Unleashing the Value of Open Government Data: Examining the Influence of Platform and Task

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Keywords: Open government data; Usability; Task; Data using behavior; Platform; Satisfaction

Citation: Ma X., Wang F.: Unleashing the Value of Open Government Data: Examining the Influence of Platform and Task. Data Intelligence, Vol. 7, Art. No.: 2025r29, pp. 879–906, 2025. DOI: https://doi.org/10.3724/2096-7004.di.2024.0050

ABSTRACT

The provision of open government data platforms (OGDP) has been increasing in the past decade. Among an increasing number of studies on OGD, few have focused on individual data-using behavior. To advance intelligent OGDP design, this study examined the effect of platform usability and task complexity on OGD-using behaviors. A 3*3 experiments were conducted on three Chinese urban OGDPs with three tasks at different complexity levels. The results showed that: (1) platform usability and task complexity have significant effect on OGD-using effectiveness; (2) platform design and OGD quality have significant effect on users' satisfaction; (3) users' satisfaction can lead to their reuse intention. This study does not only have practical implications for OGD development, but also provides new empirical evidence for the theories of usability, satisfaction, and task.

1. INTRODUCTION

Providing public access to government data has been an important way for many countries to promote digital economy in the past decade. As one of the major producers and collectors of data in various domains [1], by opening data, the government has not only promoted corruption prevention, accountability, and transparency, but also been expected to enhance citizen participation in democratic politics and drive innovation in digital economy [2, 3]. While OGD is expected to offer numerous benefits in theory, it is often used at levels that are not commensurate with these potential benefits [4]. In striking contrast to the aggressive push by the government, the willingness of external stakeholders to use OGD

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has been lukewarm [5], and the process of using the data appears to have encountered some social or technological barriers [6]. Potential barriers that hinder the use of OGD involve data availability [7], concerns about data quality [8], imperfect legislation and policy [9, 10], users' low ICT literacy [11], and privacy concerns [12], etc.

To promote the use of OGD, scholars have begun to shift the focus of their research from the disclosure of OGD to the use of OGD [8, 13, 14, 15]. Issues of relevant studies involve how people use OGD [16, 17], what socioeconomic value the use of OGD brings and to what extent it promotes society governance [18, 19], what potential factors limit its use [2, 20, 21, 22], who use OGD [23, 24, 25], etc. Wang et al (2023) revealed the dual attributes of OGD as technical products and monopolistic public goods by verifying the influence of information need on information value and reuse intention, and that of government preparation on perceived data value, perceived data quality, and user satisfaction [26].

Among them, while some studies have explored the effect of the characteristics of platform and task on OGD use, there are still some gaps. On the one hand, as administrative pressure is the primary dynamic mechanism behind the disclosure of government data, OGD platform (OGDP) designers often prioritize transparency (opening more data) over interaction design [9, 26], leading to uneven platform usability. Furthermore, the majority of existing evaluations of OGD platforms are expert-centered [27, 28] instead of user-centered, which further exacerbates the unevenness of platform design [7, 29]. So far, the effect of this kind of unevenness on OGD-using behavior has not been investigated enough. On the other hand, the contexts in which users use OGD are diverse, and they frequently need to face a variety of data tasks with varying complexity, which necessitates task-oriented interaction design. However, prior studies have not yet focused on how different task complexities affect individual users' OGD-using behaviors [2, 30]. This is detrimental to promoting OGDP use.

As OGDPs are typically underutilized, prior studies aiming to examine OGD use mainly apply qualitative research methods [31, 32], e.g., case study. The lack of empirical evidence limits the practicality of the research results in improving OGDP interaction design. This study aims to examine the effect of platform and task on individual users' OGD-using behaviors through a controlled experiment. Three research questions are proposed as follows:

RQ1: How does the platform influence individual users' OGD-using behaviors?

RQ2: How does the task influence individual users' OGD-using behaviors?

RQ3: What are the relationships between the platform, task, user, and individual users' OGD-using behaviors?

Answers to these questions can help to further our understanding of why external stakeholders are less willing to use OGD and how the government promotes OGD use in the future. The rest of this paper is organized as follows. Section 2 summarizes the related work. Section 3 describes the experiment design, including selection of platforms, design of tasks, recruitment of participants, experimental procedure, measurement of data, and strategies for data analysis. Section 4 presents the experimental results. The key research findings, implications, limitations, and future directions are discussed in Section 5.

2. RELATED WORK

2.1 Use of Open Government Data

Studies on OGD use involve four areas: value, users, application scenarios, and barriers. Many studies have discussed the value of OGD use, including enhancing transparency & accountability [33] and anti-corruption [19], promoting citizen participation [2], improving public service [34], and facilitating innovation and decision-making [18, 35]. Studies on OGD users can be divided into revenue-oriented consumers, e.g., developers [23], public-value-oriented consumers, e.g., journalists [25], researchers [3, 28], and general citizens [24], etc. Safarov et al. (2017) [11] found that OGD are used by eight different user groups, including citizens, businesses, researchers, developers, non-governmental organizations (NGOs), and journalists. The application scenarios of OGD use include settlement analysis [36], smart city building [16], etc. A variety of barriers to OGD use have also been explored, such as poor data quality [8, 20, 37, 38], imperfect legislation and policy [10, 22], privacy concerns [12, 21], limitations of ICT literacy [11], and language barrier [28].

Governments have taken some measures to promote OGD use, including organizing innovation competitions to encourage OGD use, uploading data products to the platform for more people to use [39, 40], providing applications to make OGD accessible and easier to use for ordinary users who lack technical skills, developing personalized OGDPs to help different users make data requests, give feedback, and correct data [17] etc., and thus made OGD become an effective tool for citizens and policy makers.

Despite the vibrant research and practice driving the use of OGD, focusing on both the potential value, target users, application scenarios, and barriers, as well as considering their practical impact on government decision-making and public service improvement and the possible ways in which the social and economic benefits can be realized, there has been little research on whether and how platform usability and task complexity in the OGD field can affect user behaviors [31, 32]. In this study, we aim to bridge this gap by exploring and evaluating the influence of factors such as platform usability and task complexity on OGD-using behaviors through a user-oriented experiment.

2.2 Platform Usability

The open government data platform (OGDP) is designed to meet the demands of various users for OGD, and thus to promote its value-added and innovative application [41, 42]. OGDPs have proliferated with the open data movement, and their usability is now a major concern [28, 43, 44, 45]. In practice, several indices have been proposed and implemented to evaluate the level of OGD in a country, e.g., the Open Data Barometer, the Open Data Index, the EU Open Data Maturity Report, and the OECD's OURData index, of which the usability of the OGDP is usually an indicator [28]. Similarly, the China

Open Data Index (CODI), a well-known evaluation index in China, assigns platform-related metrics a larger weight in its evaluation—about 85%—and examines the OGD level of Chinese urban governments [46].

