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RESEARCH

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Offline visit intention of online patients: the Grice's maxims and patient involvement

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Abstract
Online Healthcare Consulting Services (OHCS) can benefit physicians and patients. However, it is unclear how OHCS and what types of persuasive content enhance patients' intentions to visit offline. Based on the Elaboration Likelihood Model (ELM) and Grice's maxims of the Cooperative Principle, we formulated hypotheses related to factors in the central route, peripheral route, and patient involvement that influence patients' offline visit intentions. We used the amount of information, reliability, relevance, and understandability to measure information quality. By collecting data from an online healthcare site, we employed a regression model to evaluate our hypotheses. The results revealed that central route factors (amount of information, reliability, relevance, and understandability) and peripheral cues positively affect patients' offline visits. We also verified that patient involvement increases the impact of central route factors. This study extended the application of ELM and Grice's maxims in the field of OHCS, offering insights into how patients form intentions to visit offline through persuasive online content and providing valuable practical guidance for online physicians.

Keywords Visit intention, Online healthcare, ELM, Grice's maxims, Patient involvement

Introduction

Background

An online healthcare consulting service (OHCS) can offer patients a convenient way to receive physicians' services anytime, anywhere, at lower costs. Studies have shown that OHCS can reduce spending and unnecessary offline visits. Specifically, OHCS has been shown to prevent office visits for about 40% of patients who signed up for the service [1], and the availability of the service has decreased spending on clinic visits [2].

For patients who require an offline visit, their online physicians send messages to suggest scheduling an offline visit based on their professional ethics and knowledge. Suppose these online patients accept the recommendation to visit offline. In that case, they may avoid the possible adverse consequences of patient delay, such as missed treatment opportunities [3], severe financial burdens on families and society, and even death. Therefore, finding ways to help online physicians persuade patients to form the intention to visit offline has great practical significance.

Some studies have investigated the factors affecting online patients' offline visit intentions. Lu and Wu (2016) [4] explored the effect of word of mouth (WOM) on appointments made by online patients. Meanwhile, Liu et al. (2016) [5] studied the impact of individual and organizational reputation on patients making appointments. Wu et al. (2021) [6] found that a physician who provides online health services has more outpatient visits, less waiting time, higher patient satisfaction, and loyalty in the offline channel. Xing et al. (2019) [7] found

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that patient satisfaction and online consultation intention positively affected offline visit intention. These studies have confirmed the overall positive impact of physician participation, reputation, electronic word-of-mouth (e-WOM), and patient satisfaction on the intention to visit offline.

Given the shortage of offline medical resources in China, we believe that the social value of OHCS is that it can provide a screening platform, and physicians can persuade those who need offline treatment to visit offline while encouraging others to use online services to reduce the burden on offline resources. Previous studies, however, have neglected the necessity of offline visits and the communication content between physicians and patients before offline visits. It remains unclear which specific types of persuasive content from physicians can effectively enhance patients' intentions to make offline visits.

To fill this gap, we explored the effects of central route factors (information quality) and peripheral cues on patients' offline visit intentions based on the elaboration likelihood model (ELM) [8, 9]. We also apply Grice's maxims of the Cooperative Principle [10, 11] as a theoretical foundation to evaluate information quality. Grice's maxims are well-known guidelines for efficient and successful communication [12, 13]. As we will discuss later, using them to assess information quality can help us better understand factors related to information quality. The subjects of our study were limited to patients who required offline visits. The main research questions are as follows:

How does the persuasive content from online physicians adhering to Grice's maxims enhance patients' intentions to visit offline?

How does patient involvement influence physician compliance with Grice's maxims on patients' intention to visit offline?

We collected data on 16,738 patients from Good Doctor Online, one of China's largest online healthcare communities. We considered the information quality of messages as the central route factor, while physicians' e-WOM and expertise cues were regarded as peripheral cues. Grice's maxims (quantity, quality, relation, and manner) were used to measure information quality. To track patients' intentions for offline visits more effectively, we focused on whether patients had intentions to visit the physicians they had previously consulted online offline. We take the physician's advice regarding whether patients must go offline because physicians would only recommend offline visits for online patients who were clearly in need of an offline visit based on their professional ethics and medical expertise.

This study's contributions are as follows: First, we extend the research on online healthcare by studying online interactions and offline visit intentions. Second, this study also reveals the value of OHCS, which can screen patients for offline visits. Third, we applied ELM in the OHCS context to study patients' processing of physicians' online information about offline visit intention and considered the moderating effect of involvement. Fourth, while previous studies mainly conceptualized information quality as either an inherent property of the information itself or users' mental constructs [13], we extended information quality based on an established theory (Grice's maxims of Cooperative Principle) and thereby guided online physicians.

The rest of this paper is organized as follows: We first review the related theories and studies, then present the hypotheses and research model, followed by the presentation of data and results, and finally, we discuss and conclude.

Literature review

Prior research on OHCS

The rapid development of OHCS has received increasing attention in information systems (IS) research. Some studies have focused on patients' behaviors in OHCS in areas such as patient adoption and use patterns, patient evaluations and decisions [14, 15], patient satisfaction, and continued use [16], physician behaviors in OHCS in areas such as motivation, engagement, and returns [15, 17, 18]. Other studies have focused on the interactions and relationships between physicians and patients.

The interactions and relationships between physicians and patients have attracted increasing attention from researchers. Firstly, the social exchange behaviors of patients can influence the service quality and social support provided by physicians. The price of gifts positively affects the quality of physicians' services, while the service price charged by physicians and the total number of gifts have negative moderating effects [19]. Furthermore, small monetary gifts can elicit more timely responses and emotional support from physicians but may adversely affect patients who do not offer gifts [20]. Paid feedback significantly impacts physicians' contribution to the telemedicine market more than free feedback [21]. Secondly, online physicians' behaviors influence patients' evaluations and decisions. Physicians' prosocial behavior improves a patient's choice when the strength of a physician's prosocial behavior is below the tipping point [22]. Both emotional and informational interaction of physicians positively impact the adoption of their answers, with emotional interaction exhibiting a more significant influence [23]. The social support behaviors of physicians significantly influence patients' continuous consultation behaviors, and patients' offline experiences play a moderating role in this relationship [24]. Thirdly, online physician-patient interaction positively affected physician-patient relationships and patient compliance. Patient and physician participation significantly improved patient well-being and patient-physician relationships [25]. Online physician-patient communication positively affected patient compliance through the mediating effect of the perceived quality of online health information, decision-making preference, and physician-patient concordance [26].

Meanwhile, a few scholars have also explored the relationship between physicians' online and offline services. Physicians' participation in online medical consultations can increase offline service demand [6, 27, 28], offline patient satisfaction, and loyalty [6]. Conversely, offline activities may reduce physicians' online services but increase their online article sharing and the volume of services provided through offline channels [28]. Physicians' participation in the additional online channel significantly improves a physician's hospital performance [6].

Therefore, online physician-patient interactions can enhance physician-patient relationships, improve service quality, and promote offline visits. However, the current literature does not address what kind of persuasive content would enhance patients' intention to visit offline. No study has considered explicitly whether patients require an offline visit based on the physician's perspective. The decision to visit offline is more critical when such a visit is urgently needed. The messages provided by online physicians may be key to patients' offline visit behaviors. Our study intends to guide physicians from a communication perspective about persuading patients to go offline visits—namely, to communicate with patients via appropriate content successfully. Meanwhile, it is necessary to study how patients' information processing of physicians' messages and peripheral cues affect offline visit intention.

Elaboration likelihood model

ELM was developed by Petty and Cacioppo [8, 9]. It is a psychological theory that addresses the process of persuasion [8] and information influence [29]. The model was initially applied in the field of "persuasion" and "persuasive communication" [30]; however, in the past ten years, it has been widely adopted in different areas such as Marketing [31, 32], information systems [33] and online review [34, 35].

ELM is a "dual-process" theory that posits two routes through which persuasion takes place: a central route and a peripheral route [36]. These two routes differ in the amount of thoughtful information processing or "elaboration" by recipients [8, 9, 37]. The central route requires a person to systematically process the issue-related arguments in an informational message and scrutinize the relevance and merits of the arguments before making an informed judgment about the target behavior [37–39]. By contrast, the peripheral route requires less cognitive effort than the central route. It often relies on the heuristic clues associated with the information without any particularly deep thought [37].

According to ELM, information recipients can vary widely in their ability and motivation to process information and take different routes. With more motivation, knowledge, and cognitive ability, recipients engage in the central route, and the quality of the arguments will determine the degree of information influence [9, 29]. When recipients have less ability or motivation to elaborate on the arguments presented in the message, they take the peripheral route, and peripheral cues play a more critical role in the influence process. Peripheral cues are information indicators other than the content people use to assess content [29].

