

# Attitudinal, Normative, and Resource Factors Affecting Communication Scholars' Data Sharing: A Replication Study

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## Abstract

This study explores the factors affecting communication scholars' data-sharing intentions, a critical component of reproducibility and replicability in open science. We replicate Harper and Kim's (2018) study, which employs the theory of planned behavior to demonstrate the impacts of attitudinal, normative, and resource factors. Specifically, their original research examines data-sharing practices among psychologists, and our replication aims to reinforce their findings within the communication field. Data from a survey of Chinese communication scholars ( $N = 351$ ) are analyzed using structural equation modeling. The findings indicate that perceived benefit and perceived risk significantly influence the attitudes of communication scholars towards sharing their data, positively and negatively, respectively. Additionally, attitudes, subjective norms, journal pressure, and the conditions facilitating data sharing have a significant positive impact on communication scholars' behavioral intentions. Perceived effort inversely affects attitudes toward data sharing but does not impact behavioral intentions. This study provides a theoretical framework for understanding data-sharing intentions and behaviors in the open science movement. The role of this research as a replication study serves as a compelling demonstration of scientific inquiry. Practical suggestions, such as fostering open dialog, institutional incentives, and cooperation between different actors to increase communication scholars' data-sharing intentions, and recommendations for carrying out replication and reproduction studies, are discussed. Finally, we judiciously reflect on the methodological limitations of our research and highlight directions for future research on open science.

## Keywords

China; communication scholars; open science; replication study; structural equation modeling; theory of planned behavior

## 1. Introduction

The replication crisis, which suggested that many social science findings appeared to be unreliable, inspired the open science movement (Dienlin et al., 2021; Matthes et al., 2015). Like many disciplines, communication studies are also dealing with the promotion of openness (Bowman et al., 2021; Lewis, 2020). Following the publication of “An Agenda for Open Science in Communication” (Dienlin et al., 2021), many efforts have been proposed by various position articles to encourage and facilitate open communication science (OCS), such as the *Journal of Communication*’s special issue titled Open Communication Research (Shaw et al., 2021) and *Digital Journalism*’s special issue titled Analytical Advances Through Open Science (Haim & Puschmann, 2023).

Despite broad familiarity and support for OCS among International Communication Association (ICA) members, as evidenced by a recent survey ( $N = 330$ ; Bowman et al., 2021), there remains a notable gap in actual engagement with OCS practices. While the potential legal and ethical challenges of OCS (Grand et al., 2012; Zhang et al., 2022) have been widely noted, we lack an understanding of these low levels of engagement with OCS practices. As one of the most salient aspects of open science, data sharing also faces the problem of low engagement (Tenopir et al., 2015; Vines et al., 2014; Zenk-Möltgen et al., 2018), which significantly hinders the reproducibility and replicability of communication research (Dienlin et al., 2021).

Hitherto, only limited research efforts have used empirical data to explore the factors that motivate communication scholars to share their data. To our knowledge, only Harper and Kim (2018) employed an empirical model based on the theory of planned behavior (TPB) to illustrate the elements that impact the willingness of American psychologists to embrace an open data badge. To address the research gaps in OCS practices within the field of communication, our study replicates the research design of Harper and Kim (2018). While their study focuses on the adoption of open data badges in psychology, exploring attitudinal, normative, and resource factors, our study extends this inquiry to the behavioral intentions of Chinese communication scholars in data sharing. This represents an empirical investigation of these factors through the lens of the TPB in a non-Western context, broadening the understanding of OCS practices globally.

## 2. Literature Review

### 2.1. Data Sharing and Its Role in Open Science

Although data sharing has been a component of scientific research for many years, recent technological advancements and the development of platforms such as the Open Science Framework have significantly enhanced the ease and scale at which data can be shared. This has led to an increased focus in the literature on data-sharing behaviors, particularly in the context of these modern platforms and the wider movement towards open science. Many such studies have identified the benefits of data sharing. For example, it has been claimed that data sharing can improve the reliability and robustness of communication scholarship (Dienlin et al., 2021) because the sharing of design protocols, measures, and analytic scripts can help improve the rigor of study designs and foster public trust (Banks et al., 2019). Researchers with interests that align can leverage existing scholarly work to either validate the results of prior studies or to explore new hypotheses, ultimately reducing costs, saving time with regard to data collection (Harper & Kim, 2018), and facilitating replication of studies and reproduction of analyses (Dienlin et al., 2021).

However, merely highlighting the benefits of sharing data does not provide a complete picture of healthy OCS. As de Oliveira et al. (2021) argued, OCS encompasses two distinct perspectives. The first perspective emphasizes principles such as acceleration, efficiency, and reproducibility, while the second perspective aims to foster participation, social justice, and the democratization of knowledge. The uneven development of OCS is what Dutta et al. (2021) called “hegemonic open science,” which emerges from knowledge production systems in the Global North and primarily serves the economic interests of platform capitalism. This approach systematically excludes the voices of marginalized communities in the Global South. This concept raises important considerations. For instance, if open science practices and platforms are primarily designed with the Global North in mind, they may not be as effective or accessible for scholars in the Global South, including China. This could influence the attitudes and behaviors of Chinese communication scholars towards data sharing. Our research could therefore contribute to a more nuanced understanding of how open science can be more inclusive and equitable, ensuring that it serves the diverse needs of the global research community.