In academic research, given the increasing number of open datasets and data sources, prior studies have mostly evaluated the usability of OGDPs from the perspective of data quality [8, 20, 37, 38]. Several scholars have opted to evaluate the OGD quality from specific perspectives, such as the accessibility and interoperability of data formats [47], the accuracy of metadata [38, 48], and the completeness and timeliness of data catalogs [49]. Other scholars have tried to deliver a more comprehensive assessment of OGD quality by developing an evaluation index system. For example, Vetrò et al. (2016) [50] set up a framework of seven indicators to measure the quality of OGD, including traceability, currentness, expiration, completeness, compliance, understandability, and accuracy. In response to data duplication, data missing and other OGD quality problems, Hu and Wang (2021) [20] constructed an evaluation system including three dimensions, data source, data set and data context.

Since the primary impetus for the disclosure of government data comes from administrative pressure [9], governments tend to focus the platform design on transparency with the least resistance and fastest benefits [26], without paying attention to the actual use experience of individual users. As a result, the usability across different platforms varies greatly. Meanwhile, the expert-oriented evaluation methods for platform usability are mostly set by experts or governments themselves based on OGD initiatives, which evaluate how well platforms perform on the initiative requirements rather than how useful the platforms are to users [28]. This further exacerbates the uneven usability across platforms. And the effect of this unevenness on individual users' OGD-using behaviors has not been the subject of prior studies. To address the research gaps, this study will design and implement a user experiment to thoroughly examine the difference in individual users' OGD-using behaviors across platforms, employing a combination of quantitative and qualitative methods such as statistical analysis and user interviews.

2.3 Task Complexity

In recent years, the assessment of task complexity and the relationship between tasks with different complexity levels and search outputs have been actively investigated in the domain of text information retrieval. As an important contextual factor, the complexity of the task has been divided into objective complexity and cognitive complexity in literature [51, 52, 53, 54]. The former can be measured with the number of subtasks. The latter can be assessed according to a cognitive complexity framework [55, 56]. Other studies have attempted to measure the different effects of tasks with different complexity levels on search outputs and user behaviors. Arguello et al. (2012) [57] found that more complex tasks involve more interactions, and users investigate more outcomes when completing these tasks. Kelly et al. (2015) [58] found that more complex tasks require more search activities from users (such as more clicks and task completion time), but have no significant influence on users' satisfaction with task performance. A recent study [59] found that the complexity of music retrieval task significantly affects search effectiveness, with higher complexity being associated with more task completion time, clicks, and track plays, but has no significant correlation with the number of songs found and user's satisfaction.

Task related contextual factors have also been paid attention to in OGD research field. Janssen et al. (2012) [2] identified task complexity as one of the barriers to the application of OGD at the institutional level. Parnia (2014) [30] evaluated several user interfaces through multiple tasks and summarized numerous lessons in OGD user interface design. Similarly, Ruijier et al. (2017) [60] proposed a data requirement collection approach that integrates data, users, and social context to assist government agencies and designers in designing OGDPs that meet citizens' needs.

Users of OGD often confront a variety of data using tasks with varying complexity. Prior studies have noticed the possible influence of the task on OGD use, but have not thoroughly examined the effects of task complexity on individual users' OGD-using behaviors. To this end, this study designs three task contexts at different complexity levels, observe and record individual users' OGD-using behaviors on the platform, and assess the difference in behavior data at various complexity levels.

3. EXPERIMENT DESIGN

To answer these research questions, a 3 (platform usability: high vs. medium vs. low) * 3 (task complexity: easy vs. medium vs. difficult) user-oriented experiment was conducted. This section describes the selection of platforms, the design of tasks, the recruitment of participants, the experimental procedure, the measurement of variables, and the method of data analysis.

3.1 Selection of Platforms

China Open Data Index (CODI) is a well-known OGD evaluation index in China, with a sizeable proportion (about 85%) of usability-related indicators for the platform, such as data quality, activity feedback, category navigation, etc. From the top 50 CODI-ranked urban government platforms (which have long-standing infrastructure and robust foundations, avoiding basic issues and allowing the research to focus on deeper, more valuable platform factors affecting user behavior), we selected three ones—Shanghai, Shenzhen, and Weihai—as experimental platforms. According to the CODI rankings (2021), the Shanghai platform has the highest usability, followed by Shenzhen platform and Weihai. The selection criteria are to maximize differences in usability between the selected platforms while making sure that the Weihai platform, with the lowest usability, is not below the top 50. The descriptions of the three experimental platforms are shown in Table 1.

3.2 Design of Tasks

The experimental tasks were designed according to Krathwohl's cognitive complexity framework [57, 59]. Three experimental tasks with different complexity levels were designed to simulate the real context of OGD use. There are three reasons for selecting this framework. Firstly, OGD use is a relatively new research topic. Few studies have adopted an experimental method to examine the relationship between task complexity and OGD-using behavior. Secondly, a user often uses OGDPs to complete certain tasks (e.g., developing database, doing research, completing assignments, etc.), and the familiarity of the

Table 1. Description of three experimental platforms.

No	City	Usability	CODI score	Number of government departments	Number of datasets	Number of rows	Number of fields	Number of apps developed	Number of interfaces
P1	Shanghai	high	70.74	51	5590	997328209	46199	54	2434
P2	Shenzhen	Medium	61.64	47	2519	572691986	25601	22	2490
P3	Weihai	low	53.57	98	11606	160000000	—	43	8560

Note(s): the data were recorded before the start of the experiment (2021-11-14).

task context and the affordance of the platform may affect the user's perception of task complexity [2]. Therefore, it is not appropriate to differentiate task complexity based on the number of subtasks alone. Thirdly, the framework is widely acknowledged in the domain of education and has been adopted to measure user behavior in interactive information retrieval [57, 58, 59]. The designed tasks at three cognitive levels are listed in Table 2.

Specifically, Task T1 is the simplest, aiming to locate datasets based on given criteria, easily deduced from concise task descriptions. It only requires extracting keywords from the task description and searching for and downloading the corresponding datasets, without the need to familiarize oneself with the task background or decompose the task. Task T2 goes a step further, requiring participants to familiarize themselves with the task background, clarify and understand the logical links and data requirements of subtasks [54], and obtain datasets from the experimental platform. This task approximates the "understand" level in the cognitive framework. Task T3 involves more deliberate judgment because it requires participants to understand and decompose complex tasks in completely unfamiliar contexts, sift through ambiguous data requirements, and ensure logical links among components. Therefore, Task T3 can be considered at the "analyze" level, corresponding to the highest level of task complexity.

