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Special Communication

Exploring the impact of online information signals in leveraging the economic returns of physicians

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ABSTRACT

Introduction: With the growth in Internet technology, online rating websites encourage patients to contribute actively in rating their physicians. These rating sites provide more information for patients, such as electronic word of mouth (eWOM) and physician trustworthiness. Although several studies in e-commerce have investigated the role of eWOM and seller trustworthiness in the consumer purchase decision-making process and the price premium for products or services, studies on the role of different information sources that reflect the service quality and delivery process in choosing a competent physician remain scarce. This research develops a two-equation model to examine the effect of different signals, i.e., patient-generated signals (PGSs) and system-generated signals (SGSs), on patient choice, which is an important predictor of physicians' economic returns.
Methods: A secondary data econometric analysis and structural modeling using 2896 physicians' real data from a publicly available online physician rating site, i.e., *Healthgrades.com,* were conducted using a mixed-methods approach. A hybrid text mining approach was adopted to calculate the sentiment of each review.
Results: We find that both PGSs and SGSs have a significant impact on patient choice at different stages of health consultation. Furthermore, disease risk negatively moderates the association between PGSs and information search, while the impact of both signals on patient willingness to pay a price premium is positively moderated by the disease risk.
Conclusion: Our study contributes to the unified framework of signaling theory and Maslow's hierarchy of needs theory by making a clear distinction between PGSs or SGSs and their influence on patient decision-making across different disease risks. Moreover, PGSs and SGSs are two essential factors for physicians to increase their income.

1. Introduction

Online word of mouth has been emerging throughout the world since the rise in the Internet 2.0 usage in the first quarter of the 20th century. This emergence has attracted the attention of researchers in healthcare, who have sought to determine how health consumers have been searching physician reputation information as online reviews in different countries [1]. A recent investigation in seven European countries revealed that more than 40% of people who searched health information through these physician-rating websites (PRWs) found that information was essential in selecting a good doctor [2]. In Germany, 25% of survey respondents responded that they had frequently used Web 2.0 to explore physician information and other healthcare services [3]. In Holland, on the average, one-third of the population searched for doctor ratings to consult a good doctor [4]. A survey in the U.S. found that 59% of the U.S citizens believe that online doctor ratings are "satisfactory and somewhat important" when they searched for excellent quality clinical services and physicians [3]. PRWs provide valuable information for patients to track quality care. Physicians can enhance their popularity through these rating sites to obtain more patients [5]. Patients who obtain information from these sites about the physician's technical and interpersonal skills, care outcomes, staff manners, and hospital environment consider these features essential aspects in choosing a good doctor [5,6].

The trust level between health consumers and providers is diminishing now, which directly affects the doctor-patient relationship and has recently caused many medical disputes [7]. It is crucial for healthcare providers to become prepared for new technology and efficiently use social media to boost the level of trust with patients and establish popularity in the competitive health consultation market

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[8,9]. Trust building among health consumers is not such an easy task for doctors. If a physician does not have sufficient clinical knowledge and skills, then patients may have a difficult time evaluating the physician's reputation, even after their consumption of services [10]. To build their online reputation and popularity and charge a price premium for services, physicians have to identify a mechanism to satisfy patient needs so that the patient believes that the physician provides competent advice, responsible treatment, and empathetic care.

Historically, researchers have discussed the impact of user-generated content (UGC) (i.e., ratings and online feedback) and system-provided information (i.e., ranking of product) on consumer decision-making, i.e., hotel booking [11]; prerelease movie evaluations [12]; product ranking [13]; users' willingness to pay a price premium (WTPP), i.e., consumers' willingness to pay for accommodation [14]; reputation effects on online auctions [15,16]; and willingness to pay for products [17]. However, most of these investigations were carried out in the context of products, movies, and services, such as hotels and tourism (search and experience goods). Moreover, gaps are observed in the knowledge of the healthcare field because the consumer WTPP has not received substantial research attention in the online healthcare decision-making process.

Compared with search and experience goods, healthcare service is a credence good, i.e., a good whose quality is difficult to measure for consumers, even after consumption [18]. Compared with the purchase of the products, healthcare service is considerably different, mainly because it presents different characteristics than products, i.e., heterogeneity, inseparability, and intangibility. Evaluating the quality of online healthcare services relative to traditional e-commerce is difficult because the service provider knows the utility effect of the goods, thus leading an asymmetric information state. According to signaling theory [19], the receiver (patient) needs additional information (signals) about the sender (physicians) from different aspects to reduce the information asymmetry before they visit their doctor [20]. Furthermore, consultation decisions in an online environment, the product for sale is the healthcare provider, whereas from an e-commerce perspective, the product for sale is the product in the online store.

Extant studies on patient decision-making regarding physician consultations either focus on conventional approaches (i.e., survey-based questionnaire) or numerical ratings [3,21,22]. Using conventional approaches, the real-time behavior and emotional response of respondents is difficult to capture and data collection is costly and time consuming. Furthermore, the information from numerical rating is very limited in comparison with the review comments, results in the loss of valuable information. Although the success of online healthcare has mainly been associated with the feedback mechanism, the role of unstructured feedback along with numerical ratings has been ignored. Furthermore, the literature on online ratings reflects the low variance explained by the price premiums [16].

Since online platforms may provide a number of parallel signaling mechanisms, such platforms may represent an interesting approach to understanding how patient-generated signals (PGSs) and system-generated signals (SGSs) will impact the patient decision-making process to consult a physician. Patients' decision criteria for choosing a competent doctor may change after receiving signals from various sources. Doctors with positive signals about their service quality may receive more economic benefits than doctors with negative signals. Previous studies have established the positive association between the electronic word of mouth (eWOM) regarding physician service quality or reputation and patient consulting intention [22–24]; however, these variables are not directly related to the physician's economic benefit. Thus, it is interesting to elucidate different signaling mechanisms and their influence on physicians' economic returns. Furthermore, the effect of PGSs and SGSs on a patient decision-making process may be moderated by the patient expectation regarding the different level of needs, such as disease risk. For these reasons, this study proposes three fundamental research questions:

(1) How would PGSs affect patients' search for online health consultation information?
(2) How would PGSs and SGSs influence physicians' economic returns (i.e., WTPP)?
(3) Does disease risk moderate the relationships between PGSs or SGSs and the patient decision-making process?

To answer the above questions, this research suggests a research framework based on signaling theory and Maslow's hierarchy of needs theory. We formulate a two-equation model to investigate the impact of two types of signals, i.e., PGSs as eWOM and SGSs as physician trustworthiness on patient purchase decision-making process for a health consultation, i.e., searching for online information and paying a premium price (economic returns of physicians) in choosing a good doctor. We use a dataset of 2894 physicians including ratings and online comments collected from the U.S.-based PRW-Healthgrades.com (http://www.healthgrades.com/) on the basis of disease mortality.

The contributions of this study are fourfold. First, our research adds to the current e-health studies by investigating the impact of PGSs, and SGSs on the patient decision-making process for a health consultation. Second, we determine the impact of these two types of signals on different stages of the patient decision-making process using a mixed-methods approach. Third, because these signals are positively associated with business performance, this study identifies the impact of different signaling mechanism on physicians' financial performance. Fourth, based on the unified framework, the signaling theory improves information asymmetry to provide a better understanding of patient choice and Maslow's hierarchy of needs theory addresses individual needs because disease risk affects patient choice for a health consultation.

This study is organized as follows. In Section 2, we present a brief overview of the existing literature relevant to the constructs, then follows with the development of hypothesis and conceptual model in Section 3. Section 4 explains the proposed methodology and data collection. In Section 5, we present study results. We discuss study findings, implications, conclusions and future research in Section 6 and 7.

2. Literature review

2.1. Online health information

Information plays a vital role in changing an individual's beliefs and attitudes and dealing with uncertainty when suffering from health problems. With the growth of Internet technology, medical information is easily assessable to patients outside of the physician's clinic [5]. The Internet as an innovative technology has several benefits, such as ease of access, online interactivity, privacy, and the ability to shape messages. These benefits may explain the increase in the usage of innovative media as a source of health information, and several platforms on the Internet are available for e-health information consumption [22]. These online rating platforms provide a user friendly and helpful way for healthcare providers to interact with health consumers [5]. A health consumer could use online information channels to not only search for physicians' information but also evaluate physicians' health services as well [22]. The rapid advancements in online rating platforms have received significant consideration from the academic community [5,23,25]. According to Yang et al. [20], these rating websites provide safe and real-time information while offering the minimum cost to patients. Therefore, these platforms are considered a vital source of information to solve healthcare problems and assist patient to select a right doctor.

Some recent studies investigated the impact of online health information about service quality on patients' selection decisions [6,21,23,24,26,27]. Nonetheless, more studies are needed for how online information affect the patient's purchase behavior to consult a physician, and the current study aims to fill this research gap.

2.2. User-generated and system-provided information

PRWs offer patients a platform to find information about various physicians and then use this information for their health consultation. The information contains UGC and system-provided information [20,22]. UGC refers to the product type or information regarding different services contributed by users based on their consumption experience [28]. System-provided information refers to the information that the computer system chooses to show on a website based on the providers' popularity and contribution [29]. Previous studies have widely discussed the UGC and system-provided information [2,13,20,27,29].

With the development of online rating platforms, UGC as online feedback has played a valuable role in highlighting product and service information. This feedback mechanism supports the exchange of information, enhances trust, and helps service providers maintain a good reputation and obtain economic returns [14]. Several studies have discussed the impact of UGC on physicians, such as the star ratings and textual reviews, when evaluating the service quality of the physicians [2,20–22,24,30]. Along with UGC, system-provided information also plays a vital role in customers' decision-making. System-provided information represents the chunks of information produced by the system to display the behaviors of the system's users or quality of goods [20]. For example, a physician's reputation produced by the system is positively linked with the patient's behavior [25].

Due to information asymmetry and service characteristics, it is more challenging for patients to evaluate the service quality of physicians compared with the quality of products. Service quality not only depends on the service outcome but the delivery of service as well. Patients need additional information from various sources to evaluate the service quality outcome and delivery process of healthcare services. Two types of such information consist of (1) PGSs and (2) SGSs [20]. A PGS is defined as the signal corresponding to the outcome of a physician service quality posted by prior patients on PRWs who have experienced the healthcare provider before. PGSs cannot reveal the quality of service delivery. Therefore, SGSs can be useful because they refer to the physician trustworthiness (credibility) and attitude (benevolence) as criteria for evaluating the delivery of service quality. On this basis, this study investigates the impact of PGSs as eWOM and SGSs as physician trustworthiness on patients' decision-making process for a health consultation.