## ***2.2. Data Sharing in the Global South***

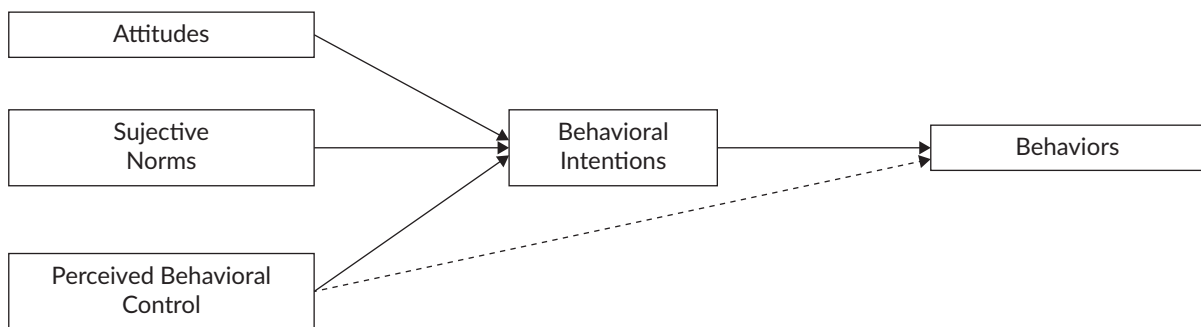
The Global South also plays a significant role in the OCS movement and faces unique challenges. In fact, studies have shown that OCS practices and scientific production in the Global South, such as Malaysia (Zhang et al., 2022), Thailand (Cheah et al., 2015), and Latin America (de Oliveira et al., 2021), are highly nuanced. As noted by Cheah et al. (2015), the Global South often exhibits little or no capacity for data sharing because data management is an expensive business, and skills in data collection, data validation, standardization of variables, and tabulation are rare. In addition, data analysis software/tools such as Statistical Package for Social Sciences (SPSS), Stata, and NVivo are costly, and only a few academic groups can afford them. In such cases, the difficulties of data sharing and researchers’ willingness to engage in such practices might be different from the situation in Western developed countries. Therefore, investigating communication scholars’ data-sharing intentions is crucial in the context of the Global South, and such an investigation could provide us with a holistic understanding of open science.

Notably, China is among the countries in which communication research is becoming more international due to the rapid development of 5G technology and the swift advancement of social media, which provides new avenues and subjects for research, thus contributing to the field’s evolution and international relevance. Some Chinese scholars are actively involved in studying and advocating open science (Xu & Zhang, 2020, 2022). Research has shown that OCS in China faces challenges with regard to weak awareness of open sharing, the fuzzy boundaries of data sharing, the lack of norms of data management, and insufficient incentives (Xu & Zhang, 2020). Chinese scholars, specifically those who are interested in qualitative research, are especially concerned with difficulties pertaining to data verification, replication, and reuse in regard to data sharing (Xu & Zhang, 2022). Considering the large number of articles published by Chinese scholars and the feasibility of sampling, we developed a questionnaire to investigate the factors that impact Chinese communication scholars’ data-sharing intentions.

### 3. Theoretical Framework

#### 3.1. The Theory of Planned Behavior

The TPB is a model used to understand and predict human behaviors across various disciplines (Ajzen, 1991). This model was proposed to improve the theory of reasoned action (Fishbein & Ajzen, 1977) by adding “perceived behavior control.” The theoretical structure of the TPB is shown in Figure 1. The TPB suggests that behavioral intentions affect actual behavior and that behavioral intentions are affected by attitudes, subjective norms, and perceived behavior control.



**Figure 1.** Conceptual model of the TPB.

The TPB has many mature applications in the social sciences, in which context researchers have explored the predictability of behaviors by explaining the formation of behaviors and the meaning of relevant influencing factors. Many studies have verified the ability of the TPB to predict behavioral intentions (Knowles et al., 2012; Kovac et al., 2016; St Quinton, 2022). Notably, the TPB is a suitable model for data policy research. For example, Sommestad et al. (2015) used the TPB to explain policy compliance intentions in information security and showed that the TPB made good predictions. Akdeniz et al. (2023) used the TPB and identified critical factors influencing intentions to share social media data, including past experiences with data sharing, attitudes towards sharing, perceived norms, and perceived behavioral control. As mentioned, Harper and Kim (2018) also employed the TPB to investigate the factors affecting American psychologists’ intentions to adopt an open data badge. Such flexibility demonstrates the TPB’s broad applicability across different domains, highlighting its value as a versatile framework for understanding the intricacies of behavioral intentions within various research settings.

