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Re-Examining the Impact of Multidimensional Trust on Patients' Online Medical Consultation Service Continuance Decision

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Abstract
Recent years have witnessed the rapid growth of an emerging digital healthcare service – online medical consultation (OMC). Despite its popularity, many OMC platforms have encountered issues in initial adoption and continuance use among patients. We posit that many of the hesitation and resistance may arise from a lack of trust toward OMC, which is a complex phenomenon that involves both interpersonal and technological-oriented considerations. This study seeks to clarify the conceptualization of online trust in the context of OMC. It compares two plausible explanations (i.e., trust as a direct cause vs. trust as a moderator) regarding how interpersonal and technological trust contributes to the service continuance decision in OMC. By contextualizing the valence framework, we identify the critical factors in making the risk-benefit assessment of patients' OMC decision. We conduct an online survey of 365 experienced OMC users and analyze our structural model using a partial least square approach. Our results show that the multidimensional conceptualization approach, which incorporates both interpersonal and technological aspects of trust, is superior to the unitary approach. Besides, our findings suggest that the role trust plays in determining service continuance decisions in OMC is more of a direct cause than a qualifier that buffers the impacts of risk-benefit evaluation. We believe the findings can help both researchers and practitioners recognize the multidimensional perspective of trust and better understand the role trust plays in OMC and other online healthcare delivery problems.

Keywords Online trust · Online healthcare consultation · Digital platform · Multidimensionality · Valence framework · Partial least square

1 Introduction

The use of online medical consultation (OMC) — a type of online healthcare provided by qualified healthcare professionals on third-party digital platforms – has been growing in recent years. According to a user survey by Kantar Health in China,[1] during the COVID-19 pandemic, around 15% of patients have been using online medical consultation platforms for healthcare information seeking, diagnosis, and treatment. Despite the popularity of such services, many OMC platforms have difficulties attracting active participation and continuous payment, limiting the platforms' sustainability (Zhang et al. 2019). We posit that the hesitation and resistance in the service continuance among OMC patients are largely due to the lack of trust in various aspects of OMC services (Yang et al. 2020). With the digital transformation of medical

[1] KantarHealth. *Health awareness and behaviors WeChat survey*. 2020 [cited 2020; Available from: https://cn-en.kantar.com/business/health/2020/health-awareness-and-behaviors-during-covid-19-epidemic/.

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procedures on OMC, trust becomes an ever-complex issue in that no face-to-face interaction exists to fertilize patients' belief in healthcare providers' reliability and the ability to provide professional services. Consequently, patients may abandon the service due to a lack of trust, and high-quality doctors may also quit the platform if there is no sufficient number of OMC orders and economic returns.

Previous studies in OMC patient retention generally focus on the impacts of service characteristics and physician qualities on patients' physician selection process (Cao et al. 2017; Liu et al. 2016), whereas the underlying psychological mechanisms relating to patient's decision on continuing the service with a doctor remain mostly an under-researched area. We start our investigation with online trust to narrow this research gap, which is an established mechanism explaining online transaction success (Chiu et al. 2012; Fang et al. 2014; Torkzadeh and Dhillon 2002; Xu et al. 2016).

Trust is especially critical in OMC for several reasons. First, OMC is a type of online transaction that requires patients to submit various sensitive personal and financial information (e.g., health condition, name, and credit card number). Thus, trust in the platform and the healthcare provider is vital to ensure patients' willingness to provide such information and continue using the doctor's service (Guo et al. 2016). Second, due to the lack of physical examination and face-to-face interactions, patients may face the threat of reducing diagnostic accuracy. Hence, patients may need more trust to have a fair valuation of OMC and accept the service (Anderson and Agarwal 2011). Third, OMC is a type of private credence information goods (Dulleck and Kerschbamer 2006; Liu et al. 2016; Mou and Cohen 2017). Patients cannot easily observe the quality of OMC services even after consumption, making the assessment of OMC's value challenging. Thus, OMC experience, in which trust may play a vital role, becomes essential in payment decisions. In summary, we expect trust to play a vital role in OMC service continuance because of its close association with long-term relationship building and online consumers' willingness to pay (Kim 2014; Kim et al. 2009).

Although the viability of trust has been well researched in various online contexts (Guo et al. 2016; van Velsen et al. 2017), conflicting approaches regarding what constitutes online trust and how trust is measured have been presented. For example, there are two main research streams in the online trust-related study: trust-in-technology (e.g., Akter et al. 2011; Meng et al. 2019a, 2019b), and trust-in-human (e.g., Deng et al. 2018; Guo et al. 2016). Both research streams frequently borrow the definition of trust from traditional interpersonal trust research (Benbasat and Wang 2005; Vance et al. 2008) and use measures such as integrity, competence, and benevolence. In the context of OMC, the concept of trust has been broadened to encompass all stakeholders such as the healthcare professional, the platform owner, and the technology (i.e., the digital platform architecture). Accordingly, the boundaries of the IT artifact and the social actors are becoming blurred, calling for a re-conceptualization of online trust to include interpersonal as well as technological aspects of trust in OMC. Thus, this research's primary objective is to re-examine the composition and explanatory role of trust in promoting patients' intention to continue the OMC service.

Our work contributes to the literature by integrating multiple streams of research to propose a multidimensional trust model and identify relevant factors in the context of the OMC service continuous. In the next sections, we review the online trust literature in various application domains. Based on the review, we summarize and compare the three popular trust models used in the relevant domains, such as online healthcare, online marketing, and information systems studies in Section 3. These models incorporate different conceptualization of trust (i.e., unitary vs. multidimensional) and explanatory mechanisms (i.e., trust as a direct cause vs. trust as a moderator). We categorize two sets of factors (i.e., risk and benefit) that contribute to trust-building in OMC based on the classic valence framework (Peter and Tarpey 1975) and e-business literature that focuses on online payment (Kim et al. 2009). They are (1) *perceived validity* and *patient-centeredness* that relate to OMC benefits, and (2) *privacy risk* and *performance risk* that relate to OMC risks. In Section 4, we use PLS path modeling to empirically validate the two commonly used trust mechanisms: (1) trust as a cause and (2) trust as a moderator. The former implies that trust gives rise to payment, while the latter suggests that trust is an "order qualifier" that buffers the impacts of OMC patients' risk-benefit evaluation. We perform data analysis and present the results in Section 5. We discuss the theoretical and practical implications, limitations, and future research directions before concluding the paper in Section 6.

2 Conceptualization of Online Trust

Online trust is a topic that has been researched in various problem domains, including online marketing, information systems, and online healthcare services. We conducted a systematic review on online trust in these areas, and the results are presented in Appendix A. At a high level, existing studies conceptualize online trust in four ways (Gefen et al. 2003; McKnight et al. 2002): (1) trust as a belief or collection of beliefs (Bhattacherjee 2002; Mcknight et al. 2011; Wang and Benbasat 2007; Kim et al. 2008); (2) trust as emotional feelings (Komiak and Benbasat 2006; Wang et al. 2016); (3) trust as an intention (Hoffmann et al. 2014); and (4) trust as a combination of these elements (McKnight and Chervany 2001; Gong et al. 2020). This study focuses on trusting beliefs (type 1), which are beliefs that a specific technology or service has the attributes necessary to perform as expected in a given situation where negative consequences are possible (Mcknight et al. 2011).

Among the various trusting beliefs, this study focuses on both interpersonal and technological trust since OMC is a patient-provider interaction process on an IT platform (McKnight and Chervany 2001). *Interpersonal trust* reflects the social tie between trustor and trustee, which measures trust between people from three dimensions: competence, benevolence, and integrity (Mayer et al. 1995; McKnight et al. 2002). *Technological trust*, on the other hand, is channel-specific. It is a type of belief that structural conditions (e.g., the OMC platform architecture) are needed to ensure a successful outcome (McKnight et al. 2002; O'Connor and O'Reilly 2018). As a technological artifact, the OMC platform provides an institutional environment where rules and requirements are embedded to shape actors' interactions. The detailed definition of each trust dimension can be found in Table 1. In terms of when these trusting beliefs are developed, previous studies have highlighted the importance of history-bounded interactions that determine the perceived benefits and risks of interdependence, thus differentiating initial trust (Benbasat and Wang 2005) from the knowledge-based trust (Lippert 2007). Knowledge-based trust assumes socialization or courtship types of interaction, in which people try to learn from others and establish an interpersonal relationship. In this study, we focus on knowledge-based trust, in which patients should already have OMC service experience but need social interactions to establish an interpersonal relationship with the OMC providers before they would continue to pay for the services.

Although previous research on trust in online healthcare has well elucidated the essential role of trust in building doctor-patient relationships and deciding to continue the service, the multidimensional nature of trust has not yet been fully explored. Besides, despite the clear conceptual distinction between trust in humans and trust in technology, researchers often use human-like dimensions to study technological trust because people tend to anthropomorphize technology and ascribe them to human attributes (Benbasat and Wang 2005; Nowak and Rauh 2005; Vance et al. 2008).

This study proposes a comprehensive trust model for OMC, which integrates interpersonal and technological trust – two knowledge-based trusting beliefs resulting from patient-physician interactions during OMC. This multidimensional trust construct incorporates physicians' quality (e.g., competence, integrity, and benevolence) and technological factors such as functionality, helpfulness, and reliability.

3 Research Model Development

3.1 Theoretical Lens: The Valence Framework

The proposed research models (see Fig. 1a-d) are based on the classic valence framework (Peter and Tarpey 1975), in which risk-benefit evaluation drives behavioral outcomes (Kim et al. 2009). The fundamental assumption is that perceived risk and perceived benefit simultaneously play a role in patients' decision-making process (Mou et al. 2016; Gao and Waechter 2017; Peter and Tarpey 1975). On the one hand, patients strive to minimize expected negative outcomes caused by paying for the continued OMC services. On the other hand, they are motivated to maximize potential benefits.

