EMPIRICAL RESEARCH

The good, the bad, and the ugly: impact of analytics and artificial intelligence-enabled personal information collection on privacy and participation in ridesharing

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ABSTRACT

Big data analytics (BDA) and artificial intelligence (AI) may provide both bright and dark sides that may affect user participation in ridesharing. We do not know whether the juxtaposed sides of these IT artefacts influence users’ cognitive appraisals, and if so, to what extent will their participative behaviour be affected. This paper contributes to the IS research by uncovering the interplay between the dark and bright sides of BDA and AI and the underlying mechanisms of cognitive appraisals for user behaviour in ridesharing. We performed two phases of the study using mixed-methods. In the first study, we conduct 21 semi-structured interviews to develop the research model. The second study empirically validated the research model using survey data of 332 passengers. We find that the usage of BDA and AI on ridesharing platforms have a bright side (usefulness, “the good”) but also a dark side (uncertainty and invasion of privacy, “the bad and the ugly”). The bright side generates perceived benefits, and the dark side shape perceived risks in users, which discount the risks from the benefits of using the ridesharing platform. Privacy control exerts a positive effect on the perceived benefits to encourage individuals to use the ridesharing platform.

1. Introduction

The combination of BDA and AI has signalled a revolution in the way data are processed, which have enabled companies to transform the workplace, business processes, and business models (Agerfalk, 2020; Benitez et al., 2020a; Conboy et al., 2020; Corte et al., 2019; Mikalef & Krogstie, 2020). This emerging technological paradigm has the potential to substantially morph and revamp the way individuals and businesses interact (Goh & Arenas, 2020; Saldanha et al., 2017). This effect is the good one or the bright side of BDA and AI. In contrast, these embryonic technologies may also have negative consequences on individual rights. This effect represents the bad and ugly ones or the dark side. In recent years, BDA and AI technologies have gained momentum and have been increasingly implemented in the sharing economy to identify threats and avert vicious incidents. Despite the technological advancement, those disruptive technologies usher in a pressing issue of information privacy and presumably affect user participation in ridesharing (e.g., BlaBlaCar).

Despite technological advancement, the implementation of BDA and AI ushers in a pressing issue of an equilibrium vis-a-vis both bright and dark sides of the emerging technologies. Whereas the bright side has been widely acknowledged, the dark side, which has negative consequences on individual rights, has received comparatively scarce attention in the IS literature. A proof of this research scarcity is the publication of this Special Issue. Worse yet, the mounting use of BDA and AI inevitably couples with privacy concerns as individual private information is widely collected through such techniques as automatic face and voice recognition. This social phenomenon becomes a rather vital predicament in the sharing economy, where digital giants are serving as the third party collect, store, process, and transmit a tremendous amount of user data between a service demander and a supplier. Ridesharing, one of the prevalent and environmentally-friendly forms of sharing economy-empowered transportation mechanism, has piqued increased public attention. It is estimated that the global ridesharing market where DiDi, Uber, and Lyft are among the leading industrial players will grow by more than 50 percent between 2020 and 2021 and that the market value will rise to 117 billion dollars in 2021 (Statista, 2020). In 2018, however, two passengers were raped and murdered by ridesharing drivers of the DiDi Chuxing platform in China, causing the entire ridesharing service to be suspended for endangering passengers’ safety (BBC News, 2018). At
the end of 2019, the service platform announced that to identify and avert passenger safety issues, users must provide personal biometrics information through BDA and AI techniques (e.g., identity card number scanning and face recognition). This automatic information collection process raises a major concern about personal privacy invasion and challenges the pendulum of the bright and dark sides of IT implementation.

Privacy invasion and uncertainty posed by BDA and AI are critical issues on the dark side of technological implementation in ridesharing. Many studies have attempted to investigate individuals’ privacy perception and behaviour from many aspects, such as antecedents to and consequences of privacy concerns, the roles of privacy control, and the relationships between privacy and self-disclosure intention (e.g., Xu et al., 2011, 2012). These insightful studies collectively laid a solid foundation for explaining and predicting an individual’s privacy perception and behaviour in the contexts of social media sites (Hajli & Lin, 2016; Liu & Wang, 2018). Diverging from prior IS research, we posit that the implementation of BDA and AI technologies for personal information collection in ridesharing may undermine individuals’ privacy perception and participative behaviour. Our conjecture is congruent with Acquisti et al. (2016, p. 481) that “the portions of our personal and professional lives that are not monitored and quantified are further reduced” given the mushrooming growth and use of new BDA and AI technologies such as facial and voice recognition.

The pendulum of emerging innovative technologies used in ridesharing reflects that users will consider both positive and negative effects of BDA and AI technologies for personal information collection, analysis, and tracking. This contradictory perspective on BDA and AI’s juxtaposed sides resonates with recent top IS journals that call for further investigation into the dark and bright sides of BDA and AI and the burgeoning symmetry. Thus far, there are no theory-based empirical studies in the IS literature that attempt to investigate the contradictory view of the dark side of BDA and AI versus users’ cognitive appraisals and behaviour in the context of share economy ridesharing. Motivated to advance this emerging line of IS research, we embraced a coping and privacy calculus perspective and proposed a holistic, theory-based research model that addresses the interplay between the implementation of personal information collection using BDA and AI technologies and the bright and dark sides that affect users’ cognitive appraisals and subsequent participative behaviour in ridesharing. In doing so, this study examines the impact of BDA and AI-enabled personal information collection on privacy and participation in ridesharing. We argue that both the dark and bright sides of BDA and AI technologies used for ridesharing reflect the overall cognition of these innovative technologies’ implementation. We predict their influence on cognition appraisals (Bala & Venkatesh, 2016; Folkman et al., 1986) through the lens of the coping theory and privacy calculus theory. As privacy control allows individual users to govern how their personal information is gathered and handled, we contextualise the benefits and risks and the role of privacy control by identifying the privacy and secondary appraisals for mitigating the mechanisms of dark sides of BDA and AI use (Tarafdar et al., 2015).

Our theorisation results in a holistic research model that we tested and validated through a mixed-methods approach (Venkatesh et al., 2013, 2016; Wunderlich et al., 2019). We performed two phases of the study in China. In the first stage, we draw on coping theory and privacy calculus theory to conduct 21 semi-structured interviews and analysed the qualitative data to develop the research model. The second stage comprises a quantitative study that empirically validated the research model using 332 ridesharing passengers’ survey data.

We find that the usage of BDA and AI on the ridesharing platforms have a bright side (usefulness, “the good”) but also a dark side (uncertainty and invasion of privacy, “the bad and the ugly”). The bright side generates perceived benefits, and the dark side shapes perceived risks in users, which discount the risks from the benefits of using the ridesharing platform. Privacy control exerts a positive effect on the perceived benefits to encourage users to use the ridesharing platform. This paper contributes to the IS research and this special issue by building IS theory that combines both the dark and bright sides of BDA and AI usage to explain the user behaviour in the ridesharing platforms.

2. Theoretical foundations

In this section, we establish the theoretical foundations for our original work. We start with an in-depth investigation of the IT implementation and user participation in ridesharing, which provides the contextual theoretical foundation. We then articulate the bright and dark sides’ key components and establish a theoretical argumentation to the specific benefits and risks through a cognitive appraisal. Finally, we explain how the primary and secondary appraisals interplay to determine the passengers’ participation in ridesharing.

2.1. IT implementation and passengers’ participation in ridesharing

IT implementation, embedded with both bright and dark sides, affects individuals’ attitudes and behaviour in organisational and non-organisational contexts
(Lapointe & Rivard, 2005). The existing research body has primarily focused on the bright side of IT implementation (Beaudry & Pinsonneault, 2010), where both individuals and organisations benefit from digital innovation (Benitez et al., 2020a). Prior IS research has suggested that IT implementation can help achieve goals (Burton & Grange, 2013). The technology acceptance literature has explicated that social efficiency, productivity, and performance can be facilitated by ITs (Venkatesh et al., 2012). By contrast, there has been an emerging body of IS literature shifting attention to IT’s dark side in recent years. New IT implementation triggers a serious caveat because it influences an individual’s psychological cognition and behaviour (Bala & Venkatesh, 2016). In essence, IT implementation can cause risk, stress, and illegal use (Soror et al., 2015). In particular, technostress and anxiety appear to affect an individual’s productivity and well-being at work and outside work (Agogo & Hess, 2018; Ayyagari et al., 2011).

Aiming to maximise resource utilisation, the sharing economy has increasingly leveraged BDA and AI technologies for personal information collection, analysis, and tracking. As a new form of sharing economy, ridesharing enables a car owner and a passenger with the same destination to share driving expenses and social interactions (Cheng et al., 2020). Thus, the ridesharing platform’s success essentially relies on the participation of users (Teubner & Flath, 2019). Examples of ridesharing platforms are Uber, Didi, Mobike, Ola, and BlaBlaCar.

