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Conceptualizing a Framework for Social Media Data Sharing

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Abstract

Information sharing is one of the most important trends on social media nowadays, but detailed research on what can encourage it is still in the early stages. This exploratory work examines three categories of antecedents to data sharing which have come up in the literature: sharing benefits, social influences, and trust / risk issues, particularly associated with reliable vs. false information. A very simple model of direct impacts shows that information value, voluntary sharing, and false data risk significantly impact data sharing, but the other antecedents do not. The dependent variable was explicitly about sharing factual data, and these results suggest some feeling of social obligation to voluntarily share, particularly when respondents are well aware of the prevalence of misinformation. Social media providers together with organizations can contribute to efforts at preventing disinformation to enhance their credibility with social media users or customers.

Keywords

Social media data sharing, Information value, Social influences, Trust, Perceived risk

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Introduction

Information sharing is one of the most important trends on social media (SM) nowadays. Recent crises, such as the Covid-19 pandemic, as well as many more localized crises, have only increased the already widespread trend (e.g., Limaye et al., 2020). Even without such crises, sharing within their SM community is very popular among SM users (Abbas et al., 2022). It is also quite useful for companies, for example, in getting input for what the company should offer and how it should interact with customers (Tajvidi et al., 2020). Sharing is the foundation of SM communities. In virtual brand communities, for example, "VBCs, regardless of being hosted by firms or consumers, strongly rely on members' knowledge contribution to survive and thrive" (Liao et al., 2020, p. 2).

This discussion looks at sharing benefits, social factors in sharing, and aspects of trust and risk, especially with some attention to the widespread problem of misinformation. Much of the recent research has focused mostly on the mechanics of sharing, such as which SM are used, and on what kind of information is shared (e.g., Abbas et al., 2022). However, "many VBCs suffer greatly from insufficient knowledge contribution" (Liao et al., 2020, pp. 1-2). Thus, there is also need to more closely examine why users share information, as well as potential barriers, so that benefits can be enhanced and barriers diminished. Some literature has started looking at relationship quality in the online communities (Rotchanakitumnuai & Speece, 2022; Zhang & Liu, 2022), and social aspects (Lin et al., 2019), but examination of motivations behind whether to participate in sharing is still scattered, and needs stronger conceptualization.

SM users gain information value from sharing (Lin et al., 2019), and they also often enjoy interaction with community members, a hedonic value (Sukhu et al., 2015). There are also social reasons (Yoo et al., 2014; Zhang & Liu, 2022). Liao et al. (2020, p. 2) argue that there is little social pressure on consumers to help the community and other members, so most knowledge sharing is largely voluntary. However, SM users also perceive security and privacy risks in sharing, so that trust becomes an important factor (Chang et al., 2017; Kim & Ahmad, 2013; Muliadi, 2022). These elements have all started to gain attention in conceptualizing social media knowledge sharing framework, but mostly piecemeal. This research looks at them all at once to ascertain which ones are most prominent. It should be regarded as exploratory, with results helping point out an approach to defining a model capturing key mechanisms which foster data sharing.

The context for examining these issues is Thailand. At the beginning of 2023, SM had nearly 52.25 million users, about 72.8 percent penetration, and users spent about 2 ¾ hours per day on SM. On average, users access just over 7 different platforms per month. The top ones in terms of number of users are Facebook (91.0% of internet users) and LINE (90.7%), but several others are well above 50 percent. In terms of stated favorite, Facebook dominates. Tiktok is a distant second, and LINE is a not-so-close third, but well ahead of any others.

According to recent surveys, 62.5 percent of SM users were concerned about what is real and what is fake on the internet, 41 percent decline cookies at least part of the time, and other security and trust issues also indicate some unease (WeAreSocial, 2023). All of this demonstrates that Thailand is a good context for this sort of research, with high usage of SM.

Literature Review

This research uses the terms data sharing, information sharing, and knowledge sharing as essentially synonymous, based on how typical SM non-expert users generally understand the terms. The academic literature sometimes distinguishes them, but even that discussion depends somewhat on what discipline is discussing the issues. There is not much agreement on exactly what the terms mean. Dong et al. (2017, p. 443), for example, say team knowledge sharing is “the extent to which team members share task-relevant ideas, information, and suggestions with each other”, i.e., knowledge sharing means sharing information. A recent review about knowledge sharing even combines the terms to summarize how social capital theory is useful for understanding “pro-social behaviors, such as individual or group knowledge/information sharing, and interactions among people or communities” (Ahmed et al., 2019, p. 84). Al-Busaidi & Olfman (2017) discuss inter-organizational knowledge sharing systems, sometimes calling them information sharing systems, and talk about what is shared as either knowledge, information, or data.