The valence framework is appropriate in our context because it provides a high-level cognitive rationale to incorporate both positive and negative aspects of OMC that may influence the decision to continue the service. It also allows us to incorporate context-specific factors that contribute to rational risk-benefit evaluation while considering the role of knowledge-based trust to reflect the OMC experience. Table 1 provides a summary of the constructs and their definitions.

3.2 The Baseline Model

We first specify patients' perceived benefits and risks of OMC to develop our baseline model. Since the physician provides the consultation service, not the technological infrastructure (i.e., the digital platform), patients expect to obtain personalized healthcare service from the physicians as their benefits. A good personalized online service should involve both outcome quality and process quality: the service outcome can fulfill the patients' needs and expectations, and patients are given individual attention during the process, which shows empathy (Collier and Bienstock 2006; Li and Suomi 2009). Hence, we propose *perceived validity* (adapted from Dai et al. 2011) and *patient-centeredness* (adapted from van Velsen et al. 2017) as two core mechanisms that measure patients' expected benefits of OMC. The former represents the outcome quality, and the latter represents the physicians' commitment to value patients' experience, which reflects process quality. The service quality and patients' feeling of being highly valued would help elicit patients' positive valuation of OMC (Mou and Cohen 2017), which in turn influences their intention to pay for the services continuously. Hence, we propose:

H1. *Perceived benefits of OMC, comprised of perceived validity and patient-centeredness, has a positive impact on patients' OMC service continuance intention.*

On the other hand, the perceived risk of OMC is patients' perceptions of any uncertainties and negative consequences associated with OMC. Whereas various risk factors exist, in this study, we consider two predominant risk aspects – *privacy risks* and *performance risks* (Featherman and Pavlou 2003). During OMC, patients are often

Table 1 Research constructs and their definitions

Construct	Definition
1. Perceived benefits	The extent to which using the OMC service helps achieve gains in obtaining healthcare objectives (Kim et al. 2009).
2. Perceived validity	The extent to which the physicians' services are helpful and responsive to patients' inquiries (Dai et al. 2011).
3. Patient centeredness	The extent to which the physicians' services are respectful of patients' preferences and needs (van Velsen et al. 2017).
4. Perceived risks	The extent to which using the OMC service exposes patients to negative consequences (Featherman and Pavlou 2003).
5. Privacy risk	The extent to which patients believe that using OMC leads to loss of control over personal information without their knowledge or permission (Featherman and Pavlou 2003).
6. Performance risk	The extent to which patients believe that OMC may not perform as it was designed and therefore failing to deliver the desired benefits (Featherman and Pavlou 2003).
7. Interpersonal trust	Patients' subjective belief that an online physician will fulfill its commitments (Mayer et al. 1995).
8. Competence	The belief that the physician has skills, abilities, and characteristics that enable them to deliver the OMC services (Mayer et al. 1995).
9. Benevolence	The belief that the physician wants to do good to the patient, aside from an egocentric profit motive (Mayer et al. 1995).
10. Integrity	The belief that a physician adheres to a set of principles that the patient finds acceptable (Mayer et al. 1995).
11. Technological trust	Patients' subjective belief that the technological infrastructures supporting OMC is dependable (Mcknight et al. 2011).
12. Functionality	The belief that the technological infrastructures supporting OMC have the capabilities, functions, or features to accomplish what needs to be done (Mcknight et al. 2011).
13. Reliability	The belief that technological infrastructures supporting OMC will consistently operate properly (Mcknight et al. 2011).
14. Helpfulness	The belief that the technological infrastructures supporting OMC will provide adequate and responsive help for users (Mcknight et al. 2011).
15. Trust in OMC	Patients' subjective belief that the OMC platform (as an organization) will enforce fair rules, procedures, and outcomes (Bansal et al. 2016; van Velsen et al. 2017)
16. OMC service continuance intention	The extent to which the patient plans to continue the OMC services in the future.

requested to provide a great deal of detailed personal information. While OMC platforms take advantage of personal information to provide personalized services, patients often view this as an invasion of privacy (Guo et al. 2016). Two types of privacy risk arise from the platforms' inability or unwillingness to effectively manage the patients' personal information: (1) the improper use of information due to the absence of appropriate controls, and (2) the secondary use of personal information without the patient's consent (Gao et al. 2015). Although many platforms have established information protection regulations, and many countries have made privacy-related laws in recent years, data breaches and inappropriate data use are still major concerns for online privacy (Anderson and Agarwal 2011; Bansal et al. 2015; Bansal et al. 2016). Even if the OMC platform strictly follows the regulations, these risks cannot be entirely avoided. In addition, in OMC, the platform is not the only data owner, and the doctors' careless in data treatment may also cause privacy invasion. However, it is difficult for the platform to manage each doctors' data usage activities. Thus, we consider privacy risks a salient inhibitor of a range of online behaviors, especially in the payment process (Chen et al. 2018; Gao et al. 2015; Mousavi et al. 2020).

Similarly, the risk perception may come from the platform's malfunctioning or the physicians' underperformance (i.e., performance risk). For example, although patients may applaud the convenience of online

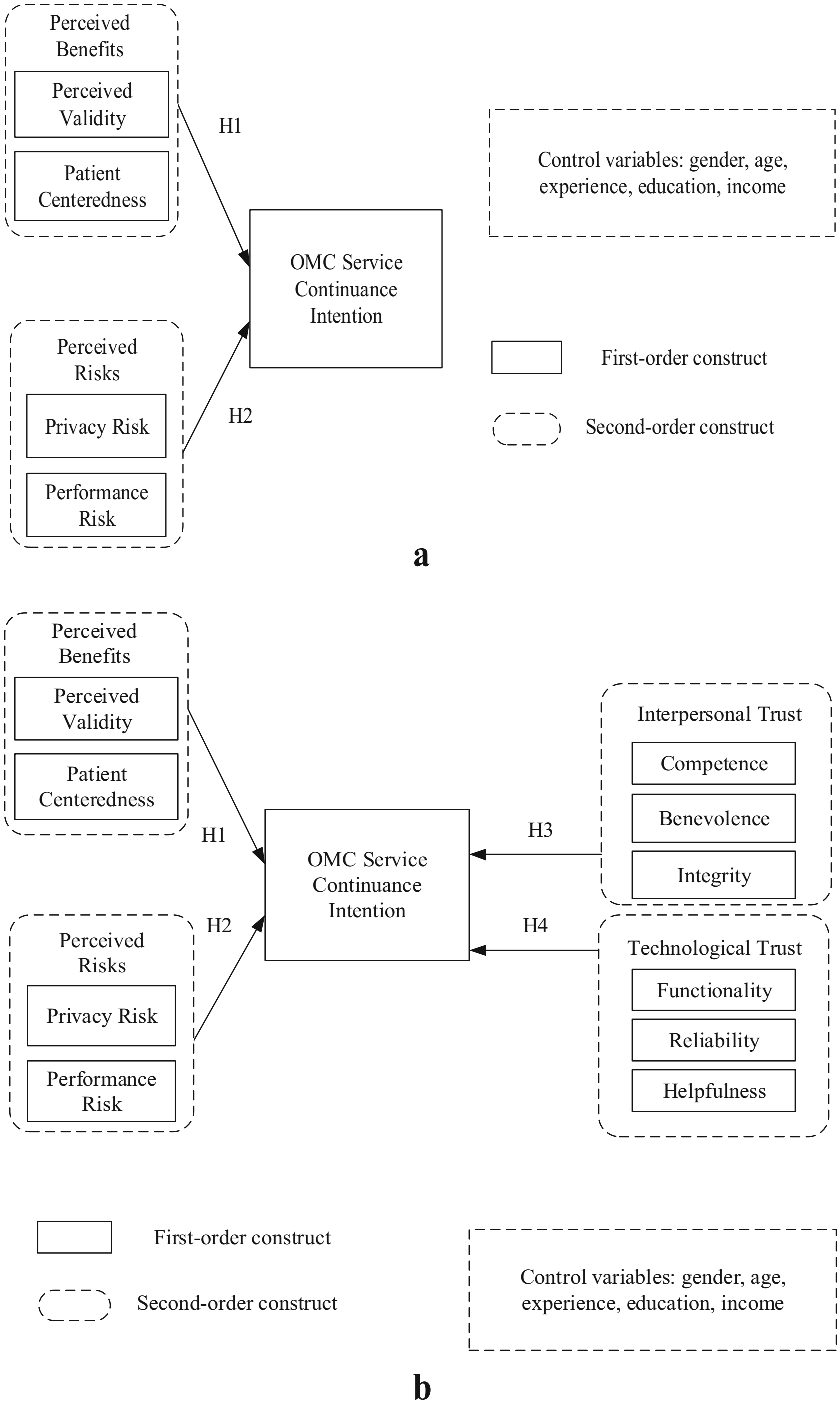

Fig. 1 **a** Baseline Model**. b** Trust as Independent Variables (see Model 1.1 in Table 5). *Note: Besides Model 1.1, we also test another two alternative models 1.2 and 1.3 that use different dimensions to measure trust.* **c** Interpersonal Trust and Technological Trust as Multiple Mediators. **d** Trust in OMC as a Moderator

communication with their doctors, the absence of face-to-face interactions in the virtual environment may reduce the physician's diagnostic accuracy (Ozdemir 2007), which may impact patients' evaluation of the physician's performance. If the patients believe that the platform cannot support the consultation process or the doctor cannot solve their healthcare problem, they are less likely to continue the service. Thus, we propose:

H2. *Perceived risks of OMC, consisting of perceived privacy risk and perceived performance risk, negatively impacts patients' OMC service continuance intention.*

