 1972), perceived benefit and perceived risk were understood as multidimensional constructs. Therefore, we treated them as second-order constructs comprised of two dimensions: technological risk and social risk (to measure perceived risk) and technological benefit and social benefit to measure perceived benefit.

We adapted and modified the measurement items based on an intensive literature review to achieve content validity. Initially, we used comprehensive multiple-item measures based on the IS literature to measure our research constructs. Tech risk and social risk were respectively measured and modified using items of perceived risk (Chakraborty et al., 2016), while tech benefit and social benefit were modified and extended from items of perceived benefit (Forsythe, Liu, Shannon, and Gardner, 2006; Kim et al., 2008). eWOM quality was measured by items developed by Awad and Ragowsky (2008). Experience was adapted from Khalifa and Liu (2007). Perceived members' trust propensity was measured using four items (Chen et al., 2016), and disclosure intention was adapted from Chen and Sharma (2015). Appendix A presents detailed measurements of the key constructs and their sources.

RESULTS

We used Smart PLS 3.0 to perform component-based structural equation modeling to examine our measurement model and test the proposed hypotheses. There are several reasons to use the partial least squares (PLS) technique: (a) PLS is suitable for exploratory research where relationships have not been fully examined (Chin 1998; Chin, Marcolin, and Newsted, 2003), and (b) PLS is able to handle formative and reflective constructs, making it suitable for validating the proposed model (Diamantopoulos, Riefler, and Roth, 2008). In our model, two independent variables (perceived risk and perceived benefit) are second-order formative constructs; therefore, they are effective for validating the research model using PLS (Gefen, Straub, and Boudreau, 2000; Hair, Ringle, and Sarstedt, 2013).

Measurement model

Two constructs (perceived benefit and perceived risk, containing two first-order constructs, respectively) were modeled as formative second-order constructs. The two dimensions (social risk and tech risk, or social benefit and tech benefit) are not interchangeable but capture some upper-level construct components. Other principal constructs were reflective. For the different effects of first-order constructs on second-order constructs, the second-order constructs were treated as formative at the second-order level since a reflective second-order construct would show high correlations among its first-order factors (Jarvis, MacKenzie, and Podsakoff, 2003; Pavlou and El Sawy, 2006).

The formative second-order constructs' measurement quality was tested following the suggestions by Diamantopoulos and Winklhofer (2001); see also (Petter, Straub, and Rai, 2007), and were directly measured using items from all the first-order constructs (Bock, Zmud, Kim, and Lee, 2005; Petter et al., 2007). Specifically, the repeated indicator approach (also known as the hierarchical component model) was applied based on the results of the reflective-formative hierarchical component model testing. This approach measures the second-order factor using the observed latent variables for loading all the first-order factors (Hair, Sarstedt, Ringle and Gudergan 2017; Ciavolino and Nitti, 2013). For second-order construct significance testing, perceived benefit and perceived risk weights from the first-order constructs (social benefit and tech benefit) to the second-order constructs were 0.44 and 0.65, respectively. The t-statistics were greater than 2.57. In addition to perceived risk, the weights from social risk and tech risk were 0.47 and 0.64, respectively, and the t-statistics were greater than 2.57, which met the formative construct specifications. The variance inflation factor (VIF) was used to check for multicollinearity among the first-order components (social benefit, tech benefit, social risk, and tech risk). The results show that the VIF values were all below the cutoff of 5 (1.998, 1.873, 1.689, and 1.694, respectively); therefore, multicollinearity is not a concern (Hair et al., 2013; Petter et al., 2007).

All first-order constructs were set as reflective. The measurement model assessment used to examine measurement items' reliability (including composite and indicator reliabilities, as well as convergent validity and discriminant validity) was conducted (Hair et al., 2013). Table 3 presents the composite reliability (CR), the average variance extracted (AVE), and the principal constructs' descriptive statistics. Measurement reliability was evaluated using CR and Cronbach's alpha (CA). Fornell and Larcker (1981) suggested that a CR of 0.70 or greater is considered acceptable for research, and a CA value (the reliability of the scales and the resources from which they were adapted) higher than 0.70 (Nunnally, 1994) indicates that there is sound internal reliability (Gefen et al., 2000; Nunnally, 1994). Table 3 shows that the CR values for all constructs are greater than 0.80, and the CA values are all above 0.70, which indicates sufficient reliability of the constructs.