3.3 Recruitment of Participants

Students in library and information science (LIS) were recruited as participants in this study. This choice was primarily based on the following considerations: Firstly, relevance and information literacy. According to some recent studies [28, 61], typical users of OGDPs are more experienced with IT, and students are considered a highly relevant user group for using OGD. Almost all LIS students have taken a variety of information resource management courses, possessing high information literacy. This reduces the impact of other confounding factors, enhances the feasibility and management efficiency of experiments, thereby enabling the possibility of random grouping in experiments; Secondly, practical data demands. These students frequently undertake various government data-related research projects, such as improving urban service quality, making management decisions, and providing public services, which makes them more likely to become target users of OGDPs. Additionally, in the future, they are likely to pursue careers in information management, providing valuable educational feedback for OGDP design and promoting the

Table 2. Designed tasks at three complexity levels.

No.	Task type	Complexity level	Cognitive level	Task description
T1	Assigned	Easy	Remember	Suppose you are a parent with a child who is about to start elementary school①. Now you need to know the situations of the local elementary schools, please select and download the datasets you need from the designated platform, and judge if they are usable.
T2	Assigned	Medium	Understand	Suppose you are a software developer of an internet company and want to develop a data product with the following functions: (1) Display the water pollution in the designated city in real time; (2) Analyze and visually display the water pollution diffusion; (3) Explain the causes of pollution②. Please download datasets you need in the designated platform and judge if they are usable.
T3	Assigned	Difficult	Analyze	Suppose your supervisor asked you to write a preliminary data analysis report on the topic of carbon peaking and carbon neutralization③. Please download datasets you need in the designated platform and judge if they are usable.

Note(s): T=task; Assigned=the task is assigned by the experimental team.

integration of academia with practical applications; Thirdly, for an exploration of using behavior of initial OGDP users, the student sample provides a solid starting point. Through this relatively homogeneous sample, this study can preliminarily validate the impact of platform usability and task complexity on user behavior.

3.4 Experimental Procedure

All participants were requested to engage in a user-oriented experiment in a controlled setting. The experiment was conducted for a month in three batches inside a lab at the Business School of Nankai University. Quantitative and qualitative data on user background, perceptions, and behaviors were collected with questionnaires, interviews, and a video recording tool. Figure 1 depicts the experimental procedure, including three stages: pilot study, formal experiment, and user interview.

① Choosing a good primary school is a top priority for many Chinese parents of school-age children, and has been experienced by almost all the students.
② Water pollution is a global environmental issue, especially for China with a population of 1.4 billion, that not only decreases crop yields but also degrades the soil and surrounding ecosystem, putting human and animal health at risk.
③ Climate change is a worldwide issue. Carbon peaking (when carbon dioxide emissions stop increasing and steadily decline after reaching a peak) and carbon neutralization (carbon dioxide emissions are equal to fixed carbon dioxide) are two of China’s aims.

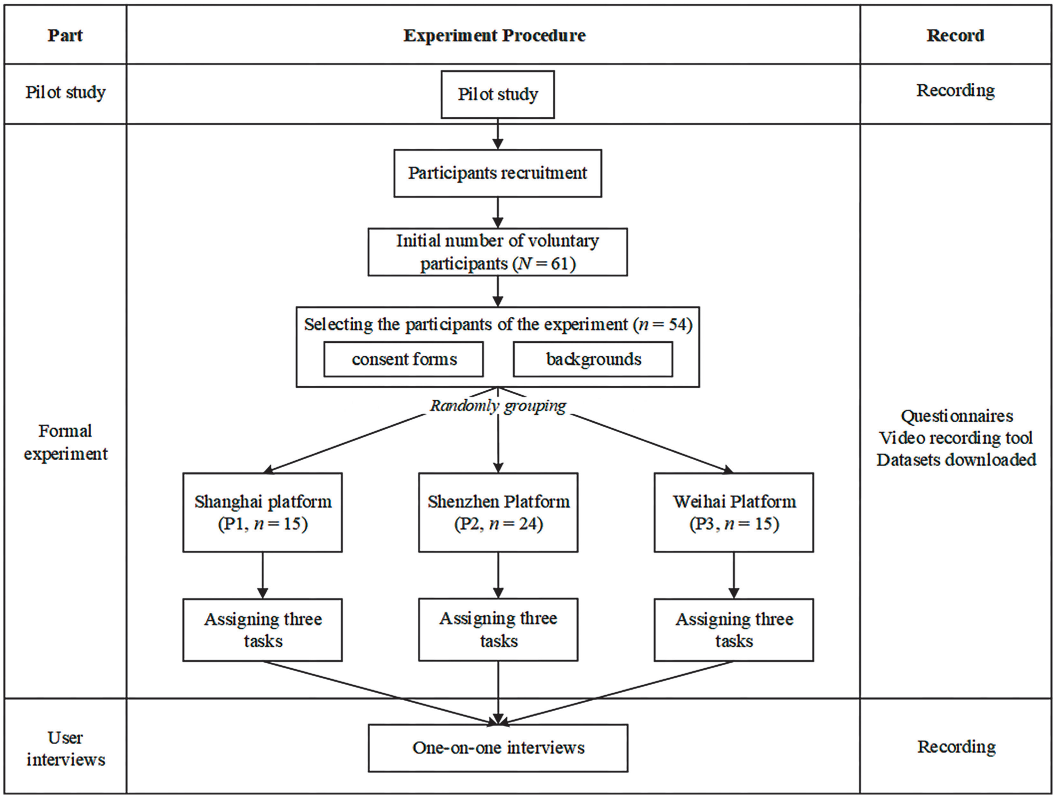


Figure 1. Experiment procedure.

3.4.1 Pilot Study

A pilot study was conducted before recruiting participants, and the experimental design was adjusted based on the feedback. An expert group (6 PhD students and 9 master students) with rich experience in e-government research were recruited. They performed the tasks in the same platforms as the formal experiment, and reported problems with the platforms, tasks, scales, questionnaires, and settings. Based on their feedbacks, the selection criteria of platforms, the design of tasks, the scales and the items of questionnaires, the selection plan of participants, the process of the experiment, and the preceding preparations for the experiment were revised. And then, the expert group was requested to give suggestions for optimizing the improved experiment again until no one had an opinion. The expert group eventually agreed that the experiment design is feasible and effective.

3.4.2 Formal Experiment

The business school of Nankai University, an outstanding business school, with students from almost all the provinces of China, was selected to publicly recruit participants from. Participants were recruited through the school's WeChat groups for undergraduate and master students. Recruitment was completely open and voluntary, and each participant was paid a nominal fee.

A total of 61 voluntary participants were recruited. Before being grouped, they were asked to sign a consent form and complete a background questionnaire. Through the consent form, participants were given information about the experiment's objective, how data will be used, and personal rights. The background questionnaire gathered the gender, grade, and professional skills of the participants. 7 participants who did not meet the experimental requirements were excluded (had used OGDPs before).