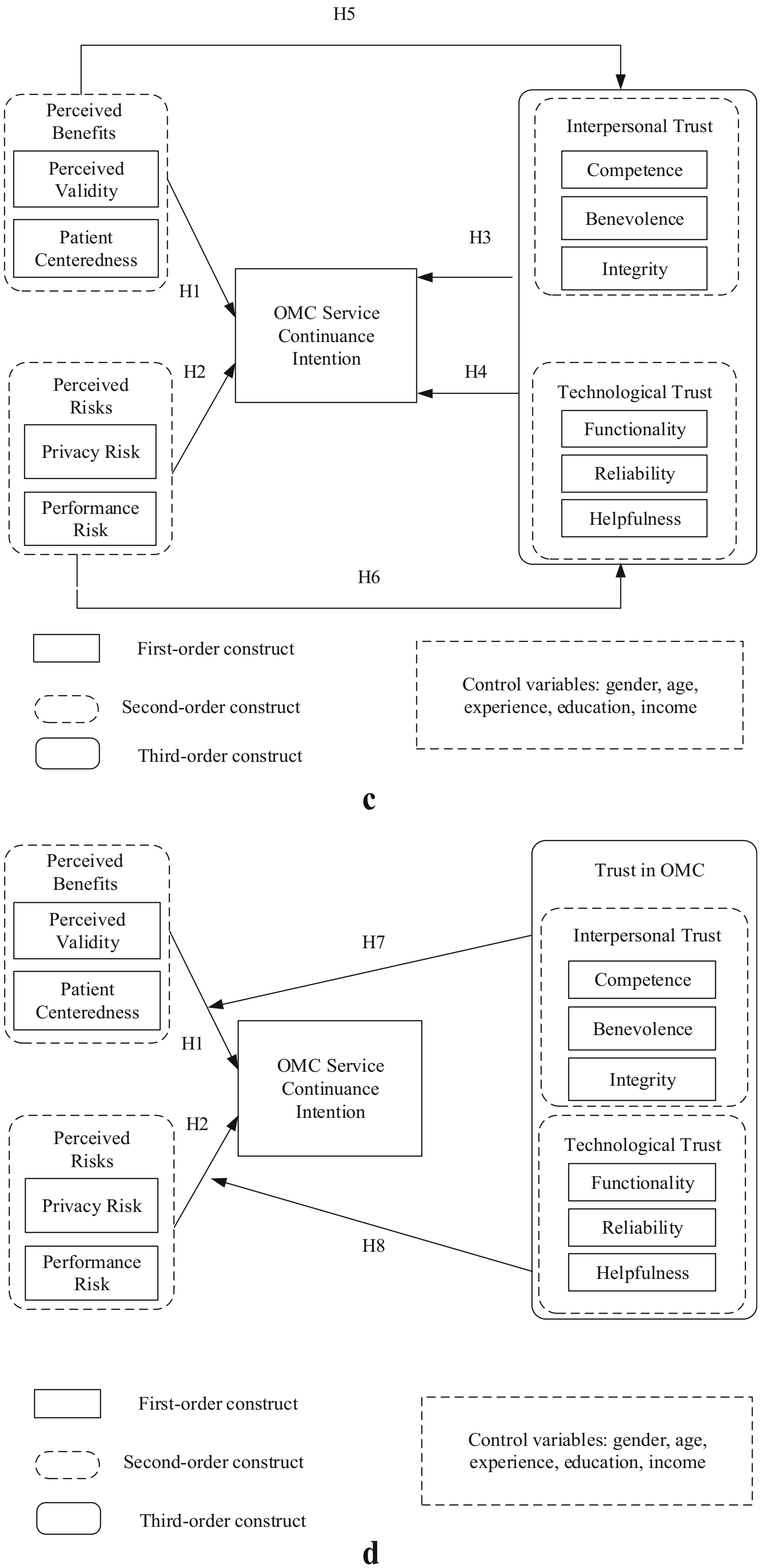

Fig. 1 continued.

3.3 I Pay because I Trust: Trust as a Direct Cause

In addition to the risk and benefit factors mentioned above, trust has been proposed as an additional driving factor that directly influences online purchase (Kim 2014). This is because under uncertain situations, like our OMC context, trust has been found to promote risk-taking behavior and service satisfaction (Mayer et al. 1995; McKnight et al. 2002; Fang et al. 2014; Mohr and Walter 2019). Previous studies mainly draw on two theories to explain the relationship between trust and service continuance — the expectation-confirmation theory and the social exchange theory (Kim 2014; Pavlou et al. 2007; Ye and Kankanhalli 2017). Bhattacherjee (2001) and Oliver and Burke (1999) described the logic of the *expectation-confirmation theory*: consumers first form an initial expectation of a specific product or service before the transaction. After their initial consumption, they form perceptions about its performance. Then, consumers compare their performance perceptions with their original expectations and determine the extent to which their expectations are confirmed. Finally, they develop a level of satisfaction. Trust contributes to expectation formation and thus influences their satisfaction and intention to continue the service.

Social exchange theory posits that individuals behave in ways to maximize benefits and minimize costs during the exchange. An important tenet of the theory is that a trustor-trustee relationship terminates or continues based on the results of two types of comparisons (Kim 2014): Alternative relationship and the give-and-take comparisons. Consumers take part in the exchange only when they expect rewards to exceed the costs that may incur (Gefen and Ridings 2002). As an indicator of how well the OMC platforms provide services, trust is critical because if patients trust the platform, both parties will build a mutual understanding, and the relationship will be more likely to continue (Mpinganjira 2018). Therefore, as OMC patients increase trust, they are more likely to continue the relationship with the doctor and pay for the service continuously. Thus, we propose:

H3. *Interpersonal trust, consisting of competence, benevolence, and integrity, positively impacts patients' OMC service continuance intention.*

H4. *Technological trust, consisting of functionality, reliability, and helpfulness, positively impacts patients' OMC service continuance intention.*

3.4 The Mediating Role of Trust

Although previous studies have suggested that trust influences online purchase and payment, it is unclear whether trust is a direct or indirect cause when other evaluation mechanisms are present simultaneously. In this study, we propose that although perceived benefits and perceived risks are important attributes that affect the *net* valence (as proposed in H1 and H2), trust mediates the impacts of risk-benefit evaluation. That is, the physician's performance and patient-centeredness, as well as the privacy and performance risks, will impact the patient's level of trust towards the OMC services, which subsequently influences the service continuance intention (Guo et al. 2016). Hence, we propose:

H5. *Trust in OMC, consisting of interpersonal and technological trust, mediates the positive relationship between perceived benefits and patients' OMC service continuance intention.*

H6. *Trust in OMC, consisting of interpersonal and technological trust, mediates the negative relationship between perceived risks and patients' OMC service continuance intention.*

3.5 I Pay for a Trusting Service: Trust as a *Moderator*

Besides modeling trust as a direct cause, a handful of studies argued that trust should be a moderator (Chung and Kwon 2009). As suggested by Doney and Cannon (1997), trust appears "to operate as an 'order qualifier', not an 'order winner'" (p. 47). From this perspective, trust does not directly elicit particular behavior outcomes but influences how people interpret or evaluate information related to their attitude and behavior (Jarvenpaa et al. 2004). For example, previous studies in e-commerce have found that trust affects how the website's past use experience is assessed, which impacts its continued use (Bansal et al. 2016; Venkatesh et al. 2016). In a highly uncertain environment such as OMC, if patients have trust in a particular provider or the OMC platform, they may have higher tolerance of the potential vulnerability of that OMC (Bonoma 1976; Mcknight et al. 2011). As a result, they may develop stronger intentions to use OMC even at the same level of perceived benefits and perceived risks (Agarwal and Prasad 1998). By contrast, patients with less trust will be less likely to expose themselves to uncertainty and risks. For example, although patients may agree that a physician provides valid and patient-centered recommendations, their concerns over the potential privacy risks are magnified due to the lack of trust in that OMC. Hence, we propose two alternative hypotheses:

H7. *Trust moderates the positive relationship between perceived benefits and patients' OMC service continuance intention.*

H8. *Trust moderates the negative relationship between perceived risks and patients' OMC service continuance intention.*

4 Research Method

4.1 Research Context and Data Collection

We conduct an online survey to test the hypotheses. We initially sent out 2000 questionnaires to the users of one of the largest OMC platforms in China. Participation in our survey was voluntary and anonymous, and a cash prize was awarded to the participants that have completed all survey questions. A total of 586 questionnaires were collected within a month. After eliminating invalid responses, including participants with limited use of OMC and those who appear to provide random answers, 365 valid responses were included for analysis. Respondents' demographic statistics are presented in Table 2.

4.2 Construct Measures

The constructs in our model have been studied in the extant e-commerce literature. Hence, we adapt the existing measurements, which are shown in Appendix B. Each construct is measured by at least three indicators to provide a more accurate representation (Wynne W. Chin 1998). Previous literature suggests that an individual's age, gender, levels of education, income, and use experience can influence their online purchase behavior (Pavlou and Fygenson 2006). Hence, we also include them in the models as control variables. The original questionnaire was in Chinese, and we conducted a back-translation procedure to ensure the validity of the translation.

Table 2 Demographic statistics of the respondents

Demographic	Category	Frequency	Percentage
Age (years)	Under 18	0	0%
	18~30	173	47%
	31~40	146	40%
	41~50	40	11%
	over 50	6	2%
Gender	Female	196	54%
	Male	169	46%
Education	High school or lower	16	4%
	College or undergraduate	302	83%
	graduate	47	13%
Monthly income	Less than ¥ 8000	155	43%
	¥ 8001~15,000	158	43%
	¥ 15,001~20,000	31	9%
	¥ more than 20,000	21	6%
Use experience	Less than 6 months	57	16%
	6 months ~1 year	129	35%
	1~2 years	115	32%
	More than 2 years	64	18%
Use frequency	Irregularly	162	44%
	Seldom	9	3%
	Occasionally	68	19%
	Often	116	32%
	Always	10	3%

5 Analysis and Results

Partial Least Squares (PLS) regression is used to test the measurement and the structural models. PLS has been extensively used in the IS and healthcare research because of its capability to handle the highly complex predictive models with formative constructs (Bhattacherjee and Premkumar 2004). Comparing with the covariance-based structural equation modeling, PLS is appropriate for this study because: (1) our model is theory-driven, yet the inclusion of a formative second-order construct makes it impossible to meet the identification requirement for covariance-based approach even with a large sample size; and (2) we seek to understand the variations in the outcome as maximally explained by the proposed antecedents, rather than how well the model fits the sample dataset to make predictions (i.e., goodness-of-fit logic for covariance-based approach).

