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Impact of Technical Support and Information Provision on Patient No-show Behavior

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Abstract

Patient no-shows pose a significant challenge in healthcare operations, disrupting appointment schedules and affecting overall efficiency. Effectively addressing the challenge of reducing patient no-shows is crucial for outpatient service management. This study evaluates how the design of appointment systems affects patient no-show behavior. Using a difference-in-differences methodology, we analyze the effects of two appointment system update events—technical support and information provision—at a Chinese hospital. Our analysis reveals that technical support and information provision are associated with average reductions of 22.40% and 10.91%, respectively. To investigate the mechanisms behind these effects, we conduct a randomized controlled experiment with 233 participants. Our findings reveal that perceived effort and credibility mediate the relationship between information provision and patient no-shows. However, for technical support, only perceived credibility acts as a mediator. This study provides valuable insights for healthcare operations, offering design recommendations to address no-show behavior in hospital appointment systems.

Keywords

Healthcare operations, System design, Patient no-shows, Technical support, Information provision

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1 Introduction

Patient no-shows present a significant challenge for healthcare operations, particularly for outpatient care providers. A multinational study indicated that the average no-show rate is 23%, with the highest rates observed in the African continent (43.0%) and the lowest in Oceania (13.2%) (Dantas et al., 2018). The consequences of patient no-shows are considerable, including extended wait times for appointments (Liu et al., 2019), adverse clinical outcomes (McQueenie et al., 2019), and financial losses for hospitals (Simsek et al., 2021). For instance, in the United States, patient no-shows result in an estimated annual loss of at least \$766 million, equating to \$725.42 per provider per day (Simsek et al., 2021). Therefore, effectively addressing the challenge of reducing patient no-shows is crucial for outpatient service management.

The increasing adoption of outpatient appointment systems as flexible IT innovations marks a significant advancement in healthcare delivery, aiming to enhance hospital operations and patient experiences. These systems enable patients to select services that best fit their individual needs, free from temporal or spatial constraints. Compared to traditional methods like phone calls, these systems offer remarkable convenience and efficiency. However, despite their advantages, there is a growing concern about their potential impact on appointment no-shows. Individuals tend to adhere to decisions in which they have invested time or resources (Arkes and Blumer, 1985).

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By significantly reducing the effort required for patients to schedule appointments, these systems can lead to impulsive bookings. When patients perceive the scheduling process as effortless, they may feel less committed to attending their appointments, increasing the likelihood of no-shows (Hong et al., 2019). This paradox highlights how a system designed to improve service quality can inadvertently result in more no-shows. Additionally, the impersonal nature of digital systems may diminish the perceived importance of appointments due to the reduced human interaction compared to traditional booking methods. This detachment might make patients less likely to honor their original appointment times. Moreover, traditional methods of managing no-show behavior, such as education or fines, may prove ineffective in the context of system-driven appointment scheduling (Liu and KC, 2023). Addressing concerns about increased appointment no-shows requires a detailed understanding of how appointment system design influences patient attendance behavior.

To address these concerns, we draw from social exchange theory (SET) to examine how technical support and information provision—key components of outpatient appointment systems—affect patient no-show behavior. Technical support involves helping patients navigate the system, providing guidance on features such as appointment scheduling and troubleshooting (Subramani et al., 2021; Venkatesh et al., 2012), while information provision involves supplying patients with pertinent details such as physician information, appointment times, and preparation instructions (Gao and Tavoni, 2024; Li et al., 2017). SET suggests that these elements influence patient behavior through perceived effort and credibility (Cropanzano and Mitchell, 2005). When patients perceive substantial effort from service providers through technical support and comprehensive information, they may feel a sense of obligation to reciprocate by attending their appointments (Homans, 1958). Furthermore, technical support and information provision can improve the quality of appointment services offered by service providers, thereby enhancing the perceived credibility of the providers. This is because well-supported and informed patients are more likely to trust the service and feel confident in their decision. These characteristics play a crucial role in guiding patients through medical services and promoting care continuity, potentially reducing no-shows (Feldman et al., 2014). Thus, our research aims to clarify how technical support and information provision impact patient commitment and attendance, and to develop strategies to reduce no-shows by investigating the following questions: *Do technical support and information provision influence patient no-show behavior? What are the underlying mechanisms, such as perceived effort and credibility, driving these relationships?*

To empirically answer these research questions, we first leverage two quasi-experiments on an outpatient appointment system through collaboration with a hospital in China. We collect a comprehensive dataset comprising two appointment system updates, namely, technical support (providing assistance related to the system) and information provision (adding more descriptions for clinical departments) events (February 2017–December 2017). We then apply a difference-in-differences (DID) model to analyze the impacts of technical support and information provision on patient no-show behavior at the individual-daily level. The analysis indicates that technical support and information provision reduce no-show behavior. Specifically, the possibility of no-show rates at the individual level decrease by 22.40% and 10.91% after the appointment technical support and information provision events, respectively. Thus the reduction in patients no-show behavior is practically significant. We conduct a series of heterogeneous analyses (i.e., patient-related, appointment-related and weather-related factors) to identify, in broad terms, the conditions under which information provision and technical support can reduce more patient no-shows. The use of propensity score matching (PSM), along with an extended observation period, department-level analysis and validity-based data exclusion analysis, produces results consistent with our primary findings, underscoring the reliability and robustness of our conclusions. Second, we conduct a scenario-based randomized controlled experiment involving 233 participants to explore the underlying mechanisms between appointment system characteristics and patients' no-show behavior. We design a fictitious hospital appointment system using the hospital appointment system from the first phase of the study and program two different types of appointment user interfaces. The second phase of the study conceptually replicates the first phase and examines the mediating roles of perceived effort and perceived credibility.

Our study makes several contributions to the literature on the interface of healthcare operations management and healthcare information systems. First, we provide evidence on how the design of appointment systems impacts patient no-shows. While prior research has mainly focused on the effects of healthcare information technology on operational and clinical outcomes (Bavafa et al., 2018; Liu, 2016), we attempt to understand the effects of specific appointment system characteristics on patient no-shows. We provide evidence that the technical support and information provision of appointment systems can reduce patient no-shows. Second, our work contributes to the literature on managing patient no-shows through appointment system design. We bridge the gap between appointment system design and no-show behavior by investigating the mediating roles of perceived effort and perceived credibility. This understanding can provide guidance for future management practices, helping to develop more effective appointment systems to reduce patient no-shows and improve the efficiency of healthcare services.

2 Literature Review

This study contributes to the literature on (i) the impact of healthcare information technology, (ii) patient no-shows, and (iii) system design.

2.1 Impact of Healthcare Information Technology

Our study contributes to the existing literature on the impact of healthcare information technology, which can be broadly categorized into two main areas: clinical outcomes and operational outcomes. In terms of clinical outcomes, previous research has investigated how healthcare professionals utilize healthcare information technology to adhere to standardized procedures in diagnosing and improving patients' health conditions (Janakiraman et al., 2023; Wang et al., 2024). For example, Janakiraman et al. (2023) demonstrated that access to health information exchange in emergency departments can reduce the length of stay and the 30-day readmission rate. Ganju et al. (2020) explored the effects of clinical decision support systems on mitigating systematic biases among patients with diabetes mellitus, particularly in rates of amputation and revascularization among black patients relative to white patients. Jussupow et al. (2021) conducted an inductive study to understand how artificial intelligence recommendations influence physicians' decision-making processes, highlighting the utilization of metacognitive processes by physicians to monitor and regulate their reasoning when assessing artificial intelligence recommendations. Lin et al. (2019) found that the impact of electronic health record technology on healthcare quality varies depending on usage levels and hospital characteristics. Hydari et al. (2018) found that advanced EMRs (electronic medical records) lead to a 17.5% decline in patient safety events, driven by reductions in medication errors, falls, and complication errors.

Scholars have also examined the impact of healthcare information technology on operational outcomes, including healthcare costs, patient satisfaction, and service efficiency. For example, Bouayad et al. (2020) investigated the roles of time pressure and cost transparency in utilizing recommender systems to reduce healthcare costs. Liu et al. (2020) revealed that physician-driven online health communities facilitate collaborative care and self-management support between patients and physicians, potentially enhancing patient well-being and relationships with healthcare providers. Bavafa et al. (2018) studied the effects of e-visits on physician productivity and found that they lead to additional office visits rather than serving as substitutes. Huang et al. (2021) discovered that integrating online and offline services can increase online demand, decrease offline demand, and enhance the professional reputation of participating healthcare providers. Additionally, Li et al. (2022) demonstrated that healthcare information technology interoperability can shorten the throughput time of interhospital transfers but has minimal impact on reducing duplicate electrocardiogram testing for transferred patients at receiving hospitals. Fan et al. (2023) showed that the number of offline appointments for doctors increases after opening an online consultation service. While most previous studies have focused on the overall impact of healthcare information technology implementation, our study advances understanding by examining how specific characteristics of healthcare information technology, such as technical support and information provision, influence operational outcomes in hospitals.

