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Digital transparency and citizen participation: Evidence from the online crowdsourcing platform of the City of Sacramento

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ABSTRACT

This paper examines the relationship between digital transparency and citizens' participation in government activity, specifically, online crowdsourcing. Many local governments have enhanced service transparency by disclosing and sharing information of government activities in digital format. These digital-driven transparency mechanisms often introduce interactive, tailor-made, and user-generating features to online government platforms. This paper explores the efficacy of digital transparency on citizens' participation in online crowdsourcing activities and its heterogeneous influences on various socioeconomic groups. Using the Propensity Score Matching and Difference-in-Differences (PSM-DID) method, this study analyzes the impact of digitized information disclosure to citizens' participation in Sacramento 311, an online crowdsourcing platform. It is found that enhancing digital transparency promotes citizens' participation in online crowdsourcing activities. Furthermore, results suggest that the influence of digital transparency on citizen participation is short termed and varies across communities of different socioeconomic conditions.

1. Introduction

Transparency is an important dimension in public value. It enhances accountability of government service, constructs citizens' trust in the government, and cultivates a participatory, democratic, and responsible governance process (Grimmelikhuijsen, Porumbescu, Hong, & Im, 2013; Schmidthuber, Ingrams, & Hilgers, 2021). Digital transparency refers to governments' transparency efforts relying on digital technologies and networks (Matheus, Janssen, & Janowski, 2021), including open government portals, smart apps, or Application Programming Interfaces (API) (Luna-Reyes, Bertot, & Mellouli, 2014). The technological advancements have enabled open government initiatives by many governments, which publishes government data in user-friendly formats and promotes digital transparency (Cucciniello, Porumbescu, & Grimmelikhuijsen, 2017). These open government initiatives use various tools for data analysis, visualization, and interpretation in digital formats to provide user-friendliness (Ho & McCall, 2016). Enhanced transparency is realized in this process by revealing information about government operations and creating more openness to government decision-making and operations. The role of citizens has been transformed in this process as well, from solely the recipients to the users and creators of data (Moon, 2020).

While transparency initiatives provide essential conditions for citizens to utilize government data in participation of administrative process (Ansari, Barati, & Martin, 2022), it is critical for governments to evaluate the effectiveness of their transparency initiatives in promoting citizen participation. However, the relationship between digital transparency and citizen participation in policy process is still yet to be clarified. While existing studies have conceptualized the participatory and interactive nature of transparency mechanisms in the digital format (Chen & Chang, 2020; Gil-Garcia, Gasco-Hernandez, & Pardo, 2020; Jaeger & Bertot, 2010; Kim & Lee, 2012, 2019; Song & Lee, 2016; Tolbert & Mossberger, 2006), empirical evidence is still lacking so is a consensus of the actual efficacy of the transparency mechanisms. While some recent studies have found preliminary results in the relationship between transparency and participation in online reporting platforms (Buell, Porter, & Norton, 2021), other previous studies have doubted the effort of digital-format government transparency in cultivating citizen participation, due to digital divide and inequitable access to government data (Jaeger & Bertot, 2010; Porumbescu, 2015), or administrative burdens imposed by digital technologies (Halachmi & Greiling, 2013). These studies provided evidence that digital technologies do not

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necessarily facilitate citizen participation in the policy process. Hence, some gaps still exist in understanding digital transparency's effectiveness in promoting participation and engagement between citizens and government.

Government online crowdsourcing platform provides an ideal testing ground for this issue. Information and communications technologies (ICT) have enabled multiple channels for governments to engage and collaborate with citizens where citizens can participate in public service delivery by directly submitting their requests for public services. These platforms, including 311, SeeClickFix, and FixMyStreet, can foster connections among government agencies, citizens, and private contractors. By providing diversified, non-emergency municipal services to residents, such platforms represent "online crowdsourcing", "digital crowdsourcing", or "ICT-enabled coproduction" (Clark & Brudney, 2018; Clark, Brudney, & Jang, 2013; O'Brien, Offenhuber, Baldwin-Philippi, Sands, & Gordon, 2017; Pak, Chua, & Vande Moere, 2017; Xu & Tang, 2020), as they rely on citizen participation in public service delivery. Citizens participate in service delivery ubiquitously by providing crucial information, tracking service updates, and providing feedback (Linders, 2012). Smart technologies in online crowdsourcing platforms have created digital transparency by generating user-oriented government data and storing them in digital formats. Users can obtain tailor-made performance information generated from online crowdsourcing platforms by tracking the real-time update information of their service requests and the requests of others, viewing geocoded service request updates around the city in the map view, and submitting comments and questions to the platform. The users of online crowdsourcing platforms are both the viewer and the creator of the government data, since they generate input to the service delivery by providing key information to collaborate with the government (Liu, 2021).

Digital transparency is an important component of the online citizen participation process by providing timely and user-exclusive performance information. Government data act as the foundation of citizen participation in government services by providing information that supports citizens' decisions (Cucciniello & Nasi, 2014; Moon, 2020). Moreover, transparency mechanism facilitates citizens' satisfaction and trust in the government, which motivates citizen's involvement with government activities (Grimmelikhuijsen, 2012; Kim & Lee, 2012; Schmidthuber et al., 2021). Our study aims to answer the following question: "*Does digital transparency promote citizen participation in online crowdsourcing?*" We use the 311 system of the city of Sacramento as our research context. 311 in Sacramento connects residents with the city's non-emergency municipal service providers through phone calls, text messages, a smart app, and a website. In 2020, Sacramento 311 experienced a major system update resulting in a significant increase in the transparency of the system. This update added a tracking function and a map view to the 311 app and website, enabling users to view the current and previous updates of all 311 requests submitted within the city limits. These reforms also added an interactive component to the 311 system and allowed citizens to participate proactively by accessing on-demand performance data of the 311 system. This event provides a favorable policy venue to study an enhancement of digital transparency and its impact on citizens' participation.

To identify a causal relationship, we use the incident of system update as a policy treatment of transparency. Sacramento is the treatment group against San Francisco as a comparable control group. A quasi-experimental approach, namely, the Propensity Score Matching Difference in Differences (PSM-DID) method is applied to a panel dataset containing the service request data of both cities. Results suggest that the improvement in transparency has a statistically significant and positive impact on citizen participation in the Sacramento 311 system. However, further analysis shows that usage increase associated with this system update is short-termed, often within the initial four weeks. In addition, we also find that enhanced digital transparency may influence resident participation differently across communities. Compared to their counterparts in more affluent communities, residents in higher poverty areas show a smaller increase in 311 requests.

Our study explores the impact of digital transparency where citizens' roles are transformed from passive recipients to active producers, how participatory behaviors change when citizens receive tailor-made information on government service delivery from government digital platforms, and whether citizens are motivated by transparency initiatives to participate in the online crowdsourcing of government services. Our study makes theoretical and practical contributions to the current study of digital transparency, citizen participation, electronic government, and open government platforms. It depicts the role of transparency in the full cycle of citizen participation by clarifying how transparency, which is highly associated with citizens' trust, could influence citizens' participation activities substantially (Kim & Lee, 2019; Schmidthuber et al., 2021). It also contributes to the literature on electronic government and online crowdsourcing by shedding light on the question of how new technologies influence citizen participation in online crowdsourcing (Lember, Brandsen, & Tõnurist, 2019; Xu & Tang, 2020). For practitioners, this study highlights the impact that transparency reforms can have on citizen participation and the broader effectiveness of web-based public services, especially non-emergency municipal services.

This article is organized as follows. First, we review the literature on government transparency, citizen participation, and government online crowdsourcing. Second, we set out hypotheses based on extant studies and our theoretical predictions. Third, we introduce the research context and data sources. Fourth, we describe our method of analysis–the PSM-DID method. Fifth, we present our results along with robustness checks. Finally, we conclude with a discussion of the findings and their implications.

2. Literature review

2.1. Digital transparency and citizen participation[1]

Transparency is one of the core public values since it promotes accountability and responsiveness of government agencies by empowering citizens to oversee governmental operations through a greater access to performance information and data (Porumbescu, 2015). Government information disclosure reduces the misconduct of government activities and constructs public trust (Chen & Ganapati, 2021; Grimmelikhuijsen et al., 2013; Heald, 2012; Schmidthuber et al., 2021). ICT technologies provide more possibilities for transparency practices. Digital transparency practices take steps further than digitizing government archives and fulfilling basic legal and administrative requirements fulfilling citizens' right to know. More importantly, digital transparency is a data-driven cycle where data are collected, published, used, and shared, fulfilling the explicit needs of open-government initiatives (Matheus, Janssen, & Maheshwari, 2020). Open government initiatives and electronic government (e-government) technologies make government data not only stored in a digital format but also highly accessible, interpretable, and user-friendly for reproduction, which creates sharing, use, and interpretation opportunities for citizens (Brown, 2005; Brown, Fishenden, Thompson, & Venters, 2017; Wirtz & Birkmeyer, 2015). Citizens can more easily track, analyze, and use public data in their favorite ways and generate products from raw government data, such as data portals, maps, and data visualizations (Wang & Shepherd, 2020; Zeleti, Ojo, & Curry, 2016). They are fulfilling differentiated demands for government information disclosure that fulfill their explicit needs. Moreover, digital transparency transforms the role of the citizen to a co-creator of government data (Moon, 2020), where citizens also actively contribute to the creation of government data. Examples of digital transparency mechanisms include open data

[1] We want to thank anonymous reviewers for their insightful comments on our discussion on the terminology and typology of "citizen participation".

portals and dashboards, government smart applications, government application programming interfaces (API), and government social media (Matheus et al., 2020; Song & Lee, 2016; Tang, Hou, Fay, & Annis, 2021; Zeleti et al., 2016).

