7th European Conference on Industrial Engineering and Operations Management
Augsburg, Germany, July 16-18, 2024
Publisher: IEOM Society International, USA DOI: 10.46254/EU07.20240252
Published: July 16, 2024

The Impact of Operational Attributes on Patient Preferences: an Analysis of Physician Review Websites

Anu Rani and Saini Das
Vinod Gupta School of Management, Indian Institute of Technology, Kharagpur, India
anurani@iitkgp.ac.in, saini@vgsom.iitkgp.ac.in

Abstract

With digital transformation, physician review websites have also revolutionized the healthcare industry, which has significantly impacted patient consultation behavior by improving the service delivery process. Also, physician review websites offer substantial information on physician profiles, including operational attributes such as pre-process wait time and appointment slot duration, to reduce uncertainty regarding service. However, there is a paucity of research on pre-process wait time and appointment slot duration and its influence on patient preference for a physician in physician review websites. To bridge the gap, this study explores the influence of pre-process wait time and appointment slot duration on patient preference using the real-time physician review website dataset. The findings of this study reveal that pre-process wait time exhibits a U-shaped relationship with patient preference. Appointment slot duration has a positive influence on patient preference. This study highlights the moderation effect of appointment slot duration between pre-process wait time and patient preference. Our study advances online healthcare literature with theoretical and practical implications on wait time and appointment slot duration for healthcare service providers and managers.

Keywords

Appointment slot duration, Healthcare, Signaling theory, Wait time.

1. Introduction

Digital transformation has improved the efficiency and effectiveness of business processes by utilizing big data, computing, communication, and connectivity technologies (Vial, 2019). This revolution has brought significant changes across various industries, including healthcare. In this era, online healthcare portals facilitate the way customers search and evaluate a healthcare service provider. Online healthcare portals provide a platform for matching patients with physicians for online and offline consultations (Ghosh et al., 2023). These portals are also known as physician review websites (PRWs) for online reporting of physician's service quality (Chen & Lee, 2024). After the COVID-19 pandemic, the emergence of these platforms has accelerated, and the global digital health market size is expected to reach $295 billion by 2028 (Xu et al., 2021).

The patients receive information on PRWs and make informed decisions. However, the healthcare market is imperfect because of asymmetric information and uncertainty (Arrow, 1963). Also, healthcare services are highly credence and complex in nature, as it is challenging to determine service quality even after consumption. According to signaling theory, the information asymmetry and uncertainty between two parties can be diminished if one side is offering reliable information to the other through signals (Khurana et al., 2019). Wait time (WT) and appointment slot duration (ASD) are the two most critical operational attributes in healthcare services that determine patient satisfaction (Patterson et al., 2017). The unavailability of information on WT and ASD can significantly contribute to uncertainty about the healthcare service delivery process (Osuna,1985). In healthcare, WT is defined as the time duration between patient check-in and being seen by the physician (Patterson et al., 2017). In the context of PRWs, it is also known as pre-processed WT because it is intimated to patients before booking the appointment (Noone & Lin, 2024). ASD is the total time spent with the patient in the examination room with the physician (Patterson et al., 2017). PRWs provide information on WT and ASD to reduce uncertainty and enhance patient satisfaction (Ghosh et al., 2023). However, extant literature on online healthcare communities has investigated the impact of various signals on patients' preferences (PP), such as online reviews, physician professional status, patient satisfaction ratings, physicians' education and experience, consultation fees, and profile picture (Ghosh et al., 2023; Khurana et al., 2019; Ouyang & Wang, 2022; Shah et al., 2019; Zhang et al., 2024),

omitting the impact of pre-process WT and ASD. The prior literature on patient satisfaction has investigated the impact of WT and ASD in offline healthcare settings where patients go without a prior appointment (Patterson et al., 2017; Xie & Or, 2017). So, there is a need to bridge this gap to understand the impact of pre-process WT and ASD in PRWs.

1.1. Objectives

Information about the healthcare operational attributes, such as pre-process WT and ASD, is mentioned on PRWs, prior to appointment booking. Our main objective is to examine the influence of this information on patients' preferences (PP) during appointment booking on PRWs.