User participation emphasises being a form of activity and contributes to the activities (Bariki & Hartwick, 1994). In brand communities, member participation has been classified as in-role behaviour and extra-role behaviour (Yi & Gong, 2013). In-role behaviour refers to the behaviour necessary for the smooth flow of activities, and the extra-role behaviour refers to behaviour unnecessary but contributing to the activities (Groth, 2005; Yi & Gong, 2013). Similarly, passengers’ participation in ridesharing is of great value in the growth of these platforms. Recent studies have identified customer social participation as a three-dimensional construct with a focus to create values through in-role behaviour and part of extra-role behaviour (Chae & Ko, 2016; Kamboj & Rahman, 2017). The conceptualisation has been applied to investigate consumers’ participation in sharing economy platforms (Nadeem et al., 2019). Due to the nature of ridesharing being a typical IT-enabled sharing economy model, we have further conjectured that passengers’ participation in ridesharing consists of information participation, actionable participation, and attitudinal participation.

2.2. Privacy-related perceptions

In the era of information, privacy has been seen as an ethical issue related to the IT-enabled sharing economy (Nadeem et al., 2019; Schlegelmilch & Oberseder, 2010). Scholars in different disciplines, such as Economics (Acquisti et al., 2016), IS (Smith et al., 2011), and Psychology (Alge et al., 2006) have investigated privacy from different perspectives. However, the definition of privacy has been found as different and inconsistent. For example, privacy has been seen as a personal right (Clarke, 1999) and a personal ability to manage or control the information (Belanger et al., 2002; Smith et al., 1996).

The information privacy of an individual is of paramount importance in the context of ridesharing. Prior studies have regarded that “control is actually one of the factors that shape general privacy and that general privacy is not control per se” (Smith et al., 2011, p. 995). We embrace privacy as a state and define it as a state of limited personal information to be accessed (Xu et al., 2012). Further, we consider privacy a context-dependent construct as individuals can show different attitudes and behaviour in different contexts (Acquisti et al., 2016). Despite privacy has become a central issue in the sharing economy, studies are scarce for understanding privacy in the IT-enabled sharing economy, especially in the context of new IT implementation, such as BDA and AI, for sensitive information collection in ridesharing.

Privacy is considered increasingly important for individuals, yet they may disclose a certain degree of personal information in a specific context. Privacy calculus theory can explain how individuals deal with the tradeoff between perceived benefits and perceived risks before disclosing personal information (Xu et al., 2009). Perceived benefits refer to the perception of value deriving from information disclosure, such as saving money and time (Chiu et al., 2014) and obtaining individualised service (Xu et al., 2009) through information disclosure in a setting of online transactions. Perceived risks refer to the perception of potential loss or danger deriving from releasing personal information (Lee et al., 2014). For example, personal information breaches can lead to financial or personal privacy loss (Chiu et al., 2014). From a specific context perspective (Chiu et al., 2014; Xu et al., 2009), we conceive that individuals make decisions about privacy after calculating both positive and negative information disclosure outcomes. The application of the privacy calculus theory to the ridesharing context suggests that these platforms’ users can evaluate the perceived benefits and risks rationally before deciding whether they participate by using these platforms.

Privacy control plays an important role in the process of privacy calculus. Actual control and
psychological control are related to the actual behaviour and behavioural intention (Xu et al., 2012). In the aspect of psychological, privacy control reflects an individual’s perception of the ability to control how personal information is collected, released, and disseminated (Xu et al., 2011). Privacy control has been regarded as a multidimensional construct, including information gathering control and information handling control (Alge et al., 2006). As a systematic understanding of how privacy control contributes to the process of privacy calculus is still intangible, we employ this two-dimensional view of privacy control in the setting of ridesharing to investigate further its effects on perceived risks and benefits (Hajli & Lin, 2016; Liu & Wang, 2018).

2.3. The coping theory

The coping theory explains how individuals react to stress, threat, and the change of environment in Psychology (Lazarus & Folkman, 1984). Coping is defined as "constantly changing cognitive and behavioral efforts to manage specific external and/or internal demands that are appraised as taxing or exceeding the person’s resources" (Lazarus & Folkman, 1984, p. 141). The approaches to coping have been identified as style and process: the former is trait or personality, and the latter describes the dynamic process of individual cognition and coping with the change of environment. IS scholars have regarded new IT implementation as a disruptive event (Bala & Venkatesh, 2016; Liang et al., 2019). In line with this theory, we view BDA and AI implementation for personal information collection, analyses, and tracking as the change of environment since the ridesharing platform has mandated that personal biometrics information through BDA and AI techniques be supplied.

Coping has been widely regarded as a process in understanding individuals’ coping behaviour compared to the static approach of style (Bhattacherjee et al., 2018; Lai et al., 2012; Liang et al., 2019). In terms of the coping process, individuals generally experience two stages, including cognitive appraisal and coping behaviour (Folkman et al., 1986). A cognitive appraisal consists of primary appraisal and secondary appraisal. Individuals perceive and evaluate the change of environment during the primary appraisal and explore how to reduce risks and enhance benefits during the secondary appraisal (Major et al., 1998). Coping behaviour subsumes two such types as emotion-focused coping, in which individuals deal with the change of environment only to comfort themselves, and problem-focused coping, in which individuals identify the cause of the change and undertake strategies to solve it (Folkman & Lazarus, 1985). Studies in the context of organisations have examined job outcomes related factors as coping behaviours. From the perspective of problem-focused coping, studies in the IS discipline have incorporated adaptation into the theory (Bala & Venkatesh, 2016; Bhattacherjee et al., 2018). Since this paper focuses on passengers’ participative behaviour in BDA and AI implementation, we emphasise problem-focused coping.

The coping theory is suitable for explaining new IT implementation, such as personal biometric information collection based on BDA and AI techniques, in ridesharing. From the theory of privacy calculus, prior research focusing on this theory to explain privacy-related outcomes has largely neglected individuals to undertake strategies to influence and respond to perceived risks and benefits. Further, these strategies can affect privacy-related outcomes, such as passengers’ participation in ridesharing. From the perspective of coping theory, the change of environment, such as the emerging implementation of BDA and AI for personal biometric information collection, analysis, and tracking, has consequences on both the bright and dark sides that can affect individuals’ cognitive appraisal and participation in ridesharing. These consequences are examined in this paper.

3. The mixed-methods approach design

To achieve scientific rigour and realism, we employ a mixed-methods approach that consists of quantitative and qualitative stages (Tashakkori & Teddlie, 1998). We choose this methodological approach for three reasons. First, there has been a call for research pluralism in the IS discipline that corresponds with the mixed-methods (Agerfalk, 2013; Venkatesh et al., 2013). Second, we choose a mixed-methods design due to its relative methodological advantages. In essence, the mixed-methods design is suitable to answer both confirmatory and explanatory research questions (Venkatesh et al., 2016). Our research problem and questions de facto reflect one qualitative, one quantitative, and one combination of research methods. The mixed-methods design is a relatively holistic approach that can provide a global view (Agerfalk, 2013; Venkatesh et al., 2016). Third, this study’s new context (i.e., BDA and AI implementation in ridesharing) leads to issues that are difficult to be described and explained by existing theories (Agerfalk, 2013; Venkatesh et al., 2013).

Since the purpose we used the mixed-methods design is developmental, which means we used results of a qualitative study to develop hypotheses and used a quantitative study to test them (Hua et al., 2020; Mattke et al., forthcoming; Venkatesh et al., 2013), sequentially. We conducted a qualitative study in the first stage, followed by a quantitative study in the second stage. From the perspective of an epistemological strand, we drew on the interpretive
perspective in the qualitative study stage and focused on a positivist perspective in the quantitative stage. Drawing on Venkatesh et al. (2013, 2016) guidelines, we first found general theories and constructs about IT implementation, privacy, and user participation. Then, to contextualise our research model, a qualitative study was conducted, and we added ridesharing-specific constructs by carefully analysing the qualitative data. Third, we tested and validated our research model through a quantitative study based on survey data. Finally, the results of our qualitative study and quantitative study were incorporated to contribute to an overall understanding of personal biometrics information collection using BDA and AI technologies vis-a-vis participation in ridesharing. Figure 1 and Tables A1 and table A2 (in the Appendix) show how this paper designed the mixed-methods approach.

4. Stage 1: the qualitative study

4.1. Context of the study

The qualitative study was conducted to examine passenger’s perceptions of personal information collection using BDA and AI technologies in ridesharing and explore privacy control’s role in the process. The study’s context is ridesharing in China, which is the largest ridesharing market in the world. Since the coping theory and the privacy calculus theory are the theoretical foundations of our research model, the data analysis strategy between a priori and inductive was accepted in this paper (Miles & Huberman, 1994).

4.2. Data collection

Semi-structured interviews were conducted to collect the data. A total of 21 individuals were interviewed in February 2020. Before the interview, online sources about the implementation had been collected to supplement our interview data. One pilot interview was conducted with a doctoral student in IS to test our interview protocol. We used two criteria to choose the sample (Song et al., 2019). First, passengers or potential passengers of ridesharing were selected. All of them accepted the ethos of ridesharing and were willing to use it. Second, we chose passengers of different ages and occupations to acquire different views. We briefly introduced the context and the interview protocol before each interview. We focused on interviewees’ perceptions of personal biometrics information collection using BDA and AI technologies in ridesharing. Then, interviewees were encouraged to talk about the perceived risks and benefits. In the final stage, feelings about privacy control and participation were asked to explore potential relationships initially. The protocol was our guideline for the interviews. However, when interesting viewpoints emerged, we inquired them in detail. Since limited new content appeared in the last few interviews, the interview data contents reached saturation.