Argument quality has been identified as an essential construct in the central route [8, 29, 37]. However, its conceptualization and operationalization remain inconsistent among researchers [40]. Initially, argument quality referred to the persuasiveness of the argument [9]. Following this definition, argument quality was defined as the persuasive strength of arguments embedded in an informational message [37]. The persuasive strength of arguments was manipulated from high to low in laboratory settings. However, what constitutes a persuasive argument has not been explicitly indicated [41], and how to improve the persuasive strength of arguments also remains unknown. Cheung et al. (2009) [42] replaced argument quality with argument strength to highlight the extent to which the message receiver views an argument as convincing or valid in supporting its position.

More recently, researchers have increasingly operationalized argument quality to capture the information quality of messages [42]. Specifically, Ferran and Watts (2008) measured argument quality by examining whether the received message is complete, consistent, accurate, or adequate. Meanwhile, Sussman and Siegal (2003) [29] used completeness, consistency, and accuracy as the dimensions of argument quality. Cheung et al. (2008) [42] used four information quality dimensions to measure argument quality: relevance, timeliness, accuracy, and comprehensiveness. In the context of OHCS, patients are influenced by persuasive messages and the disease-related information a physician communicates. Hence, we considered information quality to be the central route factor of patient information processing based on ELM.

In OHCS, the ELM offers a framework for physicians to persuade patients to seek offline visits. The ELM provides valuable insights that physicians use to persuade patients to visit offline, explaining how patients process physicians' suggestions through the central and peripheral routes. Regarding the central route, patients analyze and evaluate the physician's information, relying on logic and evidence to form their opinions and decisions.

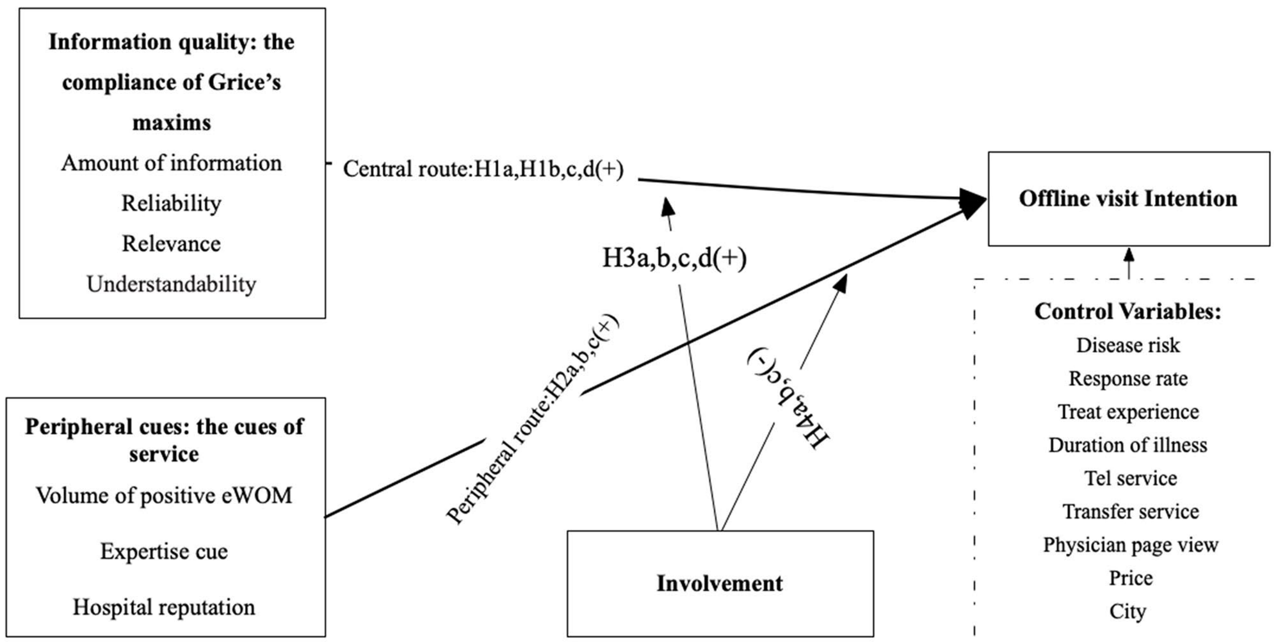

Fig. 1 Research model

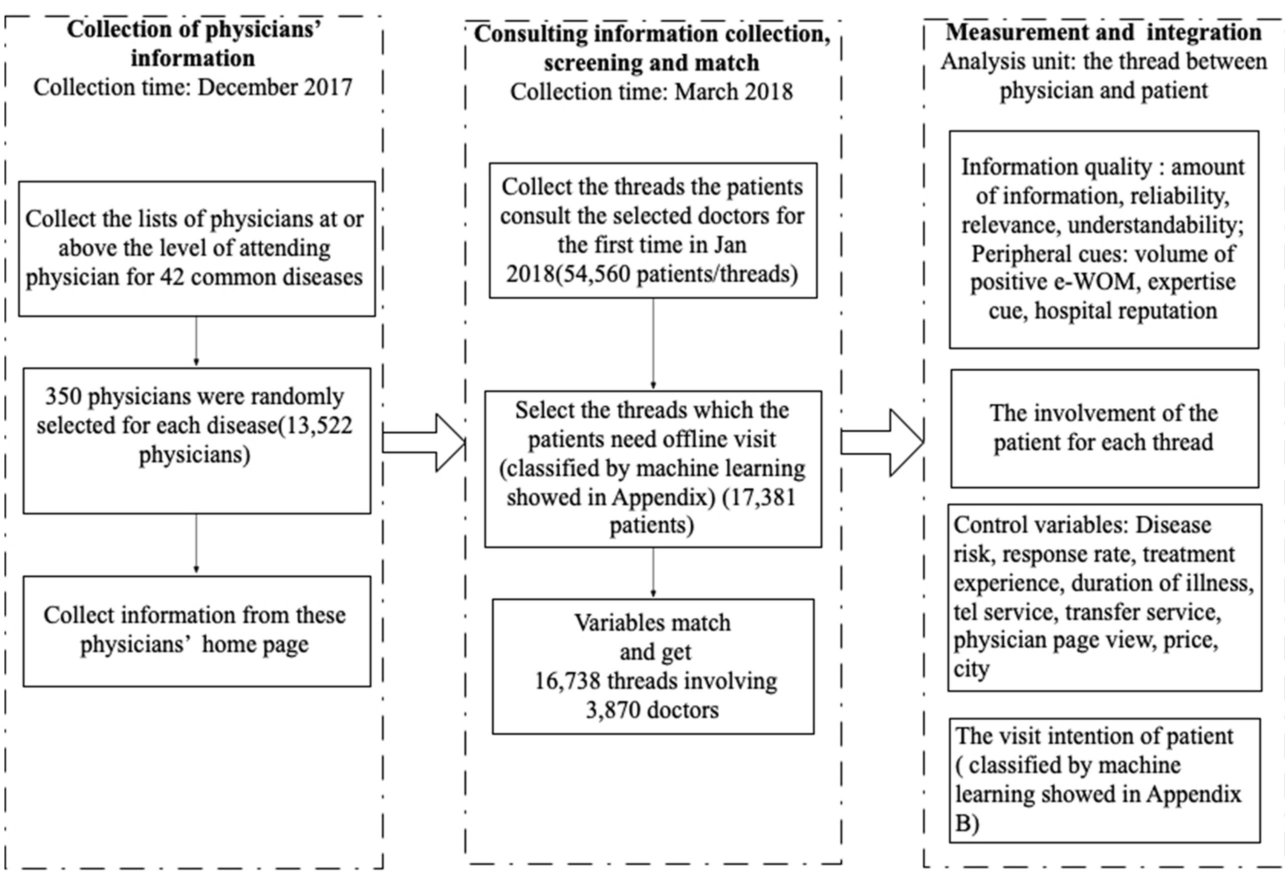

Fig. 2 Data processing flow

Patients are more likely to accept the physician's advice through the central route if the physician can give sufficient medical evidence and reasonable explanations. Regarding the peripheral route, patients can quickly make decisions through the peripheral cues, such as the physician's reputation, without the need to deeply analyze all the information.

There is a potentially infinite number of peripheral cues in the interpersonal communication context [29]. We need to identify the critical peripheral cues in our context. First, consumers make offline purchase decisions based on online information and e-WOM [43]. Second, the expertise of the message sender is a common peripheral cue in earlier studies [44]. Therefore, we mainly considered e-WOM and expertise cues by physicians as the peripheral cues that influence the offline visit decisions of online patients.