Evidence for the TPB in non-Western cultures shows that it is a robust model for predicting behaviors across different cultural contexts. Studies have found that the core components of TPB—attitudes, subjective norms, and perceived behavioral control—are relevant and influential in shaping intentions and behaviors in various non-Western settings (Alzubaidi et al., 2021; White Baker et al., 2007). For example, Liu et al. (2019) examine factors influencing scientific data retrieval behaviors within the framework of TPB, offering insights into how attitudes, subjective norms, and perceived behavioral control can shape information-seeking actions in a Chinese academic setting. The findings underscore the theory’s relevance and adaptability in understanding and predicting behavior in diverse cultural contexts. However, the specific impact and interplay of these components can differ based on cultural norms, values, and societal structures, necessitating adaptations or expansions of the model to fully capture the nuances of behavior in these contexts.

The TPB's adaptability in predicting behaviors across varied cultural contexts paves the way for an in-depth exploration of how disciplinary distinctions influence adherence to open science practices. This research delves deeper into the differences between psychology and communication studies in terms of their engagement with open science practices. Our study focuses on Chinese communication scholars, while Harper and Kim's (2018) targeted psychologists. Psychology, traditionally, has a strong emphasis on empirical, often quantitative, research that generates large datasets, making data sharing a significant aspect of open science. In contrast, communication studies encompass a broader range of methodologies, including qualitative and theoretical research, where data sharing might not always be straightforward or applicable. The discipline's diverse nature means that open science practices may vary widely, from sharing data sets to open peer review and publishing processes. The reliance on OCS in communication studies is thus a more multifaceted and nuanced issue, reflecting the diversity of its research methods and outputs.

### **3.2. Research Model and Hypotheses**

Grounded in the theoretical framework of the TPB, we focused our study on replicating the research design of Harper and Kim (2018) and evaluating their hypotheses in the context of Chinese communication scholars. As shown in Figure 2, we incorporated attitudinal (the perceived benefit, risk, and effort of data sharing), normative (subjective norms for data sharing and data sharing pressure from journals), and resource factors (facilitating conditions for data sharing) into the model. Attitude can be defined as the overall evaluation or appraisal by communication scholars of the practice of data sharing, shaped by their personal beliefs regarding its potential benefits, consequences, and the associated effort. Subjective norms are defined in terms of communication scholars' perceptions of how others (research institutes, sponsors, etc.) view data sharing. When there is widespread support and encouragement among various groups for scholars to perform or consider a particular behavior, it increases the likelihood that these scholars will intend to adopt that behavior. In addition to individuals, academic journals also generate data-sharing pressure, since these journals usually ask authors about their data availability when submitting their manuscripts. Finally, perceived behavioral control (i.e., facilitating conditions) refers to communication scholars' perceptions of favorable resources for data sharing. Based on Harper and Kim (2018), we propose the following eight hypotheses:

H1: Perceived benefit positively affects communication scholars' attitudes toward data sharing.

H2: Perceived risk negatively affects communication scholars' attitudes toward data sharing.

H3: Perceived effort negatively affects communication scholars' attitudes toward data sharing.

H4: Perceived effort negatively affects communication scholars' behavioral intentions with regard to data sharing.

H5: Communication scholars' attitudes toward data sharing positively affect their behavioral intentions with regard to data sharing.

H6: Subjective norms of data sharing positively affect communication scholars' behavioral intentions with regard to data sharing.

H7: Data sharing pressure from journals positively affects communication scholars' behavioral intentions with regard to data sharing.

H8: Facilitating conditions for data sharing positively affect communication scholars' behavioral intentions with regard to data sharing.

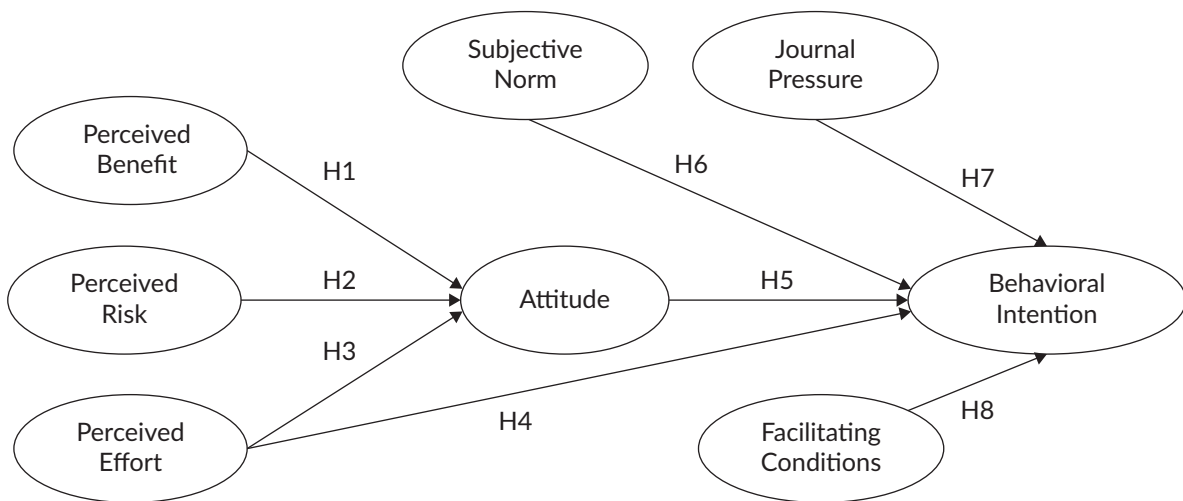


Figure 2. Research model and hypothesis. Source: Adapted from Harper and Kim (2018).