Whether or not precisely distinguishing these terms may be useful and important in some contexts, average SM community members generally use the terms somewhat interchangeably, and research on their engagement in SM communities may use all three terms, even in the same discussion (e.g., Aguilar & Terán, 2016; Pongpaew et al., 2017; Puspitasari et al., 2021). Here, the term data sharing is used to conform to how questions in the survey were asked. Mostly, what respondents report they do in the questions is to share data, information or news. In this discussion, then, readers should keep in mind that the terms often seem synonymous to SM users in everyday language. Whatever one calls such sharing, the problem of getting sufficient data sharing noted above (Liao et al., 2020) has been recognized for a long time. “The biggest challenge in fostering a virtual community is the supply of knowledge, namely the willingness to share knowledge with other members” (Chiu et al., 2006, p. 1873).

It should also be kept in mind that the three items used to measure the data sharing concept in this research all explicitly refer to factual information, not just any kind of information. Research has begun to address the problem of misinformation. Although the actual proportion of people who intentionally share false information is relatively low, they broadcast it widely (often with the help of bots), and it is fairly common (Di Domenico et al., 2021; Kaur & Gupta, 2022; Melchior & Oliveira, 2022). Many consumers are unhappy with the prevalence of false information, and somewhat discriminating in both judging information they find, and information they send (e.g., The Drum, 2020; Vraga & Tully, 2021). Nevertheless, they may unintentionally share false information simply because they have not thought carefully about it. Nudging (explicitly bringing accuracy to a more top-of-mind consideration) can reduce this unintentional element (e.g., Pennycook & Rand, 2022). There are hints from other research in Thailand that SM users are unhappy with misinformation (Rotchanakitumnuai & Speece 2022), so this project's questionnaire explicitly says factual information to provide a sort of priming nudge.

Regardless of the exact terminology, much has been discussed about sharing behaviors, but many observers point out the relative lack of much attention to its psychological antecedents, (e.g., Liao et al., 2020; Lin et al., 2019). The three sets of issues examined here are sharing benefits, social factors in sharing, and aspects of trust and risk, which are probably the most common in the relatively limited research on antecedents. Even when addressed, the somewhat scanty research is mostly piecemeal, often examining only one, occasionally two of these factors, but rarely the whole range of elements in these three antecedent issues as a set.

Sharing Benefits

Perceived value in traditional marketing context consists of functional value and utilitarian value (Zeithaml, 1988). Such considerations are important for data sharing. Lin et al. (2019), for example, include this sort of value from information as "outcome expectations." Value can be both to self and to others in the community. "The more that individuals believe their actions can provide benefits for them and others, the more likely they will be to engage in information-sharing behaviors" (Lin et al., 2019, p. 471). However, with modern SM communities, perceived value is often expanded to more dimensions. For example, early on, it was recognized that enjoyment, as well as usefulness, was an important aspect of perceived value in the expanded ability to connect with the mobile internet (Kim, Chan & Gupta, 2007). In general, it is widely recognized now that hedonic value, enjoyment and happiness, are as important as the functional and utilitarian aspects (de Oliveira Santini et al., 2020; Turel, Serenko & Bontis, 2010). A good part of that hedonic value in Thailand (as elsewhere) comes from interaction with other members of the user's SM community (Pongpaew et al., 2017; Rotchanakitumnuai & Speece, 2022).

Meta-analysis of 97 studies about customer engagement in SM indicates that both utilitarian and hedonic product value are determinants of customer engagement on SM, although the hedonic component is usually stronger (de Oliveira Santini et al., 2020). A few studies show that information value and hedonic value of the SM engagement itself contribute to continuance on SM (e.g., Ashraf et al., 2019; Li et al., 2018). There is relatively little work specifically on perceived value of engaging on the SM and how it relates to data sharing, but Ma et al. (2018) do demonstrate that both utilitarian value and fun in using WeChat contribute to sharing intentions. Baima et al. (2022) found that subjective enjoyment with the SM interaction fosters more willingness to share knowledge. Mojdeh et al. (2018) found a significant positive impact with items for their engagement concept which was actually mostly about enjoying the community interaction.

Thus, prior research supports the general sense of these proposed hypotheses, although work is still sparse on impacts specifically on data sharing. Information value and hedonic value are key benefits of sharing, and:

H1: stronger perceptions of information value will increase intention to share factual information

H2: stronger perceptions of hedonic value will increase intention to share factual information

Social Role

In the context of SM, with its potentially extensive interaction within the community, some research on perceived value has also expanded to include social value into the construct. Social value is a positive feeling about sharing data and information with others, and how it can contribute to one's position within the community. This can be understood through uses and gratifications theory, where social approval is a relevant gratification (Dunne et al., 2010; Lee & Ma, 2012). This is somewhat hedonic, although modeled as a separate construct when used. Mojdeh et al. (2018) also tested a similar concept, reputation in the community, and found that it does have a positive impact. Thus here, social acceptance includes feeling good about being accepted in the SM community.