However, in the extent of literature on WT time in a healthcare context, all the studies have attempted to examine its impact when there is no intervention of online platforms for appointment booking. The literature on the impact of pre-process WT is increasing (Liu et al., 2018; Noone & Lin, 2024), but there is no empirical evidence in the context of patient decision-making in online healthcare platforms. To address this research gap, the following research question is proposed:

RQ1: How do the pre-process wait time and appointment slot duration impact patient preference on PRWs?
To answer this question, this paper extends the work of Noone and Lin (2024) in the context of PRWs. The paper uses India's leading PRW data to understand if pre-process WT and ASD can influence PP in PRWs.

2. Literature Review

This section examines the literature on online healthcare signals and patient preference, the impact of wait time and service duration on patient satisfaction, and the significance of signaling theory for this study.

2.1. Online Healthcare Signals

To facilitate patient-decision making, PRWs disclose various physician and patient-side signals. In online healthcare literature, physician and patient-side signals have been systematically studied. The physician-side signals reveal the service delivery process of the physician, whereas patient-side signals help to know service quality and overall patient experience (Khurana et al., 2019; Shah et al., 2019; Zhang et al., 2024; Yang et al., 2015; Xu et al., 2021). Also, both categories of information are complementary and reduce information asymmetry to facilitate patient decisions (Yang et al., 2015). A thorough investigation of physician profile information reveals that a physician's online reputation in terms of online ratings and number of reviews has a positive influence on patients' choices (Chen & Lee, 2024; Xu et al., 2021; Guo et al.,2017) and make patients pay a price premium for high-quality physicians (Shah et al., 2019).

In addition, wait time and service duration are intrinsic parts of the healthcare service delivery process and the most important operational attributes (Liu et al., 2018; Parasuraman et al., 1985). For instance, the selected PRW for this study promises minimum pre-process WT and ASD and verified physician details to reduce uncertainty, which asserts the importance of WT and ASD for a patient to make an informed decision. Recent studies on WT have witnessed the importance of pre-process WT (Noone & Lin, 2024), but in the context of PRWs, the role of these signals has been unexplored.

2.2. Wait Time and Service Duration in Healthcare

WT and ASD are crucial determinants of consumers' evaluation of various services, including healthcare. In healthcare, high WT has detrimental consequences on service evaluation (Hui & Tse, 1996). To mitigate the negative effects of WT, service organizations either optimize the service delivery process or provide information about the expected length of wait, also known as pre-process WT (Hui & Tse, 1996). In healthcare settings, studies have primarily focused on the effect of WT on patient satisfaction. Many researchers have found that patients report dissatisfaction when they encounter extended WT in the case of primary healthcare, endocrinology, ambulatory care, and cancer treatments (Lee et al.,2020; McIntyre & Chow, 2020; Nottingham et al., 2018). Studies have also shown that patients are ready to increase WT and prefer longer ASD with their familiar doctors (Ahmad et al., 2017; Feddock et al., 2010; Wilson & Childs, 2002). Similarly, in orthopedic consultation, patients prefer longer ASD at the expense of WT (Patterson et al., 2017). In contrast, studies have also reported that time spent with healthcare service providers does not correlate with patient satisfaction, and WT has a negative impact on the same (Alarcon et al., 2019; Xie & Or, 2017; Elmore et al., 2016).

The intervention of PRWs empowers patients to make informed decisions using the information available on online platforms. The prior literature explored the impact of WT and ASD in offline settings with the experimental

studies. This study systematically analyzes the real-time data available on the PRWs and uncovers the impact of pre-process WT and ASD on patient preferences.

2.3.Signaling theory

Signaling theory mainly focuses on mitigating the presence of information asymmetry between two parties, where one party, A, retains information, whereas party B lacks such knowledge (Spence, 2002). The presence of information asymmetry increases the uncertainty for Party B and hinders the ability to gauge the reliability of Party A (Mavlanova et al., 2012). However, party B can gather information through signals transmitted by party A to evaluate party A's trustworthiness.

Signaling theory is commonly used to elaborate on how patients reduce their uncertainty and evaluate physicians' quality for consultation. On the PRWs, patients process various physician and service quality attributes such as WT and ASD. Patients can use WT and ASD as important signals to alleviate information asymmetry and reduce uncertainty during service encounters. Thus, signaling theory is a fundamental framework for this study to understand the impact of service delivery process indicators extracted from PRWs.

3. Research Model and Hypotheses

Drawing upon the signaling theory perspective, the following research model is proposed to address the stated research objective and questions, as shown in Figure 1. The following section will discuss all the hypotheses drawn from this research model.