## 4. Research Method

### 4.1. Population and Sampling

This study's focus is primarily on scholars in the field of communication within China. We utilized the Chinese Association for History of Journalism and Communication (CAHJC) member list for its sampling frame. The CAHJC was established in 1989 and is the largest communication association in China. Instead of using email lists for communication, the CAHJC employs official WeChat groups and shares its latest events on that platform. We used a combination of purposive and snowball sampling methods, and we initially circulated our survey in the CAHJC's WeChat groups ( $N = 871$ ). To reach as many Chinese communication scholars as possible, we then encouraged our participants to distribute the questionnaire to former or present coworkers or PhD students. Two screening questions were included to ensure that the respondents were conducting research in the field of communication and either had PhD degrees or were PhD candidates. Participants in the study were informed that their involvement was entirely optional, and they were assured that all responses would be treated with confidentiality and anonymity.

### 4.2. Measurement of Constructs

In this study, we used 28 survey items to assess eight research constructs. The majority of these measurement items were adapted from Harper and Kim (2018) and modified to suit communication scholars' data-sharing adoption contexts. Most items measuring communication scholars' diverse perceptions of data sharing were scored on a 7-point Likert scale ranging from *strongly disagree* to *strongly agree*. Multiple items were employed to gauge each research construct in this study. Detailed information on the measurement

items utilized for these constructs is provided in Table 1. The final survey commenced with the presentation of a consent form, followed by a comprehensive introduction to the concept of open science. This introduction included a detailed definition of open science and a discussion of its historical evolution and developmental context.

### **4.3. Data Collection Procedure and Results**

The survey was distributed through WJX, an online survey management software from China (<https://www.wjx.cn>), on May 17, 2022, and remained available for four weeks. We collected a total of 412 valid responses from our survey participants. The average time (in seconds) to complete the survey was  $M = 918.8$  ( $SD = 736$ ), with a median of 918. As suggested by Bowman et al. (2021), we excluded responses that were either quicker than the bottom 5% ( $\leq 361.3$ ,  $n = 20$ ) or longer than the top 90% ( $\geq 1431$ ,  $n = 41$ ). This filtering resulted in the removal of 61 responses, leading to a final sample size of 351. The adjusted average completion time for the survey was 757 seconds ( $SD = 248.7$ ). The median response time recorded was 729 seconds, with the shortest frequent response time being 363 seconds.

### **4.4. Demographics of the Respondents**

The demographic information of the survey respondents encompassed gender, academic title, and research areas of the communication scholars, categorized according to the ICA classification system. Among the 351 participants, 192 (54.7%) identified as “women.” Ninety-two respondents (26.2%) reported having “senior faculty” status, followed by 113 (36.2%) who reported having “mid-career faculty” status, 52 (14.8%) who reported having “junior faculty” status, and 94 (25.4%) who reported being “postdoctoral or doctoral students.” In terms of research interest, all 25 ICA divisions and interest groups were represented, with each individual being categorized into only the one division that was closest to their research interest. At least 10% of the sample represented two subfields: popular media and culture ( $n = 66$ , 18.8%) and communication and technology ( $n = 36$ , 10.3%). Other significant categories included journalism studies ( $n = 33$ , 9.4%), political communication ( $n = 31$ , 8.8%), and mass communication ( $n = 28$ , 8%). This distribution closely mirrors that found by surveys of ICA members (Bowman et al., 2021).

## **5. Data Analysis and Results**

### **5.1. Reliability and Validity Test**

After the questionnaire was developed, a pilot test was conducted with the participation of 30 communication scholars. These scholars could complete the questionnaire within an average time of about 10 minutes. Feedback from the respondents indicated that the instructions and question wording were clear and effectively measured the intended constructs, affirming both the face and content validity of the questionnaire (Churchill, 1979). As depicted in Table 1, the average scores for the eight variables examined in the study varied from 3.314 to 5.256, with standard deviations ranging between 1.116 and 1.405. The Cronbach's  $\alpha$  of all variables was above .7, thus suggesting good reliability.