	Mean	Std	CR	CA	1	2	3	4	5	6	7	8
1. Disclosure	3.54	0.95	0.91	0.87	**.85**							
2. eWOM	3.82	0.98	0.95	0.93	.37	**.91**						
3. Experience	3.50	1.12	0.94	0.92	.46	.20	**.93**					
4. Social Benefit	3.84	0.82	0.85	0.75	.36	.30	.32	**.82**				
5. Social Risk	3.80	0.86	0.90	0.84	.02	.09	-.05	-.03	**.87**			
6. Tech Benefit	3.91	0.87	0.91	0.87	.30	.31	.24	.65	-.01	**.88**		
7. Tech Risk	3.38	0.93	0.91	0.88	.02	.13	.03	-.05	.60	-.04	**.86**	
8. Perceived Members' Trust Propensity	3.24	0.96	0.93	0.90	.36	.21	.35	.44	-.19	.34	-.16	**.89**

Note: Std: standard deviation; CR: composite reliability; CA: Cronbach's alpha; the diagonal values (bold) represent the square root of AVE.

Table 3. The Means, Standard Deviations, Correlations, and AVE

The validity test includes the convergent validity test and the discriminant validity test (Chin, 1998). Convergent validity is used to evaluate whether the related items converge on the appropriate constructs, and discriminant validity examines whether the constructs can be differentiated from related constructs (Chin, 1998). Factor loadings measure convergent validity. Additionally, all the AVEs are greater than 0.6, exceeding the suggested threshold of 0.5 (Fornell and Larcker, 1981). These statistics are generally interpreted as a measure of reliability for the construct and as a means of evaluating discriminant validity. Appendix B illustrates that the factor loading coefficients are all greater than 0.7, indicating sufficient convergent validity (Wixom and Watson, 2001). The square roots of the AVEs are adopted to evaluate discriminant validity. All are higher than the correlations between the construct and the other variables in the model, indicating that the measurement model has strong discriminant validity.

Common method variance

Common method variance (CMV) can be a major source of measurement error for survey studies, especially when variables are latent and measured using the same survey at one point in time. CMV could potentially inflate the true correlations among latent constructs and threaten the validity of our conclusions. First, Harman's single-factor test was used to assess the extent of CMV ((Podsakoff, MacKenzie, Lee, and Podsakoff, 2003). CMV is present if the factor analysis results in a single factor or if one general factor accounts for more than 50% of the covariance. In our study, the first factor accounts for 24.25% of the variance, and all items entered the explanatory factor analysis. The un-rotated solution outcome was seven total factors, which equals the number of latent variables in our model. Second, we followed Chin et al.'s (2003) method of controlling for CMV in PLS analysis and checked the R^2 values with and without the marker variable: the results were 0.013 and

0.003, respectively, which are less than the 0.1 threshold. Appendix C presents the results of CMV testing. We, therefore, confirm that CMV is not a serious concern in this study.

Structural model results

The results of hypothesis testing, including the t-values, path coefficients, and R^2 values, are exhibited in Figure 2. R^2 is used to explain the endogenous latent variables and the model's predictive power (Hair et al., 2013). Both perceived members' trust propensity (0.426) and self-disclosure intention (0.337) can be considered to have moderate R^2 values (Hair et al., 2013).