2.2 Patient No-shows

This study contributes to the existing literature on patient no-shows. Prior research has primarily focused on mitigating the impact of no-shows by adjusting appointment rules, often utilizing analytic models to discuss potential countermeasures (Liu, 2016; Kong et al., 2020). While these analytical approaches offer valuable insights, recent studies have emphasized the importance of empirical research in providing actionable recommendations and validating phenomena in real-world settings (Fisher et al., 2020). For example, LaGanga (2011) demonstrated that implementing lean projects to realign system resources and develop new approaches to appointment scheduling effectively reduced the no-show rate by 12%. Similarly, Liu et al. (2019) highlighted the significance of patient rescheduling flexibility in lowering overall no-show rates. Liu and KC (2023) found that waits framing messaging significantly reduces no-shows by 28.6%.

While existing literature has examined the role of appointment services and policies in mitigating patient no-shows, the effectiveness of these strategies depends on the specific features of appointment systems (Venkatesh et al., 2016; Tan et al., 2016). This study complements this research strand by offering empirical insights into the specific features of appointment systems, specifically technical support and information provision, and their impact on reducing patient no-shows. Moreover, while Dantas et al. (2018) suggested that social determinants of health, such as social support and housing situations, influence no-shows, our study adopts a quasi-experimental approach to directly investigate the effects of appointment system design on no-shows. Through this empirical examination, we aim to enhance understanding of the role of appointment system design in managing patient no-shows and to provide evidence-based recommendations for healthcare practitioners.

2.3 System Design

Our study contributes to the existing literature on system design. Prior studies have explored the influences of core system-related components and peripheral system-related components on user's perception and behavior. Specifically, the core system-related components are the fundamental drivers behind the existence of systems (Roth and Menor, 2003; Venkatesh et al., 2012). The peripheral system-related components are those typically outside of the core function offerings but complementary to them (Roth and Menor, 2003; Voss et al., 2008). For example, Luo et al. (2012) identified the critical role of a retailer's service quality, website design, and pricing strategies in mitigating the adverse effects of product uncertainty and low retailer visibility, thereby enhancing online customer satisfaction. Similarly, Wells et al. (2011)

demonstrated the impact of website quality—encompassing factors such as security, download speed, navigability, and visual appeal—on consumers' perceptions of product quality and subsequent online purchase intentions. Venkatesh et al. (2012) highlighted four key attributes of e-government services (usability, computer resource requirement, technical support provision, and security provision) that influence the adoption and usage of transactional e-government services. Additionally, Gregg and Walczak (2008) suggested that enhancing an auction company's e-image could positively impact consumers' willingness to engage in transactions. Venkatesh et al. (2017) explored the influences of the hardware design (barcode scanner vs. radio frequency identification reader) and content design (product information vs. product review vs. both) on technology adoption, security beliefs, and shopping. Xu et al. (2014) investigated a novel design for a recommendation agents interface that enables it to interactively demonstrate trade-offs among product attribute values (i.e., trade-off transparency feature) to improve consumers' perceived product diagnosticity and perceived enjoyment.

Previous research has highlighted the significant impact of system design on user perceptions and behavior. However, a noticeable gap remains in understanding how these designs affect operational outcomes, especially offline patient no-shows. In an appointment system, providing relevant and accurate information—such as appointment availability, scheduling procedures, and service descriptions—is crucial for its effective functioning. On the other hand, technical support, while peripheral to scheduling, is essential for assisting users with technical issues. Drawing from SET, we fill the research gap and posit that technical support and information provision significantly influence patient behavior by enhancing perceived effort and credibility (Cropanzano and Mitchell, 2005). These factors improve patients' perceptions of the effort invested by service providers and augment the perceived credibility of both the service providers and the services offered (Buell et al., 2017; Buell and Norton, 2011; Wei and Zhang, 2023; Park et al., 2023; Kraft et al., 2022). Consequently, these elements can potentially increase the likelihood of patient attendance.

3 Theory Development

In this section, we draw from SET to propose that technical support and information provision are critical components of appointment system design, impacting patients' perceptions of appointments (through perceived effort and credibility) and subsequently reducing no-shows.

3.1 Impact of Technical Support on Patient No-show Behavior

Integrating technical support into outpatient appointment systems is a valuable supplementary service that enhances the core function of appointment scheduling. This support addresses barriers related to appointment systems, improving patient engagement and overall usage. Specifically, technical support aids patients in navigating the healthcare system, resolving technical issues, and understanding its features and services (Pipek and Wulf, 2009; Hong et al., 2011). By assisting patients in effectively using the appointment system, technical support reduces confusion and frustration, thereby demonstrating the service provider's effort. This effort fosters a sense of obligation in patients to reciprocate by attending their appointments (Homans, 1958). Moreover, technical support enhances the provider's credibility. When patients receive clear, consistent, and helpful technical assistance, they are more likely to view the service provider as competent and reliable. This increased credibility leads to greater trust in the service and a stronger commitment to keeping scheduled appointments (Khuntia et al., 2021). In summary, technical support significantly improves patients' interaction with appointment systems, enhancing their perceived effort and credibility, and subsequently reducing no-show behaviors. Therefore, we posit the first hypothesis:

Hypothesis 1. Technical support provision decreases patient no-shows.

3.2 The Impact of Information Provision on Patient No-show Behavior

Providing detailed information in the outpatient appointment system is crucial for effective scheduling. Clear and accessible information about appointment options and requirements helps patients navigate the process more efficiently, identify appropriate medical services, and understand specific medical instructions or requirements. The quality of information provided significantly shapes patients' views of the hospital's efforts to improve service delivery (Buell et al., 2017). When patients appreciate the effort hospitals invest in improving information within the appointment system, they may feel obligated to reciprocate by attending the scheduled appointments (Homans, 1958). Furthermore, providing detailed information in the outpatient appointment system significantly enhances the perceived credibility of healthcare providers, which in turn reduces patient no-shows. When patients are given comprehensive information about provider specialties, backgrounds, and awards, they are more likely to recognize the value and significance of their scheduled appointments (Venkatesh et al., 2016). This transparency cultivates greater trust and confidence in the healthcare services they are about to receive (Kang and Hustvedt, 2014). Additionally, detailed information allows patients to know what to expect, which reduces uncertainty—common barrier to attending medical appointments. This clarity enables patients to prepare adequately, fostering a more positive attitude towards keeping their appointments. When patients perceive service providers and services as credible, their likelihood of attending appointments increases, effectively reducing no-show behaviors. Therefore, we posit the following hypothesis:

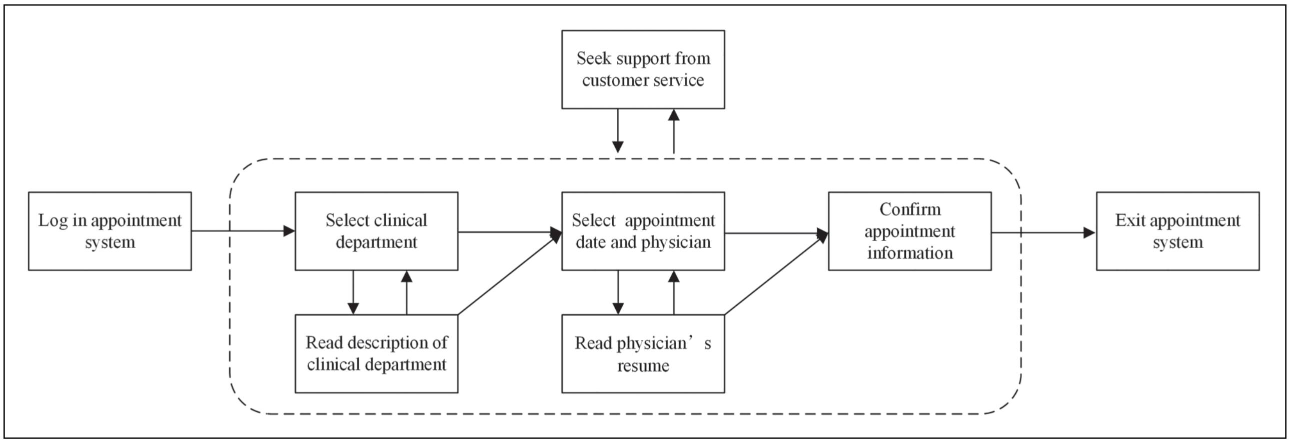

Figure 1. Flow of scheduling appointments.

Hypothesis 2. Information provision decreases patient no-shows.

4 Empirical Design

Two empirical studies are conducted to test the proposed theoretical framework. First, data from an online appointment system in a Chinese hospital are used to examine the relationship between technical support and no-show behavior (Hypothesis 1) and the relationship between information provision and no-show behavior (Hypothesis 2). Using a DID approach at the patient-day level, we leverage two software update events in the observational datasets to estimate the effects. Second, 2×2 scenarios (technical support vs. no technical support: information provision vs. no information provision) in a randomized controlled experiment are manipulated to test the underlying mechanisms (i.e., perceived effort and perceived credibility).

4.1 Background

Our data were collected from an outpatient appointment system in a Chinese hospital. The hospital is a large-scale hospital with medical treatment, teaching, and scientific research. The hospital has four medical campuses and 59 medical departments. This hospital implemented an online outpatient appointment system to optimize medical resource allocation and increase operational efficiency in 2009. The hospitals appointment system has multiple functions, including scheduling appointments, checking in, paying registration fees, reading medical reports, and receiving information prompts. Based on the system data provided by the hospital, 2017 yielded 440,822 appointment records (by app channel), and patients no-show rate is around 10.30%. The flow of scheduling appointments is shown in Figure 1. To ensure the performance of the appointment system, the hospital has taken several strategies for mitigating patients' no-show behavior. For example, if a patient does not show up for a scheduled appointment, the patient cannot reschedule within 7 days using the same appointment channel. In addition, the hospital does not strictly enforce its strategies to mitigate patient no-show behavior. For instance, even if patients are unable to secure appointments through the online channel, they have the option to use offline appointment channels provided by the hospital. Furthermore, patients have the choice to visit alternative reputable hospitals.