Depending on citizens' power, there are various forms of participation in public issues, either directly or indirectly (Arnstein, 1969). Following the terminology of Linders (2012), "citizen participation" here in this research specifically describes the activities in which citizens make direct input into the policy process and bypass other less direct democratic procedures. Specifically, our research focuses on citizen participation in the administrative process, which emphasizes citizens' direct involvement in government operations as clients, partners, or producers, instead of indirect involvement as constituents (Brudney & England, 1983; Callahan, 2007; Clark et al., 2013; Roberts, 2008; Verba & Nie, 1987). Citizens participate by providing essential information, requesting specific service, or directly providing input into public service delivery, which bypasses democratic process, integrate their opinions into policy process, and achieve democratic value and optimal governance outcomes (Callahan, 2007). Transparency is an important factor in facilitating effective citizen participation (Jun, Wang, & Wang, 2014; Lathrop & Ruma, 2010). First, transparency mechanisms improve the quality of government data, which enables citizens reusing government data and integrate their thoughts and opinions to public policies (Piotrowski & Liao, 2012). Transparency initiatives provide citizens with factual information about government and participative decision-making opportunities (Cucciniello & Nasi, 2014). More recently, new open-government initiatives shift the form of transparency from "right-to-know" and paper-format data to reusable and machine-readable data, and enable participation, collaboration, and networked collaborative governance (Ansari et al., 2022; Zhang, Puron-Cid, & Gil-Garcia, 2015). Citizens rely on government data to make inputs in participatory processes. Open government efforts simplify the participatory process of citizens and transform their role from the producer or knowledge and information in the policy process, thus participating public administration (Moon, 2020). Second, transparency influences civic trust and satisfaction, which are important motivations of citizens' participation (Grimmelikhuijsen, 2012; Kim & Lee, 2012; Schmidthuber et al., 2021). Transparency has both positive and negative associations with citizens' perceived trust on government (Grimmelikhuijsen et al., 2013; Norman, Avolio, & Luthans, 2010). Citizens' satisfaction is associated with government transparency, especially in the context of web-based participation (Kim & Lee, 2012). Government agencies that provide more openness, interactivity, and timeliness in the digital world could often build up an image of trustworthiness, which is the foundation of citizen participation (Warren, Sulaiman, & Jaafar, 2014).

2.2. Research context: online crowdsourcing

In this study, we use online government crowdsourcing platforms as our context to explore the effect of digital transparency on citizen participation. Government crowdsourcing refers to the governmental activities of collecting the public's thoughts, ideas, and inputs and integrating them into government programs (Clark, Zingale, Logan, & Brudney, 2016). Government crowdsourcing is often realized by the support of ICT, enabling the flow of ideas, labor, and problem identification from citizens to government (Clark & Brudney, 2018). Through digital government platforms and online interactions, residents can participate in public service delivery by providing their specific demands to the government and participating in decision-making while governments pursue their governance goals, such as enhancing the efficacy of public service and facilitating citizen participation. These e-government platforms provide "ubiquitous participation" (Linders, 2012) channels enabled by digital interfaces, represented by smart apps, websites, and social media. One example of government online crowdsourcing is the 311 system (Liu, 2017). 311 systems manage residents' non-emergency requests for municipal services, including streetlight repair, bulk garbage removal, animal control, etc. Residents submit their needs for non-emergency services through various digital channels, including websites, smart apps, text messages, and social media. Government agencies collect and process residents' requests and send work orders to contractors via customer relationship management systems (CRM). In such a service design, delivery, and assessment process, citizens engage with multiple stakeholders via the information exchange on the e-government platform (Meijer & Bolívar, 2016; Tang et al., 2021). Online crowdsourcing services nowadays heavily rely on smart technologies, big data, and interactive features to connect residents, government agencies, private contractors, and communities (Linders, 2012; Styrin, Mossberger, & Zhulin, 2022; Tang et al., 2021; Xu & Tang, 2020). In this process, online crowdsourcing platforms show the potential of realizing open government initiatives by making their operational data available to the public on e-government platforms (Lathrop & Ruma, 2010; Minkoff, 2016). Unlike other prevalent participation channels, such as social media, which is decentered, online crowdsourcing platforms offer a structured and purpose-built environment for citizens to report non-emergency issues, request services, and engage with the government. By focusing on this specific channel, we aimed to assess the effectiveness of transparency initiatives within the existing framework of citizen participation in the administrative process. Many studies have examined factors affecting citizens' participation in using online crowdsourcing platforms (Clark et al., 2013; Clark & Brudney, 2018; Minkoff, 2016; Sjoberg, Mellon, & Peixoto, 2017). Generally, there are two types of factors influencing citizen participation in online crowdsourcing. First, citizen participation is influenced by their political, economic, and social characteristics and traits. As Nam (2012) points out, the pattern of citizen-government engagement online reflects the offline behaviors. Individuals' characteristics, both subjective and objective, play a role in using digital crowdsourcing platforms. Socioeconomic factors are pivotal for participation in online crowdsourcing. While some studies discover small differences in the participation rate of people from different socioeconomic backgrounds (Clark et al., 2013), other evidence suggests that low-income and ethnic minority groups participate in digital crowdsourcing activities at much lower rates (Cavallo, Lynch, & Scull, 2014; Pak et al., 2017). In addition, the scenarios in which people use digital crowdsourcing platforms differ across socioeconomic groups. Low-income and minority groups are more likely to report severe public service needs through online crowdsourcing platforms (Kontokosta & Hong, 2021; Xu & Tang, 2020). Other subjective attributes, such as attitudes toward government and political activeness, are also essential factors in the usage of e-government and digital crowdsourcing platforms (White & Trump, 2018). Residents who pay greater attention to neighborhood affairs and are homeowners are likelier to report issues and request service through digital government platforms (Minkoff, 2016; O'Brien et al., 2017; Thijssen & Van Dooren, 2016). Moreover, residents' usage of ICT-enabled crowdsourcing platforms depends on the quality of the service. Users of e-government platforms care about quality and performance, including user-friendliness, personalization, and communication (Kolsaker & Lee-Kelley, 2008). A successful first experience significantly promotes users' willingness to report issues on the platform again since positive interactions lead residents to believe that the system has the capacity and willingness to respond to the users' needs (Sjoberg et al., 2017). Citizens are more willing to report on the e-government platforms when the system functions well and is responsive (Clark & Brudney, 2018; Zheng, 2017). As Sjoberg et al. (2017) propose, participation in online crowdsourcing originates from users' satisfaction with the efficacy of the crowdsourcing system.

2.3. Hypotheses: digital transparency and participation in online crowdsourcing

Previous studies have discussed the relationship between transparency and citizen participation using the context of government websites (Bearfield & Bowman, 2017; Kim & Lee, 2012, 2019; Song & Lee, 2016), where the government is the sole producer of service and information and citizens are merely the receivers of the information. Comparatively, government online crowdsourcing is unique since citizens also provide critical input to government agencies and assist in the delivery of predetermined services (Nabatchi, Sancino, & Sicilia, 2017; Young, 2021). In government online crowdsourcing, citizens make direct input to the information flows by different types of reporting in online crowdsourcing platforms, including submitting service requests, acquiring service updates, and providing comments. Proactive participation by the citizen is crucial to the service efficacy of online crowdsourcing platforms.

In this study, we propose that the enhancement in the digital transparency of government crowdsourcing platforms will cause an increase in citizen participation in online crowdsourcing activities, represented by the number of reports of the users. We expect that this is driven by tailor-made information flow, one-on-one real-time feedback, and map views. These features promote government transparency by creating novel information flows between citizens and the government while providing additional channels for residents to participate in public affairs. As discussed above, enhancing the transparency of government services will promote citizens' trust in government agencies (Grimmelikhuijsen et al., 2013; Schmidthuber et al., 2021), and trust is an important motivation for citizens' engagement with the government (Uslaner & Brown, 2005). With an easy access to the performance information of their direct service requests, citizens gain a sense of empowerment through tracking and contributing to government activities that interest them. They are more willing to reuse the system when they can see through real-time tracking functions and are aware that the government is responding to and solving their problems (Sjoberg et al., 2017). Furthermore, real-time tracking functions of online crowdsourcing could enhance government accountability. Open government data is a crucial source of government accountability (Harrison & Sayogo, 2014) as they place government officials, contractors, and street-level bureaucrats under citizen scrutiny. When service issues or disruptions occur, performance information enables users and government agencies to identify who should be accountable. The accountability that digital transparency promotes may thus also increase citizen usage of crowdsourcing platforms. For these reasons, we hypothesize that:

H1: Increase in the digital transparency of the government crowdsourcing platform will increase citizen participation in crowdsourcing.