H3: stronger perception that sharing improves one's own self-perception and social acceptance will increase intention to share factual information

Social influence is a concept often included in examining technology adoption and continuance. There is no unified terminology. Yoo et al. (2014) summarize issues such as subjective or social norms which push users to conform to community SM behaviors, and pull issues such as desire for social image or social capital. Push issues are often called social norms, sometimes other things. This is the influence exerted by other people, such as relatives, friends, and colleagues, on the user's intentions and/or behavior in using technology (Graf-Vlachy et al., 2018; Venkatesh et al., 2003). It might be explicit expression from others, or assessment of what they might think based on observation of what they do. Careful examination of its role, however, indicates that either way, it is usually based on social interactions, not simply a user's general perceptions of what people might think (e.g., Eckhardt *et al*., 2009). Dwivedi *et al*., (2019, p. 721) say social influence is a "contextual factor" in technology acceptance models, and it can have an impact on behavioral intention. SM technology is interactive in its nature; several prior studies have evidenced the use of SM to share information in several contexts, for example the use of SM to share information during crisis (Kaewkitipong et al., 2016a; Tim et al., 2017), and the use of SM to share information in education context (Kaewkitipong et al., 2016b). The social influence is certainly highly visible, but there are only a few scattered studies on whether it affects data sharing (Graf-Vlachy et al., 2018).

H4: Stronger social influence of others will increase intention to share factual information

Early research on why people engage on SM already found that social influence is not entirely about others recommending or exerting some sort of pressure. It can also include feelings that the community is interested in similar issues, and has similar values as the user, sometimes called group norms (e.g., Cheung & Lee, 2010). Pull issues come from the user's own assessment of benefits of participating in the community, and for data sharing, can slightly overlap with the sharing benefits previously discussed. In other words, users enjoy interaction with the community, and the incentive toward voluntary sharing is probably related the enjoyment from helping others in their community. Enjoyment in helping others has occasionally been modeled as a significant positive antecedent to knowledge sharing Mojdeh et al., 2018; Zhang et al., 2020). Liu et al. (2020) even use gratification theory, but defined it as enjoying contribution of content, rather than seeking social approval, and demonstrated a positive impact on content contributions.

Push or pull, there is little the community could do to actually force anyone into sharing behaviors. "That is, all knowledge contribution behaviors rely on members' volunteerism with no explicit rewards." (Liao et al., 2020, p. 2). Such feelings are present among many Thai users, who, for whatever reason, voluntarily contribute: "I answer users in most cases. I want to help those that have problems. On some fan pages it takes time to get answers back from admin staff" (user interviewee in Pongpaew et al., 2017, p. 272). The discussion above about misinformation noted that users themselves may try to combat it by being careful about the quality of what they share. This is also evident among Thai users: "I comment on topics about software updates. I will carefully choose videos and then share them. I must feel that the material I share will benefit the audience before sharing" (user interviewee in Pongpaew et al., 2017, p. 272). Thus

H5: stronger intrinsic motivation, self-voluntary, will increase intention to share factual information

Trust and Risk

SM users also perceive security and privacy risks in data sharing, so that trust is factored in with their behavioral decisions (Chang et al., 2017; Kim & Ahmad, 2013; Muliadi, 2022). Trust has been a key issue since the early days of online activity (e.g., Grabner-Kräuter & Kaluscha, 2003). Trust exists "when one party has confidence in an exchange partner's reliability and integrity" (Morgan & Hunt, 1994, p. 23). In the interactive SM world, trust includes at least two components of exchange partners on SM brand pages. Users engage both with the company and the user community (e.g., Barger et al., 2016; Pongpaew et al., 2017; Wang et al., 2020). Even in more general SM, not on brand pages, trust in the platform may be a consideration (Wang et al., 2016). This mix of trust covering different categories of SM participants is sometimes called "social commerce trust" (e.g., Nadeem et al., 2020).

Hashim and Tan (2015) demonstrate that identification trust (essentially trust in the community, i.e., one exchange partner, not all) impacts sharing. Similarly, Muliadi (2022) found that both cognitive and affective trust in community members impact sharing. On the other hand, Rotchanakitumnuai & Speece (2022) include two exchange partners (community and brand), and found that the impact of the second-order trust factor on knowledge sharing does not have a direct effect, but is fully mediated by satisfaction and commitment. Trust clearly plays an important role in data sharing, but it does not yet seem clear about exactly how the mechanism works. Here, the tested hypothesis is

H6: stronger trust in others on the SM will increase intention to share factual information

Perceived risk is an individual perception towards uncertainty and negative outcome from an action (Dowling & Staelin, 1994). It can have various dimensions such as performance risk, social risk, time risk, and psychological risk (Stone & Gronhaug, 1993). Which of the many dimensions really matter depends on context. In e-commerce, for example, customers might worry about financial risk, delivery and return risk, product risk, or legal and policy risk to support the customer if any transaction problem occurs red during online transaction, as well as simple risk that technology itself has glitches (Rotchanakitumnuai, 2008; Rotchanakitumnuai & Speece, 2003).

In the context of data sharing on SM, research often considers the most relevant risk dimensions to revolve around privacy issues and social risk for information which can be attacked or prosecuted by other users (e.g., Chang et al., 2017; Lin et al 2019). Chakraborty et al. (2013), for example, point out that some users are quite concerned about privacy, and Hsieh-Yee (2021) discuss several risks of acting on false information. These are the two components of risk this research focuses on.