We model *trust in OMC* as a third-order reflective construct using the mimic approach (Diamantopoulos 2011), and the second-order *interpersonal trust* and *technological trust* are modeled as formative constructs. As explained in the background section, patients often form a general trust belief that depicts different aspects of trust – interpersonal versus technological in our study. At the lower level, patients' perception of whether an OMC service is trustworthy depends on their experience and judgments on OMC's benevolence, competence, integrity, functionality, reliability, and helpfulness. Thus, these six first-level dimensions build higher-level interpersonal and technological trust.

All first-level trust dimensions are reflectively measured following previous studies (Guo et al. 2016; Lankton et al. 2015) based on measurement theory and the causal direction between the measures and the constructs (Diamantopoulos and Siguaw 2006). Perceived benefits and perceived risks are second-order constructs that are reflectively measured.

5.1 Testing the Measurement Model

We conduct a formal exploratory factor analysis to detect each latent construct's reliability and validity (see Tables 3 and 4).

Table 3 Descriptive statistics and reliability coefficients for the constructs

Constructs	*M*	*SD*	Alpha	CR	AVE
1. Perceived Benefits (PB)	5.88	0.87	0.783	0.866	0.684
2. Perceived Validity (PV)	5.87	0.88	0.778	0.859	0.670
3. Patient Centeredness (PC)	5.57	1.17	0.763	0.861	0.673
4. Perceived Risk (PR)	3.27	1.44	0.829	0.884	0.657
5. Performance Risk (Per)	3.10	1.34	0.720	0.885	0.806
6. Privacy risk (Pri)	3.49	1.59	0.792	0.920	0.869
7. Functionality (Fun)	5.75	0.97	0.712	0.828	0.616
8. Reliability (Re)	4.91	1.33	0.716	0.836	0.629
9. Helpfulness (He)	5.70	1.04	0.709	0.811	0.589
10. Competence (C)	5.73	1.10	0.708	0.795	0.564
11. Benevolence (B)	5.52	1.15	0.715	0.836	0.629
12. Integrity (I)	5.65	1.09	0.789	0.876	0.703
13. Trust in OMC (TO)	5.69	0.94	0.805	0.911	0.837
14. Continuance Intention (CI)	5.56	1.13	0.812	0.914	0.841

All constructs' reliability measurements of the Cronbach's alpha and the Fornell's composite score are higher than the threshold benchmark of 0.7 (Nunnally and Bernstein 1994; Fornell and Larcker 1981), indicating an adequate level of internal consistency.

As shown in Appendix C, the constructs appear to have acceptable convergent validity because all item loadings are greater than 0.50, and the items for each construct load on only one factor with an eigenvalue greater than 1.0 (Wixom and Watson 2001). Besides, as shown in Table 4, all constructs have an Average Variance Extracted (AVE) of at least 0.5, and the squared roots of the AVE of each latent construct are higher than the highest correlation with any other latent construct (Fornell and Larcker 1981), indicating that discriminant validity is established (Chin 1998). In addition, all Variance Inflation Factors (VIFs) are lower than 3.33 (Cenfetelli and Bassellier 2009; Diamantopoulos and Siguaw 2006), indicating that multicollinearity does not exist in the model.

5.2 Common Method Bias

We follow Podsakoff et al.'s (2003) recommendations and use Harmon's single factor test (Podsakoff and Organ 1986) to detect potential common method bias. Since the first un-rotated factor explains only 27.3% of

Table 4 Correlations of the latent variables

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. PB	**0.827**															
2. PV	0.477	**0.819**														
3. PC	0.432	0.585	**0.821**													
4. PR	−0.325	−0.300	−0.321	**0.811**												
5. Per	−0.354	−0.397	−0.332	0.678	**0.848**											
6. Pri	−0.300	−0.248	−0.288	0.581	0.643	**0.890**										
7. Fun	0.509	0.541	0.417	−0.280	−0.384	−0.239	**0.785**									
8. Re	0.396	0.446	0.454	−0.371	−0.398	−0.315	0.520	**0.793**								
9. He	0.501	0.584	0.552	−0.304	−0.401	−0.275	0.642	0.582	**0.767**							
10. C	0.472	0.469	0.496	−0.357	−0.414	−0.364	0.520	0.493	0.590	**0.751**						
11. B	0.428	0.442	0.537	−0.372	−0.401	−0.416	0.401	0.484	0.493	0.594	**0.793**					
12. I	0.434	0.449	0.547	−0.400	−0.448	−0.438	0.423	0.514	0.557	0.606	0.609	**0.838**				
13. PT	0.603	0.521	0.520	−0.483	−0.515	−0.375	0.463	0.417	0.501	0.532	0.511	0.528	**0.915**			
14. CI	0.590	0.463	0.440	−0.436	−0.436	−0.315	0.384	0.399	0.413	0.449	0.354	0.355	0.603	**0.917**		
15. TT[a]	0.552	0.617	0.559	−0.375	−0.465	−0.326	0.848	0.825	0.874	0.630	0.542	0.587	0.563	0.470	–	
16. IT[b]	0.516	0.528	0.615	−0.440	−0.492	−0.476	0.518	0.580	0.636	0.837	0.853	0.881	0.682	0.446	0.682	–

Notes: The diagonal values () represent the square root of the Average Variance Extracted (AVE). Off diagonal values represent latent variable correlations

[a] Technological Trust (second order); [b] Interpersonal Trust (second order)

the covariance of the main constructs in our model, we conclude that there is no substantial amount of common method bias present in our model.

We also use a modified marker variable analysis to further test the common method bias. Following Rönkkö and Ylitalo (2011), we use Internet Technicality (measured by three items) as our marker variable and perform regression analysis on four latent constructs. The results show that the marker variable has low correlations with items in our research model and has no significant impact on service continuous intention, perceived benefits, perceived risks, and trust. The hypothesized relationships are qualitatively equal to the results before the marker variable was incorporated, indicating that common method bias has little impact.

5.3 Testing the Structural Models

Following the construct-level analysis, we use PLS to obtain the second-order formative factors (i.e., interpersonal trust and technological trust) (Diamantopoulos et al. 2008) and the estimated structural model. The *T*-tests of the path coefficients are used to compare the models and draw conclusions for our hypotheses. Table 5 describes the five models.

5.3.1 Assessment of Trust as a Direct Cause

As shown in Table 6, all four models show a strong positive effect between a patient's perceived benefits and service continuous intention (e.g., the baseline model, $\beta = 0.464$, $p < 0.01$). In contrast, a patient's perceived risks show a strong negative effect (e.g., the baseline model, $\beta = -0.218$, $p < 0.01$). Hence, hypotheses 1 and 2 are supported. Table 6 also shows that the perceived benefits and perceived risk account for 45.3% of the variance in the baseline model's service continuance intention.

For the multidimensional trust model (Model 1.1), both interpersonal trust ($\beta = 0.513$, $p < 0.01$) and technological trust ($\beta = 0.559$, $p < 0.01$) show strong positive effects on the patient's service continuance intention. Hence, hypotheses 3 and 4 are supported. Moreover, when *trust in OMC* is introduced as a third-order construct (Model 1.2) to encompass both interpersonal and technological trust, the explanatory power increases to 50.5%. We also examine the explanatory power of the unitary trust model (Model 1.3), which is a commonly used approach in previous research. As indicated in Table 6, the multidimensional trust possesses more explanatory power than the unitary trust in terms of R^2. In summary, the inclusion of the third-order trust construct—trust in OMC (see model 1.2) results in a superior model with a beta of 0.318 at $p < .001$ significance, an increase in the R^2 for service continuance intention (ΔR^2 against the base is 0.105), and medium effect size.[2] For the control variables, there are considerable variations among different use experience and use frequency groups, suggesting that service preferences vary along with the OMC service experience and other individual characteristics.

5.3.2 Assessment of Trust as a Mediator

Since interpersonal trust and technological trust tackle different aspects of OMC, we conduct a multiple mediation analysis (Preacher and Hayes 2008) that investigates: 1) the total indirect effect, and (2) the specific indirect effect associated with each putative mediator. We have applied the bootstrapping method to assess the Confidence Interval (CI) of the total and the specific indirect effects. As shown in Fig. 2, all paths are significant. Tables 7 and 8 provide the mediation effects (path *a*b*) of perceived benefit and perceived risks, respectively, on service continuance intention of OMC. Tables 7 and 8 also show the indirect effects and the Bootstrapping 95% CI of the total and the two mediation effects. The results in Table 7 show that the true total indirect effect is estimated at 0.333, with the Bias-Corrected 95% CI ranges from 0.074 to 0.208. Since the 95% CI does not include zero, we conclude that the total indirect effect is significant (Baron and Kenny 1986). Similarly, the other two mediation effects, technological trust and interpersonal trust, also do not have zero included in their corresponding 95% CIs; therefore, both are considered significant.

Finally, we compare the strength of the individual indirect effects on one another. Since the 95% CI includes zero, there is no significant difference in the mediating effect between interpersonal trust and technological trust. These results indicate that the effects of perceived benefits on service continuance intention are mediated through interpersonal trust and technological trust, thus supporting H5. Similar results for perceived risks can be found in Table 8, indicating that the effects of perceived risks are mediated through both interpersonal and technological trust, thus supporting H6.

5.3.3 Assessment of Trust as a Moderator

We follow the PLS product-indicator approach (Chin et al. 2003) to perform the moderator analysis and present the results in Fig. 3a & b. Trust in OMC is modeled as a composite

[2] The difference in R^2 is used to assess the overall effect size f^2 for the interaction where .02, 0.15, and 0.35 have been suggested to be considered as small, moderate, and large effects, respectively (Cohen 1988).