Considering that online participation patterns vary across users of different socioeconomic backgrounds (Cavallo et al., 2014; Minkoff, 2016; O'Brien, 2016; Thijssen & Van Dooren, 2016), we here propose that transparency may also have heterogeneous impacts on the citizen participation of residents from different socioeconomic backgrounds. Traditionally, historically disadvantaged groups have insufficient resources to participate in public affairs. Information technology innovation has provided novel channels of participation to minority groups by minimizing the entry barriers to participation (Lember et al., 2019). Information technologies may narrow participation gaps in government by providing equal access: with ubiquitous smartphone usage, residents can more easily interact with and participate in public affairs. Moreover, reporting issues through online crowdsourcing could acquire more attention from the government and narrow the gap in service equity (Young, 2021). While online crowdsourcing platforms improve over traditional reporting methods in terms of the performance in reporting and solving residential service requests (O'Brien, 2016), users from minority groups are welcoming to the service upgrade of online crowdsourcing platforms from technological innovations, as they rely on ICT-enabled platforms to report their municipal service needs from their residential neighborhood and believe these services are effective (Xu & Tang, 2020). Hence, minority users are more likely to positively react to transparency initiatives due to their path dependence on ICT-based reporting methods.

H2: Increase in the digital transparency of the government crowdsourcing platform will lead residents from minority ethnic groups to participate in crowdsourcing at a higher participation level.

H3: Increase in the digital transparency of the government crowdsourcing platform will lead residents of lower socioeconomic status to participate in crowdsourcing at a higher participation level.

3. Research design

To estimate the influence of digital transparency on residents' participation in online crowdsourcing, this study employs an empirical approach combining Propensity Score Matching and Difference-in Differences estimation (PSM-DID). A simple comparison between the treatment group and the control group in their usage of online crowdsourcing may result in a selection bias problem and will not be able to identify causal relationships. Difference-in-Differences (DID) estimation is a frequently used quasi-experimental methodology to identify a causal relationship from non-experimental data (Angrist & Pischke, 2015). It removes time-invariant biases by comparing changes over time between the treatment and the control group. We select Sacramento as the treatment group for this study. In 2020, the city of Sacramento implemented a major update to its city-wide digital municipal service platform, 311 services. In this update, Sacramento 311 added real-time tracking, service request status inquiry, and GIS-based map view to its system. These features allowed more timely and accurate information disclosure to the users of the 311 system. These changes have illustrated that the 311 upgrades in Sacramento represent a case in which the government improved its digital transparency. We select another city with a similar online crowdsourcing platform but without such updates during the same time period as the comparison group. We implement a Propensity Score Matching (PSM) process before the DID analysis to better meet the parallel trends assumption of DID. The following sections further describe the research design, including the research context, the statistical methodologies, the data used, and the construction of key variables.

3.1. Research context selection: Sacramento 311

We use the City of Sacramento's 311 system as the research object for this research.[2] First launched in 2008, Sacramento 311 is an integrated platform that connects residents to local municipal services.[3] Using phone calls, text messages, a website, and a mobile app, residents can request non-emergency city services and information, such as bulky trash removal, and animal control, and report issues with local infrastructures, such as street potholes, broken streetlights, and graffiti. Like in many other cities, the requests submitted to the Sacramento 311 system are integrated into a back-end customer relationship management (CRM) platform and then distributed to the responding agencies. In 2019, the Sacramento 311 system received a total of 404,418 requests.[4]

Even though Sacramento 311 relies on ICT in operation, it initially lacked a transparency mechanism. Historically, service requests submitted through the Sacramento 311 system, including those submitted through the website and mobile apps, were not trackable by users, and users did not receive updates on the status of their requests. In other words, users of the Sacramento 311 system were unable to receive real-time updates and detailed information about their service requests. In

[2] http://www.cityofsacramento.org/information-technology/311.
[3] https://www.esri.com/about/newsroom/blog/sacrament-311-system-spatial-integration/.
[4] https://data.sacog.org/.

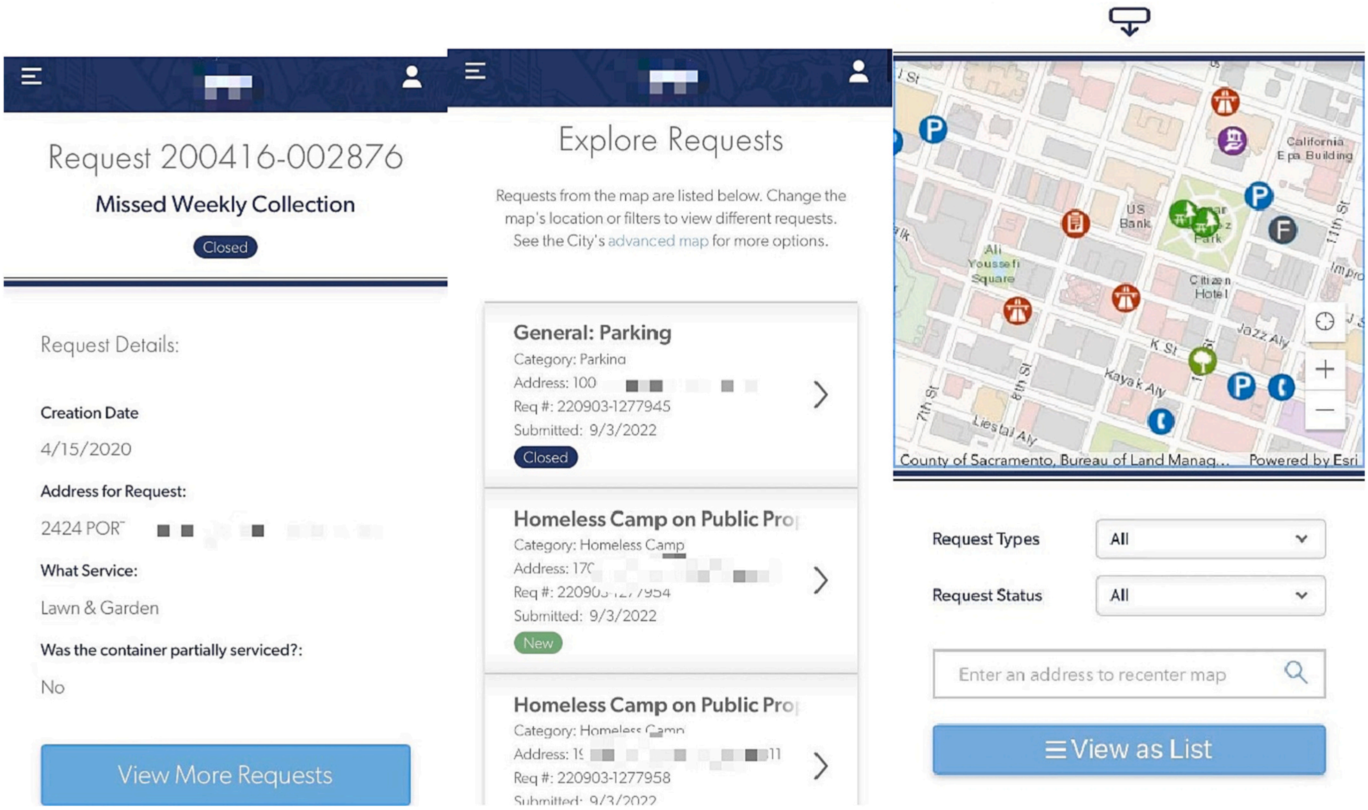

Fig. 1. The system interface of the Sacramento 311 after the update.

comparison, many other cities had already adopted interactive 311 platforms that provided users with real-time updates on responsible agencies, solutions, and locations. Before 2020, the City of Sacramento's 311 system did not provide service progress updates to users. Users could submit requests, but they were unable to trace whether the corresponding agencies had received the request, how the agencies handled their request, and whether the request had been completed. As a digital government interface, the openness and transparency of the Sacramento 311 system were relatively low compared to other cities.

In our study, we identified several system updates in Sacramento 311, including real-time tracking, GIS-based map view, and service request status inquiry, as transparency instruments that are relevant for assessing the impact of system updates on digital transparency and citizen participation. These instruments offer specific features and functionalities that contribute to enhancing transparency in government-citizen interactions. In April 2020, the city of Sacramento launched an updated version of its 311 system. On April 15th, 2020, Sacramento 311 released a redesigned and modernized 311 mobile app and webpage portal.[5] Several functions were added to the 311 system after this update. First, real-time updates were included, allowing users to view the progress on service requests through the mobile app or website. The real-time update information describes the current status of the service request, including which department or agency has been notified by the 311 system or is processing the request, and the current and future solutions and responses. Real-time tracking is an important transparency instrument as it allows citizens to monitor the progress and status of their service requests in real-time. By providing access to up-to-date information on the processing and resolution of requests, real-time tracking empowers citizens with knowledge and fosters transparency in the service delivery process. It enables citizens to stay informed and hold the government accountable for the timely and efficient resolution of their requests. Second, with the assistance of the geographical information system (GIS), location information for all service requests was made public in the update. Users could now see the location of each service request through a map on the 311 website or the 311 app. GIS-based map view is a valuable transparency instrument that utilizes geospatial data to provide a visual representation of service requests and their locations. By mapping service requests onto a geographic interface, citizens can easily identify the spatial distribution of requests within their community or across different areas. This transparency instrument promotes geographic transparency, allowing citizens to gain insights into the allocation of resources and service provision in their neighborhoods. It also enables them to identify patterns, trends, and potential disparities in service delivery, which can contribute to informed discussions and decision-making processes. Third, by combining these two features, all users of the Sacramento 311 system could track the real-time progress on all service requests within certain geographic areas, regardless of the submitter of the request or the issue of the request, simply by clicking on labels on an interactive map. Service request status inquiry provides citizens with the ability to inquire about the status of their requests and obtain relevant updates. This transparency instrument facilitates communication and ensures that citizens are kept informed about any changes, delays, or additional information regarding their service requests. It enhances transparency by enabling citizens to actively engage with the government and seek clarifications or updates on their requests. Fig. 1 shows the features of the Sacramento 311 interface on the smartphone after the system update. Local news websites, Sacramento government websites, and social media of Sacramento government all published the news of the system update in the Sacramento 311 service platform so that the users have awareness of this incident.