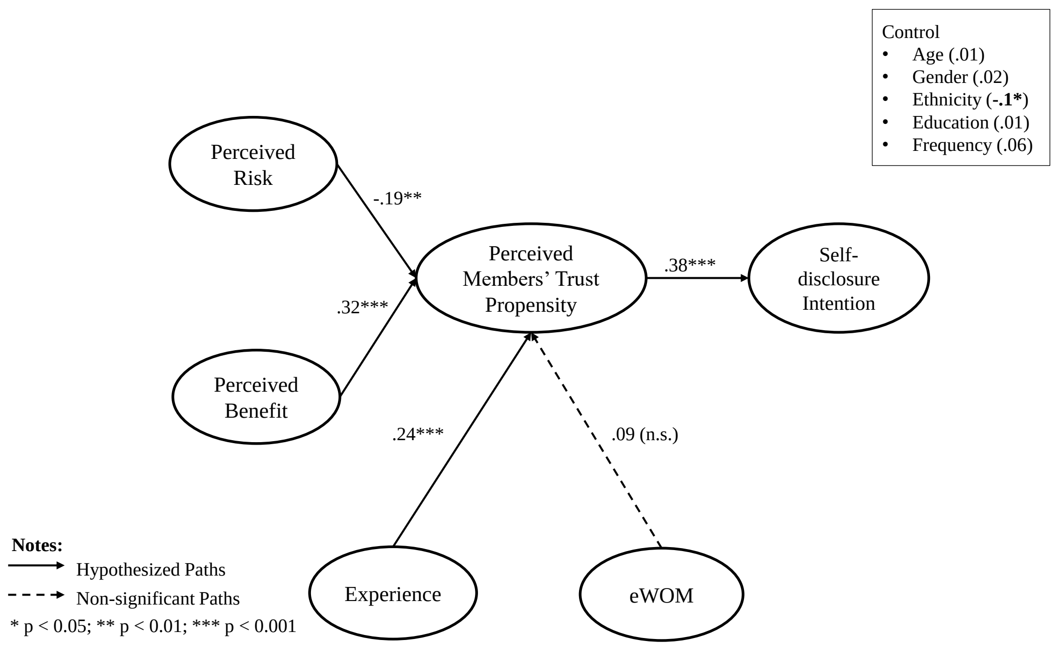

Figure 2. Results

We employed PLS bootstrapping with a 5,000 resampling procedure to test the significance of all paths in the research model (Hair et al., 2013). Table 4 shows that the relationship between perceived risk and perceived members' trust propensity was significant (β = -0.19, p < 0.01), lending support to H1. Perceived benefit was positively associated with perceived members' trust propensity (β = 0.32; p < 0.001), providing support for H2. Therefore, perceived members' trust propensity was negatively affected by perceived risk, and positively influenced by perceived benefit.

Hypothesis	**Path coefficient**	**p-value**	**Supported?**
H1: Perceived risk and perceived members' trust propensity	-0.19	< 0.010	Supported

H2: Perceived benefit and perceived members' trust propensity	0.32	< 0.001	Supported
H3: Users' experience and perceived members' trust propensity	0.24	< 0.010	Supported
H4: eWOM and perceived members' trust propensity	0.09	0.120	Not Supported
H5: Perceived members' trust propensity and self-disclosure intention	0.38	< 0.001	Supported

Table 4. Hypothesis test results

The relationship between users' experience and perceived members' trust propensity (H3) was positive and significant ($\beta = 0.24$, $t = 4.69$, $p < 0.01$), while the relationship between eWOM quality and perceived members' trust propensity (H4) was not supported ($\beta = 0.09$, $t = 1.754$, $p > 0.05$). Furthermore, users' trust toward the MBODA was positively associated with their self-disclosure intention ($\beta = 0.38$, $t = 7.105$, $p < 0.001$), so H5 is supported. Among the five control variables, ethnicity had a negative and significant impact on self-disclosure intention in the MBODA platforms ($\beta = -0.1$, $t = 2.237$, $p < 0.05$), but no other control variables were significant.

DISCUSSION

This study's objective was to discover the antecedents that may influence perceived members' trust propensity in the context of MBODAs and its impact on personal information disclosure intention. Fair (2020) reported that 55% of online dating service users have experienced some form of threat or problem in MBODAs, such as hacking, malware, online wire fraud, online romance scams, or identity theft. In this research, we empirically tested the aforementioned hypotheses, and we found that antecedents, perceived risk, perceived benefit, and prior experience with MBODAs influence perceived members' trust propensity. Specifically, two antecedents (perceived benefit and users' experience with MBODAs) positively influence perceived members' trust propensity, and perceived risk was negatively associated with it. In terms of the relationship between perceived members' trust propensity and self-disclosure intention, our results show that there was a positive relationship between them. This indicates that, when users show stronger trust toward other members of the MBODAs, they are willing to disclose more information.