H7: stronger concern about false data risks will increase intention to share factual information

H8: stronger concern about privacy risks will decrease intention to share factual information

The simple model for these eight hypotheses is shown in Figure 1. As noted in the introduction, it should be regarded as exploratory. Research on data sharing is not yet very extensive, so it is somewhat risky to build a more complex model because not very much evidence has yet accumulated that can give guidance on how to structure one. Some of the hypotheses may not be significant, but that would not necessarily indicate that they are unimportant. Rather it would suggest that that some of them may need to be modeled with indirect, mediated impacts. For example, trust in recent work had a strong indirect effect, but no direct impact on knowledge sharing in the context of examining relationship quality

(Rotchanakitumnuai & Speece, 2022).

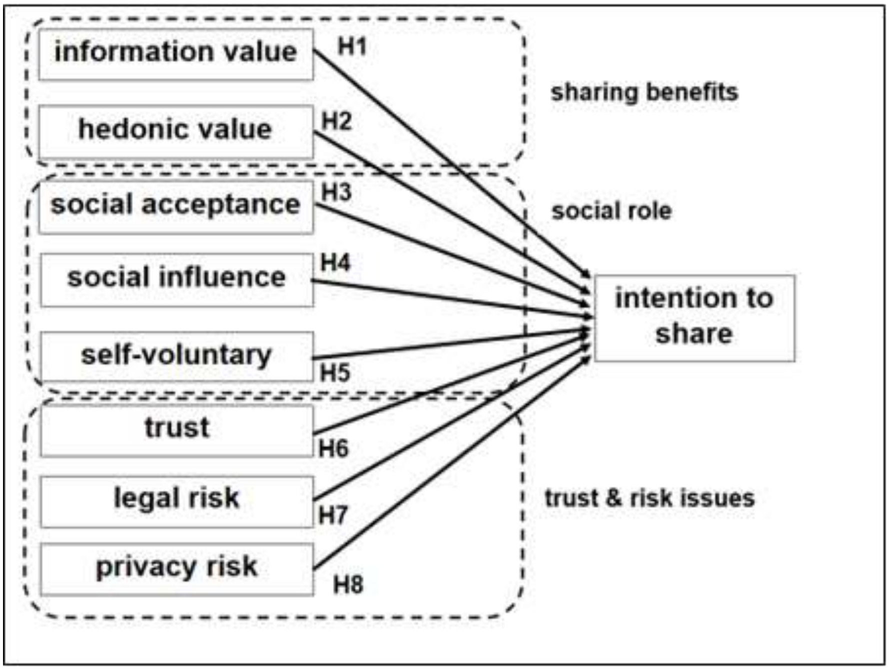

Figure 1 Research model

Source: Source of tables and figures are from the research and we draw from the results No sources to be cited.

Methodology

The questionnaire was developed from literature review. The measurement items were developed using Likert-scale measures which ranged from 1 which is strongly disagree, to 5 which is strongly agree. The questionnaire was pretested with a small sample of 30 to ensure it was understandable and to check reliability of internal consistency of the measurement items. All constructs were acceptable with Cronbach Alpha above 0.7. Then, the online questionnaire was developed via Google Forms for online data collection.

The population of this study is people who are experienced in using social media and have used it to share data via Facebook, LINE, Instagram, and Twitter platforms. Judgmental sampling was used to collect qualified respondents who have ever shared data in social media. The first question in the questionnaire was used to screen that the respondent experienced using SM and used it sometimes to share data via the aforementioned platforms. The online questionnaire link was distributed and posted to target respondents in many online platforms (e.g. LINE, Facebook, and emails of colleagues, alumni, and friends). The online questionnaire was distributed to 350 prospective respondents and the data was collected over a four-month period in 2022.

There are 292 respondents with complete questionnaires, a response rate of 82 percent. 56.5% of the respondents are female while 43.5% are male. Approximately 39% of the sample are between 20–30 years old. The education level indicated that 50% and 39% of total respondents had received a bachelor's degree and a master's degree, respectively. The average usage time on social media amongst the respondents is about 4.34 hours per day.

The study uses Structural Equation Model (SEM) to measure the construct validity of the items and test the hypotheses with path analysis. AMOS software is used to analyze SEM. Before running the SEM, the data was checked for Mahalanobis multivariate outliers, using all the variables which would be entered into the SEM model, and 17 outliers were identified. Pek & MacCallum (2011) say that such outliers can occasionally affect results, so they were not used. In practice, however, the 274 observations that were used gave essentially the same results, but the fit was slightly better without the Mahalanobis outliers.

Analysis

Table 1 shows summary statistics of the questionnaire items representing the constructs, as well as the factor loading of each item on the confirmatory factor analysis (CFA) in testing the measurement model below. The dependent variable in this research shows high intention to share factual information (composite mean = 4.12 on the 1-5 scale). As noted above, it should be kept in mind that the items in it all do refer explicitly to factual information. The item which specifically asks about sharing on SM is somewhat lower than the other items which do not specify where they share. This may indicate that users are becoming slightly disillusioned with SM as a useful platform for serious discussion. Items on several other constructs here also indicate that these respondents recognize problems with fake news.