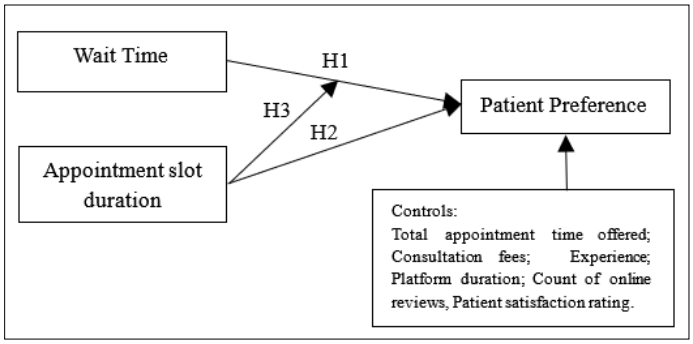

Figure 1. Research Model

Based on the queuing theory, WT incurs significant costs in terms of time and money (Kremer & Debo, 2016). Prior literature has suggested that patients report dissatisfaction when they encounter high WT (Lee et al., 2020; Nottingham et al.,2018; McIntyre & Chow, 2020). In this way, to enhance the patient experience and make it more effective and efficient, PRWs negotiate with the physicians to reduce the WT. Also, patients tend to prioritize physicians with extensive experience and high professional status (Khurana et al., 2019; Roese, 1997). Consequently, to consult with high-quality physicians, patients may prefer longer WT (Patterson et al., 2017). In recent literature, WT has been established as a quality indicator for any service (Noone & Lin, 2024; Kremer & Debo, 2016). Also, PRWs promote low-quality physicians when appointments with high-quality physicians are already booked; this leads to counterfactual thinking among patients for WT because they prefer high-quality physicians at the expense of WT (Roese,1997). Initially, patients prefer to optimize their experience with effective and efficient services with short WT. Also, patients may prefer high-quality physicians at the expense of WT. However, longer WT can increase their perception of loss in terms of time and money beyond a certain threshold(Noone & Lin, 2024; Nottingham et al., 2018b; Patterson et al., 2017). This hypothesis posits that an optimal level of WT maximizes patient satisfaction and influences patients' preferences for physicians on PRWs. Thus, the following hypothesis is proposed:

H1: WT has a U-shaped relationship with PP on PRWs.

The longer appointment duration is associated with comprehensive care and diagnosis and increased patient satisfaction (Feddock et al., 2010; Patterson et al., 2017). Physicians with longer consultations tend to prescribe less and offer more advice on lifestyle and other health-promoting activities (Azraii et al., 2017). It indicates a perceived higher quality or value of the service to patients. Hence, the following hypothesis is proposed:
H2: Physicians with longer ASD will positively influence PP on PRWs.

ASD is strongly related to comprehensive diagnosis and care. Also, patients may prefer to spend more time with physicians at the expense of WT. Hence, longer ASD may mitigate the negative effects of longer WT, as patients perceive that they will receive more comprehensive care during their appointments (Azraii et al.,2017; Feddock et al., 2010; Patterson et al., 2017). On the other hand, shorter ASD may intensify the negative impact of WT, leading to patient dissatisfaction. Thus, ASD impacts the perception of WT in shaping patient preferences on PRWs. Hence, the following hypothesis is proposed:
H3: ASD moderates the influence of WT on PP on PRWs.

3. Methodology

3.1. Research context

The proposed hypotheses are tested using data collected from India's most popular PRW. A web crawler program developed in Python was used to gather physician profile information, creating a comprehensive dataset. This PRW contains detailed and verified information about physicians, such as educational background, specializations, experience, consultation fees, wait time, appointment duration, practice hospital or clinic details, services offered, online reviews, and patient satisfaction ratings. On this website, patients can choose a physician to book an appointment to consult online or offline based on their medical condition.

3.2 Data Collection

The data collection started on 3 July 2022, with 19,349 physicians listed on the website on that day. Since the number of appointments completed by the physicians was not available on their profile due to platform design. To collect appointment booking data, the website was monitored daily for availability details over a two-month period till 26 August 2022 to create an appointment dataset based on the method proposed by Xu et al., 2021. The detailed definitions of the variables are provided in Table 1. The correlation matrix of these variables is illustrated in Figure 2, indicating that all correlation coefficients are below 60%, so there is no issue of multicollinearity, and the dataset is fit for regression analysis.