2.3. Consumer decision-making process

The customer's purchase decision is a cognitive process that affects his/her choice of a product and service [31]. So far, two research streams have made efforts to examine the purchase process. One involves the evaluation of the process through the utilization of several decision-making models, theories and frameworks [32–34]. The second stream investigates purchase decision-making by inspecting consumer behaviors, such as purchase attitudes and purchase intentions from the perspective of behavioral theories [35,36]. Consumers exhibit a similar process while purchasing online. For example, Liang and Lai [37] and Huang and Benyoucef [31] established a consumer decision-making process in an online environment that includes need recognition/product awareness, information search, evaluation of alternatives, and purchase and post-purchase.

Online feedback mechanism is emerging in the consumer market, which plays a significant role in the purchase decision-making process, i.e., information search and WTPP [14–17,28]. Information search denotes the other consumers' satisfaction towards the quality, accessibility, and ease of product or service usage [31]; whereas consumer's WTPP reflects the maximum price, a buyer is willing to pay to a seller or provider for a product or service with no transaction risk [38]. Consumers' WTPP has always been a concern for sellers for their pricing decision [16]. Several studies examined the impact of review characteristics on WTPP [39,40]. Customers' online feedback can influence price premium by providing information regarding perceived value and quality of a product and service [15]. Previous studies identified volume, valence, and variance as credible characteristics of eWOM in determining the customers' WTPP [15,17].

Trust has long been considered as a positive component of the buyer–seller relationship [16]. For example, Pavlou and Dimoka [16] examined the process through which online information shapes the price premium by engendering a buyer's trust in the seller's benevolence and credibility. Huang et al. [41] found that online product information enhances trust and credibility, in turn, lead to an increase in the price premium. Comparing existing studies in an online context, patients also search online information to seek technical and other characteristics of a physician service quality [24]. On PRWs, patients seek different stages for selection of their physicians, i.e., the process of information search, evaluation of alternatives and decision-making. In the information search stage, patients search for a primary list of physicians regarding their health status, disease information, and recommendation from other patients. In the initial search stage, patients can only access a little knowledge, i.e., the PGSs. Based on the initial information, patients decide whether to choose or visit the profile page of a physician or not. When patients visit the physician's profile page, they obtain SGSs that can help further for information evaluation regarding a physician. When patients' expectations meet their needs lead to satisfaction and pay a price premium (physicians' economic returns) for health consultation, which is the paramount criteria in choosing the right doctor [9,18,26]. A complete understanding of eWOM and trust-purchase process (i.e., information search and WTPP) in healthcare settings would bring important implications for physicians to formulate their pricing strategies-a key area of online healthcare research that needs more attention [26].

2.4. Patient motivations in online healthcare

Level of needs and motivation changes an individual's behavior. According to Maslow's hierarchy of needs theory [42], low-level needs and expectations, such as physiological requirements and care must be satisfied before high-level needs, i.e., self-fulfillment, are followed. When basic customer needs are fulfilled, it moved to a higher level of needs. In healthcare, patients' needs may vary across different disease types [43]. Adapting Maslow's hierarchy of needs theory in an online medical context, some doctors fulfill low-level needs should be essential for low-risk disease, and some other doctors fulfill high-level needs should be essential for high-risk disease. Therefore, several patients have a fewer expectation regarding online information and physician trustworthiness (i.e., low-risk disease), whereas others reflect the high-level expectations regarding online information and physician trustworthiness (i.e., high-risk disease). Patient's characteristics significantly affect their satisfaction level with service quality. Previous studies adapted Maslow's hierarchy of needs theory in an offline medical context [44,45]. Therefore, in this study, we will examine the moderating effect of disease risk on the relationship between PGSs or SGSs and patient decision-making process in an online healthcare context.

2.5. Signaling theory

Spence [46] indicated that information asymmetry regarding transactions may exist between different parties during information transmission. The signaling theory posits that signals are useful in shaping behavior and help to reduce information asymmetry between different stakeholders [47]. Signaling theory acknowledges that signalers as a sender (insiders) have access to information, while receivers (outsiders) do not have access to this information [48]. In the online environment, signals are pieces of information a sender uses to convey credible information to the receiver about the attributes of the sender. A signal represents a significant function that can diminish the information gap, which is important because spatial and temporal gaps amplify information asymmetry between different players [49]. Receivers also play an important role in the signaling cycle. Hence, the sender may send some information (signals), whereas the other player, the receiver, may select how to interpret the signal. The effectiveness of the signal depends on whether the receiver attentively scans the surroundings for signals, thus accepting a level of competency by the sender [19]. Information has a significant impact on players' decision-making, with the more the information a player has, the better the decision s/he will make [48].

Signaling theory involves the analysis of various types of signals and the contexts in which they are used. Signals transfer information about the signaler qualities and the receiver examines the credibility and validity of a signaler's quality and takes action [49]. In addition, signaling theory also assumes that the commitment transmitted by a signal is important for a receiver who believes that the sender is respected; otherwise, not fulfilling promises will be economically risky for companies, which will lose their reputation. Therefore, providers with high-status and high-service-quality signals will lead to positive consumer behavior [50]. Studies in the field of consumer behavior have extended signaling theory from information economics to fields that include management, marketing, and e-commerce [48,49].

In the case of healthcare, when patients do not have sufficient information, substantial information asymmetry occurs between the healthcare providers and consumers, with the providers having the chance to deceive their patients. To decrease information asymmetry, signaling theory is helpful for resolving this problem. Patients who are unsure about healthcare quality hope to interact with other individuals who have information. Therefore, the opinions of other stakeholders that are independent of the signalers can be helpful because they reveal the signalers' reputation, credibility, and qualities to minimize information asymmetry [20,51]. Researchers have also extended signaling theory to investigate various signals in healthcare [18–20,51]. This study fills the previous research gap, which mostly focused on the sender's perception, while receiver perception was mostly ignored. The association between signals and constructs related to the sender's performance could reveal a significant influence on the receiver's perception.

2.5.1. Signaling framework for the patient purchase decision-making process

To establish a comprehensive signaling framework for a patient purchase decision-making process, we reviewed previous studies in an online healthcare context [19,20,23,25]. Although, limited research on patient's purchase process could not offer broad signals mechanism, and differences among healthcare providers may vary the information in the decision-making process. We introduce two types of signals in a patient's perspective, i.e., PGSs and SGSs.

Patient-generated signals: Regarding the first type of signals, cues presenting others' influences are important in signaling framework. Given that the patient opinion regarding different aspects of service quality influences patient purchase decision as it diminishes the uncertainty towards a service, Yang et al. [20] indicated that substantial information asymmetry exists between healthcare providers and consumers. Online contributions, such as ratings and experience from others, can be considered in reducing the information asymmetry between them [23]. Wu and Lu [25] examined physician reputation in terms of overall ratings as an important signal that may affect health consumer perception.

System-generated signals: Regarding SGSs, we identify physician trustworthiness as an additional factor that may reduce information asymmetry. Information regarding provider trustworthiness displayed on a physician's profile page may influence the patient purchase decision. Given that, provider trustworthiness transmits the credibility signals to the sender, Hampshire et al. [51] indicated that signal of trustworthiness (honesty or courage) is a key factor in treatment decisions. Other studies like Liu et al. [23] and Wu and Lu [25] examined that a physician and hospital reputation are critical factors in the patient decision-making. In the patient's decision-making process, signals like credibility and benevolence affect a provider's trustworthiness. More efforts are required to establish trust when trust established between sender and receiver; it is hard to change.

2.5.2. Unified framework of signaling theory and Maslow's hierarchy of needs

An earlier comprehensive discussion demonstrates signaling theory can be combined with Maslow's hierarchy of needs theory to get a valuable insight on information interaction between sender and receiver and patient purchase behavior in different environments. The unified framework is applied as a theoretical foundation to support the model proposed by the current study due to two reasons. First, both signaling theory and Maslow's hierarchy of needs theory consist of information interaction across different level of human motivation. Second, we split information interactions into information transmission and their effects across different environments. Signaling theory mainly describes the impact of different signals on the receiver's opinion but neglects the receiver's perception, whereas Maslow's hierarchy of needs theory explains the receiver's perception across different level of needs and expectations but does not define the criteria for signals. Hereafter, two steps for unifying the theories could be followed: First, classify possible signals as PGSs and SGSs from signaling theory; second, transform signals in the receiver's perception and the uncertainty associated with the services that can be minimized by the different signals depending on the disease type based on Maslow's hierarchy of needs theory. All of these explanations reveal that the unified framework could not only increase the benefits of signaling theory and Maslow's hierarchy of needs theory but also fill their gaps. For signaling theory, the sender can address the receiver's concerns by identifying the psychological state of the receiver, and thus transmitting information in an effective manner. For Maslow's hierarchy of needs theory, the disease type improves the effectiveness of the differential effect of signals on the receiver's perception.

3. Research hypotheses

We developed a research framework to explore the impact of PGSs and SGSs on the patient decision-making process for a health consultation. With regards to PGSs as eWOM, we consider four eWOM dimensions: volume, valence, variance, and sentiment. Regarding SGSs as physician trustworthiness, credibility and benevolence are taken into account. For the decision-making process, we consider two stages: the search stage as the information search and evaluation and decision to pay a price premium stage as the WTPP. Finally, this study investigates how the impacts of different signaling mechanisms on patient decision-making process vary across different disease types. Fig. 1 shows the research model for this study.

3.1. Search stage

Physician information is important for health consumers when exploring and selecting alternatives for consultation. Based on available information, i.e., PGSs, patients decide to visit the physician's profile page to obtain more information [20,22]. Prior studies have acknowledged that informational social feedback is the main component in efficient signaling processes among signal receivers. One of the common information social feedback mechanisms is eWOM [18], which is a written message on a website posted by a consumer with prior consumption experience, and it may impact potential customer behavior [14]. Additionally, recent studies in healthcare found that eWOM has a substantial role in minimizing information asymmetry for health consumers by influencing their decision-making process for health consultation [18,20,23].