4.2 Identification Strategy

To test our hypotheses, we utilize two software update events that occurred in the user interface of an appointment channel (app) to create plausibly exogenous variations. These changes in the software user interface allow us to examine the influences of technical support and information provision on patient behavior.

4.2.1 Technical Support. The hospital manages two appointment channels: the app channel and the website channel. Both channels belong to the online platform and share identical lead time and appointment regulations. A pivotal moment occurred on February 23, 2017, with the release of Version 2.2.2 for the app channel, incorporating online technical support. This enhancement aimed to furnish patients with assistance on appointment system-related issues while utilizing the app, specifically focusing on technical support and excluding medical-related consulting services. The integration of technical support is expected to enhance the appointment app's service quality, constituting an exclusive feature for the app channel. In contrast, the website channel lacked a corresponding technical support feature during the study period. The introduction of technical support as a unique software attribute for the app channel offers a distinctive quality for examination in a natural experiment. We refer to the provision of technical support as the technical support event. It is crucial to highlight that while appointment information—including available slots, clinic department details, and doctor information—undergoes simultaneous updates across both appointment channels, the addition of technical support is specific to the app channel, ensuring synchronization for all app channel users.

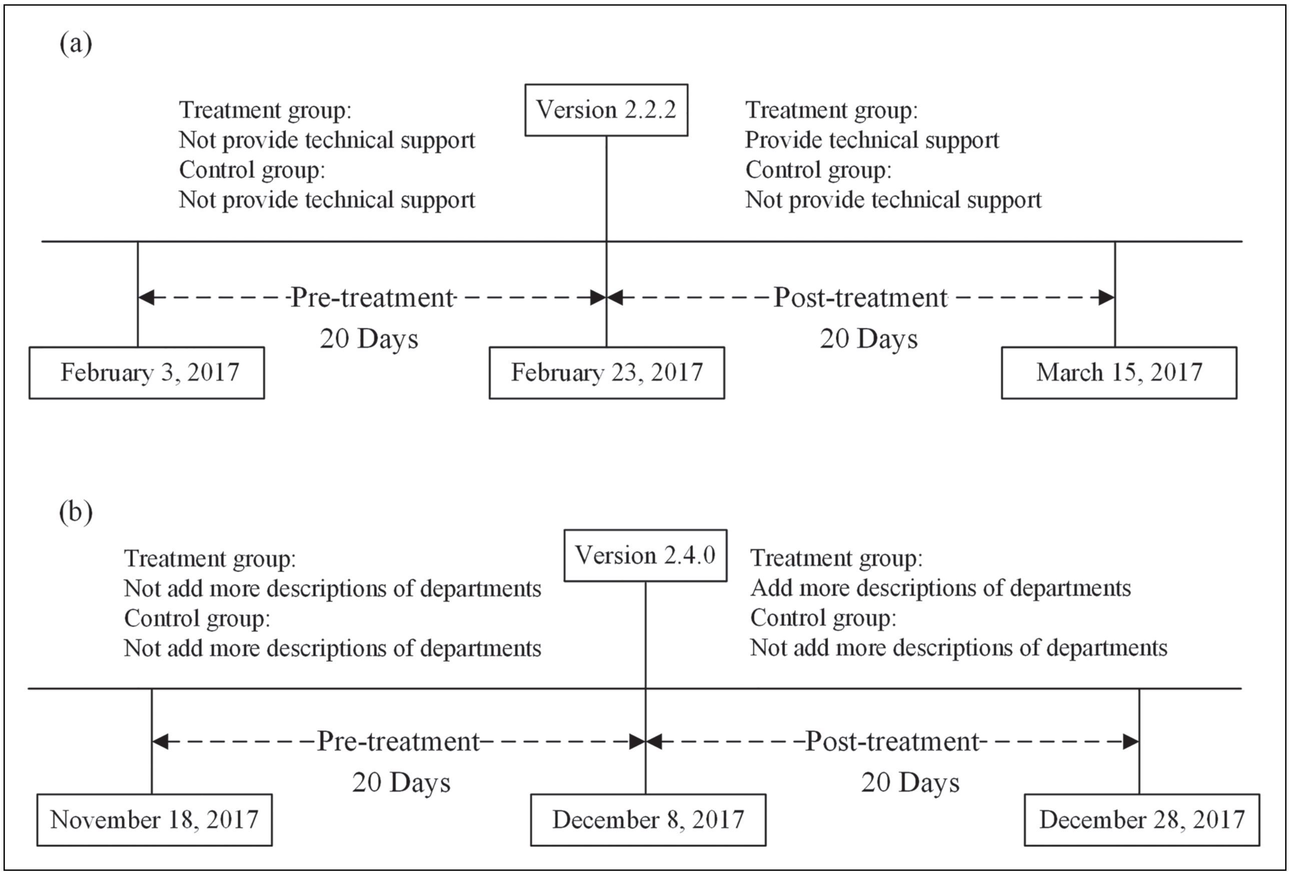

Figure 2. (a) Time line of technical support event; (b) time line of information provision event.

4.2.2 Information Provision. On December 8, 2017, the hospital updated its appointment app to Version 2.4.0. This new version included more detailed descriptions of treatment options for certain clinical departments. These treatment options were designed for specific typical diseases and provided comprehensive information about each disease, the hospital's service capabilities, and the physicians. For example, the hospital categorized three types of typical diseases within endocrinology and designated clinical specialists for each: osteoporosis specialists, thyroid medicine specialists, and diabetes specialists. The decision-making process behind this update considered various scenarios, including the incorporation of new treatment options such as therapeutic methods, surgeries, the integration of advanced medical technologies, and compliance with regulatory requirements. However, not all clinical departments enhanced their descriptions. This selective enhancement creates an opportunity for a natural experiment, enabling the identification of the causal effects of information provision on patients' no-show behavior. We refer to this enhancement as the information provision event. All appointment channels at the hospital provided updates on appointment information. However, our analysis for this specific event is confined to the app channel, which has a broad user base.

4.3 Data and Variables

Two waves of data were collected from the hospital appointment system, corresponding to the two quasi-experiments described earlier. The appointment app was updated to Version 2.1.8 on December 19, 2016, and to Version 2.2.5 on June 9, 2017. To manage potential disturbances from these updates, the first data collection phase (using Version 2.2.2 as of February 23, 2017) covered January 23, 2017, to May 23, 2017. Subsequently, updates to Version 2.2.7 on October 23, 2017, and to Version 2.6.0 on August 23, 2018, prompted the second data collection phase (using Version 2.4.0 as of December 8, 2017) from November 8, 2017, to July 8, 2018. The details regarding app updates were verified by the hospital's IT department. To ensure consistency and comparability in the two waves of data collection, we restricted the time window to 20 days before and after each update. Figures 2(a) and (b) provide a visual representation of the timelines for the two quasi-experiments, respectively.

In Figure 2(a), the natural experiment in a 41-day window between February 3, 2017, and March 15, 2017, is observed. The technical support event of providing technical support in the app on February 23, 2017, is considered a natural shock that influenced the treatment group. Similarly, the period from

Table 1. Definitions and summary statistics.

Variable	Definition	Technical support				Information provision			
		Mean	Std	Min	Max	Mean	Std	Min	Max
NS	The outcome of the scheduled appointment (1: No-show; 0: Show)	0.183	0.387	0.000	1.000	0.110	0.312	0.000	1.000
Gender	Patient' gender (1: Female; 0: Male)	0.556	0.497	0.000	1.000	0.569	0.495	0.000	1.000
Age	Patient' age	41.931	20.053	1.000	93.000	41.334	17.186	1.000	96.000
Local	Local residents (1: Yes; 0: No)	0.798	0.401	0.000	1.000	0.713	0.452	0.000	1.000
Lead time	The number of days between appointment and scheduling dates.	3.886	2.142	1.000	7.000	3.310	2.116	1.000	7.000
Physician	Physician type (1: Specialists; 0: General physicians)	0.578	0.494	0.000	1.000	0.474	0.499	0.000	1.000
Campus	1: A campus; 0: B campus	0.185	0.388	0.000	1.000	0.458	0.498	0.000	1.000
Price	Registration fee	54.695	50.868	15.000	150.000	43.057	43.678	15.000	150.000

Note: We analyze the appointment records of A and B campuses, which are the two largest campuses of the hospital.

February 3, 2017, to the launch time is defined as the pre-treatment stage, and the period from the launch time to March 15, 2017, as the post-treatment stage. Users using the app with technical support are defined as the treatment group, and the website user without technical support as the control group. In practice, patients have the flexibility to transition between different channels. To address the potential disruptions stemming from these alternative channels, our analysis concentrates solely on users who have made a single appointment within the designated observational time window.