Statistics for the 54 eligible participants' backgrounds are shown in Table 3. Then, they were randomly assigned to one of three experimental platforms (15 participants to the Shanghai OGDP, 24 participants to the Shenzhen OGDP, and 15 participants to the Weihai OGDP). Before the formal experiment started, a 5-minute pre-experiment training was conducted, including screen recording software operation, experimental precautions, and Q&A sessions. After the training, participants had 3 minutes to familiarize themselves with the designated platform and complete the registration.

Table 3. Statistics for the 54 eligible participants' backgrounds.

Background (binary)	Item	Frequency	Background (ordinal and numerical)	Mean	Std
Grade	Undergraduate	15	Age	23.3	2.27
	Master	39	Ability to download web data	4.28	0.76
Gender	Male	13	Frequency of using government data	3.24	0.99
	Female	41	Knowledge of OGDP	2.96	0.88
Experience of using data	Have	51			
	Not have	3			
Experience of social work	Have	30			
	Not have	24			
Experience of using government data (never used an OGDP)	Have	30			
	Not have	24			

To avoid any divergence of results caused by task execution order, the task order was sorted using a Graeco-Latin Square design, and the number of participants who performed Task T1 or Task T2 or Task T3 first on the same platform was equal. Besides, participants were asked to mark the usable datasets with a "#" and complete a post-experiment questionnaire. After completing all the tasks, participants were asked to complete an overall assessment questionnaire. Throughout the 90-minute task execution procedure, the participants had complete control over the task's execution progress.

3.4.3 User Interview

Participants were interviewed one-on-one after experimental data collection was completed. The interview was semi-structured and lasted about 15 minutes. Various problems encountered by the participants during the experiment and their suggestions for the construction of an OGDP were collected. It revolved around two questions: (1) What difficulties did you encounter in completing the task? E.g., platform-related, task-related, expectation, and so on; and (2) Do you have any suggestions for developing an OGDP? The interviews were conducted face-to-face, with audio recording and transcription conducted upon participants' consent. All interviews were conducted and inductively analyzed in Chinese, then translated into English by bilingual researchers for reporting, to corroborate quantitative analysis results or deepen understanding of influencing factors behind user behavior.

3.5 Data Measurement

The measures of OGD reuse intention, satisfaction, using effectiveness, perceived OGD quality, perceived OGD quantity, and perceived platform design were collected through questionnaires, interviews, and screen recording. The measure, metric, definition, and Likert scales are shown in Table 4. In particular, the values of OGD reuse intention, perceived OGD quality, perceived OGD quantity, and perceived platform design are calculated from the means of their corresponding metrics.

3.6 Data Analysis

To answer RQ1, One-Way Analysis of Variances (One-Way ANOVA) and Kruskal-Wallis test were initially performed to investigate differences in users' OGD-using behaviors (using effectiveness, satisfaction, and OGD reuse intention) on three OGDPs. The differences in perceived OGD quality, quantity, and platform design between the three OGDPs were then examined, and the possible factors influencing users' OGD-using behaviors in the platform were discussed further in conjunction with user interview texts.

To answer RQ2, One-Way ANOVAs were used to investigate differences in users' OGD-using behaviors in tasks with different complexity levels. And then, differences in users' OGD-using behaviors on different user background variables were examined across groups. Furthermore, the effect of user background on users' OGD-using behaviors was also examined.

To answer RQ3, Spearman's Rank Correlation Coefficients between the influencing factors found in RQ1 and RQ2 and users' OGD-using behaviors were calculated. Then, significantly correlated influencing factors were used as independent variables to regress user behaviors, and the LMG algorithm [62] was used to explore the contribution of the significant independent variables to the change of the dependent variable.

Table 4. Measures of user' OGD-using behaviors and perceptions.

Measure	Metric	Definition	Likert scale
OGD reuse intention	(U1) Intention of continuous use	User self-reported willingness to continue using OGD	7-point; 1: very unwilling; 7 very willing
	(U2) Recommend others to use	User self-reported willingness to refer others to use OGD	7-point; 1: very unwilling; 7 very willing
Satisfaction	(S1) Satisfaction with datasets found	User self-reported satisfaction level	7-point; 1: very unsatisfied; 7: very satisfied
Using effectiveness	(E1) Task completion time (minute)	Duration from start to end of a task	Non-negative decimal
	(E2) Number of datasets downloaded	Number of datasets downloaded as answers to a task	Non-negative integer
	(E3) Number of available datasets downloaded	Number of available datasets downloaded as answers to a task	Non-negative integer
Perceived OGD quality	(Q1) Identifiability of datasets	User self-reported difficulty of identifying whether datasets are the answer to tasks	7-point; 1: very difficult; 7: very easy
	(Q2) Format of datasets	User self-reported availability of dataset formats to be downloaded	7-point; 1: very low; 7: very high
	(Q3) Understandability of data records	User self-reported understandability of data records of the dataset	7-point; 1: very low; 7: very high
	(Q4) Adequacy of dataset fields	User self-reported adequacy of the number of fields of datasets	7-point; 1: very inadequate; 7: very adequate
	(Q5) Timeliness of datasets	User self-reported timeliness of datasets being updated	7-point; 1: very timely; 7: very untimely
	(Q6) Credibility of datasets	User self-reported data validity of datasets	7-point; 1: very low; 7: very high
	(Q7) Accessibility of datasets	User self-reported complexity of downloading datasets	7-point; 1: very complex; 7: very uncomplex
	(Q8) Classification of datasets	User self-reported rationality of the classification of datasets	7-point; 1: very irrational; 7: very rational

Table 4. *Continued.*

Measure	Metric	Definition	Likert scale
	(Q9) Help with OGD use	User self-reported adequacy of tools provided to help use OGD	7-point; 1: very inadequate; 7: very adequate
	(Q10) Availability of datasets	User self-reported availability of datasets	7-point; 1: very low; 7: very high
Perceived OGD quantity	(Y1) Number of datasets satisfying task	User self-reported adequacy of datasets that satisfy the task requirements	7-point; 1: very inadequate; 7: very adequate
	(Y2) Number of datasets	User self-reported adequacy of datasets	7-point; 1: very inadequate; 7: very adequate
	(Y3) Coverage of datasets	User self-reported range of domains covered by datasets	7-point; 1: very small; 7: very large
Perceived platform design	(D1) Friendliness of interfaces	User self-reported design level of platform interfaces	7-point; 1: very unfriendly; 7: very friendly
	(D2) Friendliness of data discovery functions	User self-reported design level of the data discovery functions of the platform	7-point; 1: very unfriendly; 7: very friendly
	(D3) Friendliness of problem feedback functions	User self-reported design level of problem feedback functions of the platform	7-point; 1: very unfriendly; 7: very friendly