Table 5 Model comparison

Models	Role of Trust	Dimensionality of Trust
Baseline	No trust	N/A
Model 1.1	Direct cause	Multifaceted trust (formative second-order interpersonal trust + formative second-order technological trust)
Model 1.2	Direct cause	Trust as a third-order reflective construct consisting of second-order interpersonal and technological trust
Model 1.3	Direct cause	Unitary trust (reflective)
Model 2	Indirect cause (Mediator)	Trust as a third-order reflective construct consisting of second-order interpersonal and technological trust
Model 3	Moderator	Trust as a third-order reflective construct consisting of second-order interpersonal and technological trust

Table 6 Hierarchical Regression Analysis Predicting Service Continuance Intentions (Trust as a Direct Cause on Three Alternative Models 1.1 ~ 1.3)

Variables	Baseline	Model 1.1	Model 1.2	Model 1.3
Control variables				
Age	−0.009	0.052	0.052	−0.009
Gender	0.018	0.056	0.057	0.016
Education	0.048	0.039	0.039	0.058
Income	0.061	0.053	0.053	0.077**
Use experience	0.094**	0.114**	0.116**	0.102**
Use frequency	0.118***	0.139***	0.140***	0.085**
General perception	0.002	0.037	0.036	−0.049
Perceived benefits	0.464***	0.434***	0.418***	0.333***
Perceived validity	0.341***	0.341***	0.341***	0.341***
Patient centeredness	0.232***	0.232***	0.232***	0.232***
Perceived risks	−0.218***	−0.188***	−0.171***	−0.126***
Privacy risk	0.248***	0.248***	0.248***	0.248***
Performance risk	0.518***	0.518***	0.518***	0.518***
Technological trust		0.513**		
Reliability		0.443***		
Functionality		0.314***		
Helpfulness		0.417**		
Interpersonal trust		0.559**		
Competence		0.349***		
Benevolence		0.381***		
Integrity		0.434***		
Trust in OMC			0.318***	0.150**
R^2	0.453	0.463	0.505	0.463
Adjusted R^2		0.007	0.052	0.010
ΔR^2 against base		0.013	0.105	0.019
Effect size [a]		small	medium	small

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

Note .[a] The difference in R^2 is used to assess the overall effect size f^2 for the interaction where .02, 0.15, and 0.35 have been suggested to be considered as small, moderate, and large effects, respectively (Cohen 1988)

moderator that includes both technological and interpersonal facets because both types of trusts should holistically play a buffering role.

We estimate the influence of perceived benefits (path *c*), the direct impact of trust (path *b*), and the influence of the interaction term (i.e., perceived benefits*trust in the platform) on service continuance intention (path *d* in Fig. 3a). The results show a standardized path coefficient of 0.060 for the synergistic effect (path *d*), which is not significant at $p < 0.05$. Similarly, the synergistic effect between perceived risks and trust is also not significant (path *d'* in Fig. 3b). Thus, the moderator propositions (H7 and H8) are not supported. We summarize all the hypotheses and findings in Appendix D.

5.4 Post-hoc Analysis

Although we developed our model from the well-established valence framework and trust literature, endogeneity issues may still arise due to omitted variables and reverse causality in PLS modeling (Benítez-Amado et al. 2016). Since our dependent variable (i.e., service continuance intention) is future-oriented, reverse causality is of less concern in our model. Following the guideline provided by Hult et al. (2018), we conducted the Gaussian copular analysis to detect the potential endogeneity issue caused by omitted variables. The procedure and results are presented in Appendix E. In Gaussian copular analysis, the copula is computed from the inverse of the Gaussian normal cumulative distribution function. The regression models are then estimated by incorporating the copula as an additional independent variable that controls the correlation between the error term and the endogenous constructs in the regression model. Our results show that no Gaussian copula is

Table 7 Mediation Effect of Perceived Benefits on Service Continuance Intention through Interpersonal Trust and Technological Trust

Mediator	Indirect effect (*SD*)	BC 95% CI		Relative Mediation effect
		LL	*UL*	
Technological trust (1)	0.141 (0.039)	0.025	0.163	22.742%
Interpersonal trust (2)	0.192 (0.041)	0.052	0.159	30.967%
Total effect of (1) & (2)	0.333 (0.044)	0.074	0.208	53.710%
(1) vs. (2)	−0.051 (0.069)	−0.138	0.106	–

Note. BC = bias corrected; CI = confidence interval; *LL* = lower limit; *UL* = upper limit

significant, thus ruling out the problem of endogeneity caused by omitted variables in our research model.

6 Discussion

We seek to examine the constitution of online trust and the two plausible explanations regarding how trust contributes to the service continuance decisions in OMC (i.e., trust as a cause vs. trust as a moderator). Our results show that the multidimensional conceptualization of trust is superior to the unitary conceptualization. The proposed model highlights the importance of enhancing the social ties between patients and physicians (i.e., interpersonal trust) and the technological capabilities of the system (i.e., technological trust) when promoting OMC. The significant multiple mediation effects of interpersonal trust and technological trust also confirmed our propositions. However, the "trust as a moderator" proposition was not confirmed.

6.1 Theoretical Implications

Our study contributes to both trust and online healthcare service literature in several ways. First, we propose an integrated model of patients' service continuance decision in OMC, which includes both the interpersonal and the technological aspects of the trust mechanisms. Since performance risk and privacy risk are major barriers to establish trust and service continuance intention, OMC platforms need to help patients resolve their concerns regarding OMC service procedures (e.g., data management) and outcomes (e.g., treatment effectiveness). We have also identified two sets of perceived benefits (i.e., perceived validity and patient-centeredness) relevant to establishing interpersonal and technological trust, which play mediating roles in affecting the relationships between perceived benefits and risks and patients' OMC service continuance intention.

Second, although prior research has examined some of our identified factors (e.g., perceived benefits and perceived risks), they primarily focused on their direct effects on unidimensional trust. By contrast, our study aims to clarify the type of trust (interpersonal vs. technological) and the inner causality between the measurements and the constructs (i.e., formative vs. reflective), which provides a comprehensive understanding of the trust-based consumer decision-making in online healthcare services. In addition, the multidimensional conception of trust allows us to implement a multiple mediation model, which sheds light on how interpersonal versus technological trust mechanisms may synergistically reduce patients' perceived risks and reinforce patients' perceived benefits, therefore

Table 8 Mediation of the Effect of Perceived Risks on Service Continuance Intention through Interpersonal Trust and Technological Trust

Mediator	Indirect effect (*SD*)	BC 95% CI		Relative Mediation effect
		LL	*UL*	
Technological trust (1)	−0.092 (0.035)	−0.206	−0.083	28.482%
Interpersonal trust (2)	−0.074 (0.043)	−0.122	−0.001	22.910%
Total effect of (1) & (2)	−0.166 (0.032)	−0.231	−0.111	51.393%
(1) vs. (2)	0.018 (0.052)	−0.138	0.106	–

Note. BC = bias corrected; CI = confidence interval; *LL* = lower limit; *UL* = upper limit

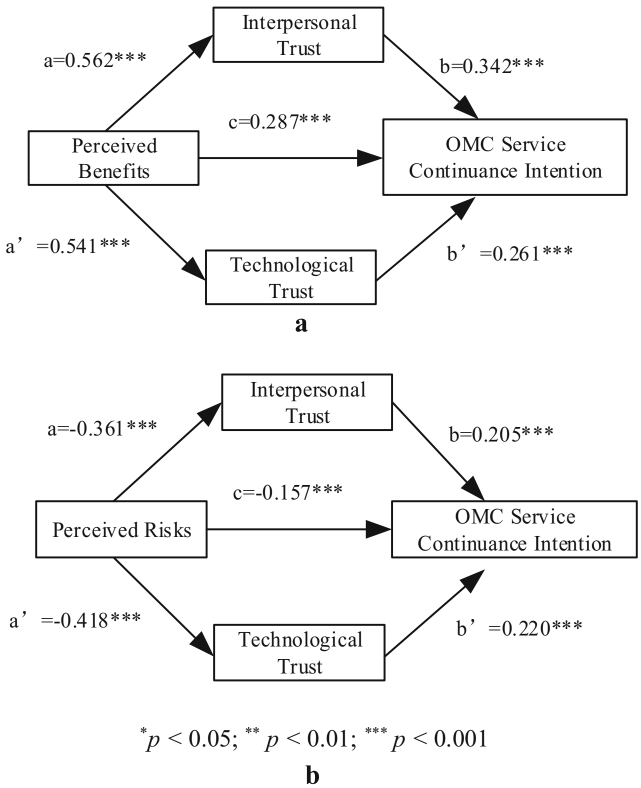

Fig. 2 **a. b** The Total Effects and the Direct Effects of the Mediation Models

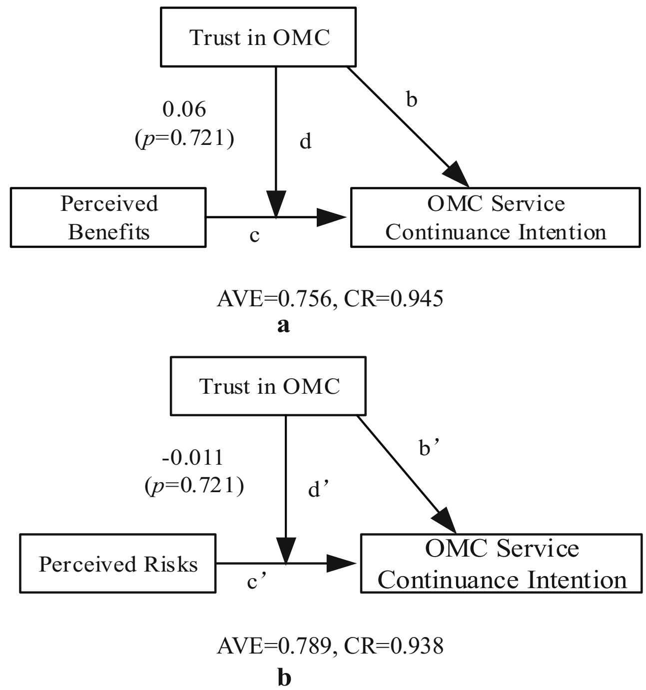

Fig. 3 **a. b** Moderating Effect of Trust in OMC

increasing the OMC service continuance intention. In particular, our findings of the partial mediation effect suggest that the interpersonal and technological aspects of online trust may complement each other in studying emerging e-services such as OMC.