Items for the two constructs about sharing benefits also indicate high agreement. Information value is higher overall (composite mean = 3.94), and the specific value of up-to-date news was among the highest individual item means in this research (4.28). Both getting news faster and getting useful information, however, are also quite high. Hedonic value is also a strong benefit (composite mean = 3.51), although not quite at the level of the information value. The process of interacting with other people has itself been shown elsewhere to be a perceived benefit of sharing, apart from the value of the information people get (Mojdeh et al. (2018; Pongpaew et al., 2017).

Table 1 Summary statistics of the questionnaire items

Measurement items / Factors	Mean	SD	CFA Loading
Sharing benefits measurement items			
Information value (Cronbach Alpha = .766)	**3.94**	**.759**	
Data sharing leads to getting up-to-date news.	4.28	.793	0.725
Data sharing leads to getting news faster.	3.94	.981	0.764
Data sharing leads to getting useful information.	3.88	.945	0.555
Hedonic value (Cronbach Alpha = .850)	**3.51**	**.906**	
Data sharing helps find enjoyable news to read from other people.	3.58	1.000	0.896
Data sharing helps create enjoyable discussion with other people.	3.57	1.011	0.847
Data sharing helps promote enjoyable interaction with other people.	3.38	1.085	0.709
Social role measurement items			
Social acceptance (Cronbach Alpha = .822)	**3.03**	**.959**	
Data and story sharing to other people makes you feel good.	3.40	1.069	0.762
Data sharing to other people makes you feel important.	2.95	1.174	0.838
Data sharing to other people makes you feel accepted.	2.73	1.105	0.741
Social influence (Cronbach Alpha = .764)	**3.53**	**.877**	
My social media community has influence on my decision to share data online.	3.70	.962	0.698
My close friends have influence on my decision to share data online.	3.65	1.128	0.773
My colleagues have influence to my decision on share data online.	3.24	1.093	0.706
Self-voluntary (Cronbach Alpha = .859)	**4.12**	**.772**	
You voluntarily share data without other people influence.	4.19	.859	0.917
You are willing to share data without other people influence.	4.25	.788	0.940
You intend to share data regularly without other people influence.	3.93	.966	0.689

Table 1 Summary statistics of the questionnaire items (continued)

Measurement items / Factors	Mean	SD	CFA Loading
Sharing benefits measurement items			
Trust & risk measurement items			
Trust (Cronbach Alpha = .846)	**2.77**	**.873**	
You share data because you have trust in service provider.	2.88	1.160	0.761
You think that information on social media is trustworthy.	2.80	.967	0.654
You share data because you believe people in social media are reliable.	2.70	1.117	0.849
You think that people who share data information to you on social media are trustworthy.	2.70	.965	0.706
False data & legal risk (Cronbach Alpha = .887)	**3.98**	**.833**	
Data sharing may lead to false information.	3.98	.947	0.828
The data that has been shared may lead to prosecution.	3.98	.917	0.780
The data that has been shared may cause other people damage.	3.97	.904	0.964
Privacy risk (Cronbach Alpha = .716)	**3.20**	**.867**	
Sharing data may lead to privacy information risk.	3.41	1.020	0.736
Sharing data may lead to risk that your data may be misused.	3.33	1.128	0.777
Sharing data may waste personal time.	2.86	1.107	0.637
Intention to share measurement items			
Future intention to share (Cronbach Alpha = .759)	**4.12**	**.824**	
You are always willing to share factual news.	4.35	.862	0.753
You always intend to share factual news	4.25	1.028	0.785
You always share facts to people on social media.	3.74	1.106	0.713

Respondents are roughly neutral on average about whether social acceptance is a factor for them (composite mean = 3.03). They do feel good about sharing, but the reference to other people on the other two items is weak. The influence of others did get moderately high agreement (composite mean = 3.53). As seen below, however, this did not relate to intention to share, so interpretation of this construct needs some careful consideration. The intrinsically motivated self-voluntary construct showed high agreement (composite mean = 4.12), and, as seen below, does relate to intention to share. The much stronger agreement with self-voluntary compared to the other two social role constructs is consistent with a sense of obligation to contribute constructively within the group in Asian societies. Some research indicates that Chinese, for example, tend to feel more responsibility to share information within the group than Westerners (Chow et al., 1999; Chow et al., 2000).

Trust is somewhat low (composite mean = 2.77), consistent with another recent sample of SM users in Thailand (Rotchanakitumnuai & Speece, (2022). The range of item means is quite narrow across trust in various people and aspects of the SM. Concern about risks associated with false data and the damage it can cause is quite high (composite mean = 3.98) with a very narrow range across the items representing several aspects. There is some concern about privacy risk (composite mean = 3.20), but it is not very strong. Some research has demonstrated somewhat different impacts from privacy risk depending on the level of privacy concern (e.g., Tan et al., 2012). Low concern, not surprisingly, has somewhat less impact on intention to use SM sites.