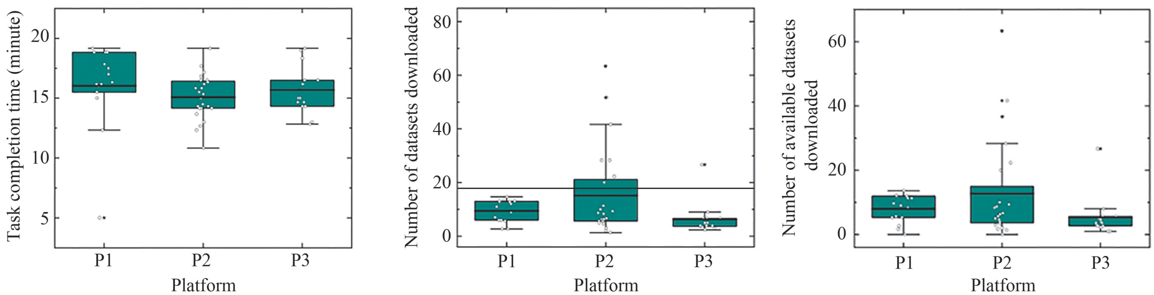
In particular, the analysis methods were chosen according to the type of factor (grouping variable) and whether the dependent variable (grouped variable) had satisfied the homogeneity of variance test [63]. For example, when a factor has multiple levels, a One-Way ANOVA is used if the dependent variable satisfies the homogeneity of variance ($p>.05$), and a Kruskal-Wallis Test or a Mann-Whitney U-Test is used if the dependent variable does not satisfy the homogeneity of variance ($p<.05$).

4. RESULTS

4.1 Effect of OGDP on Users' OGD-Using Behaviors

4.1.1 Using Effectiveness

As each user conducted three tasks, the task completion time, number of datasets downloaded, number of available datasets downloaded, and satisfaction of each of these tasks were averaged, respectively [59]. Datasets with the same name but different formats were considered the same dataset. Kruskal-Wallis tests were used to analyze whether there were significant differences in using effectiveness between the three platforms. The data distribution of using effectiveness across different platforms were shown in Figure 2. From the results (*n*=54), there were significant overall differences in the number of datasets downloaded (*p*=.025) and the number of available datasets downloaded (*p*=.046), but not in the task completion time (*p*=.109).



(a) Task completion time (b) Number of datasets downloaded (c) Number of available datasets downloaded

Figure 2. Boxplots of using effectiveness across different platforms. P1 denotes the Shanghai platform, P2 denotes the Shenzhen platform, and P3 denotes the Weihai platform.

For the task completion time, there was a significant difference between Platform P1 and Platform P2 (*p*=.045), but not between Platform P3 and either Platform P1 (*p*=.468) or Platform P2 (*p*=.696). On average (Figure 2(a)), the task completion time on Platform 2 was the least (mean=15.08), followed by Platform P3 (mean=15.38), and the most on Platform P1 (mean=16.43).

For the number of datasets downloaded, there was a significant difference between Platform P2 and Platform P3 (*p*=.026), but not between Platform P1 and either Platform P2 (*p*=.145) or Platform P3 (*p*=.466). On average (Figure 2(b)), the number of datasets downloaded on Platform P2 was the highest (mean=15.13), followed by Platform P1 (mean=9.44), and the lowest on Platform P3 (mean=6.31). According to the platform statistics (Table 1), the number of open datasets on Platform P3 was the highest, followed by Platform P1, and the least on Platform P2, which was inversely related to the number of datasets downloaded. Further analysis of the names of datasets downloaded from different platforms revealed similar degrees of fragmentation, indicating that the influence of data fragmentation on the number of datasets downloaded can be ruled out.

For the number of available datasets downloaded, Platform P2 was significantly higher than Platform P3 (*p*=.049), but there were no significant differences between Platform P1 and Platform P2 (*p*=.206) or Platform P3 (*p*=.508). As shown in Figure 2(c), Platform P2 (mean=12.72) had the highest number of available datasets downloaded, followed by Platform P1 (mean=8.02) and Platform P3 (mean=5.31), which was consistent with the shift in the number of datasets downloaded.

4.1.2 Satisfaction and OGD Reuse Intention

The satisfaction of each user was averaged over the three tasks. A One-Way ANOVA was conducted to see if there were any significant differences in satisfaction among platforms. The results showed (n=54) that satisfaction varied significantly across platforms (F=7.328, p=.002). The pairwise comparison indicated that Platform P3 (mean=2.53) was significantly less satisfying than Platform P1 (p=0.031) and Platform P2 (p=0.000). This result verified that the platform with the lowest usability was less satisfied than other platforms.

Given that there was no significant difference in satisfaction between Platform P1 and Platform P2 (p=.035), and that Platform P2 (mean=4.17) has higher satisfaction than Platform P1 with the highest usability (mean=3.46), further investigation was required. One-Way ANOVAs were applied to further analyze the differences between the three platforms in terms of perceived OGD quality, OGD quantity, and platform design. The results showed that, apart from perceived OGD quality (F=.275, p=.760) and OGD quantity (F=1.027, p=.610), perceived platform design (F=6.827, p=.001) differed significantly among platforms. Although there were no significant between-group differences in pairwise comparisons (Table 5), on average, Platform P2 outperformed Platform P1 in terms of perceived OGD quality (Mdifference=-.050) and platform design (Mdifference=-.10). Therefore, perceived OGD quality and platform design may be major causes of Platform P2's higher satisfaction than Platform P1. The absence of a significant difference in perceived OGD quality and perceived OGD quantity might be attributed to continuous platform improvement [37, 48, 64, 65, 66], a decline in the degree of discrimination of commonly used assessment metrics (Table 4) in prior studies, and the fact that some factors affecting satisfaction were ignored by the expert-oriented approach.

Table 5. Results of pairwise comparisons of perceived OGD quality, OGD quantity, and platform design.

Measure	Platform (I)	Platform (J)	$M_{difference}$ (I-J)	p
Perceived OGD quality	P1	P2	-.050	.755
	P1	P3	.069	.700
	P2	P3	.119	.460
Perceived OGD quantity	P1	P2	.106	.479
	P1	P3	.289	.223
	P2	P3	.182	.364
Perceived platform design	P1	P2	-.10	.536
	P1	P3	.467	$.008^{**}$
	P2	P3	.566	$.000^{***}$

Note(s): n=54, P1=Shanghai platform, P2=Shenzhen platform; P3=Weihai platform, * p<.05, ** p<.01, *** p<.001.