Grice's maxims of the cooperative principle

The Cooperative Principle, proposed by linguist H.P. Grice in 1975, constitutes a theoretical framework concerning effective communication. The cooperative Principle primarily encompasses four maxims: the maxim of quantity, the maxim of quality, the maxim of relation, and the maxim of manner, which aim to guide individuals on how to provide information for effective dialogue [10, 11]. The maxim of quantity emphasizes the appropriate provision of information, the maxim of quality focuses on the truthfulness of the information, the maxim of relation demands relevance, and the maxim of manner highlights the clarity and conciseness of expression [45].

In recent years, Grice's maxims of the Cooperative Principle have been widely applied and studied across various fields. Researchers have explored the applicability of these maxims in different cultural contexts [46]. For instance, some cultures may lean more towards adhering to the maxim of quality, while others might emphasize the maxim of relation, sparking new discussions in cross-cultural communication [47]. In education, applying Grice's maxims to teaching has been shown to help students enhance their communication and critical thinking abilities [48]. In artificial intelligence and natural language processing, Grice's maxims are utilized to improve the understanding capabilities and effectiveness of dialogue systems [49, 50].

Grice's maxims address human communication in general, and Grice's work established the foundation of the inferential model in human communication. Relevant research indicates that Grice's maxims are not only applicable to face-to-face communication but also to online communication [51]. The study empirically demonstrates that rewriting Wikipedia articles using Grice's maxims can improve the information quality of the articles [52]. The experiment showed that in online conversations, violations of the maxim of relation significantly impacted response times and the perceived humanness of a conversation partner [53].

Therefore, Grice's maxims can also be applied to the context of physicians' persuasion in patient-physician communications in OHCS. In OHCS, patients and physicians communicate through messages; thus, they must follow these guidelines to communicate effectively and successfully. Prior research has shown that compliance with Grice's maxims can help online articles fit users' needs, improve quality, and provide more relevance for users [52]. Thus, we used the extent to which physicians' messages complied with Grice's maxims to describe physicians' information quality.

Table 1 The number of threads and posts after the screening and matching process

Number of physicians	Number of patients/threads	Number of patient posts	Number of physician posts	Total posts
3,870	16,738	143,155	134,890	278,045

Research model and hypotheses

Our study integrates the ELM with Grice's maxims to investigate how online physicians persuade patients to visit offline. The ELM provides a framework for physicians to use in this process, and Grice's maxims describe the information quality of physicians' persuasive content.

As an essential factor of the central route, the argument quality of content still requires further clarification based on the research context. In OHCS, the ELM does not provide sufficient theoretical guidance regarding the content of communication between physicians and patients, that is, the content of the physician's persuasion and the patient's understanding of the persuasive content. We need to supplement the ELM with other theories to enrich our understanding of the argument quality.

As mentioned above, this study used information quality to replace argument quality. Although previous empirical studies have provided a more comprehensive perspective on the dimensions or attributes of information quality, they still have some limitations. First, the number of dimensions is vast. Some studies have captured 15 dimensions of information quality [54], while Mai (2013) [13] reviewed 22 attributes of information quality. It is impractical to measure all of these attributes. Second, different researchers use different terms to refer to the same dimensions (e.g., accuracy/reliability, utility/usefulness), and the factors have overlapping meanings (e.g., novelty/recentness) [12], which may confuse. Third, the dimensions and overall evaluations of information quality are treated at the same level. Variables such as usefulness, informativeness, and helpfulness should be treated as overall evaluations, and variables such as novelty and understandability should be treated as dimensions.

Table 2 Variables and description

Variable type	Variable name	Measurement	Description	Abbreviation
Dependent variable	Offline visit intention	The number of sentences containing the offline visit intention	We manually labeled the sentences of patients' posts. Then, we used the labeled data and machine learning method to get the classifier. And used the classifier to predict the patient's offline visit intention from sentences.	Intention
Independent variables	Amount of information.	The logarithm of the quantity of content words.	Content words: the adjectives, nouns, numerals, quantifiers, pronouns, and verbs. [70]	Content
		The logarithm of the quantity of unique words	The unique words in the physician's posts of the thread (Robust test)	Unique
	Reliability	Objective sentences ratio	Ratio of the number of objective sentences to the total number of sentences in replies. [68] [74]	Reliability
	Relevance	Topics relevance between the posts of the patient and the physician	LDA (an unsupervised machine learning algorithm, Appendix D) classified and predicted the topics and probabilities of physician-patient posts, respectively, and calculated the topics' relevance.	Relevance
	Understandability	Average sentence segments length.	The average sentence segment length is calculated by dividing the number of words by the number of semicolons, commas, periods, question marks and exclamation marks,	Length
	Volume of positive e-WOM	The heat index of the physician	The heat is calculated based on the number of patients recommended in the past two years and converted into a decimal value of 1 to 5	Heat
		Thank-you letters	Number of thank-you letters received by physicians (Robust test)	letters
	Expertise cue	The logarithm of clinic titles of physician	Chief physician 2,associate physician 1,other 0	Title
	Hospital reputation	Whether the hospital is a top-tier Grade A	If the hospital is top-tier Grade A then 1, else 0.	Hospital
Moderator variable	Involvement	The number of patient's topics	Calculate the number of patient topics after predicting the patient topics and probabilities by LDA (Appendix D),	Topics
Control variable	Disease risk	Whether the disease risk is high, dummy variable.	According to the mortality rate of the disease , the diseases are classified into high-risk disease or low-risk disease categories, and all malignant tumors are classified as high risk.	Risk
	Response rate	Response rate	The ratio of the number of physician's posts to that of patient in a thread.	Response
	Treat experience	Treat experience	Extract from the patient's posts whether the patient has visited the other physician offline before.	Before
	Duration of illness	The logarithm of duration of illness	The duration was extract from the posts, 1 means less than a week, 2 means less than a month, 3 means less than six months, 4 means more than six months	Duration
	Tel service	The telephone service	Whether the physician provides telephone service. If provided,1, else 0.	Tel
	Transfer services	The transfer service	Whether the physician provides the transfer service. If provided,1, else 0.	Transfer
	Page view	Page view	The physician's page's view times	View
	Price	The logarithm of web consulting price.	Patients need to pay a fee to use the physician's online counseling service	Price
	City scale	The logarithm of the city scale	The scale of the city where the physician works, based on "2018 China city business charm list"	City

Using established theories to explore information quality dimensions can effectively overcome the above-mentioned limitations. Further, theory-based hypothesis construction and testing can offer several advantages [55]. First, established theories have been tested in many different contexts, have been shown to have good generalizability, and can be used in various research situations, including ours. Second, established theories have identified the most critical constructs, and the constructs are well-defined, thus reducing ambiguity and meaning overlap. Finally, because established theories postulate relationships among key constructs, they provide a foundation for proposing new hypotheses.

Grice's maxims can be the established theories to explore information quality dimensions. Grice's maxims offer a set of standards for assessing and guiding communicative behavior, which are directly related to the quality and effectiveness of information. By adhering to these maxims, we can ensure that information is optimized in terms of quantity, quality, relation, and manner of expression, thereby enhancing the overall quality of information. However, these maxims primarily guide communication content and do not fully account for other contextual factors, such as peripheral cues in our context. Therefore, integrating the ELM with Grice's maxims allows for a more comprehensive reflection of

Table 3 The descriptive statistics of variables (15,842)

Variable	Mean	Std.Dev.	Min	Max
Intention	0.682	1.571	0	25
Content	4.194	1.174	0.693	9.120
Unique	4.083	0.951	0.693	7.737
Length	5.692	2.580	1	84
Reliability	0.356	0.249	0	1
Relevance	0.120	0.0924	0	0.732
Hospital	0.916	0.277	0	1
Title	0.736	0.415	0	1.099
Heat	4.253	0.405	0	5
Letters	3.459	1.487	0	6.757
Topics	4.804	1.564	1	11
Response	1.695	3.684	0.0909	74
Risk	0.235	0.424	0	1
Before	0.656	0.475	0	1
Duration	1.329	0.318	0.693	1.609
City	1.516	0.426	0.693	1.946
View	13.48	1.957	4.234	17.76
Tel	0.871	0.335	0	1
Transfer	0.372	0.483	0	1
Price	3.903	0.908	1.946	6.908

the impacts along both routes: on the one hand, peripheral cues in the ELM model can influence decisions through the peripheral route; on the other hand, the adherence to Grice's maxims in the physician's persuasive content enhances the information quality, which subtly influences patients to seek offline visit. This combination captures the complexity of the physician's holistic persuasion to visit offline. It deepens our understanding of information quality's role in a physician's ability to persuade patients to visit offline.

Therefore, ELM and Grice's maxims can complement each other in depicting patient information processing. We use ELM to understand physicians' persuasive behavior towards patients and use information quality to operationalize argument quality. We propose using Grice's maxims as a theoretical foundation to explore information quality dimensions.