Third, our work offers insights into patients' adoption and use of technology-mediated service. The technology adoption perspective suggests that consumers' intentions to use a technology-mediated service are driven primarily by their expectations about service-technology fit (Heinze and Matt 2018). Consumers' formation of these expectations further affects their trusting beliefs through different mechanisms. Complementing this line of research, we compare the direct-cause model, mediation model, and moderation model of trust. The non-significant buffering effect (i.e., the moderation model) implies that patients' service continuance intentions are more likely influenced by a trusting attitude than trusting beliefs that work synergistically with other OMC-related perceptions (Bhattacherjee 2001). The partial mediation indicates that the formation of such a trusting attitude depends on patients' risk-benefit evaluation of the OMC.

6.2 Practical Implications

Our findings also provide several practical implications for online healthcare service delivery. First, interpersonal and technological trust are two effective means to realize the effects of patients' beliefs regarding OMC benefits and risks. Practitioners trying to persuade patients to use the OMC platform or purchase OMC services may first need to convince patients that OMC is trustworthy, which entails the trustworthiness of both OMC service providers and the technological infrastructure. For example, many OMC platforms have implemented service rating functions to help patients select appropriate doctors. However, the star-based review only provides a generic overview of service satisfaction without differentiating the interpersonal and technological procedures. OMC managers and service providers may need to design a more targeted review and reporting system to allow patients to reveal their OMC experience from different perspectives, so that prospective patients can develop and maintain multidimensional trust.

Second, in terms of the OMC platform design, our findings suggest that perceived validity, patient-centeredness, privacy risk, and performance risk are not only important in their own right but can also affect interpersonal trust and technological trust. OMC platforms should design their informational and transactional services with these attributes in mind. For example, privacy risk may be improved via better information disclosure related to data policies. OMC platforms may actively inform patients about how the data will be collected and managed when the patients enter the platform. Similarly, performance risk may be mitigated by providing better customer support from the platform. Even the doctors' performance may not be satisfactory – thus reducing interpersonal trust – the service failure recovery effort made by the platform may still maintain technological trust, thus maintaining the intention to continue using the platform.

Third, the unsupported moderating role of trust suggests that the OMC service providers should not expect to mitigate privacy and performance risk perceptions by enhancing trusting beliefs toward the OMC. Thus, even if the patients earn trust via other OMC benefits, it cannot alleviate the negative impacts of privacy risk and performance risk. A better approach is to improve actual privacy protection and service performance, which enhances patients' perceived benefits. Overall, this research helps to understand the role trust plays to all OMC stakeholders, including healthcare professionals and digital platform owners, regarding managing patients' risk-benefit evaluation and promoting patient participation in the paid OMC services via enhanced interpersonal and technological trust.

6.3 Limitations and Future Research

We have identified several limitations of our research. First, although the extended valence framework that incorporates both risk-benefit evaluation and trust mechanism provides a good explanation of patients' service continuance decisions, various alternative mechanisms may influence the formation of a trusting attitude apart from the current benefit and risk factors. For example, patients may evaluate channel characteristics (e.g., convenience and personalization), customer support, and institutional safeguards. Our literature review in Appendix A gives many examples that fall within the risk-benefit evaluation but are not incorporated into our model. In addition, future research may also investigate cognitive mechanisms other than the risk-benefit appraisal. For example, media naturalness theory (Zahedi et al. 2016) and affect transfer theory (Hernandez et al. 2019) have been used in previous research to understand the formation of trust in the digital context.

Second, since we focus on individual psychological mechanisms, no structural factors are included in our model. Although we carefully included individual-level control variables that help alleviate the confounding effect due to individual differences, we cannot entirely rule out the potential confounding effect from the platform level. For example, the service design (e.g., the freemium business model implemented by many OMCs) may simultaneously influence patients' trust and service continuance intention. Future research may further investigate how platform-level factors differentiate individual appraisals and behaviors on OMC.

Third, our work is conducted in China; thus, the applicability of the outcomes may be constrained by the particular cultural and socio-political context. Moreover, we collect data from a unique user group (i.e., patients from one particular OMC platform), which may subject to sampling bias – for example, our sample includes more younger users who are familiar with smartphone-based healthcare services. Given the global popularity of online healthcare services, future research can examine the model in countries with different social-cultural and political settings, inviting subjects from a more diverse population to validate the generalizability of the research findings.

7 Conclusion

In conclusion, this study proposes a multidimensional approach to conceptualize the influences of trust, which includes both interpersonal and technological aspects in the OMC service continuance decision-making. We go beyond the unitary view of trust and draw on the valence framework to examine the underlying psychological mechanisms and the potential synergistic effects of trust with other OMC service-related factors. The different roles of trust (i.e., as a direct cause, a mediator, or a moderator) help clarify the different ways trust may account for patients' service continuance intentions. Considering the vast network of patients and the central role of technology in mediating and supporting the service delivery, OMC managers and service providers should consider both interpersonal and technological aspects of trust through their service to achieve OMC success.

Appendix A

Table 9 Selected Literatures on Online Trust

Study	Variables related to		Other variables	Theory	Key findings
	Interpersonal trust	Technological trust			
Sollner et al. (2016)	Trust in the Internet (IV), Trust in the community of Internet users (IV), Trust in the provider (Mev)	Trust in the information system (DV)	Perceived usefulness (Mev), perceived ease of use (DV), intention to use (DV)	Trust-TAM	TRUST_INET → TRUST_COMM (+) TRUST_INET → TRUST_PROV → TRUST_IS (+) TRUST_IS → PU → INT_USE (+) TRUST_PROV → PU → INT_USE (+) TRUST_PROV → PEOU (+) PEOU → PU → INT_USE (+) PEOU → TRUST_IS → PU (+)
Ou et al. (2014)	Trust in seller (IV)	–	Effective Use of Instant Messenger (IV), effective use of message box (IV), effective use of feedback system (IV), interactivity (IV), swift guanxi (IV), presence (IV), repurchase intentions (DV), actual repurchases (DV)	The media synchronicity theory	Effective use of instant messenger, effective use of message box, effective use of feedback system → Interactivity, presence (+) Interactivity, presence → Swift Guanxi, trust (+) Swift Guanxi, trust → Repurchase intentions (DV), actual repurchases (DV) (+)
Fang et al. (2014)	Trust in vendor (Mev)	–	Satisfaction with vendor (IV), perceived effectiveness of institutional mechanisms (PEEIM) (Mov), repurchase intention (DV)	The theory of organizational trust	Satisfaction → Trust → Repurchase intention (+) PEEIM negatively moderates the relationship between trust in an online vendor and customer repurchase. (−) PEEIM positively moderates the relationship between customer satisfaction and trust. (+)
Kim (2014)	Pre e-vendor trust (IV), Post e-vendor trust (IV)	Pre e-channel trust (IV), Post e-channel trust (IV)	Trust propensity (IV), e-vendor satisfaction (IV), e-vendor delivery fulfilment (IV), e-channel satisfaction (IV), e-channel expectation (IV), e-channel performance (IV), e-vendor performance (IV), e-channel reuse intention (DV), repurchase intention (DV)	Expectation-confirmation theory, social exchange theory	Trust propensity → pre e-channel trust, pre e-vendor trust, post e-channel trust Post e-channel trust → post e-vendor trust, e-channel reuse intention Pre e-vendor trust → post e-vendor trust, e-vendor satisfaction, e-vendor delivery fulfillment Pre e-channel trust → pre e-vendor trust, post e-channel trust, e-channel satisfaction, e-channel expectation

Table 9 (continued)

Study	Variables related to: Interpersonal trust	Variables related to: Technological trust	Other variables	Theory	Key findings
					E-channel satisfaction → post e-channel trust, e-channel reuse intention E-vendor satisfaction → post e-vendor trust, repurchase intention E-channel expectation → e-channel confirmation E-vendor delivery fulfillment → e-vendor confirmation E-channel performance → e-channel confirmation E-vendor performance → e-vendor confirmation E-channel confirmation → e-channel satisfaction E-vendor confirmation → e-vendor satisfaction Post e-vendor trust → repurchase intention
Lankton et al. (2015)	Human-like trusting beliefs (IV)	System-like trusting beliefs (IV)	Technology humanness (Mov, IV), perceived usefulness (DV), enjoyment (DV), trusting intention (DV), continuance intention (DV), social presence (DV), animation (DV), interpersonal communication (DV), dynamism (DV)	Trust, social presence, and affordance theories	Human-like trusting beliefs → Perceived usefulness, trusting intention (+) System-like trusting beliefs → Perceived usefulness, enjoyment, trusting intention, continuance intention (+) The more human-like the technology, the stronger the influence of human-like trusting beliefs. (+) The more system-like the technology, the stronger the influence of system-like trusting beliefs. (+) Technology humanness → Social presence, animation, interpersonal communication, dynamism
Venkatesh et al. (2016)	–	Trust (Mev, Mov)	Information quality characteristics (IV), Transparency (Mev, Mov), channel characteristics (IV), intention to use e-government (DV), use of e-government (DV), satisfaction with e-government (DV)	Uncertainty reduction theory	Information quality characteristics, channel characteristics → Trust, transparency → Intention to use E-government (+) Intention to use E-government → Use of E-government (+) Use of E-government → Satisfaction with E-government (+) Transparency and trust mediate moderate the effects of information quality and channel characteristics on intentions. (+)

Table 9 (continued)