The user interview results showed that data quality and platform design were the most frequently mentioned issues, apart from the 16 metrics (Q1–Q10, Y1–Y3, and D1–D3) in Table 4. Some participants mentioned that the registration process was cumbersome, data preview was unavailable, interface usage instructions were missing, and data consistency was poor. These problems may exacerbate the difficulty of accessing and using data for users lacking data science expertise [67], negatively affecting satisfaction. For example, Participant 1 comment on Platform P1, "*Many datasets are incomplete and only available in a few districts of Shanghai …, and the content and fields of the datasets published in each district differ*". Participant 7 commenting on platform P1, "*Some datasets can be previewed before downloading, while others can only be opened after they have been downloaded …, dataset visualization was not easy to use, and most datasets could not be visualized*".

The position and size of sorting options were mentioned by several participants as interface functions that should be optimized to make the platform's data more user-friendly and satisfying. For example, Participant 2 commenting on platform P1, "*The tag index is not clear … Ugly interface …The sorting options are very small and inconvenient to use. The interface should be simplified and beautified, and options (e.g., sorting, page tuning, etc.) should be reorganized*".

Participants also revealed the platform's humanistic care besides general data quality and platform design issues. They emphasized that platforms should be accessible to everyone, regardless of their abilities, experience, or knowledge. For example, Participant 29 commented on Platform P2, "*The response speed is fast, the interface is friendly and clear, the feedback position is eye-catching… and there is a barrier-free browsing mode for vulnerable groups*".

A One-Way ANOVA was conducted to compare OGD reuse intention across different platforms. The results were insignificant (p=.721). And then, pairwise comparisons also revealed no significant differences (p>.05).

4.2 Effect of Task Complexity on Users' OGD-Using Behaviors

4.2.1 Using Effectiveness

After fixing the platform, One-Way ANOVA was applied to compare the between-group differences in using effectiveness (task completion time, number of datasets downloaded, and number of available datasets downloaded) on tasks with different complexity levels. The data distribution of using effectiveness across tasks with different complexity levels are shown in Figure 3.

For the task completion time, the results indicated (n=162) that there was a significant difference at different complexity levels on Platform P2 (F=3.850, p=.026). Pairwise comparisons between Task T1 and Task T2 (p=0.013), as well as Task T1 and Task T3 (p=.007), found significant differences. Participants spent significantly less time on Task T1 (mean=14.68) than on Task T2 (mean=16.24) and Task T3 (mean=16.63), as shown in Figure 3(a). While there were no significant between-group differences in task completion time at different task complexity levels between Platform P1 (F=1.186, p=.316) and Platform

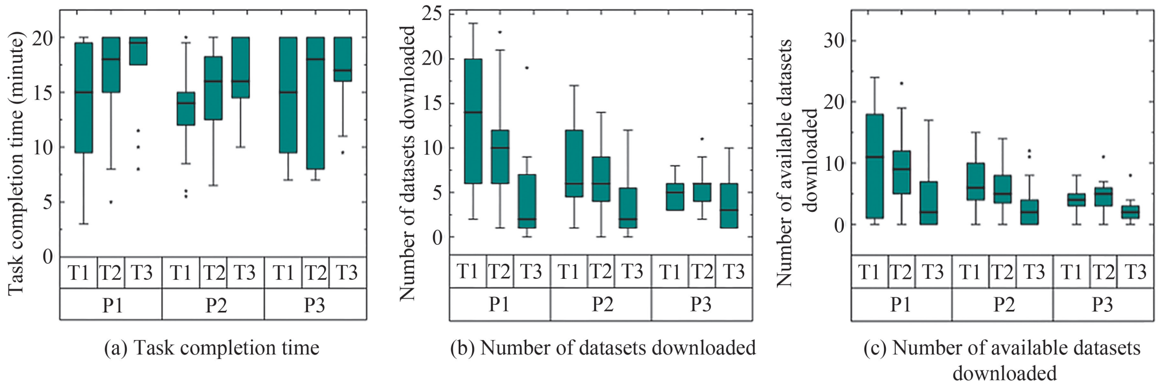


Figure 3. Boxplots of using effectiveness across tasks with different complexity levels. T1, T2, and T3 respectively denote three tasks with complexity levels of easy, medium, and difficult. P1, P2, and P3 respectively denote the Shanghai, Shenzhen, and Weihai platform.

P3 (F=.652, *p*=.526), on average, the simplest Task T1 spent less time than the more difficult Task T1 and Task T3.

Furthermore, on the Platform P3 with the lowest usability, we also noticed that participants spent 97.9 seconds less time on Task T3 (difficult complexity), than on Task T2 (medium complexity). One possible explanation is that when the task complexity is too high and the sub-tasks are not explicitly informed, participants will abandon it early if they feel it will be impossible to complete while trying. As reflected by a participant in the interview, "*The system did not contain or return any relevant results for some of the specified keywords… When it comes to terms like pollution and carbon, the data is all positive, and no relevant information can be found… The login procedure is very time-consuming, the certification and review times are too long, particularly the real-name review period after registration, and essential information can only be viewed after real-name review*" (Participant 43 who spend 9.5 minutes on Task T3).

For the number of datasets downloaded (Figure 3(b)) and available datasets downloaded (Figure 3(c)), the results showed that in the same platform, their overall differences across tasks with different complexity levels were significant (*p*<.05). Pairwise comparisons revealed that the number of datasets downloaded and available datasets downloaded for Task T3 were significantly less than those for Task T2 and Task T1 (*p*<.05), and there was no significant difference between Task T2 and Task T1 (*p*>.05). In other words, OGDPs have lower affordance for tasks that exceed a certain level of complexity.

4.2.2 Satisfaction

After fixing the platform, a One-Way ANOVA was applied to observe the effect of tasks with different complexity levels on satisfaction. The results revealed that there was no significant difference in satisfaction across tasks with different complexity levels (*p*>.05), and pairwise comparisons also revealed no significant differences (Table 6, p>.05). This result is consistent with some studies in information retrieval (IR) that found task complexity had no influence on satisfaction [59].

Table 6. Results of pairwise comparisons of satisfaction by tasks with different complexity levels.

Measure	Task (I)	Task (J)	$M_{difference}$ (I-J)	p
Satisfaction (P1)	T1	T2	.467	.413
	T1	T3	1.067	0.066
	T2	T3	.600	.294
Satisfaction (P2)	T1	T2	.042	.915
	T1	T3	.771	.052
	T2	T3	.729	.066
Satisfaction (P3)	T1	T2	-.067	.900
	T1	T3	.733	.174
	T2	T3	.800	.138

Note(s): n_{p1}=45, n_{p2}=72, n_{p3}=45, P1=Shanghai platform, P2=Shenzhen platform, P3=Weihai platform, * p<.05, ** p<.01, *** p<.001.