Information quality: compliance with Grice's maxims

In OHCS, physicians compose replies to patients' questions to address their disease-related issues. Thus, we adopted a pragmatic perspective on information quality following Zhang and Watts (2008) [41] and Y. Xu and Z. Chen (2006) [12]. From this perspective, messages pertinent to solving the problem should be of high quality. If the physician's message directly resolves the patient's issue, the quality is high; otherwise, it is low. Specifically, we define information quality as the extent to which a physician's response solves the patient's issue.

To form the hypotheses, we first addressed the effects of the central route on patients' decisions. As noted earlier, the information quality of physicians' replies was taken as the central route. Physicians' replies are specific to patients, focusing on patients' diseases or concerns. Other physician cues (e.g., e-WOM, clinical title) are the same for all patients. Information related to the patient's condition and the physician's offline visit advice is contained in the replies. Thus, the information quality of a reply is a critical factor in helping a patient understand and adopt the physician's opinion. Studies have shown that information quality positively affects knowledge adoption [38, 41].

Grice's maxims can help make information fit users' needs and improve information quality [52]. As mentioned before, to effectively share information (with better information quality) and help receivers understand their conditions and make decisions, the information provider should obey the maxims of quantity, quality, relevance, and manner. This study used the degree to which a physician adhered to these maxims to measure information quality.

The maxim of quantity calls for messages to be informative but not more so than is required [11, 56]. When the amount of information is insufficient, the greater the quantity, the more likely it is to meet the receiver's needs. Beyond that, too much information could lead to information overload [57]. We used the amount of information rather than quantity because it is more commonly found in the information quality literature. In our context, however, physicians' messages to patients are saved and can be processed by patients anytime. Limited messages might not cause information overload. Meanwhile, with their rich professional knowledge, physicians can meet patients' current perceived information needs and their potential needs with more information. Previous studies have shown that the amount of information affects perceived usefulness by the receiver [58], and perceived usefulness is an essential antecedent variable of adoption behavior. Therefore, patients may prefer that physicians provide as much information as possible. Physicians who provide more information are perceived as more concerned about patients' conditions and can better meet patients' information needs, making patients more likely to visit offline. Thus, we propose H1a:

H1a: The amount of information in replies positively affects offline visit intention.

The maxim of quality requires the communicator only to say what they believe to be true and to be supported by evidence [11, 12]. Following [12, 59], we used the term "reliability" instead of "quality" to distinguish between information quality. Here, reliability (content reliability) is different from source reliability; source reliability is the source's credibility, which can be regarded as an external cue. However, content reliability is determined by the content itself. Reliability is the degree to which

Table 4 The correlations of the variables

	Intention	Content	Unique	Length	Reliability	Relevance	Hospital	Title	Heat	Letters	Topics	Response	Risk	Before	Duration	City	View	Tel	Transfer
intention	1																		
Content	0.116***	1																	
Unique	0.139***	0.979***	1																
Length	-0.071***	-0.052***	-0.077***	1															
Reliability	0.018***	0.015***	-0.00900	-0.081***	1														
Relevance	0.142***	-0.0100	0.029***	-0.067***	-0.060***	1													
Hospital	0.076***	0.025***	0.027***	-0.018***	0.028***	0.018***	1												
Title	0.091***	-0.167***	-0.143***	0.00200	0.00600	0.087***	0.039***	1											
Heat	0.139***	0.224***	0.230***	-0.049***	0.041***	0.00700	0.251***	0.151***	1										
Letters	0.144***	0.273***	0.267***	0.00100	0.034***	0.036***	0.186***	0.192***	0.733***	1									
Topics	0.343***	0.192***	0.229***	-0.060***	-0.044***	0.041***	0.106***	0.081***	0.180***	0.180***	1								
Response	-0.109***	0.351***	0.254***	0.074***	-0.007	-0.187***	-0.062***	-0.119***	-0.019***	0.064***	-0.146***	1							
Risk	0.031***	0.049***	0.053***	-0.00100	-0.0120	0	0.087***	-0.006	0.087***	0.066***	0.125***	-0.032***	1						
Experience	0.080***	0.089***	0.099***	-0.029***	-0.0110	0.028***	0.134***	0.062***	0.122***	0.117***	0.170***	-0.047***	0.172***	1					
Duration	0.067***	0.016***	0.024***	-0.009	-0.020***	-0.009	0.076***	0.021***	0.057***	0.026***	0.101***	-0.029***	0.024***	0.148***	1				
City	0.045***	0.033***	0.036***	-0.002	0.017***	0.019***	-0.073***	0	0.127***	0.179***	0.087***	-0.054***	0.102***	0.051***	0.026***	1			
View	0.071***	0.138***	0.124***	0.013***	0.034***	0.022***	0.072***	0.333***	0.469***	0.729***	0.103***	0.050***	-0.007	0.051***	0.030***	0.111***	1		
Tel	-0.067***	0.116***	0.102***	-0.00800	-0.0120	-0.021***	-0.029***	-0.167***	0.090***	0.088***	-0.069***	0.078***	-0.017***	-0.052***	-0.046***	-0.085***	0.087***	1	
Transfer	0.096***	0.122***	0.116***	-0.017***	-0.019***	-0.022***	0.188***	0.022***	0.385***	0.385***	0.145***	0.024***	0.130***	0.148***	0.055***	0.084***	0.219***	0.080***	1
Price	0.162***	0.088***	0.103***	0.00100	-0.018***	0.121***	0.163***	0.290***	0.420***	0.492***	0.181***	-0.039***	0.019***	0.113***	0.026***	0.103***	0.395***	0.075***	0.295***

Note: $^{*}P < 0.1$, $^{**}P < 0.05$, $^{***}P < 0.01$;

physicians' replies are perceived as true, accurate, or believable [12]. Therefore, we hypothesize the following:
H1b: The reliability of replies positively affects a patient's intention to make an offline visit.

The maxim of relation requires providing only relevant information [11, 56]. In this study, our concern was whether the replies focused on the discussed topic or were disease-related. We used topical relevance to obtain a more definite meaning. We defined relevance as the extent to which patients perceive replies related to their current topic of interest [12]. When a physician's replies concern the patient's topic of interest and are directly related to the patient's questions, the patient will perceive them as more helpful and more likely to accept the recommendation for an offline visit. Thus, H1c is proposed:
H1c: The relevance of replies positively affects a patient's offline visit intention.

Finally, the maxim of manner requires communicators to avoid obscurity and ambiguity and to be brief and orderly [11]; it is therefore related to comprehensibility [56]. We call this "understandability" in the context of physicians' messages. Understandability refers to the degree of ease with which the physician's replies can be understood by patients [60]. Patients receiving more understandable messages are more likely to understand the need for an offline visit. Thus, we propose the following:
H1d: The understandability of replies positively affects a patient's offline visit intention.

Peripheral cues

Peripheral cues pertain to meta-information about a message (e.g., the message source) not embedded in the argument [37]. Previous studies, taking e-WOM as a peripheral cue, have explored the influence of peripheral cues on consumers' attitudes toward products and their willingness to purchase [14, 42]. E-WOM refers to positive or negative statements shared by Internet consumers regarding a product, service, brand, or company. Consumers' online behaviors are deeply affected by e-WOM as they rely heavily on online product reviews to make purchase decisions [61].

Volume (number of reviews) and valence (review ratings) are the typical components of e-WOM [62]. This study chose the volume of positive reviews as a peripheral cue since it reflects both quantity and evaluation direction. Patients can use such reviews to find out which physicians are most recommended. Meanwhile, medical service is a type of credence goods. Credence goods have high product intangibility, and service quality is difficult to ascertain objectively, even after consumption [63]. Thus, patients tend to be affected by the evaluations of other patients. A higher volume of positive e-WOM means more patients are satisfied with a physician, and that physician is more likely to provide high service quality. Thus, patients are more likely to visit a physician with a higher volume of positive e-WOM offline. Therefore, we hypothesize the following:
H2a: The volume of positive e-WOM positively affects a patient's visit intention.

The source credibility of information is considered another important peripheral cue [38, 42]. Source credibility refers to a recipient's perception of a message source's credibility, reflecting nothing about the message itself [29]. A message from a person who has high expertise or is associated with a reputable organization is perceived as more credible [64] and useful [42]. Previous studies have shown that the perceived usefulness of a message directly affects the receiver's adoption of the message [29]. Thus, other things being equal, patients are more likely to be persuaded by messages from a physician with a higher expertise cue (clinical title) or from a high-reputation hospital. Therefore, H2b and H2c are proposed:
H2b: The expertise cue of a physician has a positive effect on a patient's visit intention.
H2c: A physician's hospital's reputation positively affects a patient's visit intention.