The update to the 311 system in Sacramento provides an appropriate policy venue to identify the influence of digital transparency on residents' participation in digital crowdsourcing. First, the update

[5] https://sacramentocityexpress.com/2020/04/16/city-launches-updated-311-app-and-website-to-improve-customer-experience/.

Table 1
Comparison of demographic indicators between Sacramento and San Francisco.

	Sacramento	San Francisco
female population	50.8%	48.8%
Racial minority population	68.9%	60.8%
population 20–29 years old	13.2%	14.0%
resident with bachelor's degree or higher	35.1%	59.5%
households with a computer	95.5%	95.2%
households with broadband internet	91.5%	90.6%
poverty rate	14.8%	10.3%
% of owner-occupied housing	50.1%	38.2%
voter registration rate in the 2020 presidential election	86.0%	78.0%

Demographic data are from U.S. Census, year 2020. Voter registration data are from CA Secretary of State Office. All measurements are at the city of San Francisco and city of Sacramento level, except the population of 20–29 and voter registration, which are on the county level. Racial minority population is calculated by (1- % of white alone, non-Hispanic population).

significantly improved the transparency of the online crowdsourcing application by providing real-time updates, map views, and open data. This allows users to access information that reflects their direct needs for government services instead of browsing static government websites and raw data. The transparency feature provides tailor-made performance information of government services to each individual user. Second, the case of Sacramento 311 is representative of circumstances in other U.S. cities, as many cities are adopting interactive applications and information technologies to provide municipal services and connect with local residents (Ganapati, 2015). Therefore, the results of the Sacramento 311 system updates are likely generalizable to other U.S. cities when similar policy interventions occur. Third, the update to the Sacramento 311 system can be treated as a city-specific policy intervention that enhances openness and transparency. The update only occurs within the city limits of Sacramento, and limited spillover effects are expected due to the geographic boundaries within which individuals can submit service requests through Sacramento's 311 system. Therefore, it is feasible to explicitly differentiate treated and untreated areas.

We select the 311 system in the city of San Francisco as the comparison case for the following reasons. First, San Francisco and Sacramento are similar in many ways. Table 1 shows the comparison of several key demographic indicators between San Francisco and Sacramento. Both cities are within the state of California, which minimizes time-invariant differences at the state level. The two cities have well-established information technology infrastructures. The two cities both have educated residents, who are enthusiastic about citizen participation. Second, among the cities in California of a similar size to Sacramento, San Francisco has a 311 system that functions similarly to the post-update 311 system of Sacramento. Besides digital submission of service requests, San Francisco 311 allows users to track updates of their service requests and view them on a map. Third, when Sacramento adopted an update to its 311 system, no such change to the 311 system of San Francisco occurred. The 311 system of San Francisco remained the same during the time of the policy intervention in Sacramento.

3.2. Data

The raw data for this research comes from the official 311 database for the city of Sacramento. The database includes detailed information for each service request including a unique reference ID for each request, the request category (e.g., animal control, parking, street repair, garbage, and water and sewer, etc.), the location of the request (in the latitude and longitude coordinate format), and a time stamp (date and time when the request was reported by the user and completed by the agency). For this study, we decided to collect data in the period 24 weeks before and 24 weeks after the date on which Sacramento 311 adopted the system update (April 15th, 2020).

We use census tracts as the unit of analysis for this research. Reporting to the 311 system in Sacramento is completely anonymous, so the dataset does not contain any individually identifiable information on users. To study participation in the 311 system, our study compares the aggregate usage of 311 in each census tract before and after the service update as the best possible and feasible alternative to a before-and-after comparison at the individual user level. We aggregate the data to the census tract level according to the following steps. First, we geocode each request to a census tract using the latitude and longitude coordinates provided for each request. Second, we create aggregate summary measures (e.g., the total number of requests submitted, the average completion time) at the census tract level and week level based on the locations and submission times of requests. For example, the total quantity of submissions is generated by summing up all requests in the same census tract during the same week. Third, the 311 service request dataset is merged with census-tract level demographic data. To control for the potential influence of neighborhood demographics on responsiveness to 311 service requests, we collect economic, demographic, housing, and employment data at the census tract level from the American Community Survey 5-Year Estimate Detailed Data by the U.S. Census Bureau. The data for San Francisco 311 requests are also downloaded from the city database and aggregated in the same approach as for Sacramento.

3.3. Variable specification

We used as our outcome variable the total number of 311 requests submitted in census tracts by week. The archival data of the 311 service does not contain any individually identifiable information of user, so we were not able to directly observe which individual uses and whether the same user reports again in the 311 system. As a result, we implemented an indirect measurement of 311 usage by measuring aggregate usage at each census tract as our outcome variable. Similar measurements of citizen participation have been adopted by previous studies (Kontokosta & Hong, 2021; Minkoff, 2016; Pak et al., 2017). There are two reasons for doing so. First, many re-users of online crowdsourcing platforms usually make service request in the system to fix problems within a certain geographical area, such as their working or residential sites (O`Brien et al., 2017). Hence, the re-occurrence of 311 usage is likely to occur at or around the same geographical location. Second, this approach allows demographic and economic composition to be easily combined and controlled for, with the census tract as the unit of analysis. The time unit of analysis was a week. 24 weeks before and after the treatment plus the current week of treatment were included in the data set.

Several data processing steps were implemented to link service requests to census tracts and their demographic information. Each service request was matched with its census tract using QGIS software. The attribute forms containing the variables of individual requests and their affiliated census tracts were extracted, and the total number of requests for each census tract was then calculated by week. The individual requests from both the treatment group and the control group were aggregated to 363 census tracts in Sacramento and 244 census tracts in San Francisco by each week. This study accounted for requests of all service categories and reporting methods. Requests located outside of city boundaries and with completion times earlier than the reporting times were excluded from the analysis. We believed these requests were more likely to be generated by system error rather than residents' real usage.

The treatment variable was a binary variable measuring whether the service request was submitted to the Sacramento 311 system. The before/after treatment variable was a dummy variable measuring whether the request is submitted before or after the system update of Sacramento 311. This study also controlled for several variables that influence the usage of the 311 system. First, a set of demographic and economic variables were controlled at the census tract level.

Table 2
Variable specification.

Variable	Measurement	Data Source
Outcome Variable		
Citizen Participation	total number of 311 service requests at census tract at given week	Sacramento & San Francisco government websites
Treatment Variable		
Transparency Initiatives	Sacramento 311 system update	Sacramento government website
Covariates*		
Gender	% of female population	U.S. Census
Age	% of 65+ population	
Race	% of non-white population % of Black population % of Asian population	
Poverty	poverty rate	
Unemployment	unemployment rate	
Country of Origin	% of residents who were born out of U.S.	
Education	% of residents who has Bachelor's degree or higher	
Total Population	total population	
Income	median household income	
Occupation Status	% of houses occupied by owners	
Composition of Service Requests	% of parking % of solid waste % of street repair % of water and sewer	Sacramento & San Francisco government websites

* All covariates are at census tract level, except composition of service requests, which is at census tract and week level.

Demographic variables were race, gender, age, country of origin, and population. The race was measured as the percentage of white, African American, and Asian residents per census tract. Gender was measured as the ratio of female residents. Age was measured as the percentage of residents 65 or more years old. Country of origin was measured as the percentage of residents born outside of the United States. Economic variables were median household income, poverty rate, unemployment rate, and housing status measured as the percentage of homeownership.

Table 3
Propensity score calculation.

Covariates	Coefficient
% of Female Residents	7.734* (3.859)
% of Residents of 65+ Age	−18.252*** (4.139)
% of White Residents	15.520*** (4.075)
% of African American Residents	2.298 (4.051)
% of Asian Residents	8.554* (3.857)
Poverty Rate	−17.344** (5.755)
Unemployment Rate	−12.558^ (6.599)
% of Foreign-Born Residents	−23.445*** (4.327)
% of Owners	9.709*** (1.715)
Education Attainment	−14.414*** (2.891)
Total Population	0.356 (0.489)
Median Household Income	−7.061*** (1.287)
Constant	78.071*** (15.432)
Wald Chi Square (12)	88.127***
Pseudo R2	0.843

^:$p < .1$, *:$p < .05$, **:$p < .01$, ***:$p < .001$.