Figure 2(b) shows the 41-day window between November 18, 2017, and December 28, 2017; this assesses information provision. During this period, the second event of adding more descriptions of clinical departments on December 8, 2017, was considered a natural shock, generating variations in the treatment group. The period from November 18, 2017, to the launch time is defined as the pre-treatment stage, and the period from the launch time to December 28, 2018, as the post-treatment stage. Users making appointments in the clinical departments that add more descriptions are defined as the treatment group, and users making appointments with clinical departments that do not add any new descriptions are defined as the control group. Each appointment record contains the following information: patient identifier, gender, age, the time of making an appointment, clinical departments, physician type (specialists/general physicians), specialist name, scheduled time, and results of the appointment (no-show/arrive). The final sample sizes for the analyses of technical support and information provision are 16,832 and 49,698 appointment records, respectively. Table 1 presents the summary statistics.

4.4 Model Specifications

To test the proposed hypotheses, a pooled cross-sectional DID approach is adopted (Kiel and McClain, 1995). For the technical support event, equation (1) is estimated as

$$NS_{it} = \beta_0 + \beta_1 TechnicalSupport_{it} \times Post_{it} + \beta_2 TechnicalSupport_{it} + X_{it} + v_t + \mu_p + \varepsilon_{it}, \quad (1)$$

where t represents the date and i represents the patient. The dummy variable NS_{it} signifies the appointment outcome for patient i on day t. The dummy variable NS_{it} equals 1 if the outcome of the appointment is no-show and 0 otherwise. The dummy variable $TechnicalSupport_{it}$ equals 1 if patient i made the appointment using the app channel and 0 indicates that patient i using the website channel. The dummy variable $Post_{it}$ equals 1 if the time t as the day on or after February 23, 2017, and 0 otherwise. The variables X_{it} include the patient-level factors, that is, gender (*Female*), age (*Age*), local residency (*Local*), physician type (*Specialist*), registration fee (*Price*), campus (*Campus*), lead time (*Leadtime*), and week dummies (Li et al., 2019; Liu et al., 2019). v_t and μ_p represent date and department dummies, respectively. A separate term $Post_{it}$ is omitted because it is absorbed in v_t. The variable ϵ_{it} is the error term. The coefficient β_1 of the interaction term quantifies how the patients' no-show behavior changes after providing technical support in the app channel, compared to the website channel during the observation window. Thus β_1 is expected to be negative.

For the information provision event, equation (2) is estimated as

$$NS_{it} = \beta_0 + \beta_1 InformationProvision_{it} \times Post2_{it} + \beta_2 InformationProvision_{it} + X_{it} + v_t + \mu_p + \varepsilon_{it}, \quad (2)$$

where the dummy variable $InformationProvision_{it}$ equals 1 if the patient made an appointment in the clinical department that adds more descriptions and 0 otherwise. The dummy variable $Post2_{it}$ equals 1 if the time t as the day on or after December 8, 2017, and 0 otherwise.

5 Results

5.1 The Main Results

Table 2 displays the average no-show rates for technical support and information provision, which are 0.183 and 0.110, respectively (indicating approximately 18.3% and 11.0% of appointments resulted in no-shows during the observation period, respectively). When technical support is provided, the treatment group experiences a decrease in the average no-show rate from 0.122 to 0.091, while the control group experiences an increase from 0.190 to 0.206. Similarly, although both the control and treatment groups see decreases in average no-show rates during the information provision analysis, the treatment group exhibits a higher decrease rate (0.028) compared to the control group (0.005). Given the large population size, these reductions in no-show rates are significant. These findings provide empirical evidence supporting the effectiveness of technical support and information provision in reducing average no-show rates.

Table 3 presents the estimation results of equations (1) and (2). Column (1) of Table 3 shows that the coefficient of the interaction term $TechnicalSupport_{it} \times Post_{it}$ is significantly negative ($\beta_1 = -0.041$, $p < 0.05$). The possibility of no-show behavior at the individual level decreases by 22.40% (0.041/0.183) after adding technical support; thus H1 is supported. Column (2) indicates that the coefficient of the interaction term $InformationProvision_{it} \times Post2_{it}$ is significantly negative ($\beta_1 = -0.012$, $p < 0.05$). The possibility of no-show behavior at the individual level decreases by 10.91% (0.012/0.110) after adding more descriptions of clinical departments (information provision), thereby supporting H2.

Table 2. Statistics of average no-show rates.

	Technical support			Information provision		
	All	Before	After	All	Before	After
All	0.183	0.178	0.187	0.110	0.115	0.103
Treatment	0.107	0.122	0.091	0.105	0.118	0.090
Control	0.198	0.190	0.206	0.111	0.114	0.109

Table 3. DID estimations.

	Dependent variable: Patient no-show	
Variables	(1)	(2)
$TechnicalSupport_{it} \times Post_{it}$	−0.041**	
	(0.019)	
$TechnicalSupport_{it}$	−0.071***	
	(0.013)	
$InformationProvision_{it} \times Post2_{it}$		−0.012**
		(0.005)
$InformationProvision_{it}$		0.000
		(0.005)
Female	0.000	0.004
	(0.006)	(0.004)
Campus	−0.021*	−0.001
	(0.011)	(0.004)
Age	−0.009	−0.043***
	(0.019)	(0.013)
Lead time	−0.008***	0.001
	(0.001)	(0.002)
Specialist	−0.060***	−0.014***
	(0.010)	(0.005)
Price	0.000	−0.000*
	(0.000)	(0.000)
Local	−0.085***	−0.042***
	(0.010)	(0.004)
Week dummies	Yes	Yes
Date dummies	Yes	Yes
Department dummies	Yes	Yes
Observations	16,832	49,698
Within R^2	0.033	0.015

Note: DID = difference-in-differences. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$; robust standard errors in parentheses, clustered at department.

5.2 The Parallel Trends and Falsification Test

A key assumption for the DID estimation is the parallel trends assumption, which posits that before the intervention, both the treatment and control groups exhibit similar trends over time. We follow Cui et al. (2022) to estimate the treatment effect on a daily basis leading up to the intervention. The corresponding parallel trend tests for the technical support and information provision analyses are articulated in equations (3) and (4), respectively,

$$NS_{it} = \beta_0 + \sum_{\tau=-20}^{-1} \gamma_\tau Post_\tau^t + \sum_{\tau=-20}^{-1} \mu_\tau TechnicalSupport_{it} \times Post_\tau^t + X_{it} + \mu_p + \varepsilon_{it}, \tag{3}$$

$$NS_{it} = \beta_0 + \sum_{\tau=-20}^{-1} \gamma_\tau Post2_\tau^t + \sum_{\tau=-20}^{-1} \mu_\tau InformationProvision_{it} \times Post2_\tau^t + X_{it} + \mu_p + \varepsilon_{it}. \tag{4}$$

Inequation (3), $Post_t$ in equation (1) is replaced with the dummy variable $Post_\tau^t$, where $\tau \in \{-20, -19, -18, \ldots, -2, -1, 0\}$ and $Post_\tau^t = 1$ if $\tau = t$ and 0 otherwise, indicating the relative τth day before the event. The benchmark group is the day of the event. The coefficients μ_{-20} to μ_{-1} identify any day-by-day pre-treatment difference between the treatment group and control group. This difference is expected to be insignificant. The same analysis is repeated for the information provision analysis. Similarly, the coefficients μ_{-20} to μ_{-1} in equation (4) are expected to be insignificant. Figure A.1 and Figure A.2 in Online Appendix A present the estimation results of the parallel trends test for the technical support and information provision analyses, respectively. No pre-treatment

Table 4. Falsification test.

Variables	Dependent variable: Patient no-show (1)	(2)
$TechnicalSupport_{it} \times Post_{it}$	−0.009	
	(0.017)	
$TechnicalSupport_{it}$	−0.085***	
	(0.017)	
$InformationProvision_{it} \times Post2_{it}$		−0.005
		(0.006)
$InformationProvision_{it}$		−0.001
		(0.007)
Control variables	Yes	Yes
Date dummies	Yes	Yes
Department dummies	Yes	Yes
Observations	16,832	49,698
Within R^2	0.033	0.015

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$; robust standard errors in parentheses, clustered at department.

differences exist in the no-show rates between the treatment and control groups, verifying the parallel trends assumption.

We conduct a falsification test to show the estimated effects result from the two key events. Specifically, the same analysis specified in equations (1) and (2) is repeated, but with a different time shock. In the analysis of technical support, the time shock is designated as February 13, 2017—10 days preceding the actual shock. In the examination of information provision, the time shock is defined as November 28, 2017—also 10 days before the real shock. As shown in Table 4, the coefficient of interaction terms $TechnicalSupport_{it} \times Post_{it}$ and $InformationProvision_{it} \times Post2_{it}$ are insignificant, verifying that the treatment events that providing technical support and information can reduce no-show behavior. In summary, the parallel trends and falsification tests indicate that the DID analysis generates credible causal evidence.

5.3 Heterogeneity Analysis

In this section, we further delve into the heterogeneity of patient responses to technical support and information provision. By examining these variations, we can uncover whether the interventions' effectiveness in reducing no-show behavior differs across diverse conditions.