Moderating effect of involvement

In ELM, the effects of central route factors and peripheral cues are moderated by individuals' motivation and expertise regarding elaborating on informational messages [9, 37]. This study mainly focused on the online patient's motivation and did not consider expertise. Since medical expertise is specialized, and there may be no significant differences in expertise between patients, we only considered patient motivation.

Motivation can be operationalized as involvement [29, 36]. Involvement has been defined as the extent to which recipients perceive the issue as personally important or relevant [9, 36, 65]. A high level of involvement tends to motivate increased elaboration on a message [9, 29]. A high level of user involvement increases the cognitive effort to understand the replies, increasing reliance on central route processing. Thus, the following are proposed:
H3a: The effect of the amount of information on a patient's offline visit intention is stronger when patient involvement is high.
H3b: The effect of reliability on a patient's offline visit intention is stronger when patient involvement is high.
H3c: The effect of relevance on a patient's offline visit intention is stronger when patient involvement is high.
H3d: The effect of understandability on a patient's offline visit intention is stronger when patient involvement is high.

Table 5 Regression results for visit intention

Intention	Model 1	Model 2	Model 3
Content		0.200***	0.102***
		(0.013)	(0.012)
Reliability		0.118***	0.288***
		(0.038)	(0.046)
Relevance		1.789***	2.450***
		(0.133)	(0.165)
Length		-0.0264***	-0.0223***
		(0.004)	(0.005)
Heat		0.186***	0.142***
		(0.040)	(0.037)
Title		0.200***	0.149***
		(0.031)	(0.030)
Hospital		0.114***	0.112**
		(0.036)	(0.045)
Topics			0.285***
			(0.009)
Content × Topics			0.0434***
			(0.009)
Reliability × Topics			0.160***
			(0.033)
Relevance × Topics			1.211***
			(0.111)
Length × Topics			-0.0139***
			(0.004)
Heat × Topics			0.0759***
			(0.023)
Title × Topics			0.0999***
			(0.022)
Hospital × Topics			0.0918***
			(0.031)
Response	-0.0408***	-0.0499***	-0.0226***
	(0.003)	(0.004)	(0.002)
Risk	0.034	0.006	-0.0651**
	(0.032)	(0.032)	(0.031)
Before	0.131***	0.0666***	0.008
	(0.025)	(0.025)	(0.024)
Duration	0.236***	0.234***	0.145***
	(0.034)	(0.035)	(0.033)
City	0.035	0.032	-0.001
	(0.030)	(0.031)	(0.029)
View	0.010	-0.0249***	-0.0225***
	(0.007)	(0.007)	(0.007)
Tel	-0.326***	-0.338***	-0.241***
	(0.041)	(0.042)	(0.040)
Transfer	0.162***	0.120***	0.0677**
	(0.028)	(0.030)	(0.029)
Price	0.238***	0.169***	0.105***
	(0.015)	(0.016)	(0.015)
Constant	0.682***	0.688***	0.643***
	(0.012)	(0.012)	(0.011)
Observations	15,842	15,524	15,524
R-squared	0.05	0.086	0.177

Note: (1) * $P < 0.1$, ** $P < 0.05$, *** $P < 0.01$; (2) Robust standard errors in parentheses; (3) Variables are centralized

Peripheral cues can influence a patient's intention to make an offline visit. However, different effects are likely to be a function of the degree of the patient's involvement in OHCS. Recipients with lower involvement are not motivated to cognitively process a message in detail; rather, they are more likely to rely on peripheral cues [29, 66]. When a patient has low involvement, they may have no motivation to process the physician's replies; however, they can infer the usefulness of the replies from the physician's e-WOM, expertise cue (title), and hospital reputation. Generally, the influence of peripheral cues is expected to be stronger when the patient's involvement is at a lower level. The following are therefore proposed:

H4a: The effect of the volume of positive e-WOM on a patient's visit intention is stronger when patient involvement is low.

H4b: The effect of a physician's expertise cues on a patient's visit intention is stronger when patient involvement is low.

H4c: The effect of hospital reputation on a patient's visit intention is stronger when patient involvement is low.

Figure 1 depicts the research model.

Methods

Research context

We chose *Good Doctor Online* (www.haodf.coma large, popular online health community in China—to test the hypotheses. Founded in 2006, *Good Doctor Online* is an online physician-patient interaction platform. Over 5,000 hospitals and 400,000 physicians are listed on the platform, and more than 110,000 physicians provide online consultation services there. Patients can browse physicians' homepages and consult them.

We chose that website because it has rich information, including physician-patient interaction posts (messages between physicians and patients), the heat of patient recommendations for a physician, a physician's title, the physician's hospital, and the physician's department. Such information made the website suitable for collecting data to test the hypotheses.

Data and variables

Data were collected from www.haodf.com using a Python-based program. Figure 2 shows the data collection and integration flow. Data were collected at two different periods: the end of December 2017 and the end of March 2018. Our data analysis is explained as follows:

(1) We selected 350 physicians at random for each disease, resulting in a total of 13,522 physicians. At the end of December 2017, we collected the clinical title, the heat index of the physician, city, physician page views, telephone service, transfer service, and service price for these physicians. Due to technical issues such as internet speed, we obtained information on 12,296 physicians

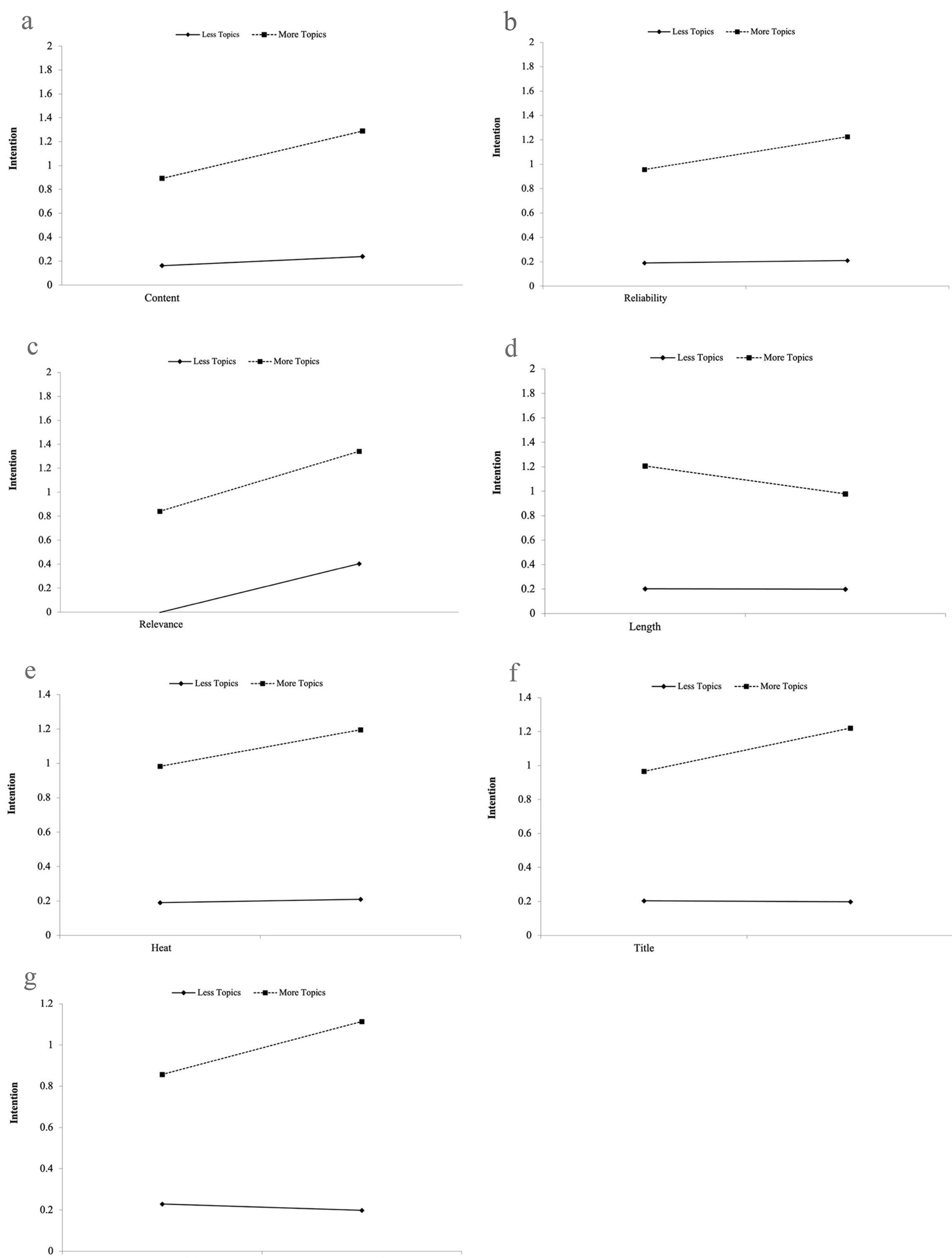

Fig. 3 Moderating effects of involvement on intention

from 342 cities across China, with 10,404 affiliated with top-tier Grade A hospitals.