Table 1. The definition of all the variables used in the study

Variable	Definition
PP	The total time spent by a doctor on consultation duration on PRW during the data collection period (in minutes).
WT	The wait time is mentioned on the website while booking an appointment (in minutes).
ASD	The appointment slot duration with the physician (in minutes).
Appt_Avail	The total time offered by a doctor for consultation on PRW during the data collection period (in minutes).
Consult_fees	Physician's consultation fees (in INR).
Exp	Year of experience in practice.
N_Reviews	Total number of reviews received by a physician.
Pt_Sat	Patient satisfaction rating received by a physician (%).
Gender	Gender of the physician
Clinic_count	Total number of clinics that a physician visits.

The initial dataset included 19,349 physicians listed on the website. After the data collection period, during the data cleaning step, physicians whose profiles were listed but inactive or did not offer any appointments were removed. This step resulted in 15,338 physicians. Further, after combining the active physician profile information dataset with the appointment dataset, only 9,988 physicians were left because a few physician profiles were unavailable for more than five days during the data collection period.

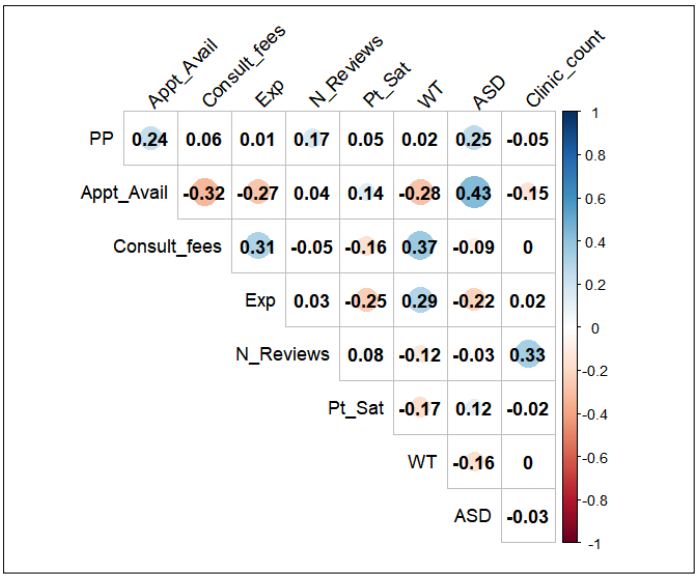

Figure 2. The Correlation heat map

3.3 Analysis Technique

The dependent variable is the PP on the PRW. As the dependent variable is measured as a count variable, using a multiple linear regression model for analysis may exhibit consistency and bias in the results (Faraj et al., 2015). Therefore, Negative Binomial Regression was employed to accommodate the count variable nature of the dependent variable. This statistical technique is appropriate for handling over-dispersed count data, providing more reliable and accurate results in this context. R language program is used to do the empirical analysis for the study.

To test H1, a cross-sectional model was constructed for the U-curve relationship of the WT and PP:

$$ln[E(PP_i)] = \beta_0 + \beta_1 \times WT_i + \beta_2 \times WT_i^2 + \beta_3 \times Appt\_Avail_i + \beta_4 \times Consult\_fees_i + \beta_5 \times Exp_i + \beta_6 \times N\_Reviews_i + \beta_7 \times Pt\_Sat_i + \beta_8 \times Clinic\_count_i + \beta_9 \times Gender_i + \epsilon i \quad (1)$$

where β_0 was the intercept term; β_1 *and* β_2 were coefficients of WT, and β_3 *to* β_9 were the coefficients of control variables. ε was the error term.

To test H2, appointment slot duration (ASD) was added to the model 1. The empirical model for this was shown as follows:

$$ln[E(PP_i)] = \beta_0 + \beta_1 \times WT_i + \beta_2 \times WT_i^2 + \beta_3 \times ASD_i + \beta_4 \times Appt\_Avail_i + \beta_5 \times Consult\_fees_i + \beta_6 \times Exp_i + \beta_7 \times N\_Reviews_i + \beta_8 \times Pt\_Sat_i + \beta_9 \times Clinic\_count_i + \beta_{10} \times Gender_i + \epsilon i \quad (2)$$

where β_3 was the coefficient of interest.
For the moderating effect of ASD, the following model was used to test it:

$$ln[E(PP_i)] = \beta_0 + \beta_1 \times WT_i + \beta_2 \times WT_i^2 + \beta_3 \times ASD_i + \beta_4 \times WT_i \times ASD_i + \beta_5 \times WT_i^2 \times ASD_i + \beta_6 Appt\_Avail_i + \beta_7 \times Consult\_fees_i + \beta_8 \times Exp_i + \beta_9 \times N\_Reviews_i + \beta_{10} \times Pt\_Sat_i + \beta_{11} \times Clinic\_count_i + \beta_{12} \times Gender_i + \epsilon i \quad (3)$$

where β_4 *and* β_5 were coefficients of interested variables. R language program was used to analyze the data and perform the empirical study.