The study utilized IBM SPSS AMOS 24 for confirmatory factor analysis to validate the measurement model's reliability and validity. This process included checking each variable's skewness and kurtosis to confirm data

**Table 1.** Measurement items and descriptive analysis for research constructs.

Construct	Items	M	SD	$\alpha$
Perceived Benefit (Harper & Kim, 2018)	I can earn academic credit, such as more citations, by sharing data. Data sharing would enhance my academic recognition. Data sharing would improve my status in the research community.	5.256	1.116	.894
Perceived Risk (Harper & Kim, 2018)	There is a high probability of losing publication opportunities if I share data. Data sharing may cause my research ideas to be stolen by other researchers. My shared data may be misused or misinterpreted by other researchers.	5.094	1.302	.835
Perceived Effort (Harper & Kim, 2018)	Sharing data involves too much time for me (e.g., to organize/annotate). I need to make a significant effort to share data. I would find data sharing difficult to do.	4.747	1.272	.834
Attitudes (Harper & Kim, 2018; Venkatesh et al., 2003)	Data sharing is a good idea. Data sharing is valuable for replication. Data sharing is valuable for reproducibility. Data sharing makes research more transparent.	5.031	1.262	.945
Subjective Norms (Harper & Kim, 2018; Taylor & Todd, 1995)	My university or research institutes think that I should share data. My editors or reviewers think that I should share data. The institutions funding my research think that I should share data. My sponsors/consultants/bosses think that I should share data.	3.314	1.405	.952
Journal Pressure (Bowman et al., 2021; Harper & Kim, 2018)	The open science journal expects me to share the datasets for my manuscripts. The open science journal expects me to share the research materials for my manuscripts. The open science journal expects me to apply for open science badges when submitting manuscripts.	4.992	1.284	.903
Facilitating Conditions (Harper & Kim, 2018; Venkatesh et al., 2003)	I have the resources necessary to share data. I have the knowledge necessary to share data. I have the data repositories necessary to share data. A specific person (or group) is available for assistance with data-sharing difficulties.	3.390	1.374	.942
Behavioral Intentions (Harper & Kim, 2018; Venkatesh et al., 2003)	I intend to share data in my future research. I predict that I will share data in my future research. I plan to share data in my future research. I will likely share my research data in the future.	4.613	1.296	.960



normality. The analysis involved calculating composite reliabilities (CRs) and average variance extracted (AVE) values through standardized loadings, which were instrumental in evaluating the constructs' convergent and discriminant validity. Results presented in Table 2, including CRs and AVE values, indicated a high level of reliability (CRs between .902 and .971) and sufficient convergent validity (AVE values over .5). The study also examined discriminant validity by comparing the AVE values' square roots with the correlations among different constructs. The square roots of the AVE values exceeded all the interconstruct correlations, supporting discriminant validity (Fornell & Larcker, 1981). All bivariate correlations between these variables were below the critical .75 threshold, which implied that they did not strongly overlap. Meanwhile, the collinearity diagnostics indicated that the Variance Inflation Factors for all variables were below the threshold of 5, suggesting no concerns about multicollinearity in the model.

**Table 2.** CRs, AVE values, and correlations among the constructs.

Variable	CRs	AVE	1	2	3	4	5	6	7	8
Perceived Benefit	.936	.829	.910							
Perceived Risk	.936	.829	-.035	.910						
Perceived Effort	.902	.755	-.106*	.568**	.869					
Attitudes	.961	.859	.475**	-.210**	-.291**	.927				
Subjective Norms	.966	.876	.200**	.047	-.073	.342**	.936			
Journal Pressure	.940	.839	.339**	-.143**	-.190**	.634**	.240**	.916		
Facilitating Conditions	.959	.853	.095	-.066	-.210**	.253**	.486**	.165**	.924	
Behavioral Intentions	.971	.893	.408**	-.154**	-.265**	.687**	.418**	.546**	.331**	.945

Notes: \*  $p < .05$ , \*\*  $p < .01$ ; The square roots of the AVE values are diagonal.

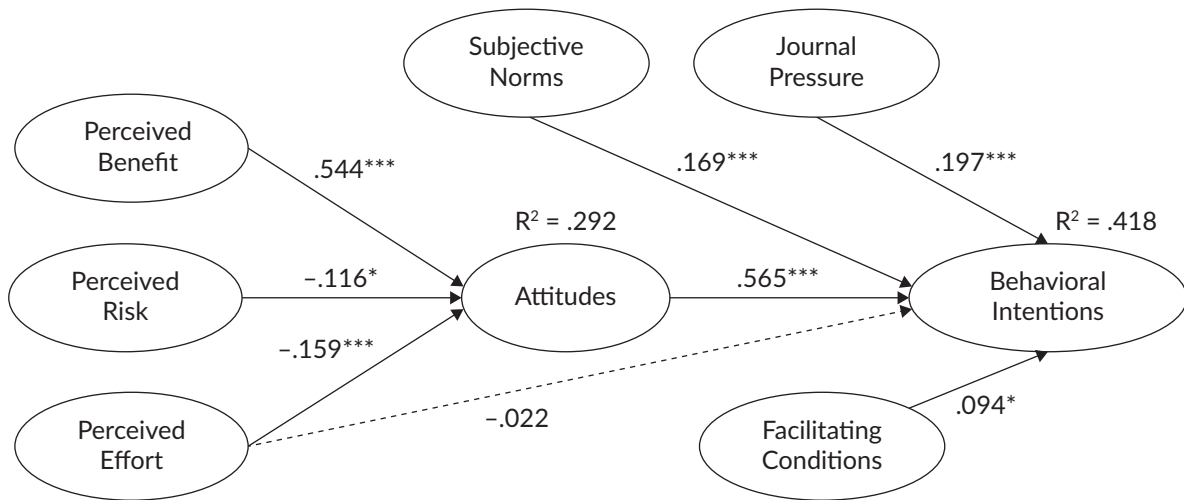
## 5.2. Structural Model and Hypothesis Testing