4.3. Data analysis

The data analysis strategy between a priori and inductive was accepted in our analysis (Miles & Huberman, 1994). The strategy contains a “start list” and allows new findings related to the list. We reviewed and summarised existing literature on the topic of IT implementation, privacy, and participation and provided the theoretical framework shown in Figure 2, which was the “start list.” We identified the primary sentences related to our “start list” by repeatedly reading and comparing each transcript. Then we generated a list of codes linking to our framework. To combine these codes with theories, we further reviewed the literature and found appropriate constructs that could be categories of the codes. Besides, we analysed the potential effects that privacy control makes on perceived risks, perceived benefits, and passengers’ participation. Table A3 (in the Appendix) presents the emergent themes. Tables A4 and table A5 include

Figure 1. Stages used in the mixed-methods approach of this study.
4.4. Building and hypothesising the proposed research model

We use the findings obtained in the qualitative study (first stage), the coping theory, and the privacy calculus theory to build and develop the proposed research model (please see Figure 3). Table A4 includes the conceptualisation of the key constructs included in the proposed research model. The proposed research model explains how the BDA and AI implementation in ridesharing platforms has both bright and dark sides that affect passenger participation in ridesharing. The usefulness represents the bright side. Uncertainty and invasion of privacy constitute the dark side. We argue that usefulness, uncertainty, and invasion of privacy may influence both the perceived benefits and risks of using ridesharing platforms, which in turn may affect passenger participation in ridesharing. Finally, we argue that in explaining passenger behaviour in ridesharing, the perceived risks are discounted from the perceived benefits (calculus of the net benefits) and that the privacy control may affect passenger’s participation through the calculus of these net benefits.

4.4.1. The bright side: the relationship between usefulness and perceived benefits

Constituting the bright side of BDA and AI usage in the ridesharing platform, these technologies can be perceived as useful. We argue that it is plausible to expect a positive relationship between usefulness and perceived benefits. Using the ridesharing platform...
may improve performance and enhance the passenger’s effectiveness since usefulness has been found as a potentially positive characteristic of IT implementation (Davis, 1989). Perceived usefulness of the ridesharing platform can enhance an individual’s positive feelings about the platform app (Ayyagari et al., 2011; Davis, 1989). In the specific case of BDA and AI implementation in the ridesharing platform, passengers perceive that the improved service quality and enhanced customer experience derived from using the ridesharing platform constitute its usefulness. This usefulness may affect the perceived convenience and safety, thus improving the perceived benefits. Therefore, we hypothesise that:

**H1:** There is a positive relationship between the usefulness of BDA and AI and its perceived benefits in ridesharing.

### 4.4.2. The dark side: the relationships between uncertainty, invasion of privacy, and perceived risks

Perceived uncertainty and privacy invasion are the two ingredients related to the dark side of using BDA and AI in the ridesharing platforms. We expect that the perceived risks increase when the passenger views uncertainty and potential invasion of privacy. The proposed research model includes H2 and H3 to reflect these arguments. Related to uncertainty, newness, complexity, and unstable development cause uncertainty in IT usage (Ragatz et al., 2002). Uncertainty indicates that it is hard to control what may happen in the future. In terms of personal information collection through BDA and AI technologies in ridesharing, passengers may perceive high uncertainty. This uncertainty may increase the perceived risks of using the ridesharing platform (i.e., identity theft, financial costs, and unauthorised secondary usage of personal information). Therefore, we hypothesise the following relationship:

**H2:** There is a positive relationship between the uncertainty related to BDA and AI and its perceived risks in ridesharing.

A feeling that personal privacy may be compromised refers to privacy invasion (Ayyagari et al., 2011). Personal information collection or disclosure can easily lead to privacy invasion because individuals may form an informational territory with clearly defined boundaries that separate personal information from public information. The privacy boundary coordination between users and vendors becomes turbulent when personal information is misused. Thus, invasion of privacy occurs when one constituent shares information outside the boundary that violates the other partner’s expectations (Metzger, 2007). Invasion of privacy has been claimed positively related to an individual’s negative feelings (Ayyagari et al., 2011). As passenger 10 stated in the qualitative study: “Our personal information or privacy will inevitably be invaded to some extent.” The feeling of invasion of privacy may be associated with the perception of risks of suffering identity theft, financial costs, and unauthorised secondary usage of personal information. In this sense, it is rational to expect a positive association between the feeling of invasion of privacy and the perceived risks of using ridesharing platforms based on the usage of BDA and AI technologies. Therefore, we include the following hypothesis in the proposed research model:

**H3:** There is a positive relationship between the potential invasion of privacy related to BDA and AI and its perceived risks in ridesharing.

### 4.4.3. The relationship between perceived risks and benefits

Passengers’ voluntary participation and value co-creation processes are valuable for the ridesharing platform (Nadeem et al., 2019). The coping theory suggests that the change of environment affects individuals’ perception and evaluation. They evaluate benefits and risks during the primary appraisal, which influences their behaviour (Major et al., 1998). Due to risk aversion, a greater degree of perceived risks may reduce passengers’ attention and sensitivity to benefits (Chiu et al., 2014). Thus, a high level of perceived risks could decrease the perceived benefits. The privacy calculus theory indicates that individuals deal with the tradeoff between perceived benefits and risks when facing privacy issues about personal information disclosure (Xu et al., 2009). All in all, it is rational to expect that individuals discount the perceived risks from the perceived benefits, thus generating the net benefits of using ridesharing platforms. Based on these arguments, we hypothesise that the perceived risks may negatively affect the perceived benefits derived from using these platforms.

**H4:** There is a negative relationship between the perceived risks related to BDA and AI and its perceived benefits in ridesharing.

### 4.4.4. The relationship between perceived benefits, perceived costs, and passengers’ participation in ridesharing

Several studies have found that perceived benefits and risks affect attitude towards information providing and behavioural reactions (Hajli & Lin, 2016; Smith et al., 2011). Based on this prior research, we expect a positive influence of the perceived benefits on the passengers’ participation in ridesharing. In this sense, the perception of benefits, such as convenience and
safety, will encourage passengers to use ridesharing platforms. Therefore, we hypothesise the following:

H5a: There is a positive relationship between the perceived benefits of BDA and AI and passengers’ participation in ridesharing.

Similarly, when individual information for BDA and AI analysis is collected across a personal boundary, individual users would assess the possibility of privacy invasion and their ability to address the potential risk. This boundary process involves the perception of potential risk and users’ self-efficacy – when perceived risk outweighs perceived self-efficacy, it is likely that users will seek risk-avoidance behaviours. In essence, when users perceive the existence of perceived risks such as identity theft, financial costs, and unauthorised secondary usage of their personal information, it is plausible to expect a reduction in their interest in using these ridesharing platforms. This argument suggests that the greater the perceived risks of using ridesharing platforms, the lower passengers’ participation on these platforms will be. Based on this argument, we hypothesise the following:

H5b: There is a negative relationship between the perceived risks related to BDA and AI and passengers’ participation in ridesharing.

4.4.5. The effect of privacy control on the passengers’ participation in ridesharing

Privacy control refers to the degree of control exerted by the user on personal information shared with the ridesharing platform provider. We have identified information gathering control and information handling control as the two privacy control ingredients (Alge et al., 2006). Drawing on the coping theory, passengers explore how to reduce risks and enhance benefits during secondary cognitive appraisal (Lazarus & Folkman, 1984). Privacy control can reduce privacy concerns (Xu et al., 2012), and it can positively affect employees’ behaviour at work (Alge et al., 2006). Thus, privacy control is an efficient mechanism to enhance positive feelings and reduce negative feelings, which further may affect user behaviour. Based on these arguments and the findings obtained in the qualitative study, we expect that privacy control positively influences the perceived benefits, which will increase passengers’ participation in ridesharing. Therefore, we hypothesise that:

H6a: There is a positive relationship between privacy control and the perceived benefits of BDA and AI in ridesharing.

Similarly, privacy control can reduce the perceived risks of using ridesharing platforms, encouraging passengers to use these platforms. This rationale suggests that privacy control may indirectly affect passengers’ participation in ridesharing through the minoration of the perceived risks. This study’s focus and interest are on the indirect effects of privacy control on passengers’ participation in ridesharing through the improvement of perceived benefits and the minoration of perceived risks. Based on these arguments, we, therefore, hypothesise for the indirect effect through perceived costs:

H6b: There is a negative relationship between privacy control and the perceived risks related to BDA and AI in ridesharing.

5. Stage 2: the quantitative study

5.1. Survey development and sample

To ensure content validity, we adopted and contextualised existing measurement scales. A seven-point Likert scale was used for all items. Table A6 presents the sources used to measure the research model’s constructs and their measurement properties. We control for age, gender, desire for information control, privacy experience (Xu et al., 2012), trust propensity (McKnight et al., 2002), and general privacy concern (Li et al., 2017) on passengers’ participation in ridesharing. The survey instrument was further validated and refined in a pilot study in China.