4. Results and Discussion

The regression results are summarized in Table 2. The stepwise regression approach was used to test the hypothesis. In model 1, The U-curve relationship of WT with PP was tested. The coefficient of WT (β = -0.0238***, p <0.001) and WT^2 (β = 0.00039,***, p <0.001) is a clear indication of a U-curve relationship between WT and PP, Thus supports the H1. In model 2, ASD was incorporated (β = 0.02257***, p <0.001), which

is positive and significant, thus supporting H2. Finally, in model 3, the coefficient of WT * ASD (β = -0.00207**, p <0.001) is negative and significant. This means that the combined effect of WT and ASD on PP is negative. In other words, as WT and ASD increase, they decrease the PP. The coefficient of WT^2 *ASD (β = 0.00004***, p <0.001) is positive and significant. The positive coefficient for WT^2 *ASD suggests that at higher levels of wait time, the combined effect with slot duration becomes positive, increasing the PP. Hence, the results of model 3 suggests support for H3.

Most of the control variables are significant throughout all the models, depicting that all of them play crucial roles along with the main variables of the study. The value of AIC decreases as more variables are added to the model, which indicates a good model fit and significant effects in all the models.

Table 2. Results of negative binomial regression, DV = PP

DV = PP	**Model 1**	**Model 2**	**Model 3**
WT	-0.0238***	-0.01999**	0.02515
WT^2	0.00039***	0.00034***	-0.00047***
ASD		0.02257***	0.0418***
WT*ASD			-0.00207**
WT^2 *ASD			0.00004***
Appt_Avail	0.00006***	0.00004***	0.00004***
Consult_fees	0.0006***	0.0005***	0.0005***
Exp	0.00475***	0.00764***	0.00662*
N_Reviews	0.00391***	0.00386***	0.00392***
Pt_Sat	0.00347^	0.00176	0.00194
Clinic_count	-0.1050***	-0.10384***	-0.11108***
Gender	-0.01751	0.00927	-0.00351
Constant	5.6538***	5.38058***	4.99094***
AIC	139298	139192	139137
N	9988	9988	9988

*Note(s): *p < 0.05, **p < 0.01, ***p < 0.001* ‘ ’ 1

The findings of this study provide significant insights into the influence of operational attributes, specifically pre-process WT and ASD, on PP in the context of PRWs. This research advances our understanding of patient decision-making in online healthcare settings by exploring the complex relationships between these variables. The discussion will focus on interpreting the results in light of existing theories, highlighting theoretical and practical implications.

A U-shaped relationship between WT and PP was observed (H1). In general, shorter WTs suggest efficiency. However, in PRWs, short WTs might signal low demand and perceived lower quality, reducing PP. Longer WTs indicate physician popularity and competence in PRWs (Noone & Lin, 2024; Kremer & Debo, 2016). This aligns with signaling theory, where WT serves as a cue for physician quality. Further, longer ASDs positively influence PP. Patients associate longer consultations with comprehensive care and attentiveness (Feddock et al., 2010; Patterson et al., 2017). Logically, it suggests a physician’s dedication and thoroughness, enhancing patient preference. This aligns with the service quality theory, indicating that time spent with patients significantly affects satisfaction and preference. ASD moderates the influence of WT on PP.

Our research has many theoretical contributions. First, vast literature explored the factors influencing patient decision-making in PRWs, but this study sheds light on the impact of wait time and service duration. Our research complements the literature on online healthcare communities by proposing the importance of pre-process wait time and service duration in PRWs (Khurana et al., 2019; Shah et al., 2019; Xu et al., 2021; Yang et al., 2015;

Zhang et al., 2024). Second, this study attempts to extend the research on pre-process waiting time and service duration into the healthcare context and discuss the upside of waiting time (Noone & Lin, 2024). Finally, this study expands the application of signaling theory and counterfactual thinking in PRWs research.