Therefore, MBODA providers need to understand the risks and benefits for users and develop security strategies to protect and create a safe environment in order to retain users. However, perceived members' trust propensity in MBODA environments plays a critical role as the central mechanism of self-disclosure intention. This is consistent with findings from previous research in other contexts about the effects of perceived members' trust propensity (Cheung and To, 2017), that key performance indicator for MBODA providers whose influence relies on the users' positive experience and their assessment of risks and benefits in using the MBODAs. Similar to Dinev and Hart (2006), membership in

MBODAs is fluid, as users leave the platform after finding a potential romantic partner. Therefore, it is highly critical and challenging to gain other members' trust, especially by uncovering unknown risks associated with the MBODA community and the technology itself (Albury et al., 2017; Buchanan and Whitty, 2014; Doffman, 2020).

Furthermore, users of MBODAs are concerned with the tech risks involved with using the technology and the social risk that arises in interacting with other members on the platform. These are often embedded within frequent unknown risks from both the social and technological sides (Albury et al., 2017; Doffman, 2020). Therefore, understanding social risk and tech risk is essential not only to users but also to dating app developers in order to make the dating environment safer and more secure. Simultaneously, social and tech benefits have to be reinforced to make sure users have a good experience and positive perceptions toward MBODAs. This study finds that perceived benefit has a stronger effect than perceived risk. When the perceived benefit is high, users' perceived members' trust propensity of MBODAs increases, encouraging users to disclose their personal information. Therefore, it is important to institute the process of balancing different salient risk and benefit beliefs, which influence self-disclosure intention.

Furthermore, in the context of MBODAs, eWOM was not a significant predictor of perceived members' trust propensity. This indicates that users form their perceived members' trust propensity on MBODAs according to their own usage experience, as well as the perceived benefit and risk.

Theoretical implications

First, this study focused on important determinants related to perceived members' trust propensity and its effects on self-disclosure intention on MBODAs. Although there is growing attention to MBODAs, few empirical studies have confirmed users' perceived members' trust propensity and self-disclosure intentions.

Second, the study focuses on user experiential factors that are critical to trust propensity formation in virtual settings such as MBODAs. The results suggest that usage experience and perceived benefit are effective in enhancing perceived members' trust propensity within the MBODAs. Previous studies explain the information disclosure behavior without considering external effects that users cannot control (social risk and tech risk embedded within MBODAs), and that may influence users' self-disclosure intentions. Also, internal mechanisms (e.g., users' experience with the MBODA) positively affect users' perceived members' trust propensity toward the apps.

Third, two dimensions of perceived risk and perceived benefit embedded within the MBODA platform are developed, which helps the privacy and security literature to extend the multidimensional understanding of risks and benefits (Barth and De Jong, 2017; Polites et al., 2012). Future studies should consider balancing social and technological factors' impacts on users' perceptions of risk and benefit so that social and technical online platforms can yield a broader understanding of how users behave differently across online platforms or contexts.

The study contributes to the literature on trust propensity that suggests that users' judgments of members' characteristics influence trust propensity. Mainly, it is relevant to consider only member dispositional characteristics, but experiential characteristics, such as experience in promoting trust in virtual platforms, are also important. Perceived members' trust propensity is a central factor in interactions, both in the traditional setting (Colquitt et al., 2007) and in the virtual setting (Chen et al., 2016; Cheung and To, 2017). However, these interactions are not influenced by members' eWOM, but their experiential MBODAs' benefit and risk factors.

Practical implications

A growing number of existing users switch between dating apps while seeking a better experience (Madigan, 2020). Our study's findings suggest three possible explanations to address this phenomenon. First, perceived benefit and user experience have positive effects on perceived members' trust propensity. Therefore, dating app developers should identify factors that influence users' self-disclosure intention in order to retain their user population and maintain their market share. Managers should also place more emphasis on benefits and enhancing users' experiences within the platform.