Assessing Reliability and Discriminant Validity

Multiple methods were checked to assess reliability and validity of the items representing the constructs. An initial exploratory factor (EFA) analysis was used on all items in these nine constructs. Nine distinct factors were obvious, clearly representing the nine constructs in this research. They accounted for 74.5 percent of variance, and every item loaded on its proper factor with negligible cross-loading. The confirmatory factor analysis (CFA) measurement model showed strong fit, but we deleted 17 Mahalanobis multivariate outliers which could potentially influence results (Pek & MacCallum, 2011). Hair et al. (2014) recommend checking whenever deleting data or measurement items to confirm that the results did not substantially change. The results did not change, but the fit was slightly better, indicating more precise estimates of the parameters and of the reliability / validity indicators.

It should also be noted that the first factor in the EFA accounted for only 22.9 percent of variance. This is essentially the Harman test, probably the most common method in international marketing research for checking common method variance (CMV). "If the first factor is the only factor with an eigenvalue > 1 and/or if the first factor accounts for > 50% of the total variance in all items, CMV is said to be present" (Baumgartner & Weijters, 2021, p. 8). This was not the case. There were multiple $\lambda > 1$, and forcing a single factor in the EFA resulted in no items at all with communality > 0.5. Thus, there is no evidence of any serious CMV.

Cronbach alpha and composite reliability were > 0.7 for all constructs, and the average variance extracted (AVE) was > 0.5 for all but the information value construct, which was 4.72 (Table 2). This construct AVE was low from a weak factor score on "data sharing leads to getting useful information" (.555; Table 1). This item did not show any substantial cross-loading on any other construct in the EFA, and the within-construct mean correlation of information value items was greater than the mean correlations with items in any other construct (Table 3), so we judged the slightly low AVE to be a minor issue. Hair et al. (2014) suggest just accepting occasional minor departures from guidelines if all other indicators are acceptable. This becomes a strong recommendation when deleting an item to improve conformance to guidelines would compromise the integrity of the construct measurement. We judged that "useful information" was a fundamental aspect of information value, and the meaning of the construct would be compromised without it, so we followed that advice and kept it.

Table 2 Reliabilities & AVE

	Cronbach alpha	Composite reliability	AVE
Information value	.766	.725	.472
Hedonic value	.850	.860	.674
Social acceptance	.822	.824	.611
Social influence	.764	.770	.528
Self voluntary	.859	.890	.733
Trust	.846	.833	.557
False data & legal risk	.887	.895	.741
Privacy risk	.716	.761	.517
Future intention to share	.759	.795	.564

Table 3 Mean correlation of items across constructs

	Info value	Hedonic value	Social accept	Social infl.	Self volun.	Trust	Legal risk	Privacy risk	Intend
Info value	**0.540**								
Hedonic value	0.352	**0.656**							
Social accept	0.245	0.369	**0.604**						
Social influence	0.145	0.255	0.299	**0.523**					
Self voluntary	0.291	0.149	0.113	0.072	**0.711**				
Trust	0.161	0.248	0.326	0.260	0.010	**0.615**			
False data risk	0.040	0.078	-0.035	0.060	0.096	-0.063	**0.725**		
Privacy risk	0.002	0.035	0.082	0.165	-0.125	0.124	0.362	**0.511**	
Future Intention	0.282	0.213	0.110	0.107	0.339	0.048	0.222	0.011	**0.561**

Note: bold is mean within-construct correlation, others are mean correlations of items across constructs

Model Results

Standard fit indices for the measurement model are all good (Table 4). This is a relatively complex model (28 observed variables representing nine constructs), with sample size of 275 after screening out the 17 Mahalanobis multivariate outliers, so Table 4 reports guidelines in Hair et al. (2014) for a model of this size. Using all the data without deleting the multivariate outliers changed fit indices slightly, but not the assessment about whether they met guidelines.

Table 4 Fit indices

	Recommended in Hair et al. (2014, pp. 579-584)	Measurement model	Comments
CMIN (df, sig)	not sig, (p > 0.05), but big samples and/or complex models rarely fit well	615 (df=311, p=0.000)	does not fit
CMIN/df	1 to 3	1.978	good fit
RMSEA (Lo90-Hi90)	< 0.07, CFI > 0.92 upper bound < .07	0.060 (0.053-0.067)	good fit
SRMR	< .08; CFI > .92	0.0687	good fit
TLI **CFI**	> 0.92 > 0.92	0.908 0.925	moderately good fit good fit
AVE **CR**	> 0.5 > 0.7	most > 0.5; one = 0.472 all > 0.7	good results good results

Note: standards from Hair et al. (2014) for n > 250 and m (number of observed variables) 12 > m > 30.

Three of the hypotheses were confirmed by the structural model results, but five were not supported (Table 5). Information value, one of the two sharing benefits, has the largest impact on intention to share factual data, as indicated by the standardized beta ($\beta = 0.472$). However, hedonic value does not have an impact on sharing factual data.