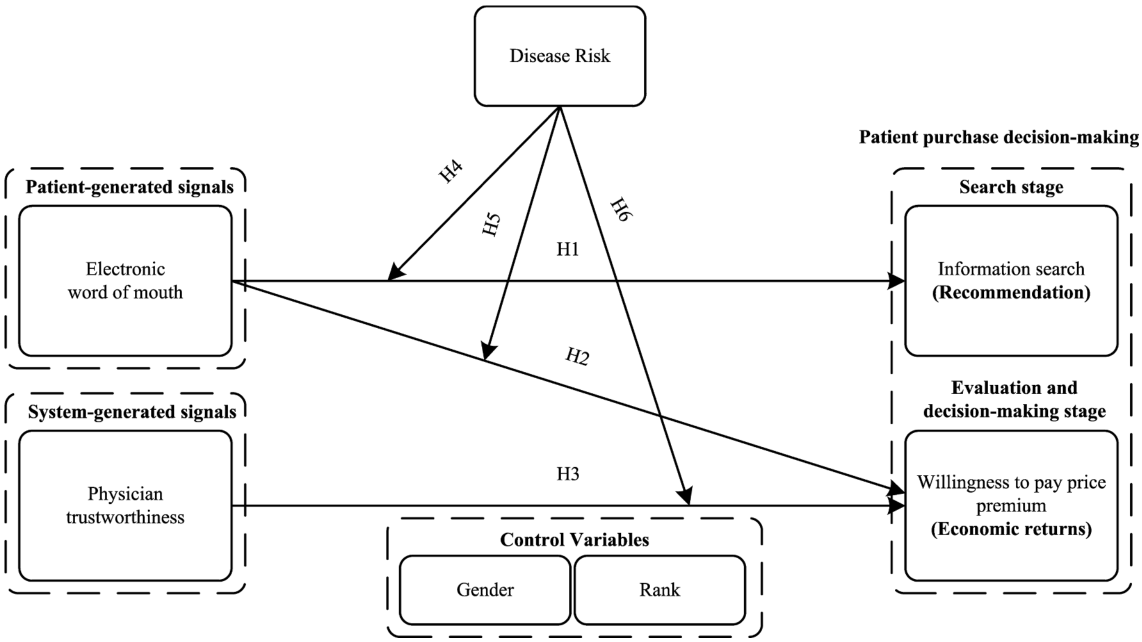

Fig. 1. Research model.

On PRWs, PGSs, i.e., ratings and feedback come from those consumers who have consulted a particular doctor before, thus helping other health consumers to assess the physician's service quality. Studies have found that online feedback influences users' behavior through three effects. The awareness effect [52] indicates that eWOM encourages consumers to be conscious of service quality for decision-making. The more consumers discuss a service, the higher the awareness among other consumers (i.e., the volume of online feedback). The persuasive effect [52] indicates that online feedback has an essential role in determining consumers' attitudes, evaluations and decision towards service consumption (i.e., the valence of online feedback). The dispersion effect indicates the extent to which people have different views about a particular service (i.e., the variance of online feedback) [53].

The marketing literature has revealed that sentiments play a vital role in changing consumers' beliefs, attitudes, and decisions. Online reviews effectively communicate message sentiments that significantly inspire the readers' perception [54]. Social media in the medical context is used to post online reviews in the form of emotional communication. Some emotional expressions, such as expressing and posting positive messages and exhibiting sympathy, can support patients with severe diseases. The sentiment is the vehicle for other patients to express their opinion through text reviews. A recent study investigated patients' emotions towards different aspects of hospital service quality [30]. James et al. [27] analyzed patient opinions to assist physicians to improve their healthcare service quality. From the earlier discussion, it is clear that information plays a key role in the patient's choice to consult a doctor. Thus we hypothesize the following:

H1. Patient-generated signals (eWOM) regarding physician service quality positively influence patient searches (recommendations) for health information.

3.2. Evaluation and decision-making stage

Online WOM creates a new information channel that can be used to evaluate the consumers' feelings towards their doctor [2]. These feelings can be valuable for doctors and organizations to improve their service delivery process to gain more economic returns [18]. In the online context, the literature proposes that the consumer's attitude towards products affects their purchase intention. For instance, in healthcare, Yang et al. [20] found that attitudinal beliefs are correlated to behaviors, e.g., information search and buying can significantly influence a consumer's intention to complete a transaction. A physician with positive online WOM can increase their income because people may pay more for health services associated with a positive online reputation [18]. Existing research shows a significant connection between eWOM and physician economic returns [26,55]. Therefore, information about physicians' service quality from other patients is important in the decisions to pay a price premium for health services. Thus, we hypothesize the following:

H2. Patient-generated signals (eWOM) regarding physician service quality positively influences the willingness to pay a price premium (WTPP) for a health consultation.

Consumers commonly search for the quality of a physician and trustable clinical information before consulting a physician [56]. Patients have a higher expectation about popular services and must explore more information about physicians' quality regarding the process of service delivery, which is produced by an intermediary platform that is autonomous of the healthcare service providers and patients. As the physicians' service delivery quality is related to the website, physicians' data on the website describe the physician's service process quality [20]. In the e-health context, patients will have a high expectation and trust in the physician's reputation [25]. Patients must trust their doctors to decide on desirable treatment outcomes regardless of the risks associated with diagnosis and treatment [56]. PRWs provide a medium for doctors to signal their trustworthiness. A trust belief is the sentiment, or expectation about an exchange partner's trustworthiness [7].

In the marketing literature, trust consists of two dimensions: credibility and benevolence. First, credibility is described as the degree to which a patient believes that a doctor has the ability and expertise to provide effective and reliable services [51,57]. Physicians can signal their credibility concerning competence along with efficient and reliable health consultation services [23,24]. Physicians who send stronger credibility signals may adopt a superior position to build a stronger relationship with the patients. Second, benevolence is described as the degree to which a patient (trustor) believes that a physician (trustee) is sincerely concerned in his/her (trustor) welfare and has an intention to benefit the patient (trustor). Researchers found that a caring manner, empathy, and honesty were the antecedents of benevolence [16,55]. Since physicians' benevolence is a substantial predictor of patient's choice, physicians who send stronger credibility signals may have a more positive impact on patients' visit intention and thus can charge a price premium.

Prior research has described the impact of provider characteristics on the patient purchase decision-making process. For example, Yang et al. [21] suggested that the physician response speed and interaction frequency could affect patient satisfaction, which in turn influences the patient's decision-making. Wu and Lu [25] found that a physician's reputation has a significant impact on patient decision-making to share his/her experience online in order to assist other patients. Wu and Lu [26] argued that the physician service quality in terms of the price of online services and the number of offered services have an impact on patient satisfaction. Lu and Wu [24] found that the high technical skills and functional quality of a physician affect the consultation intentions of patients. Patients also search online information to identify the technical and other characteristics of a physician as paramount criteria in choosing a competent healthcare provider and paying a premium price for healthcare consultation services [6,9,18,23,26,55]. The results confirmed the health consumers' perception that physician trustworthiness is the key factor underlying the search for clinical information by patients and their WTPP for health services. Thus we hypothesize the following:

H3. System-generated signals (physician trustworthiness) positively influence a patient's willingness to pay a price premium (WTPP) for a health consultation.

3.3. Moderating effect of disease risk

According to Maslow's hierarchy of needs theory, in the healthcare context, patients' needs significantly affect their satisfaction levels with online information about service quality. These needs are associated with their disease risk and illness severity [21,43]. Disease risk explains why patients' satisfaction is associated with physician services, which vary between patients. Several researchers have focused on the effects of eWOM on patient decision-making across different disease risks [21,22]. For example, Lu and Wu [24] suggested that online WOM is more influential for high-risk disease than low-risk disease.

Patients suffering from acute disease tend to be more sensitive to the aspects of physicians' trustworthiness than those suffering from mild disease. Scholars have found that patients suffering from acute disease feel more pain and anxiety than patients suffering from mild disease and thus are keen to search for competent doctors and healthcare services to deal effectively with their diseases [21,24]. In healthcare, differences in the disease risk level affect a patient's perception of the providers' competence, service quality, and satisfaction. Because disease risk is related to mortality, patients with severe disease are highly motivated to expend greater cognitive efforts to find a knowledgeable, honest and caring physician [21,22]. These patients are likely to search for physicians who are competent and provide higher-quality care and do not solely rely on PGSs. When comparing patients with high-risk disease to patients with low-risk disease, low-risk disease patients have fewer expectations regarding a doctor's trustworthiness and service quality. Therefore, we hypothesize the following:

H4. Disease risk has a negative moderating effect on the association between patient-generated signals (eWOM) regarding physicians' service quality and patients' search (recommendation) for health information.

H5. Disease risk has a positive moderating effect on the association between patient-generated signals (eWOM) regarding physician service quality and patient willingness to pay price premium (WTPP) for a health consultation.

H6. Disease risk has a positive moderating effect on the association between system-generated signals (physician trustworthiness) and patient willingness to pay price premium (WTPP) for a health consultation.

4. Methodology

4.1. The research context

Our research context is Healthgrades (*healthgrades.com*), a U.S. based corporation that provides more than 3 million U.S healthcare providers information. This site has been among the other highest traffic rankings websites, received more attention from the medical and other professions. Patients rate their physicians or write comments online based on their healthcare experience. We chose Healthgrades to investigate our hypothesis because this website contains rich data about the physician's specific skills to signify his or her competency, physician's location (city and state), specialty, and board certification, etc.

4.2. Sample and data collection

A web crawler was developed coded in Python 3.6 to scrap web pages of physicians and related information on October 4, 2018. The data were collected for those physicians who treat ten types of diseases. These diseases are selected on the basis of disease mortality rate from the U.S. health static book 2016 [58] (see Table 1). The data collection process lasted one month, after which we obtained information of 2896 physicians from two metropolitan areas (California and New York). Both these areas contain the highest number of physicians with an active board license [59]. For each physician in our dataset, we collected

Table 1
Number of reviews, physicians, and ratings across different disease specialty.

	Disease specialty	Reviews	Reviews %	Physicians	Physicians %	Reviews/Physician	Average Ratings
High-risk disease	Heart disease	16320	29.9	701	24.21	23.28	4.39
	Cancer disease	3295	6.04	276	9.53	11.94	4.28
	Chronic lower respiratory	471	0.86	45	1.55	10.47	4.25
	Unintentional injuries	2328	4.26	89	3.07	26.16	4.17
	Stroke	1805	3.31	74	2.56	24.39	4.19
Low-risk disease	Alzheimer disease	14740	27	634	21.89	23.25	4.02
	Diabetics	1202	2.2	118	4.07	10.19	3.72
	Influenza and pneumonia	8655	15.86	512	17.68	16.90	4.17
	Nephritis	2745	5.03	156	5.39	17.60	3.75
	Nephrotic syndrome and nephrosis	495	0.91	68	2.35	7.28	4.08
	Suicide	2532	4.64	223	7.70	11.35	4.12
	Total	54,588	100	2896	100		4.10