The survey data were collected online by administering an online survey in March 2020 through the Chinese social media WeChat and Weibo. 1000 ride-sharing users clicked on the survey link, and 350 responses were returned, yielding a 35% response rate, which was successful. 18 responses were removed because all items had the same answer. Thus, a total of 332 valid responses were used for the quantitative analysis. All possible analyses between early and late respondents did not yield differences statistically significant. The sample characteristics and some details of the quantitative analysis have been omitted for brevity and are available upon request from the authors.

5.2. Confirmatory analysis and evaluation of the measurement model

The quantitative empirical analysis was done using the estimator partial least squares (PLS)-path modelling (PLS-PM), which is a structural equation modelling (SEM) estimator optimal to test our proposed research model that includes factor (at first-order level) and composite (at second-order level) constructs (Benitez et al., 2017, 2020b). Construct specification is a decision of the authors, and other IS scholars may have different specifications (Lin et al., 2020). First-order constructs were estimated using consistent PLS (mode A), and the composite second-order constructs were estimated using mode B. We use the ADANCO software package (https://www.composite-modelling.com/) for these goals (e.g., Benitez et al., 2020c). We perform a confirmatory factor analysis (see the overall
fit evaluation of the saturated model of Table 1) and evaluate the content, convergent, and discriminant validity of the reflective first-order constructs. Please see Table A6 for more details. All values fulfill the recommended thresholds recommended by Benitez et al. (2020b). We evaluate the existence of discriminant validity by examining the HTMT ratio of correlations (e.g., Yiu et al., 2020), which exhibits that all values are lower than 0.850 (Table A7). Overall, these analyses indicate that our structure of measures at first- and second-order are correct and have good properties. The next step is testing the proposed research model (Benitez et al., 2020b). Table A8 provides the correlations matrix.

5.3. Evaluation of the structural model
We ran a PLS-PM with a bootstrapping with 5000 subsamples to estimate the structural model. All analyses were done considering a two-tailed test. The second-order constructs were estimated using the two-steps approach (e.g., Benitez et al., 2020c). Related to the test of hypotheses of H1-H5, we find support for all hypotheses except for H5b (please see Figure 4). The proposed research model explains 62.4%, 69%, and 38.4% of the variance of perceived risks, perceived benefits, and passengers’ participation in ridesharing. As per the control variables, only desire for information control (beta = 0.210*** and trust propensity (beta = 0.127*) were significant. Table 1 includes the overall fit evaluation of the saturated and estimated models. The evaluation of the estimated model’s overall fit indicates that the proposed research model is true and is a research model that allows us to explain theoretically how and why passengers participate and use ridesharing platforms (Benitez et al., 2020b).

5.4. Post-hoc mediation analysis
We perform a post-hoc mediation analysis to examine the indirect effects involved in the proposed research model and, especially, to test H6a and H6b. These hypotheses are focused on examining these indirect effects rather than the direct effects of privacy control on perceived benefits and risks. We find support for H6a but not for H6b. Privacy control improves the perceived benefits (beta = 0.151***). Privacy control influences passengers’ participation in ridesharing by generating these perceived benefits (indirect effect = 0.075***). The direct effect between privacy control and perceived risks (beta = 0.014) and the indirect effect (−0.002) between privacy control and passengers’ participation in ridesharing was not significant.

5.5. Prevention and evaluation of common method variance
We did every possible effort to prevent the appearance of common method variance. The survey was designed, so items did not follow a logical sequence

Table 1. Overall model fit evaluation of the saturated and estimated models.

| Discrepancy | Value for the saturated model | H10S for the saturated model | Conclusion | Value for the estimated model | H10S for the estimated model | Conclusion |
|-------------|-------------------------------|-------------------------------|------------|-------------------------------|-------------------------------|------------|
| SRMR        | 0.051                         | 0.057                         | Supported  | 0.069                         | 0.071                         | Supported  |
| d1,2        | 3.148                         | 4.022                         | Supported  | 2.476                         | 2.660                         | Supported  |
| d2           | 1.779                         | 1.850                         | Supported  | 0.900                         | 1.197                         | Supported  |

Figure 4. Results of the hypotheses testing.
6. Discussion and key conclusions

Ridesharing was originated from the paradigm of sharing economy ethos for optimising resource utilisation and ground transportation. However, due to several severe criminal incidents that occurred in recent years, it is facing unprecedented challenges for passenger safety issues. Leveraging BDA and AI technologies for personal information collection, analysis, and tracking has been seen as a new yet effective means to identify and avert safety issues. Albeit the IT advancement (e.g., Dong & Yang, 2020; Mikalef et al., 2020), the implementation of these ITs inevitably causes adverse concerns about individual privacy invasion and uncertainty. Since the specific setting of ridesharing for BDA and AI technologies has received relatively scant attention, we attempted to open the black box and conducted an in-depth investigation to understand whether and how the implementation of personal biometrics information collection using BDA and AI technologies influence participative behaviour in ridesharing. We used a mixed-methods approach (e.g., Venkatesh et al., 2013). We performed two phases of the study in China. In the first stage, we draw on coping theory and privacy calculus theory to conduct 21 semi-structured interviews and analysed the qualitative data to develop the research model. The second stage comprises a quantitative study that empirically validated the research model using 332 ridesharing passengers’ survey data.

This study discovers that the implementation of BDA and AI technologies in ridesharing for securing passengers may cause positive outcomes and negative consequences on users’ participative behaviour. In particular, usefulness from the bright side of BDA and AI implementation was found to directly affect passengers’ perceived benefits, whereas uncertainty and invasion of privacy from the dark side were found to significantly directly affect perceived risks in terms of identity theft, financial costs, and unauthorised secondary use. These empirical results supported that the implementation of BDA and AI technologies has positive and negative effects on passengers. We further found that perceived benefits in terms of convenience and safety were the priority considered by passengers. The result highlights that passengers’ participation in ridesharing was positively affected by perceived benefits. Also, perceived benefits were negatively affected by perceived risks. One meta-inference result was that perceived benefits could be enhanced by privacy control that had significant effects on passengers’ participation in ridesharing mediated by perceived benefits.

One unanticipated finding was that perceived risks (e.g., identity theft, financial costs, and unauthorised secondary use) had no significant effect on passengers’ participation in ridesharing. Notwithstanding the existence of potential risks, passengers were still willing to participate in ridesharing. This result suggested that passengers paid far more attention to the benefits than the risks of ridesharing. Only if perceived benefits decreased, they would shift their participative behaviour. Another plausible explanation is that passengers discount the perceived risks to the benefits, consistent with the privacy calculus theory.

Furthermore, contrary to our expectations, there was no significant effect that privacy control had on perceived risks, which further influenced passengers’ participation in ridesharing. Privacy control can merely influence passengers’ participation in ridesharing by increasing perceived benefits rather than decreasing perceived risks. To understand this unexpected phenomenon, we revisited the interview data. Several passengers expressed that they felt exhausted with the risks, making them focus more on the benefits and lower their sensitivity of the risks. This interesting yet reasonable finding may contribute to why perceived risks had no direct effect on passengers’ participation in ridesharing, and privacy control had no significant effect mediated by perceived risks on passengers’ participation. For example, passenger 2 stated that enhancing privacy control could increase the perceived benefits and decrease the perceived risks, which further affected the participation behaviour, but noted that: “I don’t know how many times my personal information has been provided. I can’t use most of the apps without providing my information. I feel exhausted and numb with my privacy.” Feeling exhausted with perceived risks may decrease the corresponding concerns about risks. As such, passengers focus their attention on the benefits that can be increased by privacy control and undermined by the risks. Alternatively, this result can also be explained because the perceived risks are discounted from the benefits.

This study also discovers that BDA and AI technologies’ bright and dark sides for personal information collection in ridesharing were consistent across both the qualitative study and the quantitative inference. This study reveals that passengers paid far more attention to the benefits (convenience and safety) than the (Podsakoff et al., 2003). Moreover, we included a marker variable in the survey that was not expected to be theoretically related to the constructs of the research model (Son & Kim, 2008). This marker variable was measured with the items on social desirability from Crowne and Marlowe (1960) work. We perform a marker variable test by connecting the marker variable to perceived risks (beta = 0.048), perceived benefits (beta = 0.097), and passengers’ participation in ridesharing (beta = −0.080). Both the prevention and this test suggest that common method variance does not seem a problem in our data and empirical analyses.
risks (identity theft, financial costs, and unauthorised secondary use) in ridesharing in light of the surprising yet interesting findings. This unanticipated finding can be attributed to two reasons. First, rather than having a direct negative relationship with participation, perceived risks are positively associated with passengers’ participation in ridesharing through the mediation effect of perceived benefits. Second, privacy control had no significant effect on passengers’ participation in ridesharing through the mediation effect of perceived risks. Perceived benefits, including convenience and safety, were found to play a critical role in affecting passengers’ participation in ridesharing. However, this does not infer that perceived risks are unimportant on the dark side. Although perceived risks had no direct effect on passengers’ participation, it had a significant negative relationship with perceived benefits and, more importantly, our mediation analysis found that perceived risks may negatively influence passengers’ participation through this mediated path. In other words, perceived risks could significantly reduce the perceived benefits that played a critical role in passengers’ cognitive appraisal of ridesharing.