5.3.1 Patient-related Impact on No-show Behavior. In this section, we delve into the influence of patient-related variables, particularly age and gender, on the relationship between technical support (or information provision) and no-show behavior. Older patients often display a greater resistance to technological advancements and exhibit slower rates of adopting new systems compared to their younger counterparts (Porter and Donthu, 2006; Wixom and Todd, 2005). This resistance is likely rooted in their entrenched reliance on traditional methods and their lesser familiarity with digital innovations. Given these variances in technology acceptance and adaptation, investigating the impact of technical support and information provision across various age groups enables us to assess the relative significance of perceived effort and credibility in influencing appointment attendance. Specifically, older patients are less sensitive to system improvements compared to younger patients, resulting in reduced sensitivity to perceived effort and credibility induced by technical support and information provision. Consequently, it is plausible that technical support and information provision may not effectively mitigate no-show behavior among older patients. The findings of a three-way interaction analysis are presented in Table 5. In Column (1), the coefficient for the interaction term $TechnicalSupport_{it} \times Post_{it} \times Age$ is 0.028 ($p < 0.05$). Likewise, in Column (3), the coefficient for $InformationProvision_{it} \times Post2_{it} \times Age$ is 0.031 ($p < 0.1$). These coefficients offer valuable insights into how patients of different ages perceive and engage with the appointment system, thereby enhancing our comprehension of the underlying mechanisms influencing appointment attendance.

Gender differences in problem-solving strategies and information-seeking behavior also offer valuable insights into the mechanisms of perceived effort and credibility within the context of technical support and information provision (Ahuja and Thatcher, 2005; Zhang et al., 2009). In terms of technical support, females may demonstrate a greater inclination to seek assistance and accept help compared to males. This heightened receptivity to technical assistance can augment female patients' perceived effort of improve service quality within a hospital and bolster their trust and confidence in the system's credibility. A three-way interaction analysis, as outlined in Column (2) of Table 5, reveals a noteworthy coefficient for the interaction term ($TechnicalSupport_{it} \times Post_{it} \times Female$), with a value of −0.045 ($p < 0.05$), indicating a significant negative effect. This highlights the more pronounced influence of technical support on reducing no-show behavior among female patients. Conversely, the impact of information provision may be dampened among female patients due to their distinct preferences in accessing medical information. Females may rely more on interpersonal interactions and discussions with medical staff, diminishing the influence of information provided through the appointment system. Consequently, while information provision may still affect female patients, its impact on their no-show behavior may be less pronounced compared to male patients, who may place greater value on independently accessed information. In this scenario, relative to males, female patients exhibit lower sensitivity to information provision, thus experiencing no discernible increase in perceived effort and credibility induced by information provision, consequently maintaining the likelihood of no-show behavior. The result in Column (4) of Table 5 illustrates a coefficient for the interaction term $InformationProvision_{it} \times Post2_{it} \times Female$ of 0.020 ($p < 0.1$), indicating that, in contrast to male patients,

Table 5. Heterogeneity test of patient-related characteristics.

	Dependent variable: Patient no-show			
	(1)	(2)	(3)	(4)
$TechnicalSupport_{it} \times Post_{it}$	−0.143** (0.057)	−0.018 (0.019)		
$TechnicalSupport_{it} \times Post_{it} \times$ Age	0.028** (0.014)			
$TechnicalSupport_{it} \times Post_{it} \times$ Female		−0.045** (0.022)		
$InformationProvision_{it} \times Post2_{it}$			−0.129** (0.061)	−0.026*** (0.005)
$InformationProvision_{it} \times Post2_{it} \times$ Age			0.031* (0.016)	
$InformationProvision_{it} \times Post2_{it} \times$ Female				0.020* (0.010)
Control variables	Yes	Yes	Yes	Yes
Date dummies	Yes	Yes	Yes	Yes
Department dummies	Yes	Yes	Yes	Yes
Observations	16,832	16,832	49,698	49,698
Within R^2	0.034	0.034	0.015	0.015

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$; robust standard errors in parentheses, clustered at department. To keep the table concise, we did not include the results of two way interactions (e.g., $Post_{it} \times$ Age, $TechnicalSupport_{it} \times$ Age).

the impact of information provision on female patients' no-show behavior is diminished.

5.3.2 Appointment-Related Impact on No-show Behavior. We analyze the influence of appointment attributes, particularly lead time and clinic department reputation, on the relationship between technical support (or information provision) and no-show behavior. Our study investigates how technical support and information provision influence patient no-shows across various appointment lead times, defined as the duration between scheduling and the appointment itself (Simsek et al., 2021). Lead time serves as a crucial indicator of patient willingness to wait for medical attention, influenced by factors such as disease urgency, appointment availability, and scheduling convenience. Longer lead times provide patients with more time to address uncertainties or schedule conflicts. Offering technical support and information enables patients to reevaluate their appointments or anticipate disruptions, thereby enhancing their perception of the effort and credibility associated with improved service quality. Consequently, this may lead to a reduction in patients' no-show behavior. Using three-way interaction analysis, we examine how lead time moderates the relationship between technical support (or information provision) and no-show behavior. In Column (1) of Table 6, the coefficient for the interaction term $TechnicalSupport_{it} \times Post_{it} \times Leadtime$ is $-0.009 (p < 0.1)$, indicating a potential moderating effect of lead time on the relationship between technical support and no-show behavior. However, the coefficient for the interaction term $InformationProvision_{it} \times Post2_{it} \times Leadtime$ is $-0.001 (p > 0.1)$, suggesting that lead time does not significantly moderate the relationship between information provision and no-show behavior. This discrepancy may stem from the extended period between information provision and the scheduled appointment, resulting in diminished urgency regarding the appointment's significance. Typically, patients prioritize earlier appointments if they align with scheduling constraints, disease urgency, and physician preferences (Wang and Gupta, 2011). Our interviews also indicate that disease severity influences lead time decisions, as patients tend to schedule appointments sooner for serious conditions. However, urgent cases, where patients may bypass regular appointments and seek immediate care at emergency departments, are not within the scope of this study. In scenarios with lower disease urgency, patients may perceive less sensitivity to the effort induced by providing additional information. Consequently, the impact of information provision on no-show behavior may diminish with longer lead times.

We further investigate the moderating effect of clinic department reputation. Clinic department reputation is quantified using the hospital ranking report provided by the Hospital Management Institute of Fudan University. A department is deemed to have a high reputation (assigned a value of 1) if it is listed in the report; otherwise, it is considered to have a low reputation (assigned a value of 0). The results of Columns (2) in Table 6 show that the impact of providing technical support on patients' no-show behavior is amplified in departments with a high reputation compared to those with a low reputation ($\beta = -0.054$, $p < 0.05$). These findings align with previous research indicating a relationship between service provider reputation, customers' perceptions of uncertainty, and trust towards the provider (Rice, 2012). Patients with high expectations for service quality are prone to greater dissatisfaction and

Table 6. Heterogeneity test of appointment-related characteristics.

	Dependent variable: Patient no-show			
	(1)	(2)	(3)	(4)
$TechnicalSupport_{it} \times Post_{it}$	−0.013	−0.023		
	(−0.029)	(−0.015)		
$TechnicalSupport_{it} \times Post_{it} \times$ Leadtime	−0.009*			
	(−0.005)			
$TechnicalSupport_{it} \times Post_{it} \times$ Reputation		−0.054**		
		(−0.020)		
$InformationProvision_{it} \times Post2_{it}$			−0.011	−0.013***
			(−0.011)	(−0.005)
$InformationProvision_{it} \times Post2_{it} \times$ Leadtime			−0.001	
			(−0.004)	
$InformationProvision_{it} \times Post2_{it} \times$ Reputation				−0.008
				(−0.015)
Control variables	Yes	Yes	Yes	Yes
Date dummies	Yes	Yes	Yes	Yes
Department dummies	Yes	Yes	Yes	Yes
Observations	16,832	16,832	49,698	49,698
Within R^2	0.034	0.034	0.015	0.015

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$; robust standard errors in parentheses, clustered at department. To keep the table concise, we did not include the results of two way interactions in the table.

tend to display a stronger negative reaction, including reduced perceived effort and credibility, towards perceived deficiencies in technical support. Conversely, in clinic departments with low reputation, where expectations may be more modest, the impact of technical support on attendance behavior is likely less pronounced. However, the analysis of information provision yields contrasting results. In Table 6, Column (4), the impact of information provision on patients' no-show behavior appears consistent across clinic departments with different reputation levels ($\beta = -0.008, p > 0.1$). This implies that the impact of information provision on attendance behavior remains consistent regardless of the reputation level of the clinic department. Departments with a high reputation level typically correspond to a high level of credibility. Therefore, providing additional information does not alter patients' perceived effort and credibility.

5.3.3 Weather-Related Impact on No-show Behavior. Commuting costs, particularly during adverse environmental conditions like rain and unfavorable temperatures, can significantly influence patients' decisions to attend medical appointments. Previous studies have highlighted the importance of considering these factors in understanding patient behavior (Koetse and Rietveld, 2009; Saneinejad et al., 2012). This study examines how technical support and information provision can influence appointment attendance, particularly in the context of rainy weather. The results in Table 7, Column (1), reveal interesting insights. The coefficient of the interaction term $TechnicalSupport_{it} \times Post_{it} \times Rain$ is -0.054 ($p < 0.05$), indicating that on rainy days, the negative effects of technical support on no-show behavior are more pronounced compared to non-rainy days. This suggests that offering technical support can help mitigate the impact of rain-related barriers on appointment attendance. By enhancing communication and facilitating access to the appointment system, technical support can increase patients' perceived effort and credibility, leading to a reduction in no-show behavior. However, the relationship between information provision and no-show behavior remains negative for both rainy and non-rainy days ($\beta = -0.001, p > 0.1$). While providing information is crucial for patients to schedule appointments, its ability to mitigate the impact of rain-related commuting costs on attendance may be limited without specific, actionable guidance tailored to address the challenges posed by rainy conditions.