Second, perceived members' trust propensity plays an essential role in encouraging users to disclose personal information on MBODAs. Dating app developers need to enhance their dating environments' safety by developing advanced algorithms focused on detecting "bad apples." Removing malicious users may help dating app providers gain users' trust to retain users and maintain the market share. To do so, MBODA providers need to create a transparent privacy policy and allow end-users to read and sign a confidentiality agreement with a clear explanation. Such a mechanism would motivate end-users to be engaged and know that their information is protected.

Finally, when users have a good experience, they will remain in the platform and reinforce their trust toward other members. Therefore, MBODA providers and end-users themselves need to enforce and respect safety in the online dating community. Managers could reward civil interactions between members and penalize misbehavior or suspicious acts to prevent scams on the MBODA platform.

CONCLUSION

It is important to understand both the risk and benefit associated with MBODAs. Trust in members within the MBODAs community is critical for business success and finding romantic partners since MBODAs platform is set up for users to meet new people and share emotions in their communications to form a romantic relationship. Also, due to the fact that MBODAs platform is based on person-to-person communication, it is important to form perceived members' trust during the initial interaction. In the MBODA context, the stronger the perceived members' trust propensity, the less wary members will be. This study provides insights for MBODAs providers to understand factors that can reinforce members' trust propensity. The study's findings provide clues for MBODAs companies to develop policies that allow a safe dating environment and strengthen perceived members' trust.

Despite the interesting findings, the study has limitations. First, this study was conducted in the U.S.; thus, the results may not be generalizable to other countries. In the U.S., tech companies are obliged to follow more rigorous standards. Also, U.S. society values individualism and represents a culture of low uncertainty avoidance (Hofstede, 2011). Therefore, the findings may not be generalizable to other countries where privacy laws may be less stringent. A cross-cultural study will be necessary for the future since it may help to validate the proposed model in this study and further improve our approach.

Second, to enlarge the variances of the constructs, this study examined different MBODAs during the survey. Consequently, there may be uncertainties about whether possible functionality dissimilarity across MBODAs would affect the model's validity. Therefore, future research is encouraged to categorize MBODAs by different levels of functionality (e.g., high, average, and low), and empirically examine whether the functionality dissimilarity moderates the proposed relationships found using the model. In addition, we used five-point Likert scales to collect the survey data, which may affect the variance of the responses. In future work, we will apply seven-point Likert scales to increase variability (Baron and Kenny, 1986; Preacher and Hayes, 2004).

Third, we applied a survey methodology to perform this research. which may not minimize the CMV concern and may not fully capture the broader effects of attitudinal changes and technological changes embedded in MBODAs. In future research, we plan to apply different methodologies. Longitudinal-based survey methods may capture changes over time, or experimental methods may create a more realistic situation in which one or more manipulations under different conditions may offer different effects and explanations.

Finally, MBODAs often sell premium packages to users who pay for premier services. This study did not consider possible effect differences between users with premium packages and regular subscriptions. Future studies may compare the effects of perceived members' trust propensity across these different packages.

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APPENDIX A. SUMMARY OF MEASUREMENT QUESTIONS

Perceived Risk (modified and extended from Chakraborty et al. 2016)

Social Risk

(1) Mobile-Based Online Dating App (MBODA) users can easily become victims of sexual abuse and harassment by others.
(2) MBODA users expose themselves to various physical and cyber risks by any user.
(3) Users have a high chance of encountering threats of privacy risks and harassment on MBODA.

Tech Risk

(1) MBODA is vulnerable to hackers who may steal users' information.
(2) Users' personal information (profile photo, location, job status, hobbies, etc.) stored on MBODAs is not safe due to MBODA's weak security systems.
(3) MBODA's compromised privacy and/or security systems allow hackers to steal users' information.

Perceived Benefit (modified and extended from Kim et al. 2008)

Social Benefit

(1) I can be more selective thanks to accessing a bigger potential romantic partner group from using MBODAs.
(2) Using MBODAs enables me to express myself more confidently and communicate more effectively to potential romantic partners.
(3) Using MBODAs adds to my uniqueness.