Study	Variables related to		Other variables	Theory	Key findings
	Interpersonal trust	Technological trust			
Xu et al. (2016)	Trust Benevolence (IV), Trust Integrity (IV), Trust Competence (IV)	–	Satisfaction (DV), Purchase behavior (DV)	trust theory	A buyer's belief about a seller's benevolence → Satisfaction (+) A buyer's belief about a seller's competence → Purchase behavior (+)
Wang and Benbasat (2016)	Trust in RA-benevolence (DV), Trust in RA-integrity (DV), Trust in RA-competence (DV)	–	Advice quality (IV), perceived cognitive effort (IV), perceived strategy restrictiveness (IV), perceived RA transparency (IV)	attribution theory	Advice Quality → Trust in RA-competence (+) Perceived Cognitive Effort → Trust in RA-competence (+) Perceived Strategy Restrictiveness → Trust in RA-competence (+) Perceived RA transparency → Trust in RA-competence, integrity, competence (+) Perceived RA Transparency → Perceived cognitive effort (−) Perceived RA transparency → Advice quality (+)
Hoque et al. (2017)	–	Trust (IV)	Perceived ease of use (IV), perceived usefulness (IV), privacy (IV), gender (Mev), intention to use (DV)	Extended TAM	Perceived ease of use → Intention to use (+) Perceived usefulness → Intention to use (+) Privacy → Intention to use (ns) Trust → Intention to use (+) Gender → Intention to use (+)
Fan and Lederman (2018)	–	Affective trust (IV), Cognitive trust (IV)	Information adoption (DV), formation of relational closeness (DV)	Social capital theory	Affective trust → Information adoption (+) Affective trust → Formation of relational closeness (+) Cognitive trust → Information adoption (+)
Park and Lee (2018)	Trust in government information (IV)	–	Application acceptance (DV), performance expectancy (IV), effort expectancy (IV)	The unified theory of acceptance and use of technology	Trust in government information → Performance expectancy (+) Trust in government information → Effort expectancy (+) Performance expectancy → Application acceptance (+) Effort expectancy → Application acceptance (+)
Lu et al. (2018)	–	Cognition-based trust (IV), affect-based trust (IV)	Internet health information quality (IV), source of information (IV), patient compliance (DV)	The social information processing theory and social exchange theory	Internet health information quality → Cognition-based trust (+) Internet health information quality → Affect-based trust (+) Source of information → Cognition-based trust (+) Source of information → Affect-based trust (ns)

Table 9 (continued)

Study	Variables related to		Other variables	Theory	Key findings
	Interpersonal trust	Technological trust			
					Cognition-based trust → Affect-based trust (+) Cognition-based trust → Patient compliance (ns) Affect-based trust → Patient compliance (+)
Lee et al. (2018)	Trust in newspapers/-magazines, radio, TV, and the Internet.	Trust in doctors, Trust in family/friends	–	Channel Complementarity Theory	Trust in doctors → trust in all channels, except the Internet (+) Trust in family/friends → trust in all channels, except the Internet (+) Trust in newspapers →trust in all channels (+) Trust in radio → trust in all channels (+) Trust in TV → trust in all channels (+) Trust in the Internet. → trust in all channels, except the doctors and family/friends (+)
Deng et al. (2018)	–	Trust (IV)	Perceived ease of use (IV), perceived usefulness (IV), perceived Risk (IV), adoption intention (DV)	Extended TAM	Trust → Adoption intention (+) Perceived usefulness → Trust (ns) Perceived usefulness → Adoption intention (+) Perceived ease of use → Trust (ns) Perceived ease of use → Adoption intention (+) Perceived Risk → Trust (−) Perceived Risk → Adoption intention (−)
Tams et al. (2018)	–	Trust in functionality (IV), Trust in helpfulness (IV), Trust in reliability (IV)	Internal CSE (Computer Self-efficacy) (Mev), External CSE (Mev), Trying to Innovate (DV), Deep Use (DV)	The Model of Proactive Work Behavior (MPWB)	Trust in helpfulness → External CSE → Deep structure (+) Trust in reliability → External CSE → Deep structure (+) Trust in functionality → Internal CSE → Deep structure (+) Trust in functionality → Internal CSE → Trying to innovate (+)
Meng et al. (2019a, 2019b)	Trust in offline health services (IV)	Trust in mobile health services (IV)	Physiological conditions (Mev), hospital support (Mev), intention to use mHealth services (DV)	The trust transfer theory	Trust in offline health services → Trust in mHealth services (+) Trust in mHealth services → Intention to use mHealth services (+) Physiological conditions → Trust in mHealth services (+)

Table 9 (continued)

Study	Variables related to: Interpersonal trust	Variables related to: Technological trust	Other variables	Theory	Key findings
Odusanya et al. (2020)	–	Trust in e-retail platforms (IV)	PU, PEU, Information quality (IQ), Perceived risk (PR), Social influence (SI), Hedonic motivation (HM), Continuance Intention to use (DV)	Trust building theory	PU, PEU, IQ → Trust (+) → Continuance Intention PR (−) → Trust (+) → Continuance Intention SI, HM (+) → Trust
Gong et al. (2020)	Emotional trust (IV)	Cognitive trust (IV)	Perceived entitativity (PE), Intention to use mobile payment (DV)	The trust transfer theory	PE (+) → Cognitive trust & Emotional trust → Intention to use
Yang et al. (2020)	–	Trust in platform (IV)	Service quality (SQ), Perceived risk (PR), Intention to upgrade to paid OMC (DV)	Extended valence framework	SQ → trust →Intention to upgrade (+) PR (−) → Trust→Intention to upgrade (+)

Note: The selected studies are collected from the year of 2014, since Kim (2014) had listed most of the studies of online trust that published before the year of 2014

Appendix B. Measurement Items for the Constructs

Note: we use ABC as a pseudo name for the OMC platform we studied. 7-point Likert scales with 1 as strongly disagree, and 7 as strongly agree are used.

Perceived Benefits [PB].

1. [ABC] can improve the overall quality of my healthcare experience.
2. Using [ABC] is beneficial.
3. Using [ABC] can save me time and costs.

Perceived Validity [PV].

1. Physicians at [ABC] deliver the consultation service in a timely fashion as promised.
2. Physicians at [ABC] can fulfill my consultation orders.
3. The service by [ABC] is excellent.

Perceived Centeredness [PC].

1. The service provides me a personalized experience.
2. [ABC] can address the special needs of each customer.
3. I was satisfied with the customization options in the service.

Perceived Risks [PR].

1. Using [ABC] is risky.
2. Overall, how risky would it be to use [ABC]? (not risky at all – very risky).
3. Use [ABC] exposes me to risk (improbable – very probable).
4. Use [ABC] would add considerable uncertainty to my healthcare experience.

Privacy Risk [Prr].

1. The chances of losing privacy control are high when I use [ABC].
2. My personal information may be used without my knowledge when use [ABC].
3. The risk of unauthorized access to my health records is high if I use [ABC].

Performance Risk [Per].

1. The physicians at [ABC] might not perform well.
2. The probability of receiving poor services from physicians at [ABC] is high.
3. It is risky to use [ABC] as the expected level of service performance is low.

Competence [C].

1. Physicians at [ABC] is competent in providing healthcare consulting services.
2. Physicians at [ABC] understand the needs of patients it serves.
3. Physicians at [ABC] are knowledgeable in providing health consultation services.

Benevolence [B].

1. Physicians at [ABC] would act in my best interest.
2. Physicians at [ABC] would do their best to help me.
3. Physicians at [ABC] are respectful of my well-being.

Integrity [In].

1. Promises made by physicians at [ABC] are reliable.
2. Physicians at [ABC] as honest.
3. Physicians at [ABC] keeps their commitment.

Functionality [Fun].

1. [ABC] has the functionalities I need.
2. [ABC] has features required for my tasks.
3. [ABC] has the overall capabilities I need.

Reliability [Re].

1. [ABC] has not failed me.
2. [ABC] has not malfunctioned for me.
3. [ABC] provides error-free results.

Helpfulness [He].

1. [ABC] provides the help I need to complete online healthcare consultation tasks successfully.
2. [ABC] provides competent guidance through the help function.
3. [ABC] supplies my need for help through the help function.

Trust in OMC (mimic items).

1. [ABC] is trustworthy.
2. I trust [ABC].

OMC Service Continuance Intention [CI].

1. If I were to buy the OMC again, I would likely buy it from [ABC].
2. How likely is it that you would subscribe to [ABC] for its paid services in the future? (Not at all – very likely)