Regarding implications for practice, first, the findings of this study suggest that physicians with a low waiting time may signal that physicians are freshers and lack expertise. These physicians try to show more expertise-related cues and service delivery-related information in their self-description section of the online profile. This will increase transparency about their service delivery process and competence and help them attract more patients. Second, physicians with lower ASD can increase the duration because patients' satisfaction increases with time spent with physicians in comprehensive diagnosis.

5. Conclusion

This paper explores the impact of pre-process WT and ASD and its influence on patient preference. The quantitative findings of this study highlight the significant impact of operational attributes on PP in the context of PRWs. The analysis confirms a U-shaped relationship between pre-process WT and PP, indicating that each additional minute of WT initially decreases the log of PP by 0.0238 minutes. However, WT squared suggests that as WT increases, the decrease in PP slows down and eventually reverses, leading to an increase in PP. This means that beyond a certain threshold, longer WTs can actually enhance PP, likely due to perceived physician quality and demand. ASD positively influences PP; this indicates that each additional minute of ASD increases the log of PP by 0.02257 minutes, highlighting the value patients place on comprehensive and thorough consultations. The interaction between WT and ASD is complex, indicating that WT*ASD means that for each additional minute of WT, the positive impact of each additional minute of ASD on the log of PP decreases by 0.00207 minutes. However, WT^2 *ASD indicates that as WT increases, the interaction effect with ASD becomes more positive, enhancing PP by 0.00004 for each squared minute of WT multiplied by ASD. This depicts a complex relationship that calls for further study, whether dividing wait time into categories or investigating this relationship according to disease specializations.

Overall, the study provides robust quantitative evidence that operational attributes such as WT and ASD are crucial determinants of PP in PRWs. These findings offer valuable insights for healthcare providers aiming to optimize their service delivery to attract and retain patients in the digital healthcare environment. This study has several limitations; it considered a single PRW and country for the analysis, and further studies can consider multiple PRWs and other countries to examine the impact of variables in multiple geographies. Secondly, researchers may consider the interaction effect of hospital vs clinic settings for consultations; it may be possible that clinics are smaller settings with fewer facilities, and the perception of WT and ASD differs from hospitals. Lastly, there are many specialties divided into high-risk vs. low-risk diseases, and researchers can investigate whether the perception of WT and ASD changes as per the nature of the disease.

References

Arrow, Kenneth J. Uncertainty and the welfare economics of medical care, *American Economic Review*, vol. 102, no. 5, pp. 941–973, 1963.

Azraii, A.B., Kamaruddin, K.N., and Ariffin, F., An Assessment of Patient Waiting and Consultation Time in a Primary Healthcare Clinic, *Malaysian Family Physician*, vol. 12, no. 1, pp. 14-21, 2017.

Chen, Y, and Lee, S., User-Generated Physician Ratings and Their Effects on Patients' Physician Choices: Evidence from Yelp, *Journal of Marketing*, vol. 88, no. 1, pp. 77–96, 2024.

Faraj, S., Kudaravalli, S., and Wasko, M., Leading Collaboration in Online Communities, *MIS Quarterly*, vol. 39, no. 2, pp. 393–412, 2015.

Feddock, C. A., Bailey, P.D., Griffith, C.H., Lineberry, M.J., and Wilson J.F., Is Time Spent with the Physician Associated with Parent Dissatisfaction Due to Long Waiting Times? *Evaluation and the Health Professions*, vol. 33, no. 2, pp. 216–25, 2010.

Ghosh, S., Chakraborty, S., Gupta, N., and Basu, S., What Ails Physician Review Websites? A Study of Information Needs of Patients. *Decision Support Systems*, vol. 166, p. 113897, 2023.

Khurana, S., Qiu, L., and Kumar, S., When a Doctor Knows, It Shows: An Empirical Analysis of Doctors' Responses in a Q&A Forum of an Online Healthcare Portal, *Information Systems Research*, vol. 30, no. 3, pp. 872–91, 2019.

Kremer, M., and Debo, L., Inferring Quality from Wait Time. *Management Science*, vol. 62, no. 10, pp. 3023–38, 2016.

Lee, S., Grob, S.E., Pfaff, H., and Dresen, A., Waiting Time, Communication Quality, and Patient Satisfaction: An Analysis of Moderating Influences on the Relationship between Perceived Waiting Time and the Satisfaction

of Breast Cancer Patients during Their Inpatient Stay, *Patient Education and Counseling*, vol. 103, no. 4, pp. 819–25, 2020.