To summarise, although using BDA and AI technologies in ridesharing had a bright side of usefulness in terms of providing safety and convenience to passengers, it also had a dark side of uncertainty and invasion of privacy in terms of triggering identity theft, financial costs, and unauthorised secondary use. This paper is one of the first to scientifically prove that the implementation of emerging technologies for personal information collection is accompanied by potential risks that arise from BDA and AI technologies’ dark side.

This paper makes several significant theoretical contributions to the IS research and this Special Issue. First, this research extends the existing knowledge body of new IT implementation for personal information collection, such as BDA and AI technologies, by providing in-depth insights into the bright side and the dark side that affects passengers’ cognitive appraisals and behaviour in ridesharing. Our comprehensive literature review suggests that extant studies on IT implementation have primarily focused on the bright side (Beaudry & Pinsonneault, 2010). This study resonates with recent top IS journals that call for further scientific investigation into the dark side of BDA and AI. As such, our research findings provide a novel understanding from a complementary perspective of potential negative effects in the new setting of ridesharing. As the implementation of BDA and AI technologies inevitably warrants the collection of more personal information for surveillance and risk aversion, it calls for supplementary IS research to address context-dependent privacy issues (Acquisti et al., 2015, 2016). This study is an early attempt to respond to the research inquiry. In the new setting of ridesharing, we establish a holistic model to integrate the bright side in terms of usefulness with the dark side in terms of uncertainty and invasion of privacy, which are galvanised by personal information collection through BDA and AI implementation. This theoretical lens provides us with a holistic view of the benefits of the bright side and the risks associated with the dark side.

Second, we embraced the coping theory and the privacy calculus theory to understand users’ processes of personal information collected through BDA and AI. Since the privacy calculus theory has yet to report that individuals could have strategies or take measures to influence perceived risks or benefits in the process of privacy paradox (Xu et al., 2009), this approach contributes to the theory by enriching the coping strategies, such as privacy control, into the process where users cogitate the tradeoff between perceived benefits and risks. Based on the coping theory, privacy control is considered an efficient measure to positively affect perceived benefits and further influence passengers’ ridesharing participation. Correspondingly, we extended the coping theory’s research context to the interplay between privacy issues and new IT implementation. Further, this research integrates both the bright and dark side of new BDA and AI implementation in ridesharing into the coping process. The findings suggest that the bright side positively affects the evaluation of benefits, whereas the dark side negatively influences the risks. From an integrative view of changes in the environment, this approach contributes to the coping theory in understanding the coping process from a juxtaposed perspective in emerging IT implementation.

Finally, this research takes an important step towards a comprehensive understanding of participative behaviours and privacy issues triggered by BDA and AI implementation for personal information collection. We used a mixed-methods design, including both a qualitative study and a quantitative study (Venkatesh et al., 2013, 2016), and contribute to the evolving fields of privacy and IT-enabled ridesharing. As privacy is a context-dependent construct (Acquisti et al., 2015) and is a critical concern in the IT-enabled sharing economy, our qualitative study has deeply interacted with the users of ridesharing and provided context-specific dimensions of perceived benefits and risks. The quantitative study results have epitomised that passengers focus more on the benefits than the risks in ridesharing, thus further augmenting our understanding of privacy in ridesharing. Inspired by Alge et al. (2006), the qualitative study results demonstrate that there is a difference between information gathering control and information handling control in ridesharing. Information gathering control refers to the passengers’ degree of control about the personal
information a ridesharing platform can collect and store about them. The information handling control refers to the passengers’ degree of control about the personal information a ridesharing platform can use and disseminate about them in the future. Thus, we applied the results into the quantitative study for empirical analysis on the two dimensions of privacy control. The findings confirmed our conjecture that privacy control could be used as a multidimensional construct in IS research, thus providing a fruitful path for future IS research on privacy control. Examining how the ingredient of information handling control evolves in passengers’ privacy control in ridesharing seems an exciting IS research topic to explore further.

This paper also provides lessons learned to users, ridesharing providers, and society. This study unveils that the implementation of BDA and AI technologies ushers in both the bright and dark side that can influence users’ cognitive appraisals and behaviour in ridesharing. As such, how to enhance the effects of the bright side and reduce the effects of the dark side is of crucial importance to the growth of the ridesharing platform. Our results have the following substantial pragmatic value for ridesharing. Our findings demonstrate that personal information collected through BDA and AI in ridesharing has a pivotal role in affecting passengers’ perception of risks and benefits and participative behaviour. Thus, the ridesharing platform must emphasise and articulate the implementation’s usefulness before collecting passengers’ personal information. Meanwhile, it is necessary to clarify and take efficient measures towards IT’s uncertainty and the possible invasion of privacy.

Second, perceived benefits are primarily critical for passengers in ridesharing. Thus, the ridesharing platform can meticulously emphasise and describe the benefits to advertise ridesharing service. Although perceived risks are proven to have no direct effect on passengers’ participation in ridesharing, they can affect perceived benefits and have an indirect effect on participative behaviour through perceived benefits. Therefore, the ridesharing platform is advised to consider and take measures to relieve passengers’ perceived risks. Finally, privacy control comprising privacy-gathering control and privacy handling control is associated with passengers’ participation in ridesharing through perceived benefits. Privacy control is an effective measure to enhance perceived benefits and further lead to the positive consequence of passengers’ participative behaviour. The ridesharing platform should ensure that passengers have the right to control their privacy.

Some limitations may provide directions in future IS research. First, BDA- and AI-empowered personal information collection in ridesharing is still at a nascent stage. This infers that passengers’ perception would be different over different times. Future studies are needed to observe whether the differences exist and how they morph in future IS theory building. Second, although we identified information privacy gathering control and privacy handling control as two different dimensions of privacy control in this paper, we do not focus on how to enhance them. Gaining an understanding of how to enhance privacy control could be useful to the ridesharing platform. Therefore, discovering the mechanisms to enhance privacy-gathering control and privacy handling control would be a useful avenue for further IS research. Our qualitative analysis also shows that passengers exhibit a heterogeneous degree of information gathering control but a low and homogenous perceived information handling control. Examining the evolution of the perceived information handling control guarantees exciting future IS research results. Third, we only focused on the implementation of BDA and AI in ridesharing in China. Future IS research can investigate and gauge the BDA and AI implementation in other cultural and business settings.

In conclusion, using a mixed-methods approach, this paper argues and finds that the usage of BDA and AI on ridesharing platforms have a bright side (usefulness, “the good”) but also a dark side (uncertainty and invasion of privacy, “the bad and the ugly”). The bright side generates perceived benefits, and the dark side shape perceived risks in users, which discount the risks from the benefits of using the ridesharing platform. Privacy control also positively affects the perceived benefits to encourage individuals to use the ridesharing platform. Quo Vadis?

Notes

1. This platform is similar to Uber. In fact, this platform is called informally “the Uber of China” (BBC News, 2018).
2. Individual cognition and cognitive appraisals of individuals refer how an individual know, learn, and understand the world and form their own ideas in mind about the world (Bala & Venkatesh, 2016). This paper focuses on the cognitive appraisals of passengers to use ridesharing platforms.
3. We have summarised the research questions in the introduction for the sake of brevity. For a detailed description of the research questions of the study please see Table A1 (in the Appendix).
4. H6a and H6b are focused on examining the indirect effects rather than the direct effects of privacy control on perceived benefits and risks. We thank an anonymous reviewer for providing this suggestion.
5. Our second-order constructs are privacy control, perceived benefits, perceived risks, and passengers’ participation in ridesharing. As these constructs are composite, in addition to the confirmatory composite analysis, we evaluate their VIF, weights, and loadings values. All VIF values were below 3.3. The weights for the dimensions range from 0.276*** to 0.731***. Their loadings range from 0.757*** to 0.950***.
These values indicates very good measurement properties for the dimensions of our composite constructs (Benitez et al., 2020b).

6. These values and H_10 of the saturated model refer to the confirmatory factor analysis of the first-step of the PLS estimation. The values and H_10 of SRMR, d_{ULS}, d_{U}, d_{S} of the saturated model of the confirmatory composite analysis of the second-step were 0.066 < 0.075, 2.270 < 2.975, and 0.862 < 1.214, respectively. These analyses gave support to our structure of measures at first- and second-order levels (Benitez et al., 2017).

7 IT acronym refers to information technology in the entire manuscript except on this table that refers to identity theft.