Appendix C

Table 10 Confirmatory Factor Analysis

Construct	Item	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. PB	PB1	**0.865**	0.395	0.417	−0.331	−0.285	−0.316	0.388	0.391	0.397	0.421	0.386	0.414	0.559	0.548
	PB2	**0.846**	0.415	0.356	−0.292	−0.286	−0.32	0.423	0.38	0.366	0.45	0.298	0.416	0.508	0.502
	PB3	**0.765**	0.373	0.286	−0.164	−0.158	−0.233	0.352	0.28	0.308	0.393	0.298	0.42	0.416	0.398
2. PV	PV1	0.455	**0.876**	0.466	−0.212	−0.177	−0.331	0.396	0.39	0.397	0.513	0.378	0.535	0.439	0.371
	PV2	0.331	**0.780**	0.47	−0.243	−0.178	−0.311	0.407	0.308	0.318	0.415	0.344	0.475	0.400	0.392
	PV3	0.37	**0.797**	0.512	−0.292	−0.26	−0.335	0.345	0.382	0.384	0.390	0.399	0.421	0.442	0.385
3. PC	PC1	0.324	0.486	**0.802**	−0.261	−0.205	−0.27	0.419	0.419	0.444	0.332	0.381	0.472	0.426	0.393
	PC2	0.352	0.397	**0.792**	−0.273	−0.269	−0.243	0.383	0.467	0.483	0.28	0.358	0.39	0.363	0.333
	PC3	0.383	0.555	**0.865**	−0.258	−0.234	−0.302	0.409	0.436	0.424	0.408	0.397	0.495	0.488	0.362
4. PR	PR1	−0.241	−0.217	−0.254	**0.852**	0.452	0.533	−0.306	−0.271	−0.339	−0.200	−0.313	−0.217	−0.414	−0.386
	PR2	−0.378	−0.311	−0.296	**0.812**	0.506	0.598	−0.370	−0.376	−0.381	−0.314	−0.401	−0.312	−0.463	−0.402
	PR3	−0.202	−0.251	−0.236	**0.771**	0.386	0.538	−0.233	−0.221	−0.25	−0.215	−0.218	−0.248	−0.33	−0.286
	PR4	−0.216	−0.187	−0.25	**0.806**	0.531	0.523	−0.224	−0.323	−0.318	−0.168	−0.271	−0.206	−0.348	−0.330
5. Prr	Prr1	−0.283	−0.25	−0.271	0.534	**0.857**	0.575	−0.33	−0.328	−0.384	−0.217	−0.231	−0.238	−0.358	−0.263
	Prr2	−0.271	−0.191	−0.246	0.518	**0.908**	0.564	−0.302	−0.376	−0.388	−0.185	−0.303	−0.237	−0.343	−0.311
	Prr3	−0.246	−0.218	−0.251	0.497	**0.905**	0.577	−0.321	−0.407	−0.395	−0.236	−0.307	−0.263	−0.299	−0.268
6. Per	Per1	−0.21	−0.277	−0.228	0.585	0.543	**0.843**	−0.238	−0.250	−0.282	−0.234	−0.327	−0.218	−0.37	−0.347
	Per2	−0.355	−0.382	−0.337	0.58	0.576	**0.870**	−0.421	−0.400	−0.421	−0.373	−0.316	−0.416	−0.486	−0.364
	Per3	−0.337	−0.351	−0.279	0.558	0.517	**0.831**	−0.389	−0.371	−0.439	−0.373	−0.387	−0.39	−0.456	−0.399
7. C	C1	0.378	0.361	0.353	−0.262	−0.239	−0.299	**0.818**	0.420	0.480	0.453	0.367	0.497	0.472	0.314
	C2	0.39	0.400	0.372	−0.279	−0.297	−0.297	**0.683**	0.504	0.435	0.378	0.452	0.433	0.339	0.386
	C3	0.292	0.293	0.391	−0.263	−0.285	−0.337	**0.743**	0.412	0.447	0.338	0.299	0.395	0.37	0.31
8. B	B1	0.306	0.326	0.394	−0.308	−0.373	−0.35	0.437	**0.789**	0.485	0.319	0.381	0.39	0.393	0.252
	B2	0.394	0.356	0.416	−0.316	−0.338	−0.341	0.484	**0.811**	0.476	0.317	0.375	0.41	0.415	0.314
	B3	0.316	0.369	0.467	−0.261	−0.278	−0.263	0.469	**0.779**	0.49	0.316	0.405	0.372	0.408	0.277
9. In	In1	0.412	0.38	0.489	−0.365	−0.385	−0.392	0.483	0.54	**0.845**	0.348	0.485	0.468	0.463	0.326
	In2	0.347	0.353	0.442	−0.297	−0.296	−0.307	0.502	0.464	**0.825**	0.353	0.39	0.431	0.426	0.265
	In3	0.332	0.396	0.445	−0.345	−0.416	−0.424	0.537	0.526	**0.845**	0.363	0.421	0.5	0.438	0.299
10. Fun	Fu1	0.476	0.454	0.319	−0.244	−0.21	−0.324	0.432	0.334	0.365	**0.836**	0.43	0.556	0.389	0.336
	Fu2	0.29	0.333	0.299	−0.223	−0.185	−0.261	0.407	0.344	0.3	**0.715**	0.377	0.429	0.323	0.266
	Fu3	0.419	0.477	0.363	−0.193	−0.168	−0.316	0.396	0.271	0.329	**0.799**	0.434	0.521	0.374	0.296
11. Re	Re1	0.333	0.475	0.483	−0.307	−0.208	−0.33	0.439	0.433	0.458	0.528	**0.786**	0.52	0.381	0.315
	Re2	0.289	0.263	0.285	−0.24	−0.257	−0.261	0.335	0.349	0.39	0.334	**0.771**	0.432	0.253	0.247
	Re3	0.315	0.303	0.29	−0.332	−0.289	−0.352	0.369	0.36	0.367	0.356	**0.814**	0.423	0.329	0.385
12. He	He1	0.411	0.507	0.447	−0.31	−0.284	−0.38	0.504	0.402	0.45	0.538	0.558	**0.833**	0.44	0.397
	He2	0.306	0.433	0.428	−0.196	−0.186	−0.276	0.456	0.378	0.416	0.425	0.392	**0.716**	0.336	0.258
	He3	0.432	0.4	0.397	−0.182	−0.152	−0.256	0.399	0.355	0.417	0.509	0.379	**0.747**	0.367	0.282
13. TP	TP1	0.549	0.518	0.522	−0.454	−0.332	−0.463	0.483	0.469	0.489	0.44	0.4	0.47	**0.917**	0.56
	TP2	0.554	0.433	0.428	−0.43	−0.356	−0.479	0.49	0.466	0.478	0.406	0.362	0.446	**0.912**	0.542
14. CI	CPI1	0.537	0.401	0.427	−0.402	−0.312	−0.381	0.383	0.328	0.329	0.309	0.361	0.352	0.562	**0.918**
	CPI2	0.544	0.448	0.38	−0.398	−0.266	−0.418	0.427	0.323	0.322	0.394	0.383	0.407	0.544	**0.916**

Appendix D

Table 11 Summary of Hypotheses and Findings

Hypothesis	Results
H1: Perceived benefits of OMC, comprised of perceived validity and patient-centeredness, has a positive impact on patients' OMC service continuance intention.	Supported
H2: Perceived risks of OMC, consisting of perceived privacy risk and perceived performance risk, negatively impacts patients' OMC service continuance intention.	Supported
H3: Interpersonal trust, consisting of competence, benevolence, and integrity, positively impacts patients' OMC service continuance intention.	Supported
H4: Technological trust, consisting of functionality, reliability, and helpfulness, positively impacts patients' OMC service continuance intention.	Supported
H5: Trust in OMC, consisting of interpersonal and technological trust, mediates the positive relationship between perceived benefits and patients' OMC service continuance intention.	Supported
H6: Trust in OMC, consisting of interpersonal and technological trust, mediates the negative relationship between perceived risks and patients' OMC service continuance intention.	Supported
H7: Trust moderates the positive relationship between perceived benefits and patients' OMC service continuance intention.	Not Supported
H8: Trust moderates the negative relationship between perceived risks and patients' OMC service continuance intention.	Not Supported

Appendix E. Gaussian Copula Analysis

The goal of our research model is to explain the effects of perceived benefits (PB) and perceived risks (PR) on trust and ultimately on patients' OMC service continuance intention (CI). Accordingly, our research model includes two partial regression models: (1) CI is regressed on PB, PR, and Trust; (2) Trust is regressed on PB and PR. In this post hoc analysis, we focus on the first, more complex model.

We first verify if we meet the assumptions of Gaussian copula analysis (i.e., variables exhibit endogeneity should be non-normally distributed). We use the standardized composite scores (i.e., PB, PR, and Trust) provided by the PLS estimation to test variable nonnormality using the Kolmogorov-Smirnov test with the Lilliefors correction (Sarstedt and Mooi 2014). The results show that none of the construct scores are normally distributed, thus meeting the assumption of conducting the Gaussian copula analysis.

Next, we build three regression models using PB (model 1), PR (Model 2), and Trust (Model 3) as independent variables that possibly exhibit endogeneity. We also create four regression models that include all possible combinations of these constructs to capture multiple endogenous factors simultaneously: PB and PR (Model 4), PR and Trust (Model 5), PB and Trust (Model 6), and PB, PR, and Trust (Model 7). The constructs' standardized composite scores are then used to compute the Gaussian copula of the partial regressions in the structural model. Following Hult et al.'s (2018) instruction and using the companion R codes provided in the article,[3] we implement the models using the REndo package of the R program. The copula is the inverse of the Gaussian normal cumulative distribution function. In Gaussian copula analysis, the regression models are estimated by incorporating the copula as an additional independent variable that controls the correlation between the error term and the endogenous independent construct in the regression model. The results in Table E1 show that no Gaussian copula is significant, thus, ruling out the potential endogeneity issue caused by omitted variables.

[3] The R codes can be found here: https://www.pls-sem.net/pls-sem-academy/gaussian-copula-files/

Table 12 Results of the Gaussian Copula Analysis

	Original Model		Gaussian Copula Model 1 (Endogenous Variable: PB)		Gaussian Copula Model 2 (Endogenous Variable: PR)		Gaussian Copula Model 3 (Endogenous Variable: Trust)		Gaussian Copula Model 4 (Endogenous Variable: PR and PB)		Gaussian Copula Model 5 (Endogenous Variable: PR and Trust)		Gaussian Copula Model 6 (Endogenous Variable: PB and Trust)		Gaussian Copula Model 7 (Endogenous Variable: PB, PR and Trust)	
Variable	Value	*p* value	Value	P value	Value	*p* value	Value	*p* value	Value	*p* value	Value	*p* value	Value	*p* value	Value	*p* value
PB	0.418	<.001	0.416	<.001	0.417	<.001	0.416	<.001	0.415	<.001	0.418	<.001	0.418	<.001	0.419	<.001
PR	−0.171	<.001	−0.171	<.001	−0.181	<.001	−0.175	<.001	−0.172	<.001	−0.173	<.001	−0.173	<.001	−0.173	<.001
Trust	0.318	<.001	0.318	<.001	0.318	<.001	0.311	<.001	0.321	<.001	0.319	<.001	0.319	<.001	0.319	<.001
C_{PB}[a]			0.003	0.779					0.006	0.873			0.005	0.452	0.005	0.479
C_{PR}					−0.002	0.376			−0.007	0.659	−0.007	0.713			−0.009	0.649
C_{Trust}							0.032	0.159			0.037	0.245	0.039	0.347	0.042	0.397

Note .[a] C represents the Gaussian copula (i.e., C_{PB} is the Gaussian copula of PB)

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