A set of variables reflecting the categories of requests was also controlled for, as the difficulty and complexity of the issues could also influence the reporting behavior of the users (Kontokosta & Hong, 2021). We controlled for the amount of the four most commonly reported types of 311 requests: parking, solid waste, street repairs, and sewer issues. They were measured by the percentage of each type of request over the total number of requests in the census tract each week. To test hypotheses 2 and 3, two interaction terms were constructed to explore heterogeneous effects by demographics. We first interacted treatment with the mean-centered poverty rate, and then we interacted treatment with the mean-centered non-white population ratio. Table 2 shows each variable's specification and its data source.

3.4. Method: propensity score matching – difference in differences (PSM-DID)

3.4.1. DID

This research uses a DID approach to evaluate the impacts of increased digital transparency on citizen participation. As described, the policy intervention is the system update to Sacramento 311 on April 15th, 2020, the treatment group is the city of Sacramento, and the control group is the city of San Francisco. Two dummy variables are constructed: (1) a "treatment group" dummy variable that distinguishes observations from the treatment group (census tracts in Sacramento, coded as 1) and the control group (census tracts in San Francisco, coded as 0), and (2) a "pre-post" dummy variable which denotes time before the system update as 0 and after the system update as 1. The regression model is described as follows:

$$Q_{it} = \alpha_0 + \alpha_1 C + \alpha_2 t + \alpha_3 C^* t + \alpha_4 X_{iw} + \varepsilon_{iw}$$

Where Q is the outcome variable, denoting the total quantity of 311 requests at census tract i and week w; C is the binary variable distinguishing the treatment group and the control group; t is the binary variable distinguishing the weeks before and after policy intervention; X_{iw} are a series of covariates that influence service request submission; α_0 is the intercept and ε_{iw} is the error term.

3.4.2. PSM

As a quasi-experimental method, the DID approach requires two assumptions (Dehejia, 2005): (1) common trend, where both the treatment group and control group show the same trend over time before treatment, and (2) randomized assignment of group status, where the assignment of treatment is random and not affected by the attributes of observations. As the cities of Sacramento and San Francisco are not identical, unobservable systematic differences between the two cities may affect the assignment of treatment. It is arbitrary to simply recognize all the census tracts of San Francisco as the counterfactuals for Sacramento. Instead, we apply a propensity score matching (PSM) method developed by Heckman, Ichimura, and Todd (1997) to select non-treated observations that match the treatment group. The logit regression specification used for PSM is as follows:

$$Logit(T = \lambda) = \beta_0 + \beta_1 X_{iw} + \varepsilon_{iw}$$

where T is a dummy variable measuring whether the observation is in the treatment group, and $T = \lambda$ means the entity is in the treatment group. X_{iw} is a set of cross-sectional covariates of demographic and economic measurements at census-tract level. These variables include gender, race, age, country of origin composition, education level, poverty rate, unemployment rate, housing value, homeowner percentage, household income, and total population. The regression specification produces propensity scores that indicate a census tract's likelihood of being in the treatment group (being in Sacramento) based on its demographic characteristics. Closer propensity scores indicate higher similarity between census tracts. Using kernel matching methods, we match each census tract from the treatment group (from Sacramento) to one census tract from the control group (from San Francisco) that has a

Table 4
Balance test results.

Covariate	Matched?	Mean Treated	Mean Control	t	p > |t|
Female population %	Before	0.512	0.479	5.153	0.000
	After	0.512	0.481	2.983	0.003
Elderly population %	Before	0.144	0.160	−2.143	0.033
	After	0.141	0.148	−0.705	0.481
White population %	Before	0.553	0.458	5.446	0.000
	After	0.431	0.467	−1.354	0.177
African American Population %	Before	0.095	0.053	6.348	0.000
	After	0.119	0.060	4.922	0.000
Asian population %	Before	0.161	0.328	−11.719	0.000
	After	0.247	0.298	−2.487	0.014
Poverty Rate	Before	0.102	0.096	0.956	0.339
	After	0.109	0.075	3.840	0.000
Unemployment Rate	Before	0.064	0.046	5.493	0.000
	After	0.064	0.044	3.722	0.000
Foreign-born resident %	Before	0.204	0.336	−11.728	0.000
	After	0.258	0.290	−2.074	0.039
Owner occupied %	Before	0.570	0.369	10.337	0.000
	After	0.518	0.440	2.435	0.016
Education attainment	Before	0.315	0.582	−15.797	0.000
	After	0.395	0.561	−6.126	0.000
Total Population	Before	8.272	7.984	3.987	0.000
	After	8.231	7.989	1.944	0.054
Median Household Income	Before	11.149	11.611	−11.178	0.000
	After	11.235	11.615	−6.294	0.000
Total distance	Before	0.952	0.072		
	After	0.860	0.139		

similar propensity score. The 1:1-matched census tracts are then merged with tract-level 311 request data and used for the DID analysis.

4. Results

This section reports the empirical results of the PSM-DID analysis assessing whether an improvement in the transparency of an online crowdsourcing platform, realized by information technologies, impacted users' participation. This section is organized as follows. First, we describe the process and the results of the propensity score matching. This part includes a regression specification to obtain propensity scores, the methods and results of matching, and an assessment of the matching quality. Second, we present the results of the difference-in-differences regression using matched data. This part includes regression results assessing the treatment effect and the results of an event study analysis examining effects over time. Third, we include the results of a robustness check used to examine the parallel trend assumption.

4.1. PSM results

A logit regression is implemented to obtain the propensity scores of the observations. The dependent variable is a dummy variable of treatment, and the covariates are the time-invariant covariates that describe the characteristics of the census tract, which are the unit of the observations. The same covariates are also used in the DID analysis. Table 3 presents the results of the general linear model regression used to identify propensity scores. Most of the covariates, including gender, age, white population, Asian population, poverty rate, unemployment rate, foreign-born population, percentage of the owner, education level, and income, are significantly associated with the binary treatment variable. This indicates significant socioeconomic differences between the treatment and control cities. The pseudo-R2 value is 0.843, and the result of the Wald test on the Chi-square is significant, which indicates the goodness of fit of the model. Hence, it is appropriate to include current variables in the calculation of propensity scores.

To match census tracts, we implement the optimal full matching strategy developed by Hansen and Klopfer (2006). This method is an improvement over traditional nearest neighbor matching by balancing the representation and similarity of the observations from the treatment and control groups. To avoid wasting data while also ensuring matching quality, the treatment group observations that are out of the common support area are dropped, while the control group observations are matched without replacement. We match 248 census tracts, with 124 census tracts each in the treatment and control groups.

After the matching process, a balance test is conducted to compare the difference between the treatment and control groups and ensure that the data are sufficiently balanced. Table 4 presents average covariate values in the treatment and control groups before and after matching along with *t*-test results to assess whether differences are significant.

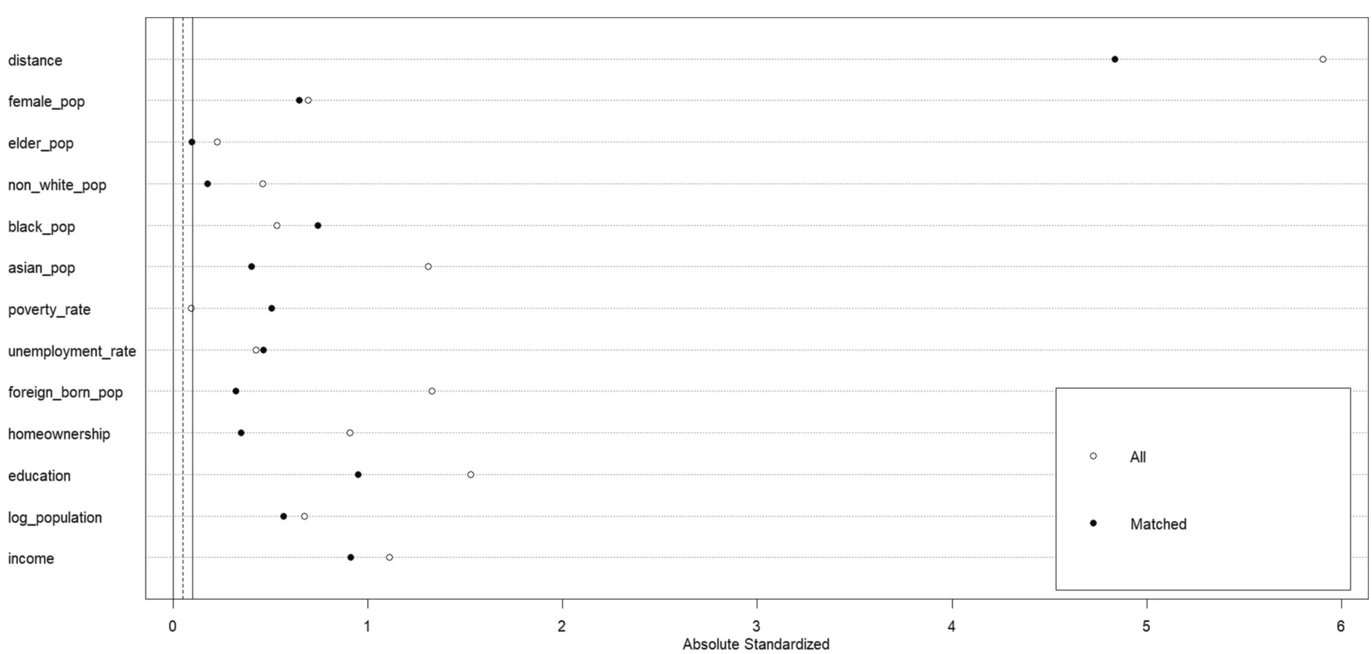

Fig. 2. Absolute standardized mean difference between the treatment and control groups before and after matching.