Tech Benefit

(1) I feel that the MBODA's technology features (matching algorithm, location-based, browsing, etc.) are useful.
(2) Using the MBODA's features (matching algorithm, artificial intelligence to suggest a meeting in real life, etc.) increases my productivity in meeting a potential well-matched partner.
(3) Using the MBODA's features (e.g., location-based, browsing, personalization) enables me to find a potential soulmate more quickly than traditional dating.

eWOM (adapted from Awad and Ragowsky 2008)

(1) Review comments about MBODAs are relevant for me.
(2) Review comments about MBODAs are helpful.
(3) Review comments about MBODAs are useful.
(4) The MBODA reviews are usually the information I need.

Experience (adapted from Khalifa and Liu 2017)

(1) I regularly log in to this MBODA.
(2) Using this MBODA is part of my daily routine.
(3) I access this MBODA frequently.

Perceived Members' Trust Propensity (Chen et al. 2016)

(1) I feel that people on MBODAs are trustworthy.
(2) I feel that people on MBODAs are generally reliable.
(3) I feel that people on MBODAs will not take advantage of me.

Self-Disclosure (adapted from Chen and Sharma 2015)

(1) I have a detailed profile on this MBODA.
(2) My profile on this MBODA tells a lot about me.
(3) I reveal much of my information on this MBODA.
(4) From this MBODA, it is easy to find out my personal interests and preferences.

APPENDIX B. CROSS LOADINGS

	DISC	EWOM	SB	SR	TB	TR	PMTP	EXP
DIS1	0.836	0.370	0.301	0.036	0.217	−0.003	0.281	0.412
DIS2	0.891	0.339	0.327	0.069	0.295	0.047	0.313	0.382
DIS3	0.868	0.277	0.304	−0.061	0.249	0.028	0.374	0.447
DIS4	0.807	0.300	0.357	0.066	0.275	0.004	0.274	0.359
EWM1	0.336	0.910	0.229	0.105	0.276	0.113	0.200	0.198
EWM2	0.340	0.921	0.304	0.095	0.327	0.110	0.233	0.179
EWM3	0.312	0.898	0.283	0.066	0.263	0.103	0.152	0.179
EWM4	0.363	0.912	0.311	0.077	0.298	0.144	0.227	0.218
SB1	0.210	0.198	0.777	0.035	0.542	−0.044	0.263	0.145
SB2	0.269	0.268	0.795	−0.053	0.516	−0.038	0.304	0.190
SB3	0.394	0.282	0.869	−0.036	0.552	−0.037	0.451	0.394
SR1	0.021	0.113	−0.024	0.889	−0.044	0.424	−0.170	−0.056
SR2	0.035	0.097	−0.018	0.862	0.047	0.541	−0.150	−0.043
SR3	0.009	0.030	−0.031	0.865	−0.035	0.565	−0.133	−0.045
TB1	0.269	0.309	0.583	0.008	0.834	−0.001	0.296	0.245
TB2	0.259	0.265	0.567	−0.011	0.908	−0.035	0.314	0.201
TB3	0.281	0.289	0.594	−0.030	0.919	−0.047	0.353	0.229
TR1	−0.011	0.106	−0.061	0.505	−0.038	0.889	−0.139	0.037
TR2	0.029	0.097	−0.057	0.492	−0.040	0.922	−0.153	0.042
TR3	0.050	0.156	−0.003	0.557	−0.005	0.859	−0.119	0.025
PMTP1	0.333	0.220	0.358	−0.159	0.326	−0.176	0.907	0.339
PMTP1	0.343	0.235	0.445	−0.164	0.360	−0.132	0.904	0.325
PMTP1	0.296	0.134	0.337	−0.135	0.262	−0.097	0.823	0.206
EXP1	0.405	0.168	0.294	−0.011	0.253	0.049	0.264	0.918
EXP2	0.446	0.242	0.277	−0.116	0.193	0.021	0.329	0.913
EXP3	0.453	0.177	0.331	−0.020	0.260	0.043	0.329	0.942

APPENDIX C. COMMON METHOD BIAS ANALYSIS WITH FANTASIZING MARKER VARIABLE

Construct	R^2 without Marker Variable	R^2 with Marker Variable (FTZ)	Delta R^2 (Difference)
Perceived Members' Trust Propensity	.269	.272	0.003 ($p < 0.10$)
Self-Disclosure Intention	.146	.159	0.013 ($p < 0.10$)

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