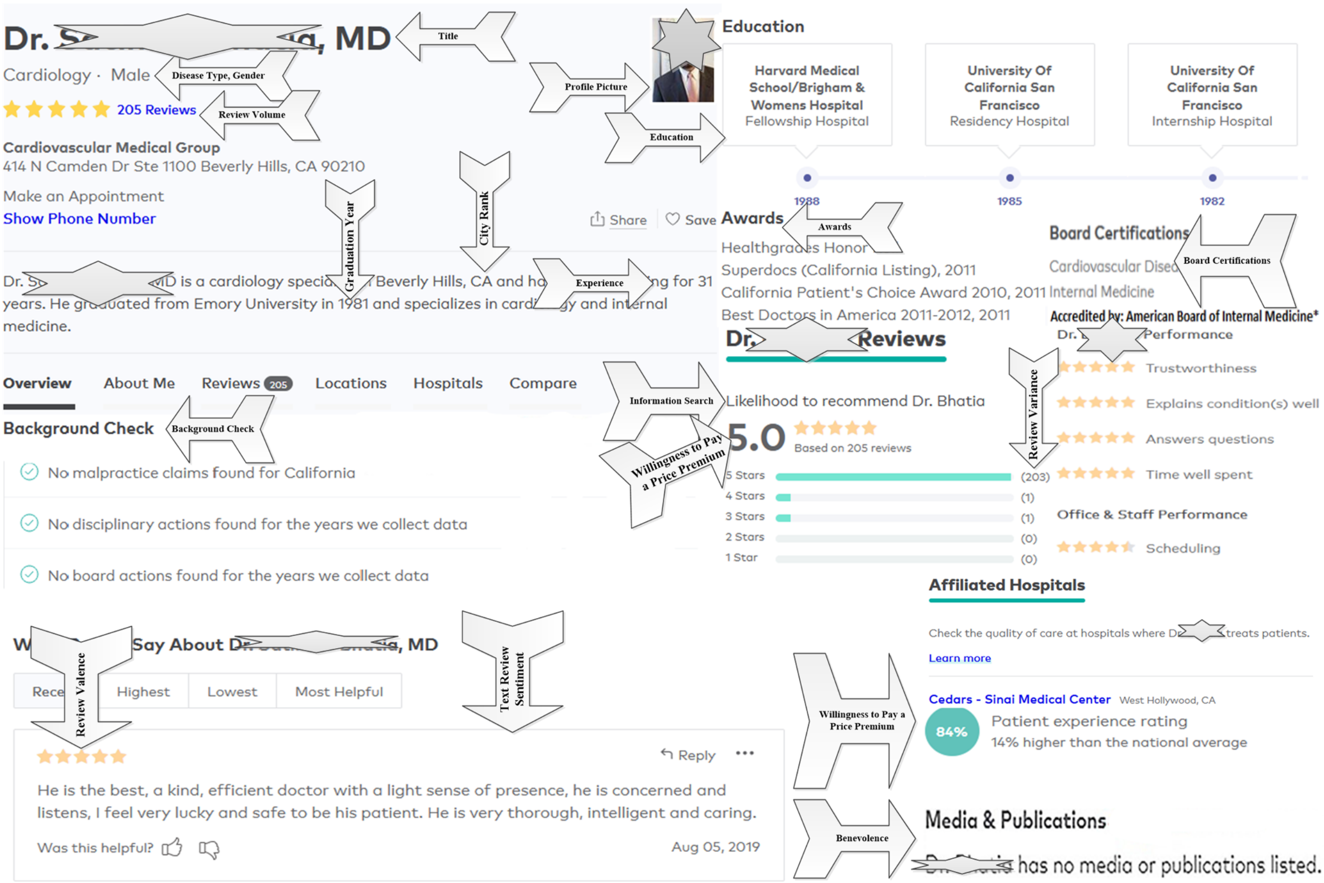

Fig. 2. Screenshot of variables defined in our model.

his/her reputation and service information, specialty, and the city physician belongs to. Details of this information are presented in Fig. 2.

Table 1 shows the distribution of reviews in our dataset. We chose the top two diseases from each category for study analysis: Physicians treating high-risk disease, i.e., Heart disease and Cancer disease received about 30% and 6% of all reviews, respectively. While for low-risk disease, i.e., Alzheimer disease and Influenza and pneumonia received 27% and 16% of all reviews, respectively. These diseases also contain a large number of physicians with approximately 24% and 10% for high-risk disease, and 22% and 18% for low-risk disease, respectively. Physicians treating Stroke receive a greater number of reviews/physician (24) than other diseases except for unintentional injuries (26). But the number of physicians treating Stroke is much smaller than Heart disease, Cancer disease, Unintentional injuries, Alzheimer disease, Diabetics, Influenza and pneumonia, Nephritis, and Suicide. For high-risk disease, patients suffering from Heart disease and Cancer disease highly rate their physicians, i.e., 4.39, and 4.28, respectively. While for low-risk disease, patients' highly rate the Influenza and pneumonia, and Suicide, i.e., 4.17 and 4.12, respectively.

4.3. Variables operationalization and empirical models

Variables and their descriptions are shown in Table 2. A two-equation model is used to examine the patient decision-making process for a health consultation.

4.3.1. Patient consultation decision-making

Our empirical strategy uses patient consultation decision-making as a dependent construct. Patient consultation decision-making comprises two variables, i.e., information search (*Recommendation*) and willingness to pay a price premium (*WTPP)* for health consultation services.

(1) Information search is measured by the total number of recommendation votes received for each doctor. Patients seek recommendation from others while searching for information online about a doctor and disease s/he treats. Since it is most likely that eWOM regarding service quality and provider trustworthiness has a positive impact on patients' *WTPP* [18,26,55], we assumed that the number of patients who repeatedly visit their doctor might be satisfied with the healthcare services received during their visit to the hospital or clinic. Posting higher ratings bring feelings in these patients that they have received great care against the money which they paid for health services. Patients who search information online, also assess satisfaction rating and overall patient experience with a particular doctor in order to pay a price premium. Greater the patient satisfaction and positive experience with a doctor, the more the patient pay price for healthcare services. Therefore, *WTPP* is measured by, (2) average satisfaction score for each doctor, and (3) a dummy variable, overall patients experience.

4.3.2. Patient-generated signals and system-generated signals

The independent constructs include PGSs and SGSs. The PGSs is measured using the proxy variable *eWOM*. We considered review volume, valence, variance, and sentiments in measuring *eWOM,* following the previous studies [14,38,53]. (4) Volume of feedback is measured by the total number of reviews, (5) valence is measured by the number of positive, negative, and neutral ratings, [38], (6) whereas standard deviation of the satisfaction ratings reflected the variance in online physician ratings, following Langan et al. [53]. 7) In order to determine the emotional response (sentiment score) of a patient toward provider, the current study adopted a hybrid approach (sentic computing) in Section 4.4 that follows the state-of-the-art text mining techniques discussed in previous studies [60–63].

We used physician trustworthiness as a proxy of SGSs.

Table 2
Variables description.

Type	Constructs	Variables and symbol	Measure items and scale type	Explanation
DV	Patient consultation decision-making	Information search (Recommendation)	1) Recommendation star (I)	The total number of recommendation votes for each doctor from patients
		Willingness to pay price premium (WTPP)	2) Service star (O)	Average satisfaction score for each doctor in a review (3, Neutral = 0; 1–2, Negative = 1, 4–5, Positive = 2)
			3) Experience (D)	Overall patient experience with the healthcare system (1 if ≥70% (i.e., National health average)), 0 otherwise
IV	Patient-generated information (PGSs)	Electronic word of mouth (eWOM)	4) Volume (I)	Total number of reviews
			5) Valence (O)	Number of positive, negative, and neutral ratings (3, Neutral = 0; 1–2, Negative = 1; 4–5, Positive = 2)
			6) Variance (I)	Standard deviation of satisfaction ratings received for each doctor
			7) Sentiment (I)	Sentiment score of a review
	System-generated information (SGSs)	Physician trustworthiness (Trustworthiness)		***Credibility***
			8) Title (D)	1 if medical doctor, 0 otherwise
			9) Picture (D)	1 if profile picture available, 0 otherwise
			10) Graduation (O)	Graduation year (before 1980 = 0, 1980–1989 = 1, 1990–1999 = 2, After 1999 = 3)
			11) Experience (O)	Doctor's practice experience (0–9 years = 1, 10–19 years = 2, more than 19 years = 3)
			12) Education (D)	1 if graduated from U.S. top 100 medical schools, 0 otherwise
			13) Certification (D)	1 if board-certified, 0 otherwise
			14) Malpractice (D)	1 if malpractice claim, 0 otherwise
			15) Action (D)	1 if board has taken action, 0 otherwise
			16) Sanctions (D)	1 if board imposed sanctions on a physician, 0 otherwise
			17) Awards (I)	The number of doctor's awards and recognitions received
				Benevolence
			18) Replies (I)	The number of doctor's replies to the reviews
			19) Publications (I)	The number of doctor's publications
MV	Disease Risk	Risk	20) Risk (D)	1 if high-risk disease, 0 otherwise
CV	Physician Gender	Gender	21) Gender (D)	1 if male, 0 otherwise
	City rank	Rank	22) Rank (D)	California = 0, New York = 1

*DV: Dependent Variable; IV: Independent Variable; MV: Moderating Variable; CV: Control Variable; I: Interval; O: Ordinal; D: Dummy.

Trustworthiness is measured by the credibility and benevolence, in line with previous studies [16,55]. Furthermore, we used medical boards data and other web sources as the measurement of credibility and benevolence [59,64–66]. (8) Every physician has his/her own professional title in the hospital, based on medical capability and skills. Our dataset includes only fewer physicians without title, so in measuring the physician title we used dummy *Title,* following Lu and Wu [24]. (9) Physician's Profile *Picture* as a dummy variable may draw more attention to the reviewers. When an image is displayed beside text on a review site, patients split their attention between the photographic and textual information in evaluating the source credibility [67].

Studies also suggested that linking ratings with the state medical board data, board-certified and doctors graduated from higher-ranked schools had superior ratings, although the differences were very small. There are several possible justifications for this motive, (10) younger physicians graduated from medical schools in early years were less likely to be rated, (11) previous statistical evidence suggested that highly experienced physicians are more likely to be preferred by patients in the future [24]. *Education* and *Certification* as dummy variables, (12) for *Education*, it is highly likely possible for patients knowing their healthcare provider school standings or (13) their state board *Certification* status; hence, these ratings may biased towards being more favorable. Furthermore, patients are keen to identify a competent physician, and their reputation reflects the quality of care. (14)(16) Researchers revealed that physicians with malpractice background during the past ten years might receive marginally lower ratings (dummy; *Malpractice*, *Action*, *Sanctions*) [68]. (17) Finally, the more awards awarded to a physician, the more credible s/he perceived to be [21].

Referring to the signaling theory, benevolence is the patient belief, a doctor is concern about his/her health [55]. Following Pavlou and Dimoka [16], Chen et al. [55], and state medical boards data, benevolence is measured by (18) the number of doctors' replies to a review, and (19) the number of publications listed by a physician.