Structural equation modeling with SPSS AMOS 24 was employed to test the hypothesis. This involved defining each latent variable by its observed variables and using six indices to evaluate the model's fit to the data. The criteria for these indices included  $\chi^2/df$  below 3, Tucker-Lewis Index (TLI), Comparative Fit Index (CFI), and Incremental Fit Index (IFI) above .90, and RMSEA and SRMR below .08 (Hair et al., 2019). The analysis yielded fit indices of  $\chi^2/df = 2.17$  ( $\chi^2 = 1552.63$ ;  $df = 737$ ;  $p < .001$ ), TLI = .93, CFI = .93, IFI = .94, RMSEA = .06, and SRMR = .06, indicating a good fit of the structural model to the data. Figure 3 shows the results of the structural model. All paths were significant with the exception of the path between perceived effort and behavioral intentions toward data sharing ( $\beta = -.022$ ). Therefore, H4 was rejected, while the other hypotheses were supported.

## 6. Findings and Discussion

### 6.1. Attitudinal Factors

Similar to Harper and Kim (2018), we found that perceived benefit ( $\beta = .544$ ,  $p < .001$ ) and perceived risk ( $\beta = -.116$ ,  $p < .05$ ) had significant positive and negative impacts on communication scholars' attitudes toward



**Figure 3.** The results regarding the standardized path coefficients for the hypothesized paths. Notes: \*  $p < .05$ , \*\*\*  $p < .001$ ; the significant paths are shown as solid lines, while the nonsignificant paths are shown as dotted lines.

data sharing, respectively, and that perceived benefit was the strongest predictor among all attitudinal factors. Our study is also in line with Akdeniz et al. (2023), who found that while altruistic motives like contributing to open science and transparency were pivotal in sharing decisions, practical concerns like legal restrictions and ethical considerations also played a significant role. Such insights are crucial in understanding the dynamics of data-sharing behavior. To promote more positive attitudes toward data sharing, the perceived benefits ought to be emphasized, and the perceived risks and costs ought to be reduced. As data sharing is seldom acknowledged in key academic progression documents like tenure and promotion guidelines (Pontika et al., 2022), we urge policymakers and research organizations to reevaluate and enhance the incentives for data publication in the field of communication research. It is essential to align the benefits of data sharing, such as increased citations, academic recognition, and enhanced research opportunities, with institutional recognition and career advancement metrics (Bock et al., 2005). Second, perceived risk can be reduced by reframing data sharing as an opportunity to build on the extant literature and to promote potential future collaboration; furthermore, by increasing support at the level of academia, communication scholars can be provided with an institutional safety net for data sharing.

However, our study found different results regarding perceived effort. Harper and Kim (2018) claimed that perceived effort negatively affected individuals' behavioral intentions but did not influence their attitudes. In contrast, our results suggested that perceived effort negatively affected individuals' attitudes ( $\beta = -.159$ ,  $p < .001$ ) but had no significant impact on behavioral intentions ( $\beta = -.022$ ,  $p > .05$ ). This discrepancy is probably due to the nuanced differences between the different measurements used. The subject studied by Harper and Kim (2018) was open data badge adoption, which differs from our emphasis on data sharing, as data sharing requires more multilayered efforts than open data badge adoption, which refers simply to the initial attempt made by the journal to promote open data sharing. Therefore, in this particular situation, the impact of perceived effort may not be sufficiently strong to change individuals' behavioral intentions. Given the negative impact of perceived effort on attitudes, we urge research institutions to provide data management protocols or easy-to-follow recommendations. Consequently, sharing data can become less burdensome for individuals, thus helping improve their attitudes toward data sharing.

## 6.2. Normative and Resource Factors

In line with Harper and Kim (2018), our study indicated that communication scholars were positively influenced by the norms of data sharing ( $\beta = .169, p < .001$ ), indicating that the more researchers believe that their research institutes, funding institutions, or sponsors expect them to share data, the more likely they are to perform that behavior. To foster a positive environment for data sharing, research institutions and academic bodies, like ICA, could actively promote data-sharing norms. This could involve distributing educational content about various data-sharing methods and incorporating data-sharing practices as a criterion in the distribution of research funding and resources.