Table 5 Structural model results

			Estimate	S.E.	C.R.	P	β	Label
Intention	←	**Information value**	**0.564**	0.146	3.859	**0.000**	**0.472**	**H1**
Intention	←	Hedonic value	-0.016	0.074	-0.220	0.826	-0.021	H2
Intention	←	Social acceptance	-0.035	0.075	-0.463	0.643	-0.043	H3
Intention	←	Social influence	0.022	0.078	0.278	0.781	0.025	H4
Intention	←	**Voluntary sharing**	**0.256**	0.080	3.181	**0.001**	**0.254**	**H5**
Intention	←	Trust	0.012	0.068	0.181	0.856	0.016	H6
Intention	←	**False data risk**	**0.260**	0.073	3.567	**0.000**	**0.279**	**H7**
Intention	←	Privacy risk	-0.034	0.067	-0.509	0.611	-0.045	H8

Note: β = Standardized beta; R^2 = 0.493

Extrinsic social considerations did not have any impact on intention to share factual information. Better social acceptance self-perception from such acceptance was not near significance. The construct representing influence from close friends, SM community, or colleagues did not show any impact either. However, voluntary sharing, basically intrinsic motivation, was significant (β = 0.254). Given that the social influence construct was moderately strong in Table 1, and evidence (noted above) that more collectivist cultures may feel stronger obligation to share within the group, we might interpret this as a feeling of obligation to contribute to educating people in the social network, by countering false information with factual data.

Trust and perceptions of privacy risk were not near significance either. In general, trust is somewhat weak among these respondents, and there is a moderate level of agreement about privacy risks. However, users seem to accept these problems, at least regarding their willingness to share data. The risk about false data which can cause others damage and lead to legal exposure was significant. Recalling that the sharing dependent construct is explicitly about sharing factual information, this can easily be interpreted as feeling an obligation to counter false information by sharing factual data.

Discussion and an Initial Step at Refining Conceptualization

Data sharing on SM has become an important issue in the modern world, but the management field is still in relatively early stages of conceptualization about what antecedents encourage it. This research pulls together several themes in work so far, to examine the impact on intention to share data of several components each for information benefits, social role, and trust / risk issues. The approach mirrors early research in many fields, where initial stages simply look at a list of potentially relevant variables to test their impact. This particular work shows that information value, voluntary sharing, and false data risk all tend to encourage data sharing; while a number of other variables often appearing in the literature were not significant.

As noted several times above, however, this is just initial exploratory work; it cannot be regarded as the final word on these issues. Some of the non-significant variables here are well known to have impact on various aspects of SM behavior, including, occasionally, on data sharing. Non-significance here does not necessarily mean they are not relevant. Rather, it could also indicate that individually they might not have much impact, but collectively, in conjunction with other similar elements, they could make small contributions to an overall composite construct which does have an impact. It might also suggest that some of them could be mediated, with indirect effects on data sharing. In other words, the next step is a more sophisticated model. The simplest approach to this is consolidating ostensibly related elements into coherent second-order constructs. Just as a test, we ran a version constructing second-order composite variables from the three sets of issues in Figure 1; this model is shown here in Figure 2.