(2) We collected physician-patient interaction threads in which patients consulted with the selected physicians for the first time in January 2018. We only considered patients who needed an offline visit, determined based on physicians' posts. The coding and machine learning processes are shown in Appendix A, Figure A1. One

Table 6 Hypotheses testing results

Hypotheses	Results
H1a: The amount of information in replies positively affects offline visit intention.	Supported
H1b: The reliability of replies positively affects a patient's offline visit intention.	Supported
H1c: The relevance of replies positively affects a patient's offline visit intention.	Supported
H1d: The understandability of replies positively affects a patient's offline visit intention.	Supported
H2a: The volume of positive e-WOM positively affects a patient's visit intention.	Supported
H2b: The expertise cue of a physician has a positive effect on a patient's visit intention.	Supported
H2c: A physician's hospital's reputation positively affects a patient's visit intention.	Supported
H3a: The effect of the amount of information on a patient's offline visit intention is stronger when patient involvement is high.	Supported
H3b: The effect of reliability on a patient's offline visit intention is stronger when patient involvement is high.	Supported
H3c: The effect of relevance on a patient's offline visit intention is stronger when patient involvement is high.	Supported
H3d: The effect of understandability on a patient's offline visit intention is stronger when patient involvement is high.	Supported
H4a: The effect of the volume of positive e-WOM on a patient's visit intention is stronger when patient involvement is low.	Not Supported
H4b: The effect of a physician's expertise cues on a patient's visit intention is stronger when patient involvement is low.	Not Supported
H4c: The effect of hospital reputation on a patient's visit intention is stronger when patient involvement is low.	Not Supported

thousand physicians' posts were randomly selected, and after dividing the posts into sentences, the necessity of offline visits for each sentence was manually labeled by two researchers. Two researchers manually labeled each sentence of the posts, which were randomly selected, as need offline visit (1) and do not need or do not show offline visit (0). Intercoder reliability was 0.967; as a rule of thumb, a value of 0.90 or greater is considered acceptable [67]. The examples of encoding for the necessity of offline visits can be found in Appendix A Table A1. We selected four classification machine learning algorithms, and based on the cross-validation accuracy scores (see Appendix A Table A2), we chose the Support Vector Machine (SVM) algorithm. In this study, the algorithm's accuracy in predicting physician recommendations is 0.904, and the AUC is 0.886, indicating that the classifier performs well. Then, we used the labeled data and machine learning to obtain the classifiers and predict the offline suggestions of the physicians (offline visit or not). As long as one sentence was predicted to be a necessary offline visit, the patient was considered to require an offline visit. Table 1 lists the data for the posts and the patients who needed an offline visit. The dataset encompasses 3,870 physicians from 217 cities, with 1,371 practicing in first-tier and new first-tier cities and 3,534 affiliated with top-tier Grade A hospitals.

(3) Our analysis unit was the thread between physician and patient. Physician information was obtained from the home page, and information quality and patient-related information were obtained from the posts in the thread. Some variables (amount of information, reliability, relevance, understandability, patient involvement) were obtained through text analysis. The patients' intention to visit offline was predicted using machine learning methods (shown in Appendix B).

The dependent variable was the patient's intention to make an offline visit. The coding and machine learning processes are shown in Appendix B Figure B1. One thousand patient posts were randomly selected, and after dividing the posts into sentences, the offline visit intention of each sentence was manually labeled by two researchers. Two researchers manually labeled each sentence of the posts as having offline visit intention (1) and not having or not showing offline visit intention (0). This was obtained as follows: The two researchers marked the offline visit intentions of the sentences separately; "1" meant the patient had intention, whereas "0" meant the patient did not show intention. Intercoder reliability was 0.936; 0.90 or greater is considered acceptable [67]. The researchers discussed sentences with different labels and decided on a label. The examples of encoding for patients' intention to visit offline can be found in Appendix B Table B1. After all sentences were labeled, we used machine learning to generate a classification model based on the labels, and this classification model was applied to predict offline visit intention in patients' posts. We selected four classification machine learning algorithms, and based on the cross-validation accuracy scores (see Appendix B Table B2), we chose the Support Vector Machine (SVM) algorithm. In this study, the algorithm's accuracy in predicting patients' offline visit intention was 0.899, and the AUC was 0.884, indicating that the classifier performed well. We used the number of sentences containing offline visit intention as the measurement.

The independent variables were the amount of information, reliability, relevance, and understandability of a physician's replies, and the physician's volume of positive e-WOM, clinical title, and hospital reputation. Patient involvement was the moderating variable. The measurements are described below.

Physicians need to follow Grice's maxims to communicate information to patients better. We measured the amount of information, reliability, relevance, and understandability of physicians' patient replies. Before obtaining these variables, natural language processing (NLP) was used to process physicians' replies. The tokenization

Table 7 Regression results for visit intention (robustness check)

Intention	Model 1	Model 4	Model 5
Unique		0.239***	0.116***
		(0.015)	(0.014)
Reliability		0.139***	0.301***
		(0.038)	(0.045)
Relevance		1.709***	2.382***
		(0.131)	(0.164)
Length		-0.0261***	-0.0222***
		(0.004)	(0.005)
Letters		0.0985***	0.0916***
		(0.012)	(0.012)
Title		0.210***	0.162***
		(0.030)	(0.030)
Hospital		0.114***	0.103**
		(0.035)	(0.044)
Topics			0.281***
			(0.009)
Unique ×Topics			0.0611***
			(0.011)
Reliability ×Topics			0.167***
			(0.033)
Relevance ×Topics			1.178***
			(0.110)
Length ×Topics			-0.0133***
			(0.004)
Letters ×Topics			0.0196***
			(0.007)
Title ×Topics			0.100***
			(0.022)
Hospital ×Topics			0.0965***
			(0.031)
Response	-0.0408***	-0.0457***	-0.0211***
	(0.003)	(0.004)	(0.002)
Risk	0.0336	0.00271	-0.0686**
	(0.032)	(0.032)	(0.031)
Before	0.131***	0.0615**	0.00529
	(0.025)	(0.025)	(0.024)
Duration	0.236***	0.243***	0.155***
	(0.034)	(0.035)	(0.033)
City	0.0354	0.0181	-0.0163
	(0.030)	(0.031)	(0.029)
View	0.00979	-0.0564***	-0.0538***
	(0.007)	(0.009)	(0.008)
Tel	-0.326***	-0.327***	-0.230***
	(0.041)	(0.042)	(0.040)
Transfer	0.162***	0.106***	0.0459
	(0.028)	(0.030)	(0.028)
Price	0.238***	0.152***	0.0897***
	(0.015)	(0.016)	(0.015)
Constant	0.682***	0.687***	0.639***
	(0.012)	(0.012)	(0.011)
Observations	15,842	15,524	15,524
R-squared	0.05	0.088	0.178

Note: (1) * $P<0.1$, ** $P<0.05$, *** $P<0.01$; (2) All variables are centralized. (3) Robust standard errors in parentheses

of raw text is a standard preprocessing step for many NLP tasks. In English, tokenization usually involves punctuation splitting and separating some affixes, such as possessives. However, Chinese is written without spaces between words. Therefore, Chinese tokenization requires more extensive token preprocessing, usually called tokenization [68]. We used PKUSEG [69] to split the Chinese text into a sequence of words. PKUSEG is a multidomain Chinese word segmentation toolkit, and we applied the medicine domain model to segment the words. Appendix C shows examples of word segmentation results after applying PKUSEG.

We used the logarithmic number of content words to measure the amount of information. Content words contain adjectives, nouns, numerals, quantifiers, pronouns, and verbs [70]. These words convey the content of the communication [71]. Therefore, this is a good proxy for measuring the amount of information in replies. PKUSEG can provide the part of speech of each word while segmenting, and we wrote a Python program to calculate the number of content words in the replies.

We used the ratio of objective sentences to measure reliability. Objective sentences are considered to deal with facts and are not distorted by personal feelings, prejudices, or interpretations [73]. Objective sentences are more likely to be perceived as true, accurate, or believable. Following previous studies [68, 74], we judged a sentence to be subjective or objective based on the model of the lexical combination of continuous two-word parts of speech.