Additionally, both data sharing pressure from journals ( $\beta = .197, p > .001$ ) and facilitating conditions ( $\beta = .094, p < .05$ ) positively impacted communication scholars' intention toward data sharing, a finding which differs from those reported by Harper and Kim (2018), who found no significant impacts on pressure from open science journals or the availability of data repositories. According to Harper and Kim (2018), the nonsignificant effects might be due to a lack of data repositories, and the pressure for researchers to share data with a publication generated by journals was optional rather than mandatory in 2018. However, at the time we conducted our research, journal requirements for data sharing had become more pervasive (e.g., through standardized preregistration, open-sharing protocols, and open data statements), and free data repositories such as Open Science Framework had become more easily accessible. Hence, the impacts of these two factors have become more significant. Given the significant impacts of journal pressure and open data badge adoption, we suggest that more measures should be taken to facilitate data sharing, including knowledge sharing on the part of experts and data scientists, lectures and skill training in data sharing, and customized librarian services and consultations. These efforts can encourage communication scholars with the necessary expertise and resources to engage in data sharing and enable them to receive help in a timely manner when they encounter difficulties.

## 7. Implications

### 7.1. Theoretical Implications

Our study focuses on examining the factors that influence data sharing within a new context, aiming to evaluate the actual impact and magnitude of variables based on the TPB. Our study aims to establish the generalizability of the predicted effects in a non-Western context. The innovative double nature of the study lies in the fact that it is both (a) an empirical investigation of the factors that impact communication scholars' data-sharing intentions and are relevant for replication work and (b) a replication study in its own right that aims to obtain insights from other disciplines in the social sciences (namely, in this case, psychology).

First, this research offers valuable insights into the cognitive decision-making process of communication scholars regarding open science. While it's notable for pioneering this area of inquiry, the significance of the study extends beyond its novelty. It delves into the intricate interplay of attitudinal, normative, and resource factors shaping scholars' intentions to share data. Drawing from Harper and Kim (2018), we construct a comprehensive theoretical framework, enhancing our understanding of data-sharing behaviors within the open science context. This approach not only fills a gap in existing literature but also enriches our

comprehension of scholarly behaviors in relation to the evolving open science movement, underscoring its broader implications and relevance in the field of communication.

Second, our focus on the non-Western context underlines the diversity and complexity in data-sharing practices globally. By exploring the factors influencing data sharing among Chinese communication scholars, this research not only provides empirical evidence from a non-Western perspective but also highlights the need for a more inclusive understanding of open science practices. It challenges the predominantly Western-centric view of data-sharing norms and opens up avenues for further research in diverse cultural and academic settings. Our findings suggest that Chinese researchers' attitudes towards data sharing do differ from their counterparts in other regions. These differences could stem from various factors, such as cultural attitudes towards intellectual property and collaboration, the influence of local academic and research policies, infrastructural and resource availability specific to China, and differing levels of emphasis on open science practices in the academic community. Understanding these nuances is crucial for developing effective strategies to promote data sharing across diverse academic cultures.

Third, replication represents a significant theoretical contribution (DeAndrea & Holbert, 2017) and is a fundamental component of scientific inquiry. If an effect is genuinely robust and valid, any competent researcher should be able to observe it when using the same procedures with sufficient statistical power (Simons, 2014). Our study confirms the effectiveness of the TPB in this context and further indicates that the adapted structural equation model leads to better interpretations of communication scholars' data-sharing intentions. As indicated in Figure 3, approximately 29.2% of the variance in attitudes ( $R^2 = .292$ ) is explained by perceived benefit, perceived risk, and perceived effort, and approximately 41.8% of the variance in behavioral intentions ( $R^2 = .418$ ) can be explained by perceived effort, attitudes, subjective norms, journal pressure, and facilitating conditions, both of which are higher than the  $R^2$  values reported by Harper and Kim (2018). These two numbers indicate a good fit of the theories with regard to analyzing communication scholars' data-sharing intentions.

## **7.2. Practical Implications**

This research has practical implications for both the academic field of communication studies and the broader community of researchers in the social sciences. Although this study focuses on data sharing, the model it proposes can be utilized to understand broad OCS-related practices. By employing the framework presented in this study, universities and research institutes can be better prepared to motivate communication scholars to share their research data, among many other OCS behaviors. More specifically, this study has the following practical implications.

The findings of this study emphasize the fact that attitudinal factors, including perceived benefits, risks, and benefits, have the most significant impacts on the willingness of communication scholars to share their research data. By encouraging open dialog within the research community to address concerns with perceived risks and enhance the perceived benefits of data sharing, communication scholars can collaboratively take steps toward promoting greater transparency within their profession. Universities and research institutions should consider implementing supportive institutional incentives for OCS. However, it is important to note, as revealed in the study by Bowman et al. (2021), that there is currently no consensus among scholars on mandating the publication of research data or giving hiring and promotion preference to

applicants who share their data. Therefore, while encouraging OCS practices, institutions should also be mindful of the diverse perspectives within the academic community and aim to foster an environment that balances open science initiatives with respect for scholarly discretion and diversity of opinions. In this case, communication scholars can perceive data sharing as less intimidating and more rewarding. If the benefits of data sharing are expanded, the risks are minimized, and the costs in terms of time and effort are decreased, communication scholars can become more willing to adopt positive attitudes toward data sharing.