Table 5
Difference-in-differences results.

Variable	Model 1 no covariates	Model 2 with covariates	Model 3 covariates and minority interaction term	Model 4 covariates and poverty interaction term	Model 5 covariates and both interaction terms
Treatment effect (treatment*after treated)	12.729*** (1.887)	12.933*** (1.886)	13.015*** (1.953)	10.299*** (1.873)	10.348*** (1.890)
minority*treatment			−7.102 (14.973)		−2.061 (14.459)
poverty*treatment				−83.278** (28.180)	−82.489** (26.449)
Treatment group	−30.984*** (3.854)	−27.662*** (6.090)	−27.126*** (6.234)	−28.907*** (6.164)	−28.740*** (6.297)
After treatment	0.372 (1.097)	−0.305 (1.100)	−0.312 (1.103)	−0.254 (1.095)	−0.257 (1.098)
Female population %		−111.325** (35.799)	−112.424** (35.736)	−109.282** (35.120)	−109.620** (35.071)
Elderly population %		18.942 (28.690)	18.423 (28.577)	18.665 (28.945)	18.517 (28.770)
Non-White population %		15.806 (33.312)	18.796 (34.952)	15.274 (33.302)	16.147 (34.935)
Black population %		−22.102 (32.285)	−22.109 (32.230)	−23.425 (32.238)	−23.415 (32.214)
Asian population %		−8.297 (38.463)	−9.293 (39.047)	−9.264 (38.319)	−9.544 (38.920)
Poverty rate		60.459 (44.090)	62.466 (45.218)	100.277* (47.387)	100.482* (47.930)
Unemployment rate		−62.147 (51.688)	−61.442 (51.793)	−64.451 (52.010)	−64.225 (52.016)
Foreign-born resident %		−39.470 (34.069)	−38.495 (34.353)	−38.205 (34.021)	−37.934 (34.328)
Median household income		25.605 (16.207)	26.482 (16.930)	27.739^ (16.418)	27.973 (17.049)
Owner occupied %		−39.623* (15.944)	−40.378* (16.380)	−40.518* (15.922)	−40.729* (16.318)
Education attainment		−38.028^ (20.708)	−37.588^ (20.527)	−39.994^ (20.818)	−39.848^ (20.619)
Total population		13.153** (4.747)	13.280** (4.789)	13.263** (4.733)	13.298** (4.776)
Parking %		−9.094 (7.912)	−9.275 (7.938)	−8.256 (7.889)	−8.316 (7.924)
Waste %		1.261* (0.627)	1.260* (0.628)	1.121^ (0.618)	1.122^ (0.619)
Street Repair %		−0.067 (4.439)	0.034 (4.470)	0.686 (4.460)	0.708 (4.483)
Sewer %		−73.224*** (18.117)	−73.456*** (18.305)	−70.235*** (17.744)	−70.331*** (17.980)
Constant	45.154*** (3.637)	−251.917 (192.816)	−262.766 (201.613)	−280.029 (195.408)	−282.910 (203.158)
Adjusted R-Square	0.154	0.260	0.260	0.267	0.267
N	8936	8936	8936	8936	8936

Clustered standard errors at the census tract level are given in parentheses.
***p < .001, **p < .01, *p < .05, ^*p* < .1.

After matching, the treated and control units become more similar on average across several socioeconomic covariates. In particular, there is greater similarity with respect to the elderly population, the white population, and the total population. However, significant differences persist (such as for the African American population, the poverty rate, the median household income, and educational attainment) and thus we suggest some caution in interpreting the results of the subsequent DID analysis. Fig. 2 illustrates the absolute standardized mean difference across covariates before and after matching. For only three covariates did the difference increase, although to a small degree, and for all other covariates the absolute standardized mean difference decreased, indicating greater similarity between the treatment and control groups.

4.2. DID results

After performing PSM, we identified 311 requests in the balanced sample of 248 census tracts (124 census tracts in each group) from the treatment group (Sacramento) and the control group (San Francisco), resulting in 8936 observations for further DID analysis. Table 5 presents the results of the DID analysis. We tested five different models: (1) a baseline DID model without any covariates, (2) DID with covariates, (3) DID with an interaction term of racial minority * treatment, (4) DID with an interaction term of poverty * treatment, and (5) DID with both interaction terms.

The results show that the transparency upgrade to Sacramento 311 significantly increased the usage of the 311 system. The coefficient on the effect of digital transparency for the total request quantity is positive and significant in all five models ($p < .001$). The results suggest that after the upgrade added request tracking and map-view functions to the 311 website and mobile app, the residents of Sacramento submitted significantly more service requests. In particular, service requests submitted in Sacramento after the upgrade increased by about 10 to 13 requests per week per census tract more than in San Francisco. This proves our hypothesis 1 that the improvement of digital transparency promotes citizens' participation in online crowdsourcing behaviors. Bringing service request information in a timely manner convinces the users that

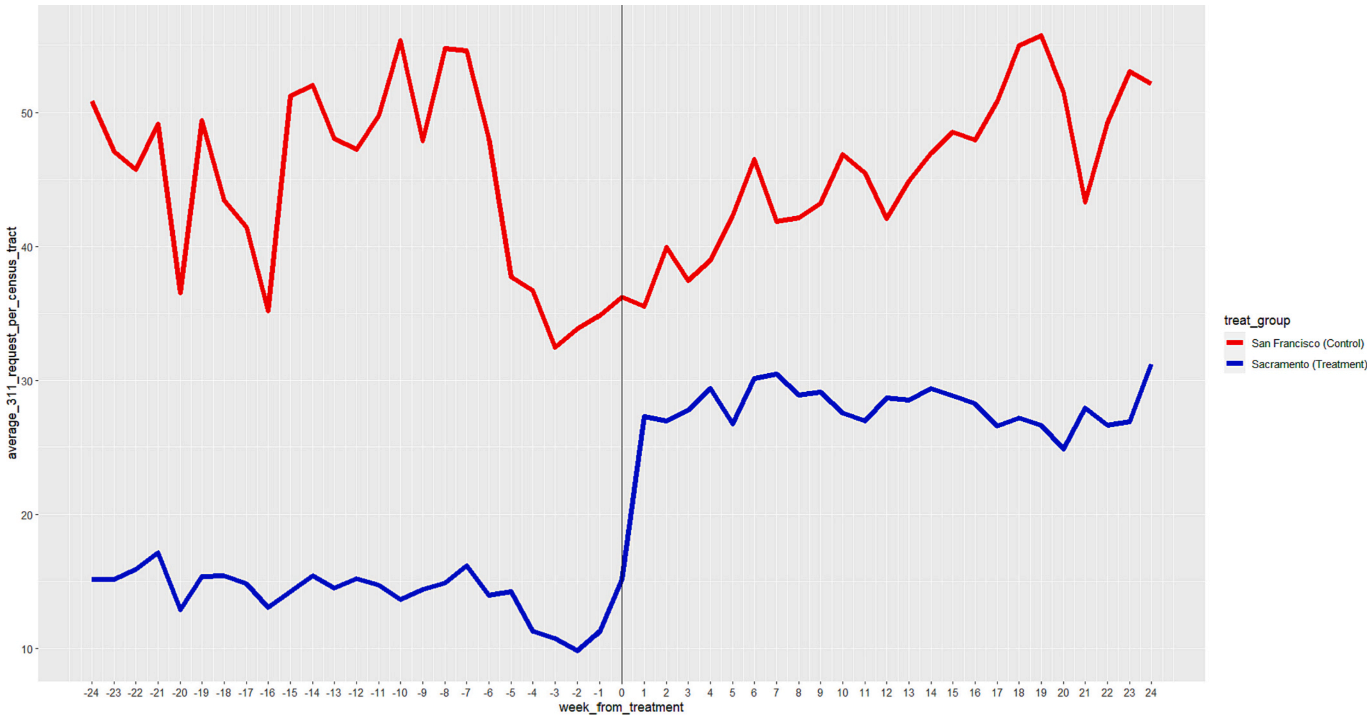

Fig. 3. Average total numbers of requests before and after treatment.

their requests matter to the government agency, which makes the crowdsourcing platform trustworthy. As our data does not contain individual information, we do not know who exactly the users were. Hence, the increase could be caused by the same users' repeating participation or the novel entry of new users (Sjoberg et al., 2017). A reinforcing effect (Nam, 2012) could occur for those who have previously participated in the 311 system, as the real-time update function and interactive features in the system update create more channels for engagement for those users. New users could also have been attracted by observing previous users' successful experiences from the map view on the website and smart app. Observing successful previous experiences with the system could convince them of the efficacy of the service by showing that the government has the willingness and ability to solve problems for residents.