Relevance is the extent to which replies offer relevant information in response to patients' questions. Based on the idea of problem and reply category consistency [74], we used the topics and probabilities of physician and patient posts to obtain the topic correlation rate to measure relevance, as shown in Eq. (1). The topics and probabilities of physician-patient posts were classified and predicted by LDA [75] (an unsupervised machine learning algorithm). Appendix D shows the topic classification process for posts by physicians and patients via LDA:

$$R_{pd} = \sum_{i=1}^{T} P_{pi} P_{di} \tag{1}$$

We have renumbered the Equation in order to maintain sequential order of Equation citations within text. Please check.Thank you for your attention to detail. We have checked and confirmed that the equations have been renumbered correctly to maintain the sequential order of equation citations within the text.

where R_{pd} represents the relevance of the posts between the physician and the patient, T represents the total number of topics in physician and patient posts, i represents the *i*th topic, *Ppi* represents the probability of a patient's post belonging to the *i*th topic, and P_{di} represents the probability of a physician's post belonging to the *i*th topic. Appendix E provides detailed examples of physician-patient communication. In Table E1, the physician's responses are highly relevant to the patient's responses, such as when the patient describes their symptoms, the physician asks for more detailed information about the symptoms; when the patient asks if a runny nose is related to a cold, the physician replies that a runny nose caused by a cold usually lasts three to five days. If it lasts more than a week, it might be due to a nasal allergy caused by the cold virus. In Table E2, the physician does not address the patient's questions and instead directly advises the patient to call for a consultation, resulting in low relevance. In Table E3, the physician's responses are low in relevance to the patient's questions. After the patient describes their symptoms, the physician does not ask for more details and proceeds directly to diagnosis.

Understandability, which refers to clarity and concision, has been conceptualized regarding the average sentence length of words [56]. Unlike English sentences, as many as 75% of Chinese sentences are composed of more than two segments, separated by segment separators (commas and semicolons); these punctuation marks can make natural language statements quite clear and precise [76]. Considering Chinese characteristics, we used average sentence segment length to measure understandability. The average sentence segment length was calculated by dividing the number of words by the number of sentence terminators and segment separators. The shorter the average sentence segment length, the better the reader could understand.

Peripheral cues include the volume of positive e-WOM, expertise cues, and hospital reputation. We used the heat of patient recommendations for physicians as a proxy for the volume of positive e-WOM. This was calculated based on the number of patient recommendations in the past two years and converted into a decimal value of 1–5 for patients to view and compare.

The expertise cue was operationalized by the physician's clinical title. The clinical title refers to a physician's medical professional status as evaluated by government health authorities according to the physician's overall medical abilities [5]. It includes the titles of chief physician, associate physician, attending physician, and physician. However, the number of chief and associate physicians was much greater than that of other physicians on the platform, so we combined attending physicians and lower-level physicians into the "other physicians." Thus, we obtained three types of physicians: chief physicians (coded as 2), associate physicians (coded as 1), and other physicians (coded as 0).

Hospital reputation concerns whether a physician works at a top-tier Grade A hospital. A dummy variable was used to represent it.

We hypothesized that patient involvement would moderate the relationships between central route factors, peripheral cues, and offline visit intention. To measure involvement, we used the number of patient topics after predicting patient topics and probabilities using LDA (Appendix D). The more topics shown in a patient's posts, the more involved the patient was in the consultation.

In the model, we also included other variables that would affect a patient's visit intention: the scale of the city in which the hospital was located, the consulting price, whether the physician provided telephone service, whether the physician had an open transfer treatment service, the patient's disease risk, treatment experience, and duration of illness. These variables were intended to control other variables' effects on patients' visit intentions. Table 2 lists all variables and their descriptions.

Tables 3 and 4 show the descriptive statistics and correlations of the variables, respectively. As shown in Table 4, all independent variables were significantly correlated with the dependent variable (intention) and consistent with the hypotheses.

Model estimation

The dependent variable was the patient's visit intention. We used regression models to model patient offline visit intention (dependent variable). To model the effect of central route factors and peripheral cues, Eq. (2) was used for estimation:

$$\begin{aligned}&reg(Intention_i)\\&=\alpha_0+\alpha_1Content_i+\alpha_2Reliability_i\\&+\alpha_3Relevance_i+\alpha_4Length_i\\&+\alpha_5Heat_i+\alpha_6Title_i\\&+\alpha_7Hospital_i+\beta\gamma_i+u_i\end{aligned} \tag{2}$$

.

Let i index the patient. α_0 is the intercept, and α_1 to α_7 are the focus parameters to be estimated. γ represents the vector of the control variables, and β represents the coefficient vector of the control variables. u_i is the error term associated with observation.

Equation (3) was used to estimate the moderating effects of involvement (*Topics*):

$$\begin{aligned}&reg(Intention_i)\\&=\alpha_0+\alpha_1Content_i+\alpha_2Reliability_i\\&+\alpha_3Relevance_i+\alpha_4Length_i+\alpha_5Heat_i\\&+\alpha_6Title_i+\alpha_7Hospital_i\\&+\alpha_8Content_i\times Topics_i+\alpha_9Reliability_i\times Topics_i\\&+\alpha_{10}Relevance_i\times Topics_i+\alpha_{11}Length_i\times Topics_i\\&+\alpha_{12}Heat_i\times Topics_i\\&+\alpha_{13}Title_i\times Topics_i+\alpha_{14}Hospital_i\times Topics_i\\&+\alpha_{15}Topics_i+\beta\gamma_i+u_i\end{aligned} \tag{3}$$

Let i index the patient. α_0 is the intercept, and α_1 to α_7 are the coefficients of the independent variables; α_8 to α_{15} are the coefficients of the interaction items of independent variables and involvement. γ is the vector of the control variables, and β is the coefficient vector of the control variables. α_0 is the intercept, and u_i is the error term associated with observation.

Results

Table 5 presents the model results estimated by regression. No VIF (variance inflation factor) statistics for the variables were greater than 1.7, which indicates the absence of multicollinearity. Model 1 examined the effects of the control variables; some had significant effects on offline visit intention. Model 2 examined the main effects of central route factors and peripheral cues on offline visit intention.

The central route factor hypotheses (H1a, H1b, H1c, H1d) predicted that compliance with Grice's maxims (quantity, quality, relation, and manner) would positively affect offline visit intention. As expected, the coefficient of Content (α_1=0.200, $p<0.01$), the coefficient of Reliability (α_2=0.118, $p<0.01$), and the coefficient of Relevance (α_3=1.789, $p<0.01$) in Model 2 were significantly positive. Thus, H1a, H1b, and H1c are supported. The coefficient of Length (α_4=-0.0264, $p<0.01$) was significantly negative. Since length is an inverse measurement of understandability, understandability significantly positively affected offline visit intention. Thus, H1d is supported.

The peripheral cue hypotheses predicted that the volume of positive e-WOM (H2a), physicians' expertise cues (H2b), and hospital reputation (H2c) would positively affect patients' offline visit intention. In Model 2, the coefficient of Heat (α_5=0.186, $p<0.01$), the coefficient of Title (α_6=0.200, $p<0.01$), and the coefficient of Hospital (α_7=0.114, $p<0.01$) were significantly positively associated with offline visit intention. Thus, H2a, H2b, and H2c are supported.

Model 3 examined the moderating effects of patient involvement (Table 5). We could examine the moderating effects by creating product terms using the moderator and causal variables. To facilitate the interpretation of the results, we examined the moderating effect of involvement on the impact of central route factors and peripheral cues on offline visit intention.

The ELM hypotheses proposed that involvement would amplify the effect of central route factors (H3a, H3b, H3c, H3d). Expectedly, the coefficient of the product term of Content and Topics (α_8=0.0434, $p<0.01$), the coefficient of the product term of Reliability and Topics (α_9=0.160, $p<0.01$), and the coefficient of the product term of Relevance and Topics (α_{10}=1.211, $p<0.01$) in Model 3 were significantly positive. Thus, H3a, H3b, and H3c are supported. The coefficient of the product term of Length and Topics (α_{11}=-0.0139, $p<0.01$) was significantly negative. Since length significantly negatively affects intention, Topics amplifies the effect of length on offline understandability and offline visit intention. Thus, H3d is supported.

For the moderating effect of involvement on peripheral cues, the coefficient of the product term of Heat and Topics (α_{12}=0.0759, $p<0.01$), the coefficient of the product term of Title and Topics (α_{13}=0.0999, $p<0.01$), and the coefficient of the product term of Hospital and Topics (α_{14}=0.0918, $p<0.01$) in Model 3 were significantly positive. This means that involvement amplified the effects of these variables on offline visit intention. Thus, H4a, H4b, and H4c are not supported.