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### Table A1: Elaboration of decision choice of mixed-methods (adapted from Venkatesh et al., 2016).

| Step | Property | Decision consideration | Other design decision(s) that can affect the current decision | Design decision and reference to the decision tree |
|------|----------|------------------------|---------------------------------------------------------------|--------------------------------------------------|
| Step 1: Decide on the purposes of mixed-methods research |  | appropriateness of a mixed-methods approach | Research questions | The qualitative or quantitative method alone was not adequate for addressing the research question. Thus, we used a mixed-methods research approach |
|  | None |  |  |  |
|  |  |  |  |  |
|  | Purposes of mixed-methods research |  |  |  |
|  | The purpose of our mixed-methods design was to explore factors and develop hypotheses for empirical testing using the qualitative study results given the lack of research on the impact of the implementation of personal information collection based on BDA and AI” The quantitative research question was: “How does the implementation of personal information collection based on BDA and AI affect passenger participation in ridesharing?” The mixed-methods research question was, “What is the role of privacy control in the process?” We wrote the research questions in the question format. The qualitative research question depended on the results of the qualitative research question. The mixed-methods question depended on the results of both qualitative and quantitative research questions. The relationship between the questions and the research process was predetermined. |  |  |
|  | Epistemological perspectives | The qualitative and quantitative components of the study used different paradigmatic assumptions. | Research questions | Developmental purposes and the results from the qualitative strand were used to develop the research model and the hypotheses tested in the quantitative strand. |
|  | Purposes of mixed-methods research | The scholars believed in the importance of research questions and embraced various methodological approaches from different worldviews. | Research questions and the purposes of mixed methods |  |
|  | Paradigmatic assumptions |  |  |  |
|  | Step 2: Developing strategies for mixed-methods research design | The mixed-methods study aimed to develop and test a theory. The study involved multiple phases. The qualitative and quantitative components of the study were mixed at the data-analysis and inferential stages. We started with the qualitative stage, followed by the quantitative phase. methodological approach | Research questions, paradigmatic assumptions |  |
|  | Design investigation strategy |  |  |  |
|  | Strands/phases of research |  |  |  |
|  | Mixing strategy |  |  |  |
|  | Time orientation |  |  |  |
|  | The priority of the study being the more dominant paradigm |  |  |  |

(Continued)
### Table A1 (Continued).

| Step | Property | Decision consideration | Other design decision(s) that can affect the current decision | Design decision and reference to the decision tree |
|------|----------|------------------------|---------------------------------------------------------------|---------------------------------------------------|
| Step 3: Develop strategies for collecting and analysing mixed-methods data | Sampling design strategies | The samples for the study’s quantitative and qualitative components differed, but they came from the same underlying population. | Design the investigation strategy, time orientation | Purposive sampling for the qualitative study given the general experience and knowledge on the technology of BDA and AI, and ridesharing. Probability sampling for the quantitative study. |
| | Data collection strategies | - Qualitative data collection in stage 1. Quantitative data collection in stage 2. | Sampling design strategies, time orientation, stages of research | - Qualitative study: Closed- and open-ended questioning using but not entirely relying on interview guidelines. Quantitative study: Closed-ended questioning with one open-ended questioning (i.e., traditional survey design). |
| | Data analysis strategy | - We accepted a strategy that is between a priori and inductive to analyse the qualitative data. We analysed the qualitative data first and the quantitative data second. | Time orientation, data collection strategy, stages of research | Sequential qualitative-quantitative analysis |
| Step 4: Drawing meta-inferences from the mixed-methods results | Types of reasoning | In our analysis, we focused on developing and then confirming hypotheses. | Design-investigation strategy | Both inductive and deductive theoretical reasoning |
| | Inference quality | - The qualitative inferences met the appropriate qualitative standards. The quantitative inferences met the appropriate quantitative standards. We assessed the quality of meta-inferences. | Mostly primary design strategies, sampling-design strategies, data-collection strategies, data-analysis strategies, and type of reasoning. | Conventional qualitative and quantitative standards were used to ensure quality. Design and explanatory quality, sample integration, inside-outside legitimation, and multiple validities. |
| Step 5: Assess the quality of meta-inferences | Inference quality | We discussed all potential threats to inference quality in the limitations. | Data-collection strategies and data-analysis strategies. | Threats to sample integration, and sequential legitimation. |
| Quality aspects | Quality criteria | Explanation on how this study has followed the Venkatesh et al. (2013) guidelines |
|----------------|-----------------|--------------------------------------------------------------------------------|
| Purpose of the mixed-methods approach | Development | This study is divided into two stages: 1) qualitative study involving interviews to understand the individuals’ perceptions about BDA and AI for personal information collection in ridesharing, and 2) a quantitative survey to verify the contextualised research model developed by the qualitative study and theory. |
| | Sequential less-dominant qualitative followed by a dominant quantitative investigation | Only using a set of interviews with passengers is limited. The quantitative investigation is primarily used to support and confirm the results of the qualitative study. |
| Design quality | Design suitability/appropriateness | The study used qualitative interviews followed by a quantitative survey to answer the research question. This strategy of exploring data ensured that the research model developed by the qualitative study and tested using the quantitative study was relevant to the phenomenon of interest, which combines the advantages of the two approaches. |
| Design adequacy | Qualitative: (1) Selecting suitable interviewees: The interviewees were all online car-hailing users of a giant car-hailing platform in China and were passengers or potential passengers of ridesharing. They had enough knowledge of ridesharing and would use future service, which was suitable for our research. (2) Understanding the field with credibility: The author team had enough knowledge about the ridesharing service and reviewed related literature to design the interview protocol before conducting the interviews. (3) Conduct of the interviews: Based on a protocol, but being sensitive to the principles of flexibility, non-direction, specificity, and range. Quantitative: • 1) Sampling: The sample was randomly selected in China, and all were passengers or potential passengers of ridesharing. • 2) Measures: To ensure content validity, all scales were selected from prior studies, which have been validated. • 3) Data collection procedure: An online survey was used for collecting the survey data in China. |
| Analytical adequacy | Qualitative: • 1) Detailed interview documents and other related documents (e.g., online news and comments about ridesharing) were stored as the qualitative data. • 2) A “start list” was established based on existing literature. The process of identifying codes related to the “start list” was iterative. • 3) Triangulation of data from the 21 interviews; comparison of responses. • 4) Using quotes given by individuals in our sample, which enhanced plausibility. Quantitative: • 1) Justification for the choice of the estimator (PLS-PM and SEM). • 2) Professionally collected data avoiding or, at least, minimising bias in sampling. • 3) An analysis of common method bias was conducted. |
| Explanation quality | Qualitative inference | All constructs identified in the qualitative study were relevant to prior studies, but they were not investigated in the context of ridesharing. The constructs are useful in explaining the phenomenon of study in ridesharing. |
| | Quantitative inference | 1) Internal validity: We developed the research model based on the coping theory and the privacy calculus theory. We used well-established measurements and carefully collected data, and conducted statistical tests. 2) Statistical conclusion validity: We found an appropriate level of significance for hypotheses and common method bias tests. 3) External validity: Ridesharing service was not only provided in China. Our results may be applied in other countries. |
| Integrative inference | Since personal information collection based on BDA and AI has recently been implemented in ridesharing, specific factors of the bright and dark sides, perceived risks, and perceived benefits and some relationships are attributed to our qualitative interviews conducted in the context of ridesharing. These specific factors provide innovative insights into the body of IS research on IT implementation and privacy control. The specific factors found in the qualitative study were used as dimensions of constructs in the quantitative study. The quantitative survey empirically validated most of the results found in the qualitative study and driven from theory. Based on the qualitative study, followed by a quantitative study, we provided a research model by efficiently integrating both studies’ results. The results indicated that the qualitative study and the quantitative study complemented each other well. |
Table A3 Emergent themes.

| Dimensions | A | BS | DS | PC | PR | PB | PC to PPR | PC to PB | PC to PR |
|------------|---|----|----|----|----|----|-----------|----------|----------|
| Themes     | US | UC | IP | IGC | IHC | IT | FR | US | UC | IP | IGC | IHC | IT | FR | USU | S | CO | PC to PPR | PC to PB | PC to PR |
| Passenger 1| √  | √  | √  | L  | L  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  |
| Passenger 2| √  |√   | √  | L  | L  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  |
| Passenger 3| √  | √  | √  | L  | L  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  |
| Passenger 4| √  | √  | M  | L  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  |
| Passenger 5| √  | √  | L  | L  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  |
| Passenger 6| √  | L  | L  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  |
| Passenger 7| √  | √  | L  | L  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  |
| Passenger 8| √  | √  | √  | L  | L  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  |
| Passenger 9| √  | √  | H  | L  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  |
| Passenger 10| √  | √  | L  | L  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  |
| Passenger 11| √  | √  | H  | L  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  |
| Passenger 12| √  | √  | M  | L  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  |
| Passenger 13| √  | √  | √  | M  | L  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  |
| Passenger 14| √  | H  | L  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  |
| Passenger 15| √  | √  | L  | L  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  |
| Passenger 16| √  | √  | L  | L  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  |
| Passenger 17| √  | √  | L  | L  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  |
| Passenger 18| √  | √  | H  | L  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  |
| Passenger 19| √  | √  | L  | L  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  |
| Passenger 20| √  | √  | H  | L  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  |
| Passenger 21| √  | √  | H  | L  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  | √  |

Note: A: Adoption, BS: Bright side, DS: Dark side, PC: Privacy control, PR: Perceived risks, PB: Perceived benefits, R: Relationships, US: Usefulness, UC: Uncertainty, IP: Invasion of privacy, IGC: Information gathering control, IHC: Information handling control, IT: Identity theft, FR: Financial risks, USU: Unauthorised secondary use, S: Security, CO: Convenience, PPR: Passengers’ participation in ridesharing, L: Low degree, M: Medium degree, H: High degree.
### Table A4 Selected quotes by respondents (key constructs).