Besides task complexity, participants also mentioned in the interviews the possible effect on satisfaction of the large discrepancy between the expected data required for the task and the platform data. For example, Participant 26 comment on Platform P3, "*I feel frustrated and powerless to complete the task because the discrepancy between the data expected to be collected and the data collected in practice is too great* ...".

Bhattacherjee (2001) [68] believed that user satisfaction with using an information system (IS) was influenced by the confirmation of expectations from prior IS use. There is no exception in the use of OGD. When the platform's data exceeds or falls short of prior expectations, users may feel more or less satisfied.

4.3 Effect of User Background on Users' OGD-Using Behaviors

4.3.1 Using Effectiveness

Mann-Whitney U-Tests were used to investigate the effect of binary variables in users' background on using effectiveness. The metrics for operationalization of using effectiveness were the same as that in Section 4.1.1. The results showed (n=54) that only task completion time differed significantly across experience of using data (p=.005), while the rest of the differences were not significant (p>.05 for grade, gender, experience of social work, and experience of using government data). On average, participants with experience of using data took 199 seconds longer on average to complete tasks than those without. Maybe they had more consideration in the process of downloading data based on their richer experience.

For ordinal and numerical variables, Spearman's rank correlation coefficient was calculated, and the results showed that there was no significant correlation (p>.05 for age, ability to download web data, frequency of using government data, and knowledge of OGDP).

4.3.2 Satisfaction and OGD Reuse Intention

The relationships between user background and satisfaction were examined. The satisfaction of each user was averaged over the three tasks. The Mann-Whitney U-Tests were performed on binary variables, and the results showed (n=54) that there were no significant differences between groups in satisfaction with grade (p=.291), gender (p=.483), experience of social work (p=.175), experience of using data (p=.561), and experience of using government data (p=.752).

For ordinal and numerical variables, Spearman's rank correlation coefficients between satisfaction and self-reported background were calculated. The results showed that there was no significant correlation at the P=.05 level. In other words, age (r=-.011, p=.934), ability to download web data (r=.051, p=.714), frequency of using government data (r=.202, p=.142), and knowledge of OGDP (r=.182, p=.187) did not have a consistent relationship with satisfaction.

Like the above analysis, the relationships between OGD reuse intention and user background were also investigated. The results showed that there were no significant differences in OGD reuse intention at the different levels of user background variables (p>.05).

4.4 Regression Analysis

Furthermore, to improve the OGDP's capacity to dynamically sense user behaviors, two sets of linear regressions were conducted to confirm the predictive power of using effectiveness, platform, and user metrics on satisfaction and OGD reuse intention, respectively.

4.4.1 Satisfaction

Firstly, Spearman's rank correlation coefficients were calculated to investigate possible correlations between using effectiveness metrics, platform metrics, user metrics, and satisfaction. Significant correlation coefficients are shown in Table 7, ranked by strength of correlation. The coefficients in Table 7 show weak ($r<|0.3|$) or moderate ($|0.3|\leq r\leq|0.5|$) or strong ($|0.5|<r$) correlations [69]. Perceived platform design (r=.727, p=.000) and perceived OGD quality (r=.489, p=.000) were strongly or moderately correlated with satisfaction. Number of datasets downloaded (r=.244, p=.002) and number of available datasets downloaded (r=.295, p=.000) were weakly correlated with satisfaction.

Table 7. Significant correlations between using effectiveness, platform, task, user, and satisfaction.

Metric 1	Metric 2	*r*	*p*
Satisfaction	Perceived platform design	.727***	.000
	Perceived OGD quality	.489***	.000
	Number of available datasets downloaded	.295***	.000
	Number of datasets downloaded	.244**	.002

Note(s): *n*=162, * *p*<.05, ** *p*<.01, *** *p*<.001.

Secondly, to examine if satisfaction is impacted by relevant metrics, linear regression was conducted with perceived OGD quantity, perceived OGD quality, perceived platform design, number of available datasets downloaded, and number of datasets downloaded as independent variables. Due to the multi-collinearity (VIF=8.952) between the number of datasets downloaded and the number of available datasets downloaded, stepwise regression was chosen. The results showed (Table 8) that the model fitting effect was good (R2=.656) and there was no multi-collinearity among variables (VIF<5). Satisfaction was significantly influenced by perceived OGD quality (B=.310, *p*=.002), perceived platform design (B=.702, *p*=.000), and number of available datasets downloaded (B=.011, *p*=.025).

Table 8. Regression analysis on satisfaction.

Measure	Coefficient (B)	t	*p*	VIF	Relative importance
Perceived OGD quality	.310	3.102**	.002	1.386	28.19%
Perceived platform design	.702	7.328***	.000	1.335	65.37%
Number of available datasets downloaded	.011	2.035*	.025	1.077	6.43%

Note(s): *n*=162, * *p*<.05, ** *p*<.01, *** *p*<.001.

Finally, to assess which variables had a stronger influence on the change in satisfaction, we compared the relative importance of all variables in the regression model. Since the independent variables were measured on different scales (e.g., number of available datasets downloaded was determined by the participants according to the task requirements), it was misleading to judge relative importance by comparing the coefficients directly [70]. Therefore, a dominance analysis was performed, defining relative importance as the independent variables' contribution to the prediction of the dependent variable [71]. The analysis utilized the LMG algorithm to decompose the R-squared of the model into contributions of the regressors [72]. As shown in Table 8, the number of available datasets downloaded only contributed 6.43% of the variation in satisfaction. In contrast, perceived platform design and OGD quality contributed 65.37% and 28.19%, respectively.

4.4.2 OGD Reuse Intention

To evaluate probable correlations between using effectiveness, platform, task, satisfaction, and OGD reuse intention, Spearman's rank correlation coefficient was calculated. Using effectiveness and satisfaction were measured across the three tasks. As shown in Table 9 (n=54), satisfaction was strongly correlated with OGD reuse intention (r=.771, p=.000), and using effectiveness was not correlated with OGD reuse intention (p=.187 for task completion time, p=.226 for number of datasets downloaded, p=.078 for number of available datasets downloaded).

Table 9. Significant correlations between using effectiveness, satisfaction, and OGD reuse intention.

Metric 1	Metric 2	r	p
OGD reuse intention	Satisfaction	.745***	.000

Note(s): n=54, * p<.05, ** p<.01, *** p<.001, satisfaction was the mean across the three tasks.

A linear regression analysis was conducted with satisfaction as independent variables and OGD reuse intention as the dependent variable. The results showed (Table 10) that the model fitting effect was good (R2=.745). Satisfaction (B=.811, p=.000) had a significant effect on OGD reuse intention.

Table 10. Regression analysis on OGD reuse intention.