Compared to rainy days, days with unfavorable temperatures, such as excessive heat or cold, pose unique challenges that can affect patients' ability to travel to appointments and increase commuting costs. It is essential to understand how commuting costs due to unfavorable temperatures affect patient attendance (Koetse and Rietveld, 2009). This study accounts for potential differences in commuting challenges by coding the variable *UnfavorableTemperature* as 1 if the temperature is above the monthly average maximum temperature or below the monthly average minimum temperature, and 0 otherwise. In Column (4) of Table 7, the coefficient of the interaction term for the information provision event $InformationProvision_{it} \times Post2_{it} \times UnfavorableTemperature$ is -0.027 ($p < 0.05$). This indicates that the negative influence of information provision on no-show behavior is stronger on days with unfavorable temperatures. Enhanced information provision not only improves appointment accuracy but also boosts

Table 7. Heterogeneity test of weather-related variables.

	Dependent variable: Patient no-show			
	(1)	(2)	(3)	(4)
$TechnicalSupport_{it} \times Post_{it}$	−0.022	0.007		
	(−0.016)	(0.066)		
$TechnicalSupport_{it} \times Post_{it} \times Rain$	−0.054**			
	(−0.026)			
$TechnicalSupport_{it} \times Post_{it} \times UnfavorableTemperature$		−0.052		
		(−0.060)		
$InformationProvision_{it} \times Post2_{it}$			−0.015**	−0.003
			(−0.006)	(0.008)
$InformationProvision_{it} \times Post2_{it} \times Rain$			0.011	
			(0.023)	
$InformationProvision_{it} \times Post2_{it} \times UnfavorableTemperature$				−0.027**
				(−0.013)
Control variables	Yes	Yes	Yes	Yes
Date dummies	Yes	Yes	Yes	Yes
Department dummies	Yes	Yes	Yes	Yes
Observations	16,832	16,832	49,698	49,698
Within R^2	0.034	0.034	0.015	0.015

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$; robust standard errors in parentheses, clustered at department. To keep the table concise, we did not include the results of two way interactions in the table.

patients' perceived effort and credibility in service enhancement efforts. This increased sense of trustworthiness motivates patients to overcome discomfort, such as unfavorable temperatures, thereby reducing instances of missed appointments. In Column (2), the coefficient of the interaction term for the technical support event $TechnicalSupport_{it} \times Post_{it} \times UnfavorableTemperature$ is −0.052 ($p > 0.1$). This suggests that technical support's efficacy in mitigating physical discomfort or safety apprehensions related to unfavorable temperatures may be limited, thus impacting its ability to enhance patients' perceived credibility. Consequently, its effectiveness in reducing no-show behavior on such days is constrained.

5.4 Robustness Checks

Our benchmark analyses unveil a significant negative relationship between appointment system features and patient no-shows. In this section, the results of several additional analyses are reported to ensure that our estimated effects are robust. Initially, we employed PSM with DID to address potential selection biases and enhance comparability between the treatment and control groups. Subsequently, we conducted a robustness check using the DID analysis over an extended time period to validate our primary findings. Additionally, we ensured result robustness by verifying them at the department level, ensuring consistency across different units. Finally, three data restrictions were implemented on the initial sample to bolster validity.

5.4.1 DID Combined With PSM. While the DID method can help alleviate some selection bias through rich fixed-effects settings, concerns may persist if the treatment assignment is not strictly random. In the analysis of the technical support event, we primarily utilize data from patients with only one appointment record to mitigate bias associated with switching appointment channels. However, it is important to note that patients may demonstrate differing propensities for utilizing app channels versus website channels. Consequently, the assignment of patients to treatment and control groups may not strictly adhere to randomization principles. In relation to the information provision event, while our analysis has elucidated that augmenting informational content is not expressly intended to address no-show behavior, it is imperative to acknowledge the potential presence of selection bias between the treatment and control groups.

To address this potential issue, we complement our DID model with a PSM design to assess the impact of matched treatment and control groups. By combining PSM with DID analysis, we aim to control for the influence of unobserved characteristics and enhance the robustness of causal inferences. Specifically, propensity scores for app channel selection are calculated for each patient, representing the probability of choosing either the app channel or website channel, using a logit model. The model incorporates various characteristics, including gender (female), age (age), local residency (local), physician type (specialist), registration fee (price), campus (campus), and lead time (leadtime). We then match each treated unit with a control unit using the nearest-neighbor matching algorithm with replacement. This application of PSM brings our natural experimental setting closer to a randomized design. To assess the quality of the PSM matching procedure, we conduct t-tests to compare the means of

Table 8. PSM-DID estimations.

	Dependent variable: Patient no-show	
	(1)	(2)
$TechnicalSupport_{it} \times Post_{it}$	−0.040***	
	(0.014)	
$TechnicalSupport_{it}$	−0.069***	
	(0.012)	
$InformationProvision_{it} \times Post2_{it}$		−0.009*
		(0.005)
$InformationProvision_{it}$		−0.005
		(0.007)
Propensity scores of technical support	Yes	No
Propensity scores of information provision	No	Yes
Control variables	Yes	Yes
Date dummies	Yes	Yes
Department dummies	Yes	Yes
Observations	10,802	36,399
Within R^2	0.036	0.019

Note: PSM-DID = propensity score matching and difference-in-differences. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$; robust standard errors in parentheses, clustered at department.

Table 9. DID estimations for long time window.

	Dependent variable: Patient no-show	
	(1)	(2)
$TechnicalSupport_{it} \times Post_{it}$	−0.039**	
	(0.019)	
$TechnicalSupport_{it}$	−0.072***	
	(0.013)	
$InformationProvision_{it} \times Post2_{it}$		−0.013***
		(0.004)
$InformationProvision_{it}$		0.011***
		(0.003)
Control variables	Yes	Yes
Date dummies	Yes	Yes
Department dummies	Yes	Yes
Observations	21,469	82,750
Within R^2	0.037	0.017

Note: DID = difference-in-differences. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$; robust standard errors in parentheses, clustered at department.

matching variables between the treated and control units. The summary statistics of the data sample before and after using PSM are presented in Table B.1 in the Online Appendix B. Post-matching, the differences in means between the treatment and control groups are not highly statistically significant, indicating the correction of selection bias associated with observable covariates. Subsequently, we re-estimate the DID analysis (equation (1)), and the results are presented in Column (1) of Table 8. The results of this robust analysis align consistently with those from the main analysis of the technical support event, indicating the robustness of our results. We also utilize PSM to enhance comparability between the treatment and control groups in the information provision event. We employ a matching procedure to pair each treated unit with a control unit. Summary statistics of the dataset, both before and after PSM, are presented in Table B.1 in Online Appendix B. Equation (2) is then re-estimated, and the results in Column (2) of Table 8 consistently corroborate the primary analysis of the information provision event.

5.4.2 Long Time Window. In our primary analysis, we employ a time window spanning 20 days before and after the event. To delve into the enduring impacts of technical support and information provision on no-show behavior, we extend the time window to encompass 30 days before and after the event. Revisiting equations (1) and (2), the findings are presented in Table 9. In the first column of Table 9, the coefficient of the interaction term $TechnicalSupport_{it} \times Post_{it}$ is notably negative at -0.039 ($p < 0.05$), signifying a statistically significant and negative relationship between providing technical support and patients' no-show behavior. Moving to Column (2) of Table 9, a substantial and negative coefficient is observed for the interaction term $InformationProvision_{it} \times Post2_{it}$ ($\beta = -0.013, p < 0.01$). This result suggests a negative relationship between information provision and patients' no-show behavior. Additionally, we perform parallel trend tests, and the outcomes are detailed in Appendix C.

5.4.3 The Department-Level Analysis. A DID approach is adopted to identify whether such a decline in no-show behavior also occurs at the department-week level. We further test the technical support event using department-level data in equation (5):

$$NR_{it} = \beta_0 + \beta_1 TechnicalSupport_{it} \times Post_{it} + \beta_2 Post_{it} + \beta_3 X_{it} + \mu_i + v_t + \epsilon_{it}, \tag{5}$$

where NR_{it} represents the average no-show rates of department i at week t. The dummy variable $TechnicalSupport_{it} = 1$ represents using app channel; $TechnicalSupport_{it} = 0$ represents using the website channel. The time dummy variable $Post_{it} = 1$ represents that week t is after the event; $Post_{it} = 0$ represents that week t is before the event. μ_i represents department dummies. v_t represents week dummies. X_{it} represents the control variables (gender proportion, average age, average waiting interval, and the number of physicians at the department level). To obtain the average value of patients' age and lead time, these control factors are averaged within a specific period (1 week). The number of male patients is divided into the total number of patients within 1 week (the proportion of male patients) to code the gender variable for each department. The number of physicians is measured by the number of physicians at work for each department. The variable ϵ_{it} is the error term. A separate term $TechnicalSupport_{it}$ is omitted because it is absorbed in μ_i. The coefficient β_1 of the interaction term

Table 10. DID estimations at department level.