4.3.3. Moderating variable

20) We operationalized the moderator disease risk with a dummy variable (*Risk)* from the perspective of mortality rate. *Risk* with high

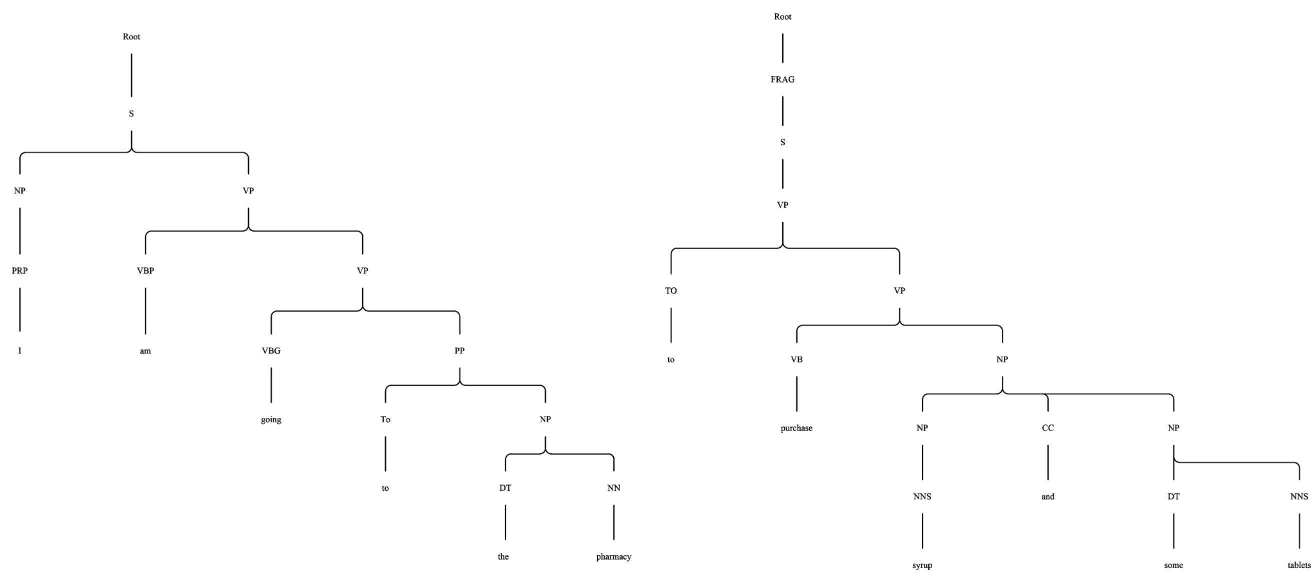

Fig. 3. Parse tree.

disease mortality is equal to 1; otherwise 0 [24].

4.3.4. Control variables

To investigate the empirical rigor, a robust set of control variables were introduced in our model. These control variables might influence patient decision-making process [18,55]. For controls, two dummy variables, (21) *Gender*, and (22) *Rank* are used to measure the physician gender and city rank, respectively.

To verify our hypothetical relationships regarding the direct impact of PGSs (*eWOM*) and SGSs (*Trustworthiness*) on patients' decision-making process, we formulate two equations: Therein, we investigate patients' information search (*Recommendation*) as Eq. (1) (search equation), and Eq. (2) examines the patients' willingness to pay price premium (*WTPP*) for health consultation services (decision equation). Due to the abnormal distribution, log transformation was used in our empirical models for dependent and continues variables. The patient purchase decision-making process equations are as follows:

$$\log(Recommendation_i) = \beta_0 + \beta_1(eWOM_i) + \beta_2(eWOM_i) \times Risk_i + \beta_3(Gender_i) + \beta_4(Rank_i) + u_i \quad (1)$$

$$\begin{aligned}\log(WTPP_i) = {} & \beta_5 + \beta_6(eWOM_i) \\ & + \beta_7(Trustworthiness_i) + \beta_8(eWOM_i) \times Risk_i \\ & + \beta_9(Trustworthiness_i) \times Risk_i \\ & + \beta_{10}(Gender_i) + \beta_{11}(Rank_i) + \varepsilon_i \end{aligned} \quad (2)$$

$$eWOM_i = \beta_{11}\log(Volume_i) + \beta_{12}(Valence_i) + \beta_{13}(Variance_i) + \beta_{14} \log(Sentiment_i)$$

$$Trustworthiness_i = \beta_{21}(Credibility_i) + \beta_{22}(Benevolence_i)$$

$$\begin{aligned}Credibility_i = {} & \beta_{31}(Title_i) + \beta_{32}(Picture_i) + \beta_{33}(Graduation_i) \\ & + \beta_{34}(Experience_i) + \beta_{35}(Education_i) \\ & + \beta_{36}(Certification_i) + \\ & \beta_{37}(Malpractice_i) + \beta_{38}(Action_i) + \beta_{39}(Sanctions_i) + \beta_{40}\log(Awards_i)\end{aligned}$$

$$Benevolence_i = \beta_{41}\log(\mathrm{Replies}_i) + \beta_{42}\log(Publications_i)$$

where β_s are the parameters estimates for the Physician$_i$, β_0 *and* β_5 are the intercepts. Further, we define dummy variables as *Title, Picture, Education, Certification, Malpractice, Action, Sanctions, and Risk.* The variables ($eWOM_i$) × $Risk_i$ and ($Trustworthiness_i$) × $Risk_i$ are interaction terms, and μ_i, ε_i are the error terms. Lastly, *Gender* and *Rank* are dummy control variables.

4.4. Sentiment analysis via sentic computing

Sentic computing has been used to address classification (positive or negative) tasks of natural language text. Sentic computing is a hybrid approach to the affective computing and sentiment analysis, which exploits both knowledge-based methods and statistical methods to perform emotion recognition and detect sentiments in natural language text [61].

4.4.1. Pre-processing

Given the dataset contains 54,588 online reviews of 2896 physicians, we performed some initial data filtering by removing URLs, filtering repeated words, i.e., Niceeeee (eliminate extra letters), sort out question words, such as who, why, whom, etc., do not contribute to polarity detection, and removing special characters ($, #, &, etc.). We also adopted an unsupervised approach in correcting the non-standard vocabulary (i.e., misspellings, acronyms, emoticons, internet slangs, and incorrect punctuations, etc.) [69].

4.4.2. Concept extraction

To extract concepts from the text, a semantic-based approach is adopted using semantic parser. The semantic parser splits a review into clauses and, hence, decompose such clauses into bags of concepts, to be later inputted to a vector space model.

In the proposed algorithm, we first split the text into clauses. Each verb and its allied noun phrase are considered to extract one or more concepts. To structure sentences, the Stanford Chunker [70] was applied to chunk input text, e.g., I am going to the pharmacy to purchase syrup and some tablets" would be split into "I am going to the pharmacy" and "to purchase syrup and some tablets". Next, the semantic parser uses a tree structure to deconstruct clauses into noun chunks and verb chunks [61,63,71] (see Fig. 3).

Next, clauses normalization is performed in two stages: (1) *Verb* chunk is normalized using the Stanford WordNetLemmatizer algorithm, (2) each potential *noun* chunk allied with individual verb chunks is coupled with the lemmatized verb in order to identify multi-word expressions in the order 'verb plus object'. The Stanford Part-of-speech (POS) based bi-gram algorithm scans noun phrases for stop-words and adjectives. Furthermore, noun phrases are first divided into bigrams and then processed through POS arrangements, as presented in

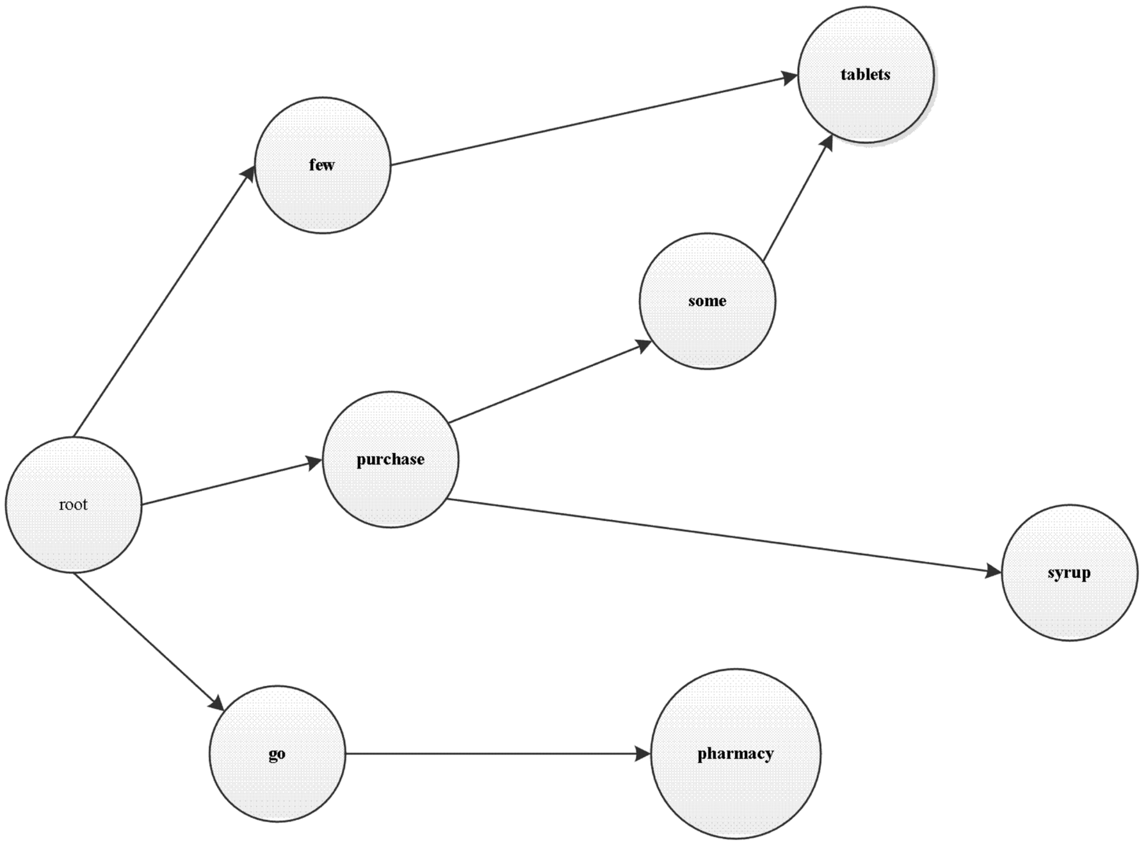

Fig. 4. A pattern of parse graph for multi-word expressions.

Algorithm 1 (Appendix A) and according to the work of Cambria et al. [72].

Furthermore, a parse graph that maps all the multi-word expressions in the knowledge bases is used for event concepts identification (Fig. 4). To identify the event concepts, associations among the object concept and normalized verb chunks are examined [73]. Redundant information is discarded, single-word concepts, such as doctor occurrence in the clause as a multi-word concept, e.g., competent_doctor is redundant information. Algorithm 2 adopted from the work of Poria et al. [60], extracts event concepts, such as go pharmacy, purchase syrup, purchase some tablets, denoting concepts to be inputted to the common-sense reasoning algorithm for further processing (Appendix A).