Furthermore, normative and resource factors, such as the subjective norms of data sharing, data sharing pressure from journals, and facilitating conditions, positively influence communication scholars' behavioral intentions. Therefore, research institutions, academic associations such as the ICA, and publishers in the field should unite to encourage and facilitate data sharing. For example, these actors can establish friendly systems or produce helpful tools to facilitate data sharing, offer OCS-related training to increase communication scholars' skills with regard to data sharing, verification, and reuse (Zhang et al., 2022), and promote a shift toward the standardization of open data practices within their research community. Such efforts can help establish a better research environment, and greater engagement in data sharing and other OCS practices can thus be promoted within the field of communication.

## 8. Conclusion

### 8.1. Limitations

While we conduct this empirical investigation with great care, it is important to acknowledge certain limitations in the methodologies we use. First, our assessment primarily focuses on scholars' behavioral intentions to share data rather than their actual behaviors. This approach is chosen because data sharing has not yet become a common practice in China, and the majority of Chinese communication scholars lack experience in this area. It is worth noting that, consistent with Harper and Kim (2018), we do not include control variables such as personal traits and social factors. However, these variables could potentially influence an individual's behavioral intentions and might introduce confounding variables into our results.

Furthermore, our sampling methodology exhibits certain imperfections. Identifying a sampling frame that fully encompasses all Chinese communication scholars is a challenging task. While the CAHJC is the largest communication association in China, it is important to recognize that not all Chinese communication scholars participate in its WeChat contact groups.

Finally, our study exhibits a relatively low response rate, receiving only 412 responses from 871 individuals surveyed, and 351 of these responses are ultimately included in our final analysis. It is possible that individuals who chose to respond to our survey may have been more inclined to support OCS than those who did not participate.

### 8.2. Directions for Future Research

In conclusion, while our study provides valuable insights, it is essential to interpret our results in light of these methodological limitations, and future research in this area should aim to address these challenges to obtain

a more comprehensive understanding of the subject matter. Specifically, future research can be expanded in the following ways.

First, prior studies have indicated the presence of differences in the ways in which open science-related practices are embraced and adopted among individuals from diverse demographic and professional backgrounds (Bowman et al., 2021; Markowitz et al., 2021). It is advisable for future investigations to explore the impacts of personal characteristics, such as gender, career advancement, methodological preferences, and research interests, on communication scholars' perceptions of OCS. Furthermore, factors such as age, familiarity with OCS, publication history in academic journals, and experience in sharing research data could be subject to more extensive analysis. It will also be meaningful to investigate the correlation between expressed intentions and actual involvement. Such investigations would provide a comprehensive understanding of how these characteristics influence aspects such as the individual's self-efficacy with regard to adopting OCS and readiness for change.

Second, our study's focus on Chinese communication scholars might have limited our ability to capture other significant attributes. We acknowledge that the nuances between various academic systems worldwide could significantly impact open science practices. Different countries may have unique characteristics in terms of their academic culture, policies regarding intellectual property and data ownership, levels of funding support for open science initiatives, and the maturity of digital infrastructures for managing and sharing research outputs. These differences can lead to variations in how scholars perceive, adopt, and engage with OCS practices, including but not limited to data sharing. Future research conducted on a broader scale should take into careful consideration the nuances of different academic systems and the overall progress of OCS in different countries.

Finally, our focus on data sharing may have overshadowed other crucial dimensions of open science practices. Given the theoretical underpinnings of this model, which are centered around individual beliefs, social pressures, and available resources, it is plausible to hypothesize that similar mechanisms would operate when applied to other aspects of OCS, such as preregistration, replication, and reproducibility (Bowman et al., 2021). However, while there might be similarities in how these factors impact different OCS aspects, we acknowledge that unique characteristics associated with each dimension could lead to differential effects. For example, the specific challenges related to data sharing (e.g., privacy concerns, technical difficulties) may not be directly transferable to the context of preregistration, where issues like predicting outcomes and committing to methods before data collection become central. Similarly, the incentives and barriers surrounding replication might differ from those pertaining to data sharing due to the complexities involved in reproducing entire studies versus simply making data accessible. The study by Krähmer et al. (2023) sheds light on this aspect, examining the factors that influence researchers' willingness to share their analysis code. Their findings reveal that the framing of code-sharing requests, particularly those that underscore the replication crisis, significantly impacts researchers' sharing behavior. Therefore, future research should explore the application of our model across other dimensions of OCS, which may exhibit differences from the findings we obtained regarding data-sharing intentions.

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## Conflict of Interests

The author declares no conflict of interests.

## Data Availability

Our data are available at <https://osf.io/g8qwd>, reference number <https://doi.org/10.17605/OSF.IO/G8QWD>.

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