	Dependent variable No-show rate	
	(1)	(2)
TechnicalSupport$_{it}$× Post$_{it}$	−0.018**	
	(0.008)	
InformationProvision$_{it}$× Post2$_{it}$		−0.039**
		(0.018)
Post$_{it}$	0.037***	
	(0.013)	
Post2$_{it}$		−0.235***
		(0.038)
Number of physicians	−0.000	0.002
	(0.001)	(0.002)
Average lead time	−0.076***	0.105
	(0.026)	(0.063)
Male percent	0.071***	−0.072
	(0.026)	(0.063)
Average age	−0.026	−0.034
	(0.044)	(0.087)
Week dummies	Yes	Yes
Department dummies	Yes	Yes
Observations	769	364
Within R^2	0.110	0.155

Notes: DID = difference-in-differences. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$; robust standard errors in parentheses, clustered at the department level; using long time window data.

quantifies how the no-show rate changes after providing technical support in the app channel, compared to the website channel during the observation window. Thus β_1 is expected to be negative.

Similarly, we test the impact of information provision event on no-show rate with department-level data in equation (6):

$$NR_{it} = \beta_0 + \beta_1 InformationProvision_{it} \times Post2_{it} + \beta_2 Post2_{it} + \beta_3 X_{it} + \mu_i + \nu_t + \epsilon_{it}. \quad (6)$$

The dummy variable $InformationProvision_{it} = 1$ represents the treatment group; $InformationProvision_{it} = 0$ represents the control group. The time dummy variable $Post2_{it} = 1$ represents that week t is after the event; $Post2_{it} = 0$ represents that week t is before the event.

The estimations in Column (1) of Table 10 support our main findings related to technical support event. The coefficient of the interaction term $TechnicalSupport_{it} \times Post_{it}$ is −0.018 ($p < 0.05$), indicating that technical support is significantly negatively related to patients' no-shows. The estimations in Table 10 also support the main findings related to information provision event. The coefficient of the interaction term $InformationProvision_{it} \times Post2_{it}$ is −0.039 ($p < 0.05$). Table D.1 in Online Appendix D presents the results of the parallel trends test for the technical support and information provision analyses at department level, respectively.

The novel synthetic DID (SDID) estimator by Arkhangelsky et al. (2021) is employed to infer the treatment effects of technical support and information provision events. The SDID method relaxes the parallel-trends assumption for non-randomized treatment and allows for a more flexible pre-adoption pattern. The results of SDID show that (1) the optimal unit weights such that the weighted average time trend of control groups is parallel to that of the treatment groups before the two events, and (2) the optimal time weights such that the weighted average outcome of control groups in the pre-treatment period predicts the average outcome of control groups in the post-treatment period. The SDID result is reported in Table D.2 in Online Appendix D, further confirming the robustness of our main findings.

5.4.4 Validity-Based Data Exclusion. We implemented three restrictions on the initial sample to enhance validity. First, to ensure a standard workload across departments, only clinical departments with more than 10 appointment records per day were included. The analysis results for this criterion are presented in Columns (1) and (4) of Table E.1 in Online Appendix E. Second, after thorough observation and investigation, we identified that patients outside the age range of 18–70 often rely on family assistance for appointment scheduling. Given our focus on examining the correlation between appointment system improvements and reduced appointment no-shows, patients under 18 or over 70 were excluded under the assumption that they may not directly benefit from the system enhancements. The analysis results for this criterion are found in Columns (2) and (5) of Table E.1 in Online Appendix E. Third, clinical departments that ceased operations during the study period due to hospital restructuring, renovation, or relocation were excluded. These closures, unrelated to the technical support and information provision events under study, resulted in temporary or permanent closures. Only clinical departments that continued to operate throughout the study period were considered to improve comparability. The analysis results for this criterion are detailed in Columns (3) and (6) of Table E.1 in Online Appendix E.

6 Testing the Underlying Mechanisms

6.1 Design and Procedure

In this section, the underlying mechanisms of how technical support and information provision influence a patient's intent to arrive at an appointment are explored. The interface of the hospital's appointment app was recreated by a computer engineer in the research to provide participants with a simulated appointment experience. A total of 233 participants (38.62% male, 69.95% in the 26–50 years old group) were recruited on the crowdsourcing platform (Wenjuanxing) to participate in the randomized experiment in exchange for 4 RMB. Participants were asked to use the simulated appointment app to book an appointment with the Neurology department. They were instructed to select the clinical department, physician, and appointment time, and then click on the submit button. The appointment system interface is shown in Online Appendix G. On the basis of Schilke (2018), a series of ambiguous decision trials, in which participants made binary choices about different appointment-related factors, were also conducted. Participants were asked to score the importance of specific factors when making appointments using the app. For example, participants were asked to evaluate the importance of the physician's gender when making appointments, using a 7-point Likert scale, with 1 representing "Strongly disagree" and 7 representing "Strongly agree." These questions represent common choices faced by patients, ensuring high levels of ecological validity. Online Appendix F presents these questions.

We design a 2 (technical support vs. no technical support) × 2 (information provision vs. no information provision) experiment to test the effects of technical support and information provision on the intent to arrive. Technical support was manipulated by providing an online chat robot when the appointment system crashed. Information provision was manipulated by adding more descriptions of clinical departments. The manipulations of technical support and information provision in this section completely correspond to the two appointment system updates (Version 2.2.2 and Version 2.4.0). Then, participants were randomly assigned to the four scenarios and recorded their perceived effort, perceived credibility, and arrival intention ratings. Given that participants were randomly assigned, the differences in the three variables were driven by technical support and information provision.

6.2 Measures

6.2.1 Technical Support. This variable is represented as a dummy variable. A value of 1 indicates the presence of technical support, while a value of 0 indicates its absence.

6.2.2 Information Provision. This variable is also coded as a dummy variable. A value of 1 signifies the presence of information provision, while a value of 0 denotes its absence.

6.2.3 Perceived Effort. This scale was adapted from Buell et al. (2021) and includes the following four items: "I think the hospital exerts much effort on behalf of its patients," "I think the hospital has much medical expertise," "The hospital has much medical experience," and "The hospital is thorough in addressing the needs of its patients."

6.2.4 Perceived Credibility. Perceived credibility was assessed using five items adapted from Spaeth et al. (2015): "Employees in this hospital are technically skilled," "Medical resources and activities in this hospital are well managed," "This hospital would be a good choice for visiting," "I trust this hospital," and "This hospital supports the medical services."

Table 11. Descriptive statistics.

Variable	*N*	Mean	Std	Min	Max
Technical support	233	0.50	0.50	0.00	1.00
Information provision	233	0.40	0.50	0.00	1.00
Perceived effort	233	5.51	0.75	3.00	7.00
Perceived credibility	233	5.46	0.80	2.00	6.80
Arrival intention	233	5.75	0.86	1.67	7.00

Table 12. Manipulation checks.

Level	*N*	Mean	Std	*F*	*p*
Technical support					
Low	116	5.10	1.14	3.140	0.078
High	117	5.35	1.01		
Information provision					
Low	130	5.27	1.04	15.547	0.000
High	103	5.74	0.70		

6.2.5 Arrival Intention. Building on Venkatesh et al. (2016), arrival intention was measured using the following three items: "I intend to attend the scheduled appointment on the scheduled day," "I predict I will attend the scheduled appointment on the scheduled day," and "I plan to attend the scheduled appointment on the scheduled day." Possible responses for all questions are "Strongly agree" (7), "Neutral" (4), and "Strongly disagree" (1). The responses were averaged to the items to create a composite measure for each construct.

6.3 Data Analysis and Results

Table 11 presents the descriptive statistics for the variables introduced above. Before testing the hypotheses, a manipulation check (see Table 12) was performed. Specifically, technical support is perceived as enhancing the system quality of the appointment system. To conduct a manipulation check for technical support, we utilize three items adapted from Xu et al. (2013): "In terms of system quality, I would rate the appointment system highly for the appointment-making task," "Overall, the appointment system that I used was of high quality for the appointment-making task," and "Overall, I would give the quality of the appointment system a high rating for the appointment-making task." Similarly, information provision is regarded as enhancing the information quality of the appointment system. To conduct a manipulation check for information provision, we utilize a three-item scale adapted from Xu et al. (2013): "Overall, I found the information provided by the appointment system very satisfactory when making an appointment," "I was highly satisfied with the information I received from the appointment system for making an appointment," and "The appointment system provided me with very satisfactory information for making an appointment." Consistent with previous methodology, participants were instructed to use a scale ranging from "Strongly agree"

Table 13. Regression results of underlying mechanisms.

	Arrival intention (1)	Perceived effort (2)	Perceived credibility (3)	Arrival intention (4)
Technical support	0.199*	0.142	0.222**	0.036
	(0.109)	(0.097)	(0.100)	(0.083)
Information provision	0.377***	0.306***	0.463***	0.135
	(0.112)	(0.099)	(0.103)	(0.088)
Perceived effort				−0.007
				(0.084)
Perceived credibility				0.846***
				(0.081)
Age	−0.009	0.055	0.086*	−0.015
	(0.053)	(0.047)	(0.049)	(0.040)
Gender	0.180	0.110	0.077	0.170
	(0.114)	(0.101)	(0.105)	(0.086)
Observations	233	233	233	233
R-squared	0.067	0.054	0.105	0.563

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$; robust standard errors in parentheses.