4.4.3. Affective space and similarity detection

Affective Space is a multi-dimensional vector space built from WordNet Affect and Concept Net used for knowledge representation and semantic and affective similarity calculation between concepts [74,75] A dimensionality reduction technique called truncated singular value decomposition (TSVD) is applied to the matrix representation of AffectNet (from now termed A) to measure the cross-correlations among affective common-sense concepts [60]. TSVD follows the compression principle by compressing the semantically related features connected with each concept without conceding excessive knowledge representation [76].

After performing TSVD on A, the resulting matrix $\tilde{A} = U_K \sum_k V_K^T$ representing a low-rank approximation of A (the original data) is obtained. This approximation is based on reducing the Frobenius norm of the difference between A and $\tilde{A}$ under the constraint $\text{rank}(\tilde{A}) = K$. For the Eckart–Young theorem [77], it signifies the best approximation of A in the least-square sense, hence:

$$\min_{\tilde{A}\,|\,rank(\tilde{A})=K} |A-\tilde{A}| = \min_{\tilde{A}\,|\,rank(\tilde{A})=K} \left|\sum -U^*\tilde{A}V\right| = \min_{\tilde{A}\,|\,rank(\tilde{A})=K} \left|\sum -S\right| \tag{3}$$

where $\tilde{A} = USV^*$, and S consists of K non-zero diagonal entries. The minimum of the above affirmation is as follows:

$$\min_{\tilde{A}\,|\,rank(\tilde{A})=K} \left|\sum -S\right| = \min_{S_i} \sqrt{\sum_{n}^{i=1} (\sigma_i^2 - s_i)^2} \tag{4}$$

$$\min_{S_i} \sqrt{\sum_{i=1}^{n} (\sigma_i^2 - s_i)^2} = \min_{S_i} \sqrt{\sum_{i=1}^{k} (\sigma_i - s_i) + \sum_{i=k+1}^{n} \sigma_i^2} = \sqrt{\sum_{i=k+1}^{n} \sigma_i^2} \tag{5}$$

Hence, $\tilde{A}$ of rank K is the finest estimate of A in the Frobenius norm sense where$\sigma_i = s_i (i = 1, ...,K)$ and the parallel singular vectors are identical as those of A.

In A, concepts and emotions are characterized by vectors of K coordinates along with 'eigenmodes' that configure the axes of AffectiveSpace. Following TSVD, concepts like feel relax, comfort environment, and hygienic food carrying positive affective valence (similar features) are found very adjacent in the direction in the vector space, whereas concepts like bad day, painful treatment, and make people painful are found in entirely different direction (almost in the opposite direction from the center of the vector space).

4.4.4. Emotion categorization

The Hourglass of Emotions is an affective categorization model developed from Plutchik's model [74] and is used for polarity detection based on the four dimensions (24 basic emotions) of human attitudes and feelings. The polarity p associated with each concept c_i defined in terms of *Pleasantness*, *Attention*, *Sensitivity*, and *Aptitude* is expressed as:

$$p = \sum_{i=1}^{N} \frac{\text{Pleasantness}(c_i) + |\text{Attention}(c_i)| - |\text{Sensitivity}(c_i)| + \text{Aptitude}(c_i)}{3N} \quad (6)$$

N the total number of concepts, and 3 the normalization factor (the Hourglass dimensions are defined as float $\in [-1, +1]$) [78]. The emotion categorization framework using extreme machine learning (ELM) and SenticNet is designed to accept a natural language concept as input characterized according to *K*-dimensional space, and predict the equivalent sentic level for the four affective dimensions, according to work of Cambria et al. [72]. Sentic API[1] is used to get the parallel sentic vector for each concept. For each affective dimension, the intensity of emotion lies within the range $[-1, 1]$. For each affective dimension, the polarity values are finally remapped to obtain six different sentic levels. Furthermore, when no SenticNet entry is found or pattern matched, we applied ELM classifier on a bag of words, as proposed by Cambria et al. [63] (Fig. 5). The overall sentiment score of a review (*d*) is computed by averaging the concept polarities (p_i) of a review sentences as shown in Eq. (7), where *N* is the total number of concept occurrences in a review *d*. The process of sentiment score calculation is adopted from the previous work of Weichselbraun et al. [79] and Mirtalaie et al. [80].

$$Sentiment\_score(d) = \frac{\sum_{p_i \in d} polarity(p_i)}{N} \quad (7)$$

Repeating the above process can lead to a sentiment score for the rest of the reviews in the dataset. An example of SenticNet polarities from Healthgrades dataset is presented in Table 3.

5. Results

Ordinary least square (OLS) model was applied to test our hypotheses. Our estimations were carried out using STATA 15.0 and AMOS 23.0 (IBM, 2015). Furthermore, the study performed several statistical estimations and diagnostic tests to determine the stability of our results.

5.1. Descriptive statistic and correlations

Table 4 provides descriptive statistics and correlations for variables. The rating of 1.79 (0–2 rating scale as in Table 2) indicate that a majority of patients are satisfied with the physicians' quality of service, and therefore, these patients showed their WTPP for clinical consultation. There were 17% female and 83% male doctors in our data set. A significant proportion of the physicians (73%) belong to the California city.

5.2. Measurement model

Using AMOS 23.0, the structural equation modeling was run to obtain the composite reliability (CR) and average variance extracted (AVE). The values for all variables were above the threshold, i.e., 0.70 for CR, while 0.50 for AVE (see Table 5), indicating good construct reliability [81]. In our measurement model, all of the loading items are greater than 0.50, indicating convergent validity [82]. To achieve discriminant validity, the squared root of the AVE for each variable is found larger than the inter-construct correlations [81] (Table 4). Our measurement model fitness is good with (χ^2/df = 2.17, CFI = 0.867, NNFI = 0.821, and RMSEA = 0.05) at significance level $p < 0.001$.

5.3. Empirical results

Table 6 and Fig. 6 present the heteroscedasticity consistent regression results. We estimated the two-equation model, Eq. (1) tests H1 and H4, whereas Eq. (2) tests H2, H3, H5, and H6, respectively. Our independent variables well explained dependent variables, and the adjusted R^2 and F-values of OLS are significant and within an acceptable range [21]. VIF statistics for every independent variable fall below 3.30 [82], confirmed the absence of multicollinearity. Furthermore, we accounted for heteroscedastic error distribution; heteroscedasticity-consistent standard errors were calculated for all models.

Model 1 in Table 6 showing control variables. Control variables *Gender* and *Rank* produced consistent and significant results across all models.

For hypothesis 1, i.e., the association between PGSs (*eWOM*) and information search (*Recommendation*), the results of model 2 shows that there is a significant and positive impact of PGSs on patient searches for health information (β = 4.230, $p < 0.001$) (see Table 6). H1 is supported. These results demonstrate that patients are more likely to search for information about those physicians who have positive online WOM posted by prior patients.

Hypothesis 2 predicts the impact of PGSs (*eWOM*) on patient willingness to pay a price premium (*WTPP*) for a health consultation. For model 5 in Table 6, we find the coefficient of eWOM (β = 2.285, $p < 0.001$) is positive and statistically significant. These results suggest that patients are more likely to pay a price premium to those physicians for health consultation having a high online reputation.

Hypothesis 3 examines the impact of SGSs (*Trustworthiness*) on patient willingness to pay a price premium (*WTPP*) for a health consultation. For model 5 in Table 6, SGSs positively affect the patients' WTPP for health consultation (β = 0.186, $p < 0.001$), thus supporting H3. These results indicate that the positive SGSs in the form of high trustworthiness signals significantly influence patients' choice to pay a price premium for a health consultation.

Hypothesis 4, 5, and 6 test the moderation effect of the disease risk (*Risk*). For model 3 in Table 6, disease *Risk* highlights the significant and negative moderating effect on the relationship between PGSs (*eWOM*) and information search (*Recommendation*)(β = −0.194, $p < 0.001$), which supports H4. From model 6 in Table 6, our results confirm that the disease *Risk* significantly and positively moderates the relationship between PGSs (*eWOM)* and patient willingness to pay price premium (*WTPP*) for health consultation (β = 0.210, $p < 0.001$), supporting H5. Lastly, disease *Risk* significantly and positively moderates the association between SGS and patient willingness to pay price premium (*WTPP*) for health consultation (β = 0.076, $p < 0.001$), thus supporting H6.

In Fig. 7, the interaction effect shows a significant association between the PGSs (*eWOM*) and information search (*Recommendation*) under the diseases *Risk*, but the impact is stronger for patients with low-risk disease than high-risk disease. Meanwhile, the impact of PGSs on patient willingness to pay a price premium (*WTPP*) is also significant under the disease *Risk*, but the impact is stronger for patients with high-risk disease than low-risk disease. Furthermore, the similar effect was observed, i.e., the disease *Risk* significantly and positively moderates the association between SGSs and patient willingness to pay a price premium (*WTPP*), but the impact is stronger for high-risk disease patients than low-*risk* disease.

5.4. Robustness check

To examine the model robustness, the regression analysis was run on two sub-samples, based on the disease severity. We need to verify the validation of main effects (H1-H3) in the sub-samples. Referring to the regression analysis, the results are still in line with the findings shown in Table 6 using the entire dataset (see Table 7).