Figure 3 shows the moderating effects of involvement on offline visit intention. Figure 3a, b and c, and Fig. 3d show that the impact of content, reliability, relevance, and length on intention was significant under both the less-topics and more-topics conditions, but the relationships were stronger under the more-topics condition. Thus, consistent with the hypotheses, involvement magnified the effect of information quality on offline visit intention.

Figure 3e and f, and Fig. 3g show that the effects of heat, title, and hospital reputation on intention were stronger under the more-topics condition than the less-topics condition. Meanwhile, the impact of title and hospital reputation on intention was not significantly positive under the less-topic conditions. One possible reason is that patients with low involvement might not pay attention to the physician's title or hospital, or these patients feel the attending physician (the lower title) can also meet their needs.

Model 3 (Table 5), Fig. 3e and f, and Fig. 3g show that involvement amplified the positive effects of heat, title, and hospital reputation on intention, which is different from the assumption of ELM. One possible reason is that medical knowledge differs from other knowledge areas. We will provide a more detailed explanation in the discussion section. Thus, the negative moderating effect of involvement on the impact of title and hospital reputation on intention was not supported.

The results of the hypotheses test are shown in Table 6.

Robustness check

To check the robustness of the results, we used the unique words in a physician's posts on the thread to measure the amount of information. We also used the number of thank-you letters received by physicians to measure the volume of positive e-WOM. Table 7 presents the model results estimated by regression. The model was significant since the F-value was reasonable (Prob > chi^2 = 0.000), and no VIF statistic for the variables was higher than 2, indicating the absence of multicollinearity. The hypotheses supported by the previous model were all supported by this model. Appendix F Table F1 shows the Robustness Test Results of Random Subsamples, which remain robust. Therefore, the results are robust.

Discussion and implications

Discussion

In this study, we posit that central route factors—such as the amount of information, reliability, relevance, and understandability—and peripheral cues from physicians positively influence patients to visit offline. We primarily considered three peripheral cues: electronic Word of Mouth (e-WOM), expertise, and hospital reputation. Additionally, we hypothesize that patient involvement positively moderates the influence of central route factors and negatively moderates the impact of peripheral route factors.

The study confirms that the information quality of content provided by physicians, including the amount of information, reliability, relevance, and understandability, directly affects patients' intentions to visit offline. This aligns with the ELM, which suggests that the quality of information in the central route is crucial for physicians to persuade patients to visit offline. Therefore, physicians should provide more informative, reliable, relevant, and comprehensible information to enhance patients' intentions to visit offline.

The results also revealed a positive effect of peripheral cues on offline visit intention. Thus, patients are more likely to visit offline when physicians have higher e-WOM, higher expertise cues, and associations with reputable hospitals.

The positive effects of peripheral cues such as electronic Word of Mouth (e-WOM), expertise cue, and hospital reputation on the intention to visit offline indicate that, although information quality is essential, peripheral cues also play a significant role. This is especially true for patients who may not be motivated to process central information in detail, aligning with the peripheral route of the ELM. The study's results suggest that a physician's online reputation, as reflected in e-WOM, expertise cues, and associations with reputable hospitals, can significantly influence patient behavior. This highlights the growing importance of online reputation management for online physicians.

The study found that patient involvement strengthens the impact of the information quality of physicians' responses on patients' intentions to visit offline. Patients with higher involvement are more likely to be persuaded by responses with high information quality. This suggests that online physicians must respond with higher-quality information to attract these patients more effectively.

However, patient involvement does not negatively moderate the impact of peripheral cues on the intention to visit offline. The results show that highly involved patients place more emphasis on peripheral cues than those with lower involvement. A possible reason is that medicine is a highly specialized field with significant information asymmetry. Highly involved patients may be able to analyze the quality of information in physicians' responses to infer the quality of medical services. Still, other potential factors affect the quality of medical services. Patients with higher involvement can use peripheral cues to judge the impact of different potential factors. Therefore, compared to patients with lower involvement, they also care more about peripheral cues. Thus, highly involved patients are not satisfied with judging the quality of physicians' services solely based on the central route; they need more information and clues to assess the quality of physicians' services as much as possible, and therefore, they also care more about physicians' peripheral cues.

Theoretical implications

This study integrated the ELM and Grice's maxims and applied them to the field of OHCS, enriching the application of these theories and offering a new perspective on how patients form intentions to visit offline through persuasive content provided by online physicians. The results show that information quality and peripheral cues positively affect patients' intentions to visit offline and that involvement positively moderates the impact of information quality.

Secondly, by quantifying the amount of information, reliability, relevance, and understandability to assess the quality of physicians' persuasive content, this study offers a new perspective on evaluating the quality of information in online medical communication. It also underscores the pivotal role of this quality in the communication process between physicians and patients. The quality of online medical communication can significantly affect patients' trust in online physicians and their adherence to medical advice. Patients receiving high-quality communication are more likely to accept the physicians' advice, reducing the losses associated with delays in seeking offline visits.

Thirdly, this study enriches the literature on patient behavior regarding offline visits. Previous research has not fully explored the impact of information and persuasive content in OHCS. OHCS offers a convenient communication platform for patients and physicians, enabling physicians to persuade patients of the need for offline visits, thereby reducing the chances of patient delays. This work examines how physicians' persuasive messages affect patients' intentions to visit offline and finds that online information and interactions influence patients' offline visit behavior.

Lastly, contrary to expectations in the context of OHCS, the study did not confirm the negative moderating effect of involvement on peripheral cues; instead, it showed that peripheral cues still strongly impact highly involved patients. When patients are more involved, they pay more attention to the quality of physicians' services and focus more on peripheral cues. Concurrently, the abundance of online physician resources and the convenience they offer enable patients to obtain information about both the information quality of physicians' responses and peripheral cues.

Practical implications

This study has several practical implications. First, online physicians can help patients decide to visit offline by following Grice's maxims (quantity, quality, relevance, and manner). The results indicated that the amount of information, reliability, relevance, and understandability could promote patients' offline visits. Therefore, when replying to patients, physicians should provide more information closely related to their conditions, use concise and easily understandable sentences, and ensure the reliability of their responses (as shown in Appendix E, Table E1). This approach can enhance patients' perception of information quality and help them intend to seek offline visits.

Second, the volume of positive e-WOM, expertise cues, and hospital reputation positively affect offline visit intention. Physicians can benefit from their past efforts. Other physicians should aim to improve their e-WOM and clinical titles if they want more online patients to visit them offline.

Thirdly, patients who are highly involved are more likely to be affected by the quality of information. Therefore, for highly involved patients, physicians should pay more attention to the quality of information (that is, Grice's Maxims). Expanding on this, the practical implications suggest that physicians must recognize the high sensitivity of highly involved patients to the quality of medical information they receive. By adhering to Grice's maxims—the maxim of quantity (providing more information), the maxim of quality (ensuring the reliability of information), the maxim of relation (maintaining relevance), and the maxim of manner (expressing clearly and concisely)—physicians can enhance the effectiveness of their communication with these patients. This adherence strengthens the patients' intention to seek offline medical services.

Limitations and suggestions for future research

First, we selected appropriate proxy variables and used machine learning and other methods to measure the variables. However, we could not obtain data on patient characteristics for privacy reasons. In the future, we will consider using interviews and questionnaires to directly measure patients' behavioral and psychological variables to verify our conclusions further.

Second, since patients had screened physicians before consultation, there were inevitable biases in the data collected online. In the future, experiments simulating real situations can be used to study the information quality of physicians' responses, peripheral cues, and patient involvement in offline visit intention.

Third, our results showed that involvement enhanced the influence of peripheral cues on intention. Further exploration is needed to determine whether this is attributable to patients' lack of confidence in medical knowledge, physician resource abundance online, or both.

Conclusion

This research explored the effects of central route factors (following Grice's maxims) and peripheral cues (e-WOM, expertise cues, and hospital reputation) on patients' offline visit intentions. We also investigated the moderating effects of patient involvement on these relationships. The results showed that (1) central route factors, e-WOM, expertise cues, and hospital reputation positively affected patients' offline visit intentions, and (2) patient involvement positively moderated the effects of central route factors and peripheral cues on offline visit intention.

This study can help researchers better understand online patients' evaluations and offline visit behaviors in OHCS, thereby contributing to online and offline healthcare research. Moreover, this work provides some implications for practice.

Supplementary Information

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Supplementary Material 1

Supplementary Material 2

Supplementary Material 3

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Author contributions

Xianye Cao: Conceptualization, Methodology, Data Curation, Writing- Original draft preparation, Revision; Yongmei Liu: Conceptualization, Funding acquisition; Zian Fang: Data curation, Validation, Revision; Zhangxiang Zhu: Conceptualization, Revision.

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Data availability
Data is provided within the supplementary information files.

Declarations

Ethics approval and consent to participate
This article does not contain any studies with human participants or animals performed by authors.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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