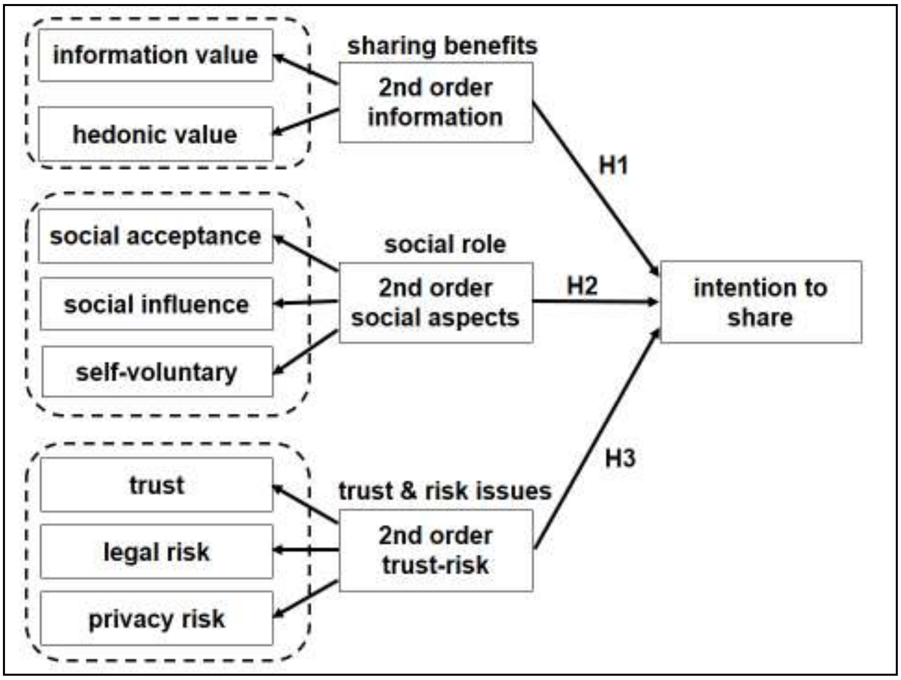

Figure 2 Alternative model with second-order constructs

This model did not work. Composite reliabilities and AVEs were very close to the values reported above, and some of the fit indices were within recommended range (e.g., cmin/df = 2.287, RMSEA = 0.069), although a little weaker than for the first model. However, TLI and CFI were both somewhat weak, and SRMR could not be computed at all because of a major (Heywood) problem estimating variance on the residual for the trust-risk composite variable, as well as a smaller problem with the standardized β on info benefit → intention (Table 6). The standardized residual covariance table showed many serious problems by the benchmarks recommended in Hair et al. (2014), whereas there were no problems with this in the first model. With Heywood problems, results are suspect, but even when they could be trusted, they are not consistent with some known effects. Consolidating the voluntary aspect of social interaction washes out its impact, so the social second-order construct is not significant. Similarly, the trust-risk construct is not significant in this test, although one of its components is when modeled separately.

Table 6 Results for the structural model in Figure 2

			Estimate	S.E.	C.R.	P	β	Label
Intention	←	Info benefit	**1.436**	0.559	2.57	**0.010**	**1.009**	**H1**
Intention	←	Social	-0.525	0.388	-1.353	0.176	-0.504	H2
Intention	←	Trust-Risk	0.001	0.016	0.035	0.972	0.006	H3

Future Research and Managerial Implications

Simply consolidating into second-order constructs clearly does not work here (although it can work in some cases), so the way forward seems to be careful assessment of how all of these eight antecedents fit together in several levels. Lin et al. (2019), for example, test a model with eight antecedents to intention to share information, many of which have mediated rather than direct impacts. They mostly focus on various social aspects, so do not examine the full range issues in this research, but their example does illustrate this approach. Rotchanakitumnuai & Speece (2022) use a hybrid approach, recognizing the coherent construct of relationship quality, but breaking the composite variable down to examine its internal structure. Some of its components have a direct impact on information sharing, but some have indirect mediated impact through the other components of the construct. However, there is not yet very much research on data sharing in conceptualizing a social media data sharing framework.

Thus, this exploratory research suggests that a very simple model with a list of individual antecedents to data sharing on SM is useful as a first cut at investigating this issue, but it is not sufficient for more detailed understanding. This work does help point out a direction for future research. Partly, it demonstrates that the somewhat piecemeal approach so far, which tends to look at one set of issues, is not enough for gaining a thorough understanding of determinants of data sharing. Information issues do have an impact, but it is not enough just to look at information benefits. Social issues also play a role, but they also are frequently investigated alone in the somewhat sparse research so far. Similarly, trust – risk issues are known to have some influence, but rarely integrated into a coherent package of multiple determinants of data sharing.

This research shows that each of these three sets of antecedent issues has some impact, suggesting that a more comprehensive model will need to account for all three sets. However, the very simple model that just throws in all the individual components does not seem to fully capture how data sharing can best be facilitated. The simple solution of only consolidating the antecedents into several second-order constructs does not work well at all. Future work on determinants of data sharing on SM will need to go through a careful process of putting together a coherent structure which fit the antecedents together into several stages to investigate both direct and mediated impacts.

Many detailed managerial recommendations to foster data sharing necessarily depend upon first gaining more sophisticated understanding of how the range of antecedents work. A few points, however, are already evident from this work. Managerially, the result that user perceptions about information value encourages data sharing confirms prior understanding. On brand pages, for example, posting lots of useful information can encourage users to share their own information. This is not as simple as it may sound on the surface, because “posting lots of useful information” is not really about manager posts. Trust is weak, including trust in the service provider, and even posting the brand’s factual information may lack credibility. “On the Facebook page you can hear the high and low points of the product from other users. On the website the company tells you only the good parts. They just want to sell to us” (user interviewee in Pongpaew et al, 2017, p. 270).

On the other hand, user enjoyment about providing factual information is high, and willingness to provide factual information is very high. Skillful admin moderators are considered part of the community, and thus, credible contributors, but user participation in information sharing is the key. “I Want to hear other people’s comments about upgrading devices, how to fix them. The fan page is a good place for finding a variety of users, who share information and share links or resources that may benefit you” (user interviewee in Pongpaew et al., 2017, p. 271).

Thus, here, the most useful finding for managers is that voluntary sharing has the most important direct impact on data sharing among several social factors. This has occasionally been noted, but has not received much attention. Much research about social issues focuses instead on the other two components included here – gaining social acceptance by the group, and influence of the group on the user. Those components were not significant here, but the sense of responsibility to voluntarily share is strong.

The focus on sharing factual information in this research probably plays a role in this. The findings show that the more strongly users see some of the problems stemming from disinformation, the more likely they are to share factual information. This parallels the voluntary sharing, and supports the assertion that users feel some responsibility to fight this problem in their SM community. Managers of SM brand pages can contribute to efforts at countering disinformation, but the goal here is not simply to directly provide correct information. Managers can contribute to the discussion, but by encouraging the community to investigate and provide most the factual information, the information becomes more credible, and the cohesiveness of the brand community is enhanced.

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