6. Discussion

The primary focus of this study is to investigate the role of different

[1] http://sentic.net/api/

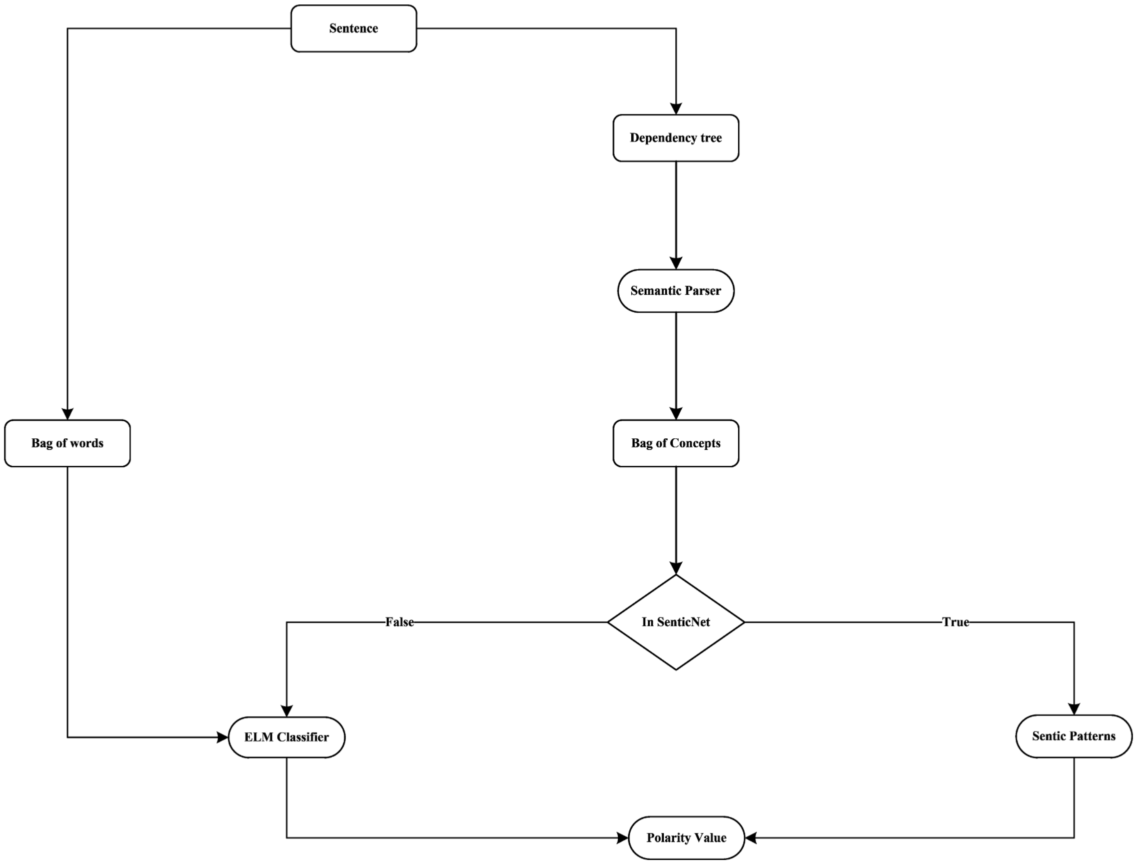

Fig. 5. Sentic computing's hybrid model for polarity detection.

Table 3
Examples of SenticNet concept polarities and labels.

Concept	Polarity	Label
Frustration	−0.320	Anger
Throat infection	−0.436	Disgust
Birthday party	+0.418	Joy
Emotional distress	−0.302	Fear
Embarrassingly	−0.286	Sadness
Furious	−0.293	Anger
Aggregate sentiment score of a review	0.342	

online information signals, such as PGSs (*eWOM*) and SGSs (physician *trustworthiness*) in patient purchase decision-making process, i.e., information search (*Recommendation*) and paying a price premium (WTPP) for a health consultation. Compared with previous research investigating the effect of online information on consumers' decision to purchase [11–13], we move a step forward and consider the WTPP, which is a significant factor for a physician's economic returns. Both PGSs and SGSs have significant effects on patient information searches and WTPP for a health consultation. By including disease risk, which is related to disease mortality, we also reveal its moderating effect on the relationship between online information signals and the patient purchase decision-making process. The empirical results of a two-equation model support all of our hypotheses.

First, our statistical evidence suggests that the amount of positive PGSs significantly influences a patient's search for health information. Our results posit that patients are anxious about healthcare quality, which is similar to consumers of hospitality and other services, and they are keen on searching physician information online and evaluating UGC to choose a competent physician who can satisfy their healthcare needs.

Second, the amount of positive PGSs significantly and positively influences a patient's choice to pay a price premium for a health

Table 4
Descriptive statistics and correlation.

Variables	1	2	3	4	5	6	7
1. Recommendation	**0.913**						
2. WTPP	0.425**	**0.746**					
3.eWOM	0.466**	0.423**	**0.715**				
4. Trustworthiness	0.131**	0.151**	0.114**	**0.714**			
5.Gender	0.160**	0.175**	0.147**	0.026**	1.000		
6. Rank	0.321**	0.287**	0.326*	0.028**	0.119**	1.000	
7. Risk	0.199**	0.249**	0.191*	0.085**	0.122**	0.179**	1.000
Mean	3.841	1.791	1.391	0.603	0.834	0.271	0.362
S.D.	1.682	0.311	0.273	0.251	0.362	0.443	0.481
Range	1–55	1–5	0.49–2.15	0.08–2.17	0–1	0–1	0–1

Note:*p < 0.05, **p < 0.01, ***p < 0.001.
* Square root of AVE in bold using Fornell and Larcker [81].

Table 5
Item loadings, CR, and AVE.

Variables	Items	Loadings	CR	AVE
Recommendation	Recommendation star	0.913	0.833	0.834
WTPP	Service star	0.698	0.714	0.557
	Patient experience	0.792		
eWOM	Volume	0.902	0.802	0.510
	Valence	0.653		
	Variance	0.635		
	Sentiment	0.631		
Trustworthiness	Title	0.677	0.925	0.511
	Picture	0.631		
	Graduation	0.619		
	Experience	0.674		
	Certification	0.673		
	Education	0.747		
	Malpractice	0.899		
	Action	0.796		
	Sanctions	0.812		
	Awards	0.695		
	Replies	0.633		
	Publications	0.672		
CMIN (χ^2)				1511.45
Degree of freedom (df)				694
CMIN/Degree of freedom (χ^2/df)				2.17
Comparative fit index (CFI)				0.867
Non-normed fit index				0.821
Root mean square error of approximation (RMSEA)				0.05

consultation. Consequently, when there is a positive eWOM about a physician, this physician is expected to be preferred by new patients. This finding indicates that physicians who receive a positive response from patients will ultimately have more economic benefits. Thus, the price turns out to be a critical factor in evaluating service quality. Patients can obtain a better quality of life by seeking assurances and paying more for medical services. Patients feel that they can obtain higher-quality services and satisfaction by paying more to the physician.

Third, SGSs are positively related to a patient's decisions to pay a price premium for a health consultation. The SGS reveals that the delivery process quality of a physician's service can motivate other patients to pay a price premium. Our results indicated that whenever there is a strong tie between a doctor and patients, the patient may have frequent interactions with and an awareness of the provider and hence would be expected to have a greater WTPP. Therefore, SGSs send a strong signal to patients and in return, patients pay a price premium for a health consultation.

Fourth, the effect of PGSs on patent information search for health consultation is higher for low-risk disease. A patient suffering from high-risk disease relies less on eWOM to search for health information. One possible justification is that a patient suffering from a high-risk disease experiences both physical and psychological pressures and may be more anxious about the service quality of the physician; however, they may have a preference to visit a physical hospital. Second, although PRWs assist patients to access health information at a much lower cost, most of the rating sites are not updated in a timely manner. Therefore, visiting the physician's office at the hospital can provide precious information within a short period, and the patient may feel comfortable and place more trust in the physical approach.

Fifth, the effect of PGSs on a patient's WTPP is stronger for patients with high-risk disease than low-risk disease. For example, a patient with heart or cancer disease will be willing to pay more to a physician with positive online WOM signals than a patient who only has a cold.

Finally, the effect of SGSs on the patient WTPP for a health consultation is stronger for high-risk disease than low-risk disease patient. One possible explanation could be that when a patient suffers from a severe illness, s/he needs a trustworthy physician with high technical and functional skills; as a result, the patient pays the physician more for a health consultation.

6.1. Theoretical contribution

The current study presents several significant theoretical contributions. First, although prior studies have examined the impact of consumer feedback and system-generated information (i.e., product ranking) on consumer decision-making [11–14], most of these investigations focused on products, movies, and services, such as hotels and tourism. In contrast, the literature regarding the effect of various types of signals on the patient decision-making process in healthcare is

Table 6
Regression output with Heteroscedasticity-consistent.

	Search equation			Decision equation		
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	1.529*** (0.021)	−1.992*** (0.009)	−2.104*** (0.018)	2.353*** (0.012)	0.307*** (0.010)	0.373*** (0.013)
Gender	0.364*** (0.022)	0.052*** (0.006)	0.047*** (0.006)	0.234*** (0.012)	0.067*** (0.004)	0.051*** (0.004)
Rank	−0.732*** (0.018)	−0.011* (0.005)	−0.0185** (0.005)	−0.358*** (0.010)	0.034*** (0.004)	0.008* (0.004)
eWOM		4.230*** (0.009)	4.209*** (0.010)		2.285*** (0.007)	2.080*** (0.014)
Trustworthiness					0.186*** (0.011)	0.232*** (0.016)
Risk			0.113*** (0.015)			0.033* (0.018)
eWOM × Risk			−0.194*** (0.018)			0.210*** (0.015)
Trustworthiness × Risk						0.076*** (0.019)
Adjusted-R^2	0.1179	0.9350	0.9357	0.1027	0.8919	0.8969
F	264.27***	549.34***	575.48***	611.40***	716.77***	760.72***
N	2896	2896	2896	2896	2896	2896

Notes: Standard errors are in parentheses.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

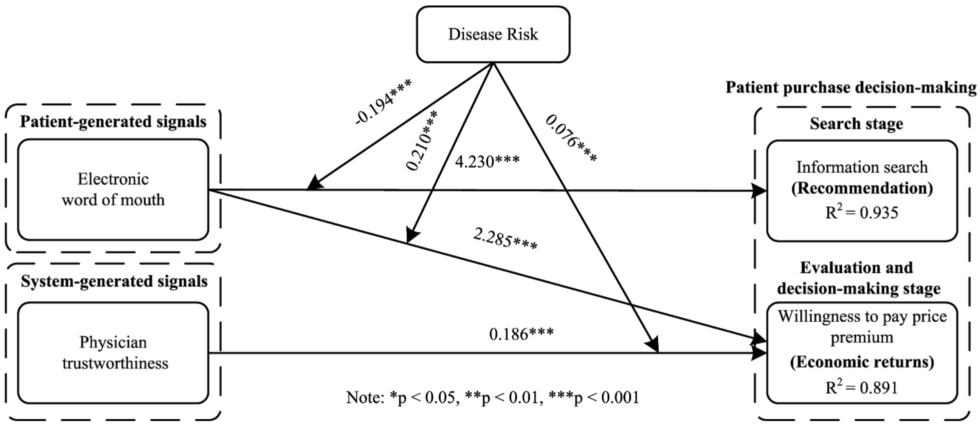

Fig. 6. Research model analysis.