| Construct               | Definition                                                                 | Selected Quotes                                                                                                                                                                                                 |
|-------------------------|---------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Usefulness              | The degree that passengers consider using BDA and AI technologies will enhance the performance of ridesharing service. | “I think BDA and AI will reduce some workforce and make the whole process of information processing smarter. From the perspective of information gathering, I think these technologies allow us to process the information on a large scale and extract valuable knowledge from the information. This valuable knowledge can improve service quality and passengers’ experience” (passenger 1). “By collecting our personal information, the ridesharing platform can further analyse data to improve ridesharing services” (passenger 21). |
| Uncertainty             | Passengers’ perception of complexity about BDA and AI related to the personal information collection and the uncertain effects these technologies will take on themselves. | “The technology has both a bright and dark side; passengers can be better served if the ridesharing platform uses data properly and publicly. However, we cannot control well personal information at present, and it is not clear what the ridesharing platform will do with the data” (passenger 3). “Sometimes, I am unclear about the purpose of the collection of personal information by the ridesharing platform. Is it for convenience or multiple authentications?” (passenger 20). |
| Invasion of privacy     | Passengers’ perception that their privacy may be compromised due to BDA and AI implementation. | “The development of AI relies heavily on BDA, and the application of AI needs massive data to support. One of the sources of this data is personal information. I hope that personal information and personal privacy can be better protected after these IT implementation” (passenger 9). “The development of AI is too powerful. Personal information was collected and released on the Internet and used in algorithms, making us not have privacy” (passenger 17). |
| Convenience             | The time and effort that may be saved by users providing personal information. | “For passengers, providing personal information can enhance the accuracy of position and can further save time” (passenger 5). “The platform can better match the car owners and passengers after collecting personal information. It is possible to reduce the unnecessary effort in ridesharing” (passenger 10). |
| Safety                  | Passengers’ perception that providing personal information may reduce their feeling of danger and safety guarantee. | “To some extent, providing some personal information can ensure the safety of both car owners and passengers. For example, when you are in danger, if you have provided personal information, you can be located through the app, which will contact your family and friends” (passenger 16). “On one hand, from the perspective of safety, providing some personal information will reassure both car owners and passengers and reduce the frequency of security accidents. On the other hand, it will be more convenient to determine who should take responsibility for conflicts and accidents” (passenger 5). |
| Identity theft          | When an impostor obtains personal information from the passenger and uses it illegally. | “Since my job is related to risk control, I usually deal with the issues about identity theft. We often contact persons who had been defrauded. The BDA and AI-enabled personal information collection can be used to theft their personal information, and provoke some losses for passengers” (passenger 7). “I am worried about my personal information. Who can access my information? How can it be used? There are many cases of hackers stealing information” (passenger 8). |
| Financial risks         | Potential financial losses derived from providing personal information through BDA and AI to the ridesharing platform | “Since many mobile phones are unlocked by facial recognition and mobile payments are also verified by facial recognition, the disclosure of facial information may bring financial risks” (passenger 11). “I do not know whether the ridesharing platform will sell my personal information, which may lead to personal safety issues and financial risks” (passenger 13). |
| Unauthorised secondary use | Concern that personal information is collected from passengers for one purpose but is used for another secondary purpose. | “If other companies want to buy the user information accumulated on the ridesharing platform with a high price for, it may lead to information transactions” (passenger 4). “It would be better if car owners could not see my information on facial recognition, but I would also consider the possibility that my information could be used for other purposes” (passenger 20). |
| Relationships                              | Degree   | Description                                                                 | Selected quotes                                                                                                                                                                                                 |
|-------------------------------------------|----------|-----------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Degree of information gathering control   | Low      | Passengers believe that they can not control what personal information a ridesharing platform can collect and store. | “I do not know and cannot control what of my personal information will be collected by the app.” (passenger 2). To be honest, I can not fully understand what my personal information is being collected. I do not usually pay attention to the privacy policy. Thus, if the ridesharing platform wants to collect much of my personal information, I might not know how to control it” (passenger 3). |
|                                           | Medium   | Passengers believe that they can generally control what personal information a ridesharing platform can collect and store. | “I know what personal information they collected because I have provided information on my ID card and student card. However, this information cannot be changed. There is some information that might be updated in real-time such as my job position. I do not know more about that” (passenger 4). “When I used the ridesharing platform, I am clear the information asked by the app that will be collected, but I am not clear if there is default information collection that I am not aware” (passenger 13). |
|                                           | High     | Passengers believe that they can control what personal information a ridesharing platform can collect and store. | “Generally, the information is manually filled in the ridesharing app, so I know what information I fill in. Ridesharing service seems to collect more information, such as facial recognition information, than other types of car-hailing services, but I think I know what personal information is collected” (passenger 11). “The steps of information collection in ridesharing make clear what personal information will be collected” (passenger 14). |
| Degree of information handling control     | Low      | Passengers believe that they can not control how the ridesharing platform uses and disseminates their information. | “No, I can not control how the ridesharing platform uses and disseminates my personal information after collection. I feel uncertain about it. I know my information was collected, but I do not know well how and why they use and spread my information” (passenger 6). “No, I can not control how the ridesharing platform uses and disseminates my personal information after collection. They will not proactively inform you how they use your information. I have no way and no energy to know it” (passenger 12). |
| Privacy control to perceived benefits      |          | Privacy control will positively influence the perceived benefits.            | “Yes. It would be beneficial for me. It is necessary to provide some personal information. If the process of using the information can be transparent, I would identify with the collection” (passenger 3). “It would be beneficial for me to have more control over my personal information” (passenger 19). |
| Privacy control to perceived risks         |          | Privacy control will negatively influence perceived risks.                 | “I do not want my information to be secondarily used. If I can control my personal information, I can ban the ridesharing platform from further using or analysing my information, which can reduce my risk” (passenger 15). “Enhancing the control of personal information and knowing how the information is used will reduce the risk” (passenger 18). |
| Privacy control to passengers’ participation in ridesharing |          | Privacy control will positively influence participation in ridesharing.   | “Increasing my control over my personal information will make me more willing to use ridesharing” (passenger 2). “To some extent, if my privacy control was increased, I will be more willing to use ridesharing” (passenger 10). |
Table A6 First-order construct measurement properties.

| Code | Construct/indicator                                                                 | Mean | S.D. | Loadings | Cronbach’s alpha | Dijkstra-Henseler’s rho | AVE | Source            |
|------|------------------------------------------------------------------------------------|------|------|----------|-------------------|-------------------------|-----|--------------------|
| UF1  | Using identification information collection based on BDA and AI would improve the performance of the ridesharing service. | 5.117 | 1.477 | 0.863*** 0.355*** | 0.911               | 0.911                   | 0.773 | Davis (1989)       |
| UF2  | Using identification information collection based on BDA and AI would enhance the effectiveness of ridesharing service. | 5.214 | 1.499 | 0.884*** 0.364*** | 0.911               | 0.911                   | 0.773 |                |
| UF3  | I would find identification information collection based on BDA and AI useful in ridesharing. | 5.130 | 1.441 | 0.890*** 0.366*** | 0.911               | 0.911                   | 0.773 |                |
| UC2  | What was the level of “newness” or uncertainty of the BDA and AI technology involved in identification information collection? | 4.762 | 1.154 | 0.856*** 0.425*** | 0.911               | 0.911                   | 0.773 |                |
| UC3  | How uncertain and unpredictable are BDA and AI shifts for identification information collection? | 5.009 | 1.115 | 0.945*** 0.673*** | 0.911               | 0.911                   | 0.773 |                |
| IOP1 | I feel my privacy can be compromised because of identification information collection based on BDA and AI. | 5.401 | 1.324 | 0.940*** | 0.911               | 0.911                   | 0.773 |                |
| IOP2 | I feel the ridesharing platform could violate my privacy through the information collection based on BDA and AI. | 5.334 | 1.349 | 0.926*** 0.349*** | 0.911               | 0.911                   | 0.773 |                |
| IOP3 | I feel that identification information collection based on AI and big data analytics makes it easier to invade my privacy. | 5.446 | 1.301 | 0.920*** 0.347*** | 0.911               | 0.911                   | 0.773 |                |
| IGC1 | I can keep a ridesharing platform from collecting personal information about me that I would like to keep privately. | 5.024 | 1.523 | 0.780*** 0.534*** | 0.911               | 0.911                   | 0.773 |                |
| IGC2 | I can determine the type of information that the ridesharing platform can store about me. | 5.145 | 1.597 | 0.830*** 0.568*** | 0.911               | 0.911                   | 0.773 |                |
| IHC2 | Ridesharing platform respects my right to control who can see my personal information. | 4.907 | 1.652 | 0.952*** 0.359*** | 0.911               | 0.911                   | 0.773 |                |
| IHC3 | The ridesharing platform allows me to decide how my personal information can be released to others. | 4.861 | 1.677 | 0.894*** 0.337*** | 0.911               | 0.911                   | 0.773 |                |
| IHC4 | I control how the ridesharing platform uses my personal information. | 4.810 | 1.742 | 0.939*** 0.354*** | 0.911               | 0.911                   | 0.773 |                |
| CO1  | Providing identification information based on BDA and AI to the ridesharing platform would allow me to save time. | 4.783 | 1.568 | 0.866*** 0.354*** | 0.911               | 0.911                   | 0.773 |                |
| CO2  | Providing identification information based on BDA and AI to the ridesharing platform would be convenient for me. | 4.970 | 1.472 | 0.887*** 0.367*** | 0.911               | 0.911                   | 0.773 |                |
| CO3  | Providing identification information based on BDA and AI to the ridesharing platform would give me a convenient way to travel. | 4.946 | 1.524 | 0.890*** 0.366*** | 0.911               | 0.911                   | 0.773 |                |
| SF1  | Providing identification information based on BDA and AI makes me feel safe in ridesharing. | 4.907 | 1.541 | 0.841*** 0.420*** | 0.911               | 0.911                   | 0.773 |                |
| SF2  | Providing identification information based on BDA and AI makes me less concerned about crime issues using ridesharing. | 5.003 | 1.516 | 0.750*** 0.375*** | 0.911               | 0.911                   | 0.773 |                |
| SF3  | To what extent would you provide identification information based on BDA and AI due to the security issue in ridesharing? | 4.883 | 1.493 | 0.741*** 0.370*** | 0.911               | 0.911                   | 0.773 |                |
| FR1  | Providing my identification information based on BDA and AI would make me lose money. | 4.819 | 1.374 | 0.862*** 0.332*** | 0.911               | 0.911                   | 0.773 |                |
| FR2  | Providing identification information based on BDA and AI would subject my bank account to potential fraud. | 5.078 | 1.425 | 0.961*** 0.370*** | 0.911               | 0.911                   | 0.773 |                |
| FR3  | Providing my identification information based on BDA and AI would lead to a financial loss for me. | 4.843 | 1.412 | 0.926*** 0.356*** | 0.911               | 0.911                   | 0.773 |                |
| IT1  | Providing identification information based on BDA and AI makes the ride less safe. | 5.542 | 1.276 | 0.945*** 0.416*** | 0.911               | 0.911                   | 0.773 |                |
| IT2  | Providing identification information based on BDA and AI would make the ride less safe. | 5.033 | 1.428 | 0.739*** 0.325*** | 0.911               | 0.911                   | 0.773 |                |
| IT3  | Somebody will use my identity to crime issues if I provide my identification information based on BDA and AI. | 5.386 | 1.334 | 0.842*** 0.370*** | 0.911               | 0.911                   | 0.773 |                |