As for heterogeneous effects, we find that the interaction of the treatment with the percentage of non-white residents is not significant in both models, indicating that the increase in the usage of the 311 system after the update did not differ systematically across census tracts of different racial compositions. However, we do find that the interaction of the treatment with the poverty rate is significant and negative in both models ($p < .01$). This suggests that the treatment effects are concentrated in higher-income areas—the transparency upgrade to Sacramento 311 led to greater boosts in service request submission in areas with a lower poverty rate than in areas with a higher poverty rate. Thus, our H2 and H3 are both rejected. The participation stimulated by digital transparency has a stronger effect on the residents in better economic situations.

A graph of the time trend of the average total quantity of 311 requests submitted by week across census tracts in Sacramento and San Francisco is presented in Fig. 3. It shows that a significant increase in request submission in Sacramento occurred starting from the first week after the improvement of transparency. While San Francisco initially had much greater service request submission, partially likely due to the more interactive and transparent 311 system that San Francisco had implemented earlier, the transparency upgrade in Sacramento elevated citizen participation and closed the gap relative to San Francisco. The treatment effect is illustrated by the decrease in the gap between the control and the treatment group after treatment.

Table 6
average treatment effect by week.

Week	ATT Effect	Std. Err.
0	2.547	1.822
1	15.366*	2.572
2	10.612*	2.774
3	13.885*	2.781
4	13.989*	2.937
5	8.036	3.124
6	7.184	3.459
7	12.231*	2.901
8	10.316*	2.762
9	9.483*	2.834
10	4.287	2.695
11	5.094	2.605
12	10.202*	3.032
13	7.260	3.189
14	6.013	3.543
15	3.930	3.838
16	3.885	3.482
17	−0.646	4.874
18	−4.199	3.770
19	−5.471	3.085
20	−3.056	2.613
21	8.211	2.967
22	0.976	2.832
23	−2.599	3.012
24	2.638	3.379

* Significantly different at 95% confidence interval.

Table 6 presents the results of an event study exploring the weekly average treatment effect on the treated. The results show that the influence of transparency was significantly effective in most of the first 12 weeks (the 1st, 2nd, 3rd, 4th, 7th, 8th, 9th, and 12th weeks) after the system update ($p < .05$). This suggests that transparency was effective mostly in the early stages after its introduction. No impacts were found after the 12th week after the treatment. Therefore, combined with the evidence in Fig. 3, the impacts of the transparency upgrade seem to be best characterized as producing a level shift in the number of service

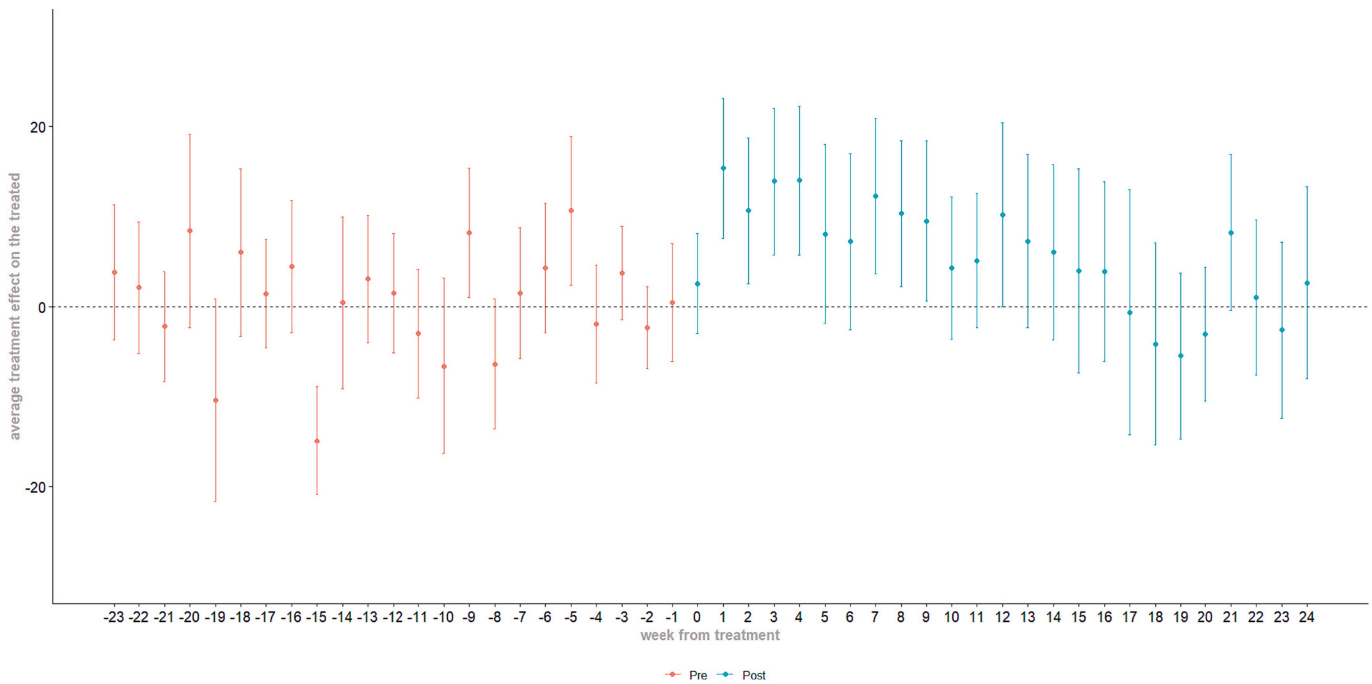

Fig. 4. Weekly average treatment effect on the treated (ATT).

requests submitted—request submission increased in the first few months after the upgrade and then the effects persisted without significantly changing or dropping off in subsequent months. Fig. 4 displays the corresponding weekly average treatment effects on the treated with 95% confidence intervals.

4.3. Robustness check: parallel trend test

This section introduces the results of a robustness check for the DID analysis. The key assumption when using the DID method is the parallel trends assumption (Dehejia, 2005), which requires similar trends in the dependent variable in the treatment and the control groups absent treatment. This is usually assessed by examining pre-treatment trends in the control and treatment groups. Therefore, Fig. 5 presents a plot with trend lines for the total number of 311 requests by week per census tract in the treatment and the control groups before the system upgrade. The trends in the treatment and control groups appear to be parallel.

However, the simple comparison in the scatter plot does not provide decisive evidence of parallel trends (Cunningham, 2021). Some studies suggest supplementary event study analysis to assess the parallel trend assumption (Angrist & Pischke, 2015; Marcus & Sant'Anna, 2021). Fig. 4, which presents ATTs by week, is thus useful for this purpose. If ATTs are consecutively significant for several time periods before the actual treatment occurs, it raises concerns that the outcome in the treatment group might be influenced by unobserved time-varying factors. However, we do not find that to be the case in our study. The red ATT estimates in Fig. 5 illustrate the ATTs before treatment, and the estimates are only significant in three, non-consecutive periods (periods −15, −9, and − 5). This is also displayed in Table 7. Moreover, the significant estimates are in different directions. Hence, we discover no evidence of systematic unobserved factors that might be influencing differences between the treatment and control groups prior to treatment and maintain our confidence in the parallel trend's assumption.

5. Discussions and conclusions

Transparency is an important dimension of public value. Smart applications, user-oriented data management, interactive interfaces, and social media, have digitized the government information disclosure process and provided transparency to government services. Citizens now have easier and more direct access to performance information about public services addressing their interests and concerns. This study explores the influence of digital transparency on civic participation through online crowdsourcing. The 311 system of Sacramento experienced a system update in April 2020, providing users with greater transparency through direct access to improved service request information, including real-time updates and map views. We use this system update to examine the influence of digital transparency on civic engagement with the government.

Using propensity score matching and difference-in-differences approach, we find a boost in service requests submitted by users after the system update of the Sacramento 311 system. This supports our hypothesis (H1) that digital transparency in government enhances citizen participation in online crowdsourcing for service delivery. The increase in participation could stem from either previous users or new users (Sjoberg et al., 2017). Nonetheless, the results also demonstrate that the thrive of participation aroused by digital transparency is limited to a certain duration. Significant increases in participation occur in the first few months after the system update, but then wane after that. One possible explanation is that excitement about and attention to the novel features could have been exhausted after several weeks, and new users might not have developed routines for continued reporting in the system. It is also important to acknowledge that transparency can influence residents' attitudes toward the government in both positive and negative ways. Residents' impressions of the government could turn negative over time as more information on unfavorable policy outcomes is revealed (Grimmelikhuijsen et al., 2013). That is, users of the updated 311 system can observe positive and negative performance, such as long wait times and insufficient responses. The stimulation effect on users' participation in the early stages after the system update could have been diluted in later months by users' negative perceptions of government performance derived from the government's open data. However, we find no evidence of significant decreases in participation in later months - while boosts do not persist, they also do not turn into declines.