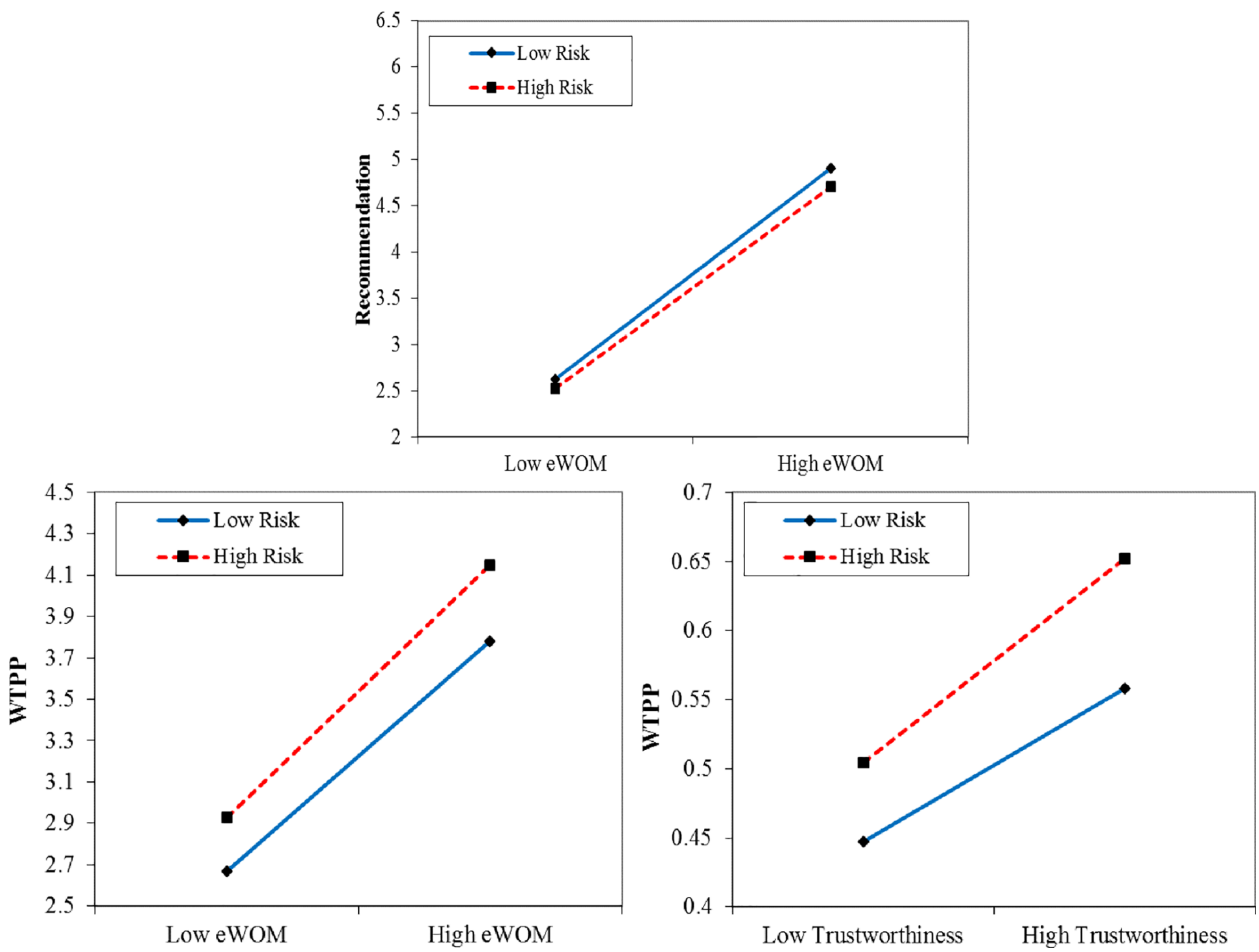

Fig. 7. The interaction plots.

limited. To fill the existing research gap, this study explores the impact of different signaling mechanisms on patient choice. The results of our study confirmed that both PGSs and SGSs significantly influence patient decision-making for a health consultation.

Second, previous studies have discussed the consumer purchase process in an online context [31,37,83], although limited research has focused on patients' behavior at different stages of the decision-making process in online healthcare. We formulate two equations to verify the impact of PGSs and SGSs on the patient decision-making process. At the search and decision stage, both PGSs and SGSs have a positive role in patient choice. Further, most studies focused on patient decision-making by using conventional methods, i.e., survey questionnaire or numeric ratings. This study investigates the impact of PGSs and SGSs on patient search, evaluation and decision to pay a price premium for health consultation stages using a mixed-methods approach. We not only considered the impact of numerical ratings on the patient decision-making process but also online physician information and unstructured feedback as well. Therefore, these findings contribute from a theoretical

Table 7
Parameter estimate of the robust check.

	Search equation		Decision equation	
Variables	High Risk	Low Risk	High Risk	Low Risk
Constant	−2.067***	−1.962***	0.435***	0.355***
	(0.011)	(0.015)	(0.012)	(0.015)
Gender	0.027*	0.116*	0.029***	0.069***
	(0.005)	(0.009)	(0.005)	(0.00)
Rank	−0.093***	0.002***	−0.015**	0.016**
	(0.006)	(0.007)	(0.005)	(0.004)
eWOM	4.395***	4.140***	2.065***	2.291***
	(0.012)	(0.013)	(0.011)	(0.009)
Trustworthiness			0.238***	0.154***
			(0.013)	(0.015)
Adjusted-R^2	0.9658	0.9236	0.8974	0.8884
F	630.77***	705.87***	766.91***	793.82***
N	1185	1711	1185	1711

Notes: Standard errors are in parentheses.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

and methodological perspective to our understanding of PGSs and SGSs in an e-health context.

Third, this study contributes by investigating physician's economic returns in an evolving context of e-health. Although studies have claimed that UGC and system-provided information significantly influence consumer WTPP for products or services [14–17], limited knowledge exists in the healthcare context. Our study is among the first to use real data to empirically investigate the role of PGSs and SGSs on the patient's WTPP (physician economic returns). Financial success is not only beneficial for physicians but also for hospital managers and online consultation web platform designers, and it also has a positive effect on service provisioning and continued physician participation.

Fourth, to better understand patient choice, we propose a unified framework that fills the gaps of signaling theory and Maslow's hierarchy of needs theory. Previous studies have indicated that both theories are associated with offline health services, product sales, customer purchase intentions, and similar areas [45,49,50]. Although Connelly et al. [48] applied signaling theory to study information asymmetry from a sender context, the signaling context from the receiver perspective is still under-researched. According to the unified framework presented in this study, for signaling theory, PGSs and SGSs help to improve patient choice, while for Maslow's hierarchy of needs, individual needs, in the form of disease risk affect patient decision-making associated with a health consultation. Patient choice is solely dominated by individual characteristics [24]. However, limited information is available in this area, and our findings indicate that patient choice relies on eWOM (receiver) and physician trustworthiness (sender) signals, which differ across the level of disease severity of the patient. Through these channels, patients can minimize information asymmetry to choose a competent physician.

6.2. Practical implications

This research has substantial practical implications for physicians, website managers, and healthcare providers. For physicians, the study results recommend that online WOM and physician trustworthiness play a more significant role in patient health consultation decision-making. Thus, positive WOM or trustworthiness can certainly lead to an increase in income. Innovative technology in the healthcare field improves our living standards, and the demand for clinical care is increasing. Physicians can enhance their online reputation and trust by providing a better quality of service and charging a price premium. Although physicians cannot control the sentiment contained in online WOM, they still can improve their credibility to attract more patients. Physicians should more frequently communicate with their patients, which will lead to increased physician economic returns. Our findings also indicate that young physicians may have the opportunity to attract additional patients by focusing more attention on improving service quality and other deficiencies to increase their income and credibility.

For physicians, the study results indicate that patient choice is not only significantly influenced by credibility and clinical skills but also by the physicians' attitude towards other patients. With recent advances within medical science, patients judge a physician based on factors other than their clinical skills, such as their expressiveness. As a result, physicians may need to make greater efforts to treat patients with care and kindness and improve their service attitude to maintain an equilibrium.

For both website managers and hospital administrators, this research reveals methods of attracting more patients. Our results indicate that eWOM and physician trustworthiness are the two significant aspects that PRWs should provide. Such platforms can plan their commercial strategies to encourage patients to post more UGC (i.e., ratings and comments). Several firms in the service industry have launched affiliate programs as a promotional instrument to maintain customer loyalty by offering high-quality, customized services, especially to their potential and high-paying members. When loyalty is established, health consumers are less attracted by competitors' services. As a result, physicians can charge a price premium for healthcare services delivered to the patients. Satisfaction is the prime concern of patients. Loyal and satisfied customers might be inclined to write positive reviews about the doctor. Refreshing patients' positive memory of their past involvement and knowledge about the physician and provide an extra credit or coupon for posting UGC could represent an effective method of a driving price premium, which is a highly desirable marketing outcome.

7. Conclusions and future research

Online health information has gained popularity among health consumers in making their healthcare decisions. The current study provides support to this assertion by investigating the impact of different online information signaling mechanisms on the patient decision-making process for a health consultation using a mixed-methodology. We develop a two-equation model to empirically test our study hypothesis under the theoretical foundation of the unified framework. Our results suggest that PGSs are positively associated with patient searches for health information. We find that the PGSs and SGSs positively influence patients' choice to pay a price premium for a health consultation. In addition, we find that disease-risk moderates the relationship between different signals and patient choice for a health consultation. The study methodology provides new opportunities in measuring people's behavior regarding information search and paying a price premium for a health consultation (i.e., economic returns of physicians) by analyzing real data using the econometric analysis, structural modeling, and a hybrid text mining approach to the sentic computing.

Although the findings of this study regarding patient decision-making process are promising, certain limitations should be addressed in future research. First, only a single service category was chosen to investigate the research questions, and although the internal validity is improved, such a narrow context may reduce the generalizability of our findings. Thus, further investigations should be performed to validate our findings in other service context. Second, due to data collection limitations, the study findings were based on cross-sectional data. Future research could use a longitudinal design involving larger and diverse samples of the population, which would help us uncover dynamics changes over time. Third, we conducted our analysis at the physician level, which allowed us to control for patient heterogeneity. Future studies can implement data analytics techniques to examine the role of patients' demographic characteristics in their experience sharing behavior. Fourth, this study considered physician performance only from an economic success perspective. Although economic success has a large role in physician performance, future research should also include honor, achievement, and rewards as indicators of physician performance.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

POS-based bigram and event concept extraction algorithms.

Algorithm 1: POS-based bigram algorithm

```
Input: NounPhrase
Output: Valid object concepts
Split the NounPhrase into bigrams;
Initialize concepts to Null;
for each NounPhrase do
  while For every bigram in the NounPhrase do
POS Tag the Bigram;
  if adj noun then
    add to Concepts: noun, adj + noun
  else if noun noun then
    add to Concepts: noun + noun
  else if stopword noun then
    add to Concepts: noun
  else if adj stopword then
    continue
  else if stopword adj then
    continue
  else
  Add to Concepts: entire bigram
  end
  repeat until no more bigrams left;
  end
end
```

Algorithm 2. Event concept extraction algorithm

```
Input: Natural language sentence
Output: List of concepts
Find the number of verbs in the sentence;
for every clause do
  extract VerbPhrases and NounPhrases;
  stem VERB;
  for every NounPhrase with the associated verb do
  find possible forms of objects;
  link all objects to stemmed verb to get events;
end
  repeat until no more clauses are left;
  end
```

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