(Continued)
| Code | Construct/indicator                                                                 | Mean  | S.D.  | Loadings | Weights | Cronbach’s alpha | Dijkstra-Henseler’s rho | AVE  | Source                                      |
|------|------------------------------------------------------------------------------------|-------|-------|----------|---------|------------------|-------------------------|------|--------------------------------------------|
| USU1 | Providing my identification information based on BDA and AI would make me lose money.| 5.208 | 1.595 | 0.856*** | 0.345***| 0.933            | 0.935                   | 0.823| Smith et al. (1996)                        |
| USU2 | Providing identification information based on BDA and AI would subject my bank account to potential fraud. | 5.262 | 1.493 | 0.912*** | 0.357***|                  |                         |      |                                            |
| USU3 | Providing my identification information based on BDA and AI would lead to a financial loss for me. | 5.268 | 1.595 | 0.953*** | 0.372***|                  |                         |      |                                            |
| Actionable participation | I am willing to spend time to make clear how to participate in ridesharing. | 5.346 | 1.091 | 0.927*** | 0.619***| 0.810            | 0.835                   | 0.684| Kamboj and Rahman (2017)                   |
| ACP3 | I provide feedback related to participation in ridesharing. | 5.181 | 1.229 | 0.713*** | 0.476***|                  |                         |      |                                            |
| Attitudinal participation | I think participating in ridesharing would be good for me. | 5.361 | 1.087 | 0.862*** | 0.354***| 0.912            | 0.915                   | 0.776| Kamboj and Rahman (2017)                   |
| ATP2 | I have a positive opinion about participation in ridesharing. | 5.364 | 1.091 | 0.835*** | 0.343***|                  |                         |      |                                            |
| ATP3 | I think participating in ridesharing would be beneficial for me. | 5.271 | 1.138 | 0.942*** | 0.387***|                  |                         |      |                                            |
| Information participation | I would comment online about ridesharing. | 4.910 | 1.277 | 0.775*** | 0.580***| 0.725            | 0.726                   | 0.569| Kamboj and Rahman (2017)                   |
| INP3 | I would read online reviews of other users about ridesharing. | 5.377 | 1.275 | 0.734*** | 0.549***|                  |                         |      |                                            |

Note: All Likert scales are 1: Totally disagree, 7: Totally agree except if it is indicated other way.
### Table A7 HTMT ratio of correlations.

| Construct                  | 1     | 2     | 3     | 4     | 5     | 6     | 7     | 8     | 9     | 10    | 11    | 12    |
|----------------------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| 1. Usefulness              |       |       |       |       |       |       |       |       |       |       |       | 0.348 |
| 2. Uncertainty             | 0.348 |       |       |       |       |       |       |       |       |       |       |       |
| 3. Invasion of privacy     | 0.088 | 0.179 |       |       |       |       |       |       |       |       |       |       |
| 4. Information gathering control | 0.061 | 0.269 | 0.027 |       |       |       |       |       |       |       |       |       |
| 5. Information handling control | 0.203 | 0.180 | 0.258 | 0.175 |       |       |       |       |       |       |       |       |
| 6. Convenience             | 0.846 | 0.425 | 0.216 | 0.133 | 0.259 |       |       |       |       |       |       |       |
| 7. Safety                  | 0.689 | 0.394 | 0.140 | 0.244 | 0.187 | 0.716 |       |       |       |       |       |       |
| 8. Financial risks         | 0.043 | 0.183 | 0.562 | 0.031 | 0.207 | 0.056 | 0.030 |       |       |       |       |       |
| 9. Identity theft          | 0.067 | 0.248 | 0.703 | 0.231 | 0.007 | 0.155 | 0.119 | 0.733 |       |       |       |       |
| 10. Unauthorised secondary use | 0.134 | 0.237 | 0.702 | 0.179 | 0.088 | 0.184 | 0.177 | 0.120 | 0.654 |       |       |       |
| 11. Actionable participation | 0.470 | 0.380 | 0.033 | 0.402 | 0.280 | 0.421 | 0.513 | 0.033 | 0.080 | 0.216 |       |       |
| 12. Attitudinal participation | 0.523 | 0.293 | 0.060 | 0.685 | 0.251 | 0.505 | 0.576 | 0.044 | 0.024 | 0.140 | 0.822 |       |
| 13. Information participation | 0.404 | 0.342 | 0.650 | 0.015 | 0.247 | 0.403 | 0.407 | 0.721 | 0.032 | 0.721 | 0.128 | 0.074 |

### Table A8 Correlations matrix.

| Construct                  | 1     | 2     | 3     | 4     | 5     | 6     | 7     | 8     | 9     | 10    | 11    | 12    | 13    |
|----------------------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| 1. Usefulness              | 1.000 |       |       |       |       |       |       |       |       |       |       |       |       |
| 2. Uncertainty             | 0.296 | 1.000 |       |       |       |       |       |       |       |       |       |       |       |
| 3. Invasion of privacy     | −0.088| 0.172 | 1.000 |       |       |       |       |       |       |       |       |       |       |
| 4. Information gathering control | 0.064 | 0.248 | 0.243 | 1.000 |       |       |       |       |       |       |       |       |       |
| 5. Information handling control | 0.203 | 0.158 | −0.010| 0.332 | 1.000 |       |       |       |       |       |       |       |       |
| 6. Convenience             | 0.845 | 0.366 | −0.215| 0.136 | 0.260 | 1.000 |       |       |       |       |       |       |       |
| 7. Safety                  | 0.687 | 0.338 | −0.142| 0.245 | 0.186 | 0.713 | 1.000 |       |       |       |       |       |       |
| 8. Financial risks         | −0.043| 0.169 | 0.650 | 0.257 | 0.075 | −0.057| −0.031| 1.000 |       |       |       |       |       |
| 9. Identity theft          | −0.065| 0.236 | 0.705 | 0.233 | 0.008 | −0.153| −0.116| 0.722 | 1.000 |       |       |       |       |
| 10. Unauthorised secondary use | −0.134| 0.217 | 0.721 | 0.205 | −0.085| −0.184| −0.179| 0.561 | 0.654 | 1.000 |       |       |       |
| 11. Actionable participation | 0.456 | 0.329 | 0.078 | 0.255 | 0.207 | 0.414 | 0.507 | 0.058 | 0.085 | 0.046 | 1.000 |       |       |
| 12. Attitudinal participation | 0.523 | 0.255 | 0.016 | 0.175 | 0.184 | 0.506 | 0.576 | 0.027 | 0.027 | −0.031| 0.672 | 1.000 |       |
| 13. Information participation | 0.404 | 0.295 | 0.127 | 0.280 | 0.189 | 0.402 | 0.405 | 0.036 | 0.033 | 0.792 | 0.400 | 1.000 |       |