Measure	Coefficient (B)	t	p
Satisfaction	.811	8.056***	.000

Note(s): n=162, * p<.05, ** p<.01, *** p<.001.

5. DISCUSSION

5.1 Key Findings

By conducting a 3*3 experiment, this study revealed the effects of platforms, tasks, and user-related factors on OGD-using behaviors. The key findings are as follows:

In terms of the effect of platform, it was found that there are significant differences in OGD using effectiveness (task completion time, number of datasets downloaded, and number of available datasets downloaded) and users' satisfaction between three platforms with different usability levels. No significant difference was found in OGD reuse intention between the three platforms, indicating that the platform has no direct significant effect on users' reuse intention.

In terms of the effect of task, it was found that after controlling the platform factors, task complexity has significant effect on OGD using effectiveness, but has no direct significant effect on users' satisfaction. The interviews showed that the discrepancy between the expected data quantity and quality required for a task and that the platform can provide result in user's dissatisfaction.

OGD users' satisfaction was found to be significantly affected by perceived platform design (65.37%), perceived OGD quality (28.19%), and the number of datasets downloaded (6.43%). OGD reuse intention was found to be significantly affected by satisfaction, but not by using effectiveness.

In terms of the effect of user-related factors, except for the significant effect of experience of using data on task completion time, no other significant effects were found on using effectiveness, satisfaction, and OGD reuse intention.

5.2 Implications

5.2.1 Implications for Theory

Firstly, this study provides empirical evidence in the OGD field for usability theory by proving the significant impact of platform usability on OGD using effectiveness (task completion time, number of datasets downloaded, and number of available datasets downloaded) and users' satisfaction, which have been proven in studies on information retrieval systems or other kinds of interfaces [73], further expanding the application scope of usability theory. Meanwhile, some indicators of platform usability that OGD users care about were identified and explored, including minimum effort (registration process), data previews, interface layouts, humanistic care, etc., enriching the understanding of usability and providing new perspectives on its application in the OGD field.

Secondly, this study once again reveals the impact of task complexity on users' information behavior [2], proving the importance of the design of task sensitive OGDP, named as intelligent platform or intelligent data in Artificial Intelligence field [74]. Prior studies have noticed the possible impact of tasks on the utilization of OGD, but paid little attention to how task complexity affects users' OGD-using behaviors [2, 30]. This study finds that more complex tasks usually involve more user behavior, e.g., longer task time consumption, fewer datasets downloaded, and available datasets downloaded, etc., but have no significant impact on users' satisfaction with downloaded data. This result is consistent with the findings in the field of text information retrieval [58].

Thirdly, this study reveals the complex interaction between user satisfaction and OGD reuse intention by indicating that perceived platform design (65.37%), perceived OGD quality (28.19%), and the number of available datasets downloaded (6.43%) metrics together can predict satisfaction, and then predict OGD reuse intention. This not only deepens the understanding of the formation and functioning mechanisms of satisfaction and OGD reuse intention, enriching the content of satisfaction theory, but also validates the applicability and importance of information quality in explaining user behavior, and lays a solid empirical foundation for the application and practice of information quality theory in the OGD field.

Finally, this study advances OGD research by introducing the perspective of user behavior. This is an important supplement to the current expert dominant OGD evaluations [7, 29], and helpful in changing the focus of OGD research from "is there any?" to "is it good?".

5.2.2 Implications for Practice

The findings of this study can assist the government and the designer of OGDP to improve OGD service from the following aspects:

Firstly, this study found that OGDP usability can significantly affect users' using effectiveness, and can somewhat predict users' satisfaction and OGD reuse intention. This suggests the government and OGDP designers to make more efforts to improve the usability of OGDP. This study found that the platform design contributes to 65.37% of the variation in satisfaction. The interaction design of OGDP can be improved from the following aspects: (1) simplify users' registration and data application process, e.g., free access, real-time feedback of the result of identity authentication, etc.; (2) add facilities to help OGD use, e.g., platform using guidance and data preview function; (3) refine the layout of the interface and make it adapt to user's behavior; (4) provide barrier-free access for vulnerable people, e.g., the elderly, the blind, etc.

Secondly, as the task complexity significantly affects OGD using effectiveness, task sensitive OGDP design is suggested. For complex data tasks, a more intelligent data service that can detect and respond to user behavior in real time is necessary.

Finally, as data quality and downloaded data quantity, instead of task completion time, have significant effects on OGD users' satisfaction, which then leads to reuse intention, continuously supplying rich and high-quality data is still the key task of OGD projects.

5.3 Limitations

There are several limitations worthy of further discussion. First, prior studies have identified students as one of the target user groups of OGDPs [28, 61], but we expect that future work can broaden the diversity and number of participants to further improve the reliability of experimental results. Second, while laboratory experiments are viewed as the best option in the scenario of limited use of OGDPs, the propensity of participants to respond (e.g., give the answers the organizers want) in artificial environments is an objective concern. Future studies may mine the OGDP's server log files or conduct application collaboration with the urban government's OGDP to further evaluate the study's findings. Third, to compare the impact of different platforms' usability on users' OGD-using behaviors, this study formulated appropriate and explicit criteria for platform selection based on CODI. However, judging from participants' feedback, the difference in usability between Platform P1 and Platform P2 does not seem to be significant. It may be a limitation of expert-oriented evaluation.

6. CONCLUSION

Promoting OGD utilization is a particularly challenging issue since it is still unclear how users' OGD-using behaviors and some influencing factors (e.g., platforms, tasks, etc.) are related. By designing and implementing a user-oriented controlled experiment, this study examined the relationship between factors such as platform and task and users' OGD-using behaviors: using effectiveness (task completion time, number of datasets downloaded, and number of available datasets downloaded) is significantly affected by platform usability, task complexity, and experience of using data. Users' satisfaction is significantly affected by perceived platform design (65.37%), perceived OGD quality (28.19%), and the number of available datasets downloaded (6.43%). While task complexity does not affect users' satisfaction, the discrepancy between the expected data required for the task and the platform data does. OGD reuse intention is only affected by users' satisfaction.

AUTHOR CONTRIBUTIONS

X. Ma (xxin_ma@163.com) designed the research framework, performed the research, collected and analyzed the data, and coordinated the writing of the manuscript.

F. Wang (wangfangnk@nankai.edu.cn) proposed the research problems, designed the research framework, and revised the manuscript.

All the authors have made meaningful and valuable contributions in revising and proofreading the resulting manuscript.

ACKNOWLEDGEMENTS AND FUNDING

We would like to thank the editors for their assistance and the reviewers for their insightful comments and suggestions. We also appreciate all the experts who have given constructive suggestions on the revision of the experiment design and all the experiment participants for their time and work. This study has been made possible through the financial support of the National Social Science Foundation of China under Grant No. 20ZDA39.

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