Table 14. Results of the multi-mediator model.

	B	SE	*p*	LL	UL
Technical support – Perceived effort/Perceived credibility – Arrival Intention					
Total effect	0.198	0.112	0.079	−0.023	0.418
Direct effect	0.049	0.085	0.570	−0.120	0.217
Indirect effect (Perceived effort)	0.035	0.030		−0.016	0.102
Indirect effect (Perceived credibility)	0.139	0.075		0.008	0.297
Information provision – Perceived effort/Perceived credibility – Arrival Intention					
Total effect	0.377	0.113	0.010	0.155	0.599
Direct effect	0.065	0.090	0.469	−0.112	0.243
Indirect effect (Perceived effort)	0.077	0.048		0.005	0.189
Indirect effect (Perceived credibility)	0.287	0.086		0.127	0.464

Note: SE = standard errors, LL = lower limit, UL = upper limit.

(7) to "Strongly disagree" (1) to provide their responses. These responses were then averaged across all questions to generate a composite measure for each construct. Results of the one-way analysis of variance (ANOVA) reveal significant differences in technical support across the four groups, $F\ (1, 231) = 3.140$, $p = 0.078$. Participants using the technical support version report a higher mean technical support score ($M = 5.35$, $SD = 1.01$) than those using no technical support version ($M = 5.10$, $SD = 1.14$). The result also shows that the mean level of information provision reported by the group using the information provision version of the app ($M = 5.74$, $SD = 0.70$) is significantly higher than the mean for the group using the no information provision version ($M = 5.27$, $SD = 1.04$), $F\ (1, 231) = 15.547$, $p = 0.000$. These results demonstrated that the manipulation of the app is successful in achieving its experimental goals.

We employed a regression model to investigate the impact of technical support and information provision on arrival intention, while controlling for participants' age and gender. In Table 13, Column (1) demonstrates that both technical support and information provision yield significant and positive coefficients (technical support: $\beta = 0.199$, $p < 0.1$; information provision: $\beta = 0.377$, $p < 0.01$), indicating their substantial positive effects on arrival intention. This finding supports both H1 and H2. Moving to Column (2), information provision exhibits a significant and positive impact on perceived effort ($\beta = 0.306, p < 0.01$), whereas technical support does not significantly affect perceived effort ($\beta = 0.142$, $p > 0.1$). In Column (3), both technical support and information provision significantly influence perceived credibility (technical support: $\beta = 0.222$, $p < 0.05$; information provision: $\beta = 0.463$, $p < 0.01$). Finally, in Column (4), the coefficient for perceived credibility is significant and positive ($\beta = 0.846$, $p < 0.01$), while perceived effort's coefficient is not significant ($\beta = -0.007, p > 0.1$).

Then, indirect effects were assessed and compared using a multiple mediator model (i.e., simultaneous mediation by multiple variables) using a bootstrapping approach (the mediation tests were run with 5,000 bootstrap samples). This model allows us to simultaneously test each mechanism of the mediator while accounting for the shared associations between the two mediators. Table 14 shows the results of the multi-mediator model. We find that the effects of perceived effort and perceived credibility are significant in the relationship between information provision and arrival intention; this is indicated by the fact that the 95% bias-corrected confidence interval for the size of the indirect effect excluded zero for both mediators ((0.005, 0.189) and (0.127, 0.464)). The effect of perceived credibility is significant in the relationship between technical support and arrival intention; in this case, the 95% bias-corrected confidence interval for the size of the indirect effect is (0.008, 0.297). However, the perceived effort is insignificant in the relationship between technical support and arrival intention; in this case, the 95% bias-corrected confidence interval for the size of the indirect effect is $(-0.016, 0.102)$. One possible explanation is that a good appointment system can give users a reliable impression and improve their positive perception of medical services, whereas a good appointment system fails to show the efforts of the patient's hospital before the medical service delivery.

7 Concluding Remarks

Reducing patient no-shows is crucial for effective healthcare operations. Previous studies in service operations and healthcare management have examined approaches to manage patient no-shows, for example, appointment reminders, overbooking, open access, and rescheduling policy (Robinson and Chen, 2010; Zacharias and Pinedo, 2014; Liu et al., 2019). Building on prior research highlighting the impact of healthcare information technology on individual behavior and perception, our study pioneers the examination of how specific features of appointment systems (technical support and information provision) affect patient no-show behavior. Through analyzing two quasi-experiments conducted using data from a Chinese hospital's appointment system, we consistently find empirical evidence suggesting that both technical support and information provision are effective strategies for reducing patient no-shows by improving their perceptions of service provider and service quality. Furthermore, using a randomized controlled experiment, we delve into the underlying mechanisms of this phenomenon. Our experiment reveals that while the relationship between information provision and no-show behavior is mediated by perceived effort and perceived credibility, the relationship between technical support and no-show behavior is solely mediated by perceived credibility.

Our study, though conducted within a specific hospital, highlights system design components—technical support and information provision—that have universal applicability. Offering technical support during appointment scheduling and providing clear, accessible information to patients are relevant across various healthcare settings and can be tailored to the unique needs of different hospitals. The diversity of our patient population, medical departments, and external environment enhances the generalizability of our findings, reflecting a wide range of real-world conditions and patient behaviors. Consequently, hospitals can adopt similar designs for their appointment systems, anticipating comparable improvements in patient outcomes, such as reduced no-shows. This adaptability makes our study a valuable reference for healthcare providers aiming to optimize their appointment systems and overall service delivery.

This study contributes to the literature by documenting the effects of appointment system design on patient no-shows. We demonstrate a causal relationship between appointment system characteristics and no-shows through multiple analyses. The results underscore the importance of appointment system design on patient behaviors and their potential implications for no-show reduction. While previous research has primarily focused on appointment policies to manage patient no-shows, such as rescheduling and resource allocation, our study delves into the design of the appointment system itself. We found that the inclusion of technical support and detailed information in appointment services can significantly reduce no-shows. This research also adds to the body of knowledge on the intersection of healthcare information technology and healthcare operations management. Previous studies in this field have largely focused on the impact of healthcare information technology implementations on clinical and operational outcomes (Kumar and Qiu, 2021; Wang et al., 2024; Yan et al., 2022). However, our study expands on this by demonstrating that specific system features, such as technical support and information provision, can also affect no-show rates. Additionally, the perceived effort and credibility of the system mediate the relationship between these specific system characteristics and patient no-shows.

Our findings have important implications for policy and practice. First, our study highlights that the design of appointment systems can be a powerful tool in reducing patients' no-show behavior. Specifically, hospital managers should prioritize user-friendly designs and incorporate high levels of technical support and information provision. This approach can enhance patients' perceived effort and credibility, potentially leading to a reduction in no-shows. Hospital managers should adopt a mindset of continuous improvement for appointment systems. This includes regularly updating and refining the system based on feedback and data analysis to ensure that it remains user-friendly and meets the needs of both patients and staff.

Second, the diversity in patient demographics necessitates personalized designs for appointment systems. For instance, elderly patients may benefit from educational demonstrations that highlight the advantages of using an appointment system over traditional methods. This approach can improve their understanding and adoption of the system, making them more receptive to updates. Female patients might prefer online support, aligning with their inclination for interactive assistance, while male patients may favor self-service options, reflecting their preference for streamlined and efficient processes. By tailoring appointment system features to meet the unique needs and preferences of various patient groups, healthcare providers can enhance usability and overall patient satisfaction, ultimately reducing patient no-shows.

Third, healthcare providers, renowned for their credibility, should prioritize delivering exceptional appointment services to meet patient expectations effectively. It is crucial for these institutions to allocate resources and efforts towards enhancing the appointment scheduling process, ensuring it is efficient, convenient, and reliable. By consistently striving for excellence in appointment services, providers not only uphold their esteemed reputations but also increase patient satisfaction and loyalty. This commitment to excellence underscores a dedication to meeting the evolving needs and expectations of patients, ultimately improving overall healthcare delivery and patient experience while reducing no-show instances. Our study also highlights the importance of helping patients overcome potential barriers, such as lead time and perceived commuting costs on the appointment date. By addressing these challenges, healthcare providers can improve perceived credibility and effort, leading to a decrease in patient no-shows. This underscores the necessity of implementing strategies to alleviate potential hurdles, thereby enhancing the overall appointment experience and improving attendance.

Our study has several limitations that deserve consideration. Although our data was collected from a single hospital, the findings can be applied to various healthcare settings due to the universal nature of the issues addressed—namely, patient no-show behavior and the interventions aimed at mitigating it. The fundamental principles of technical support and information provision are relevant across different healthcare environments, suggesting that similar patterns of behavior and intervention efficacy may be observed elsewhere. Nonetheless, to bolster the robustness and generalizability of our findings, future studies should replicate and expand upon our results in diverse contexts. Second, we did not have precise data capturing the urgency of patients' conditions, although we used lead time as a proxy. Future research could explore the impact of appointment systems on different diseases by collecting new data on patients' symptoms, health beliefs, and past experiences, which may reveal more nuanced and heterogeneous treatment effects. Third, while we employed diverse methodologies to enhance comparability between control and treatment groups for both events, there still remains the possibility of contamination between the treatment and control groups, which could potentially impact our causal inference. Future research could explore cleaner contexts to more accurately estimate causal relationships.

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