Mavlanova, T., Benbunan-Fich, R., and Koufaris, M., Signaling Theory and Information Asymmetry in Online Commerce, *Information and Management*, vol. 49, no. 5, pp. 240–47, 2012.

McIntyre, D, and Clara K. C. Waiting Time as an Indicator for Health Services Under Strain: A Narrative Review, *INQUIRY: The Journal of Health Care Organization, Provision, and Financing,* vol. 57, pp. 1-15, 2020.

Noone, B. M., and Lin, S.M., Exploring the Upside of Waiting: The Positive Effects of Waiting as a Cue to Brand Popularity, *International Journal of Hospitality Management*, vol. 118, pp. 103691, 2024.

Nottingham, Q.J., Johnson, D.M., and Russell, R.S., The Effect of Waiting Time on Patient Perceptions of Care Quality, *Quality Management Journal*, vol. 25, no. 1, pp. 32–45, 2018.

Osuna, EE., The Psychological Cost of Waiting, *Journal of Mathematical Psychology*, vol. 29, pp. 82–105, 1985.

Ouyang, P., and Wang, J.J., Physician's Online Image and Patient's Choice in the Online Health Community, *Internet Research*, vol. 32, no. 6, pp. 1952-1977, 2022.

Patterson, B.M., Eskildsen, S.M., Clement, R.C., Lin, F.C., Olcott, C.W., Del Gaizo, D.J. and Tennant, J.N., Patient Satisfaction Is Associated with Time with Provider but Not Clinic Wait Time among Orthopedic Patients, *Orthopedics*, vol. 40, no. 1, pp. 43–48, 2017.

Roese, N.J., Counterfactual Thinking, *Psychological Bulletin*, vol. 121, no. 1, pp. 133–48, 1997.

Shah, A.M., Yan, X., Shah, S.A.A.S., Shah, S.J., Mamirkulova, G., Exploring the Impact of Online Information Signals in Leveraging the Economic Returns of Physicians, *Journal of Biomedical Informatics*, vol. 98, p. 103272, 2019.

Spence, M., Signaling in Retrospect and the Informational Structure of Markets, *The American Economic Review*, Vol. 92, no. 3, pp. 434-459, 2002.

Vial, G., Understanding Digital Transformation: A Review and a Research Agenda, *Journal of Strategic Information Systems*, vol. 28, no. 2, pp. 118–44, 2019.

Xie, Z., and Or, C., Associations between Waiting Times, Service Times, and Patient Satisfaction in an Endocrinology Outpatient Department: A Time Study and Questionnaire Survey, *INQUIRY: The Journal of Health Care Organization, Provision, and Financing* vol. 54, pp. 1-10, 2017.

Xu, Y., Armony, Mor., and Ghose, A., The Interplay Between Online Reviews and Physician Demand: An Empirical Investigation, *Management Science*, vol. 67, no. 12, pp. 7344–61, 2021.

Yang, H., Guo, X., and Wu, T., "Exploring the Influence of the Online Physician Service Delivery Process on Patient Satisfaction, *Decision Support Systems*, vol. 78, pp. 113–21, 2015.

Zhang, X., Wang, Y., Xiao, Q., and Wang, J., The Impact of Doctors' Facial Attractiveness on Users' Choices in Online Health Communities: A Stereotype Content and Social Role Perspective, *Decision Support Systems*, vol. 182, pp. 114246, 2024.

Biographies

Anu Rani is a PhD research scholar at Vinod Gupta School of Management, Indian Institute of Technology Kharagpur in India. She holds a B.Tech in Computer Science Engineering from Punjab Technical University, Ludhiana, Punjab, and an M.E in Software Engineering from Thapar University, Patiala, Punjab. Her areas of research interest are e-commerce platforms, user-generated content analysis, and healthcare analytics.

Saini Das is an Assistant Professor in the Information Systems area at Vinod Gupta School of Management, Indian Institute of Technology Kharagpur in India. She received her Ph.D. from Indian Institute of Management Lucknow, India. Her research interests are managing information security risks in networks, management information systems(MIS), e-commerce technology and applications, data privacy, digital piracy and data analytics. She has published her research work in various international journals of repute such as Decision Support Systems, Information &Management, International Journal of Information Management, Information Systems Frontiers, Behaviour &Information Technology, Journal of Global Information Technology Management (JGITM), Journal of Information Technology Case and Application Research (JITCAR), etc