Moreover, this study explored the effect of digital transparency on participation in online crowdsourcing by users of different

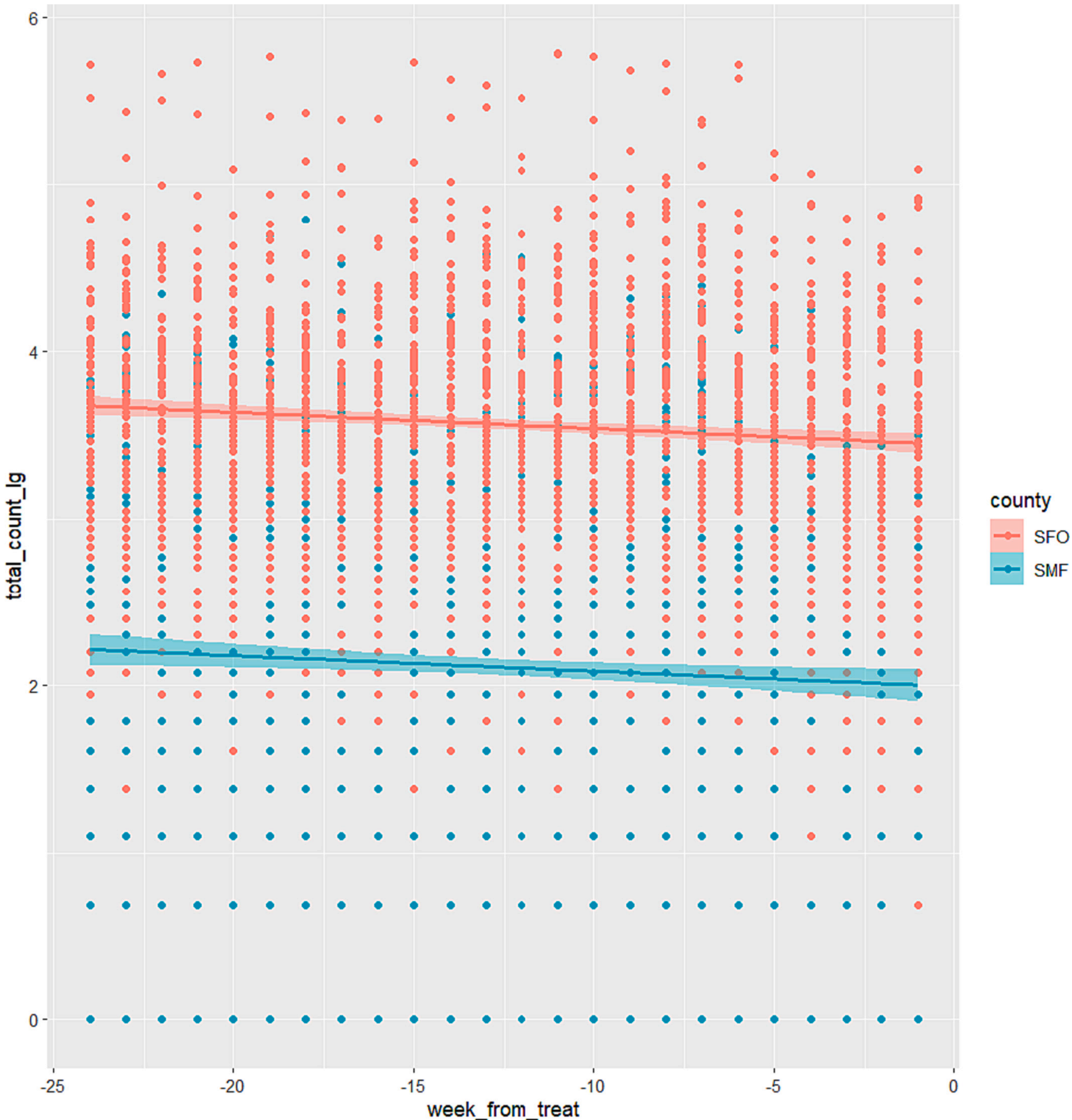

Fig. 5. Scatter plot of total request counts before treatment.

socioeconomic backgrounds. We find that the increases in participation are not significantly different between white and non-white residents (H2 rejected). We find evidence of significant differences by income, but not in our favor: treatment effects are more prominent for residents in areas with higher income and lower poverty (H3 rejected). This difference in the effect of digital transparency could be explained by the civic participatory patterns of users of different socioeconomic backgrounds. Public participation in service delivery is generally higher among homeowners and individuals with higher incomes (White & Trump, 2018). At the same time, recent developments in information technology have lowered barriers to entry for individuals of lower socioeconomic status, and online participation has become an alternative channel for civic engagement for citizens who have experienced unequal access to conventional political resources (Nam, 2012; Xu & Tang, 2020). Even so, information technologies and increased transparency may not increase trust in government for citizens who have been historically neglected in service delivery, perhaps explaining the gap in treatment effects that we find between lower-income and higher-income areas.

This study contributes to the academic literature on technology, transparency, and trust in government, as well as the practice of government service delivery. First, this study expands the knowledge on the relationship between digital transparency and citizen participation.

Table 7
ATT effect before treatment.

Week	ATT Effect	Std. Err.
−23	3.793	2.400
−22	2.089	2.590
−21	−2.206	1.904
−20	8.405	3.679
−19	−10.417	3.932
−18	6.003	3.081
−17	1.432	2.192
−16	4.471	2.368
−15	−14.888*	2.080
−14	0.414	3.205
−13	3.053	2.278
−12	1.504	2.013
−11	−3.008	2.621
−10	−6.610	3.261
−9	8.168*	2.691
−8	−6.359	2.513
−7	1.486	2.386
−6	4.278	2.550
−5	10.624*	2.919
−4	−1.949	2.110
−3	3.725	1.751
−2	−2.337	1.509
−1	0.430	2.097

* : significantly different at 95% confidence interval.

Information technology is crucial in the evolution of open government reforms in terms of the nature of information and the role of citizens (Moon, 2020). The user-friendly features of smart technologies make government data more accessible, interpretable, presentable, and reusable. Citizens have greater freedom to access government information and can even participate in the production and reproduction of government data. More importantly, smart app updates allow them to access the government information that is tailor-made to their needs of services. These changes improve the relevance of government open data to citizens' concerns, where citizen can solely focus on the government information of their interests. The role of the citizen has also changed from the passive recipient of government information disclosures to the active participant in citizen-government collaboration. Furthermore, transparency has moved from an intrinsic value to also an extrinsic value that promotes other important public values, including responsiveness, equity, and engagement (Meijer, 2013). This study specifically examines how citizen participation is affected by improvements to transparency in a digital format. Second, this study contributes to the literature on the transparency and citizen engagement in the context of online crowdsourcing following previous research, such as Buell et al. (2021). Previous studies on the relationship between transparency and civic engagement focus primarily on conventional e-government platforms, such as websites. Government online crowdsourcing services, such as 311 platforms, are highly reliant on citizens' input to the service design and delivery. Citizens are sensitive to the transparency of the system since they have direct concerns about their requested services. This study illustrates the promises and pitfalls of digital transparency in online crowdsourcing—there may be increases in citizen participation in online crowdsourcing, but only for a certain period of time and for certain types of users. Finally, this study is helpful for practitioners because it demonstrates a tangible and practical benefit to increased transparency in service delivery systems—increased citizen engagement—although, again, benefits may not last and may be concentrated among users who are already active in government.

This study has several limitations. First, this study does not encompass all the participation channels, especially social media. Social media platforms have been increasingly used in citizen participation to gain public opinions, to distribute information, and to foster citizen-government cooperation (Lin & Kant, 2021). As our research focuses solely on government online crowdsourcing platforms, which is a structured, government-dedicated participation channel, social media is not included in our research. Even so, we still realize its importance and potential in facilitating transparency and operating as a citizen participation platform. Future research could explore the impact of system updates on civic engagement through a broader range of channels and platforms. Analyzing social media data, could provide valuable insights into how citizens engage with government services and express their concerns outside the dedicated platforms. Specifically, we here propose that analyzing the effect of government-led transparency initiatives (e.g., open government data) on the citizen participation on social media, which could further develop our analysis using the context of social media platforms. Second, due to limitations of the data, we cannot identify individual-level impacts and have to instead assess aggregate changes at the census tract level. Without individual-level data on service requests, use of the interactive platforms, and attitudes toward 311 services, we are unable to explore mechanisms driving individual users to initiate or continue participation on the online crowdsourcing platforms. Further studies could address this issue by identifying individual users and explore how their participation patterns are influenced by transparency initiatives. Third, as the technology evolves frequently, cutting-edge information technology, represented by big-data and algorithms, has raised concerns over novel forms of transparency mechanisms and their implications for citizen trust and engagement (Grimmelikhuijsen, 2023). This study is unable to capture the influence of novel forms of transparency mechanisms on citizen participation. We believe our research design and methodology could inform future studies on novel forms of transparency mechanisms and citizen participation enlightened by the latest information technologies. Fourth, even though Sacramento and San Francisco resemble each other in many aspects, and we adopted the PSM method to minimize the differences between the treatment and the control group, unobserved contextual differences between the two selected cities may still exist and influence the information technology adoption and diffusion among the residents in the two cities. Future studies could further explore digital transparency's influence on citizen participation by considering the impact of citizen's access to information technology in the same political and demographic context, such as through exploiting over-time changes in technology rollout in other alternative cities.

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