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A text-messaging chatbot to support outdoor recreation monitoring through community science

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ABSTRACT

Public land managers depend on reliable and readily available data about outdoor recreation in parks and greenspaces. However, traditional recreation monitoring techniques including visitor surveying and counting cannot be implemented over large spatial and temporal scales, especially in remote and undeveloped settings where monitoring is costly. To fill these data gaps, and thereby inform decision-making, this study develops and tests the efficacy of a novel recreation monitoring technique that engages visitors in data collection using a chatbot and text-messages. Drawing on knowledge and methods from community science and crowdsourcing, we present a relatively low-cost and low-barrier approach to counting and characterizing recreational visits on public lands. In an 18-month pilot implementation on a national forest in Washington, USA, we found that crowdsourced data collected using the chatbot were consistent with results of controlled counts and in-person surveys. Furthermore, some sites received relatively high participation rates, up to 12% of recreating parties, regardless of cellular connectivity at the site. This study, which is the first to engage public land usersin community science using a text-messaging chatbot for the purposes of studying outdoor recreation, demonstrates the potential for technology to support new community science approaches that involve visitors in land stewardship and the development of recreation monitoring systems.

1. Introduction

Parks, greenspaces, and other public lands provide many societal benefits including opportunities for outdoor recreation. Time spent outdoors improves physical, social, and psychological health, and the outdoor recreation economy generates nearly 2% of gross domestic product in the US (Barnes et al., 2019; BEA, 2022; Frumkin et al., 2017; Kirkland, White, & Kline, 2018; Mantler and Logan, 2015). As increasing numbers of recreationists visit public lands (Outdoor Foundation, 2020), there is growing demand from managers for accurate, relevant, and timely information to support decision-making (Winter et al., 2020). Data on recreation patterns and visitor characteristics, for example, help managers compete for and prioritize funds to improve infrastructure, make decisions about the types and levels of services to provide, and ultimately promote equitable access to high-quality recreation opportunities. However, acquiring such data can be logistically challenging and expensive (Leggett, 2017). Standard operations and maintenance are often prioritized over data collection. As a result, and despite the need for high quality data, crucial information is often lacking during decision-making and strategic planning.

A variety of techniques exist for monitoring recreation in parks and public lands. These include sending personnel to interview and count visitors, enumerating trailhead registrations or permits, and deploying passive trail and vehicle sensors (Arnberger et al., 2005; Watson, et al., 2000). These data collection methods are often constrained by personnel and equipment costs, thus limiting the temporal or geographic scope of the data (Cessford and Muhar, 2003; Monz, et al., 2019). To overcome these constraints, researchers have recently begun using volunteered geographic information from social media as an additional source of information that has more spatial and temporal granularity (Ghermandi

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and Sinclair, 2019; Tenkanen et al., 2017; Wood et al., 2013). By using social media as data on visitation rates, researchers are able to produce fine-scale estimates of recreational participation with greater spatio-temporal coverage (Fisher et al., 2018; Wood et al., 2020). These data have several drawbacks, however, including limited amounts of geolocated user-generated content available at low-use sites and potential issues with representation due to self-selecting subsets of visitors who share their experiences on social media (Toivonen et al., 2019; Wood et al., 2020).

To ameliorate data limitations in other fields, researchers and practitioners often implement community science and crowdsourcing programs (Bonney et al., 2016; See et al., 2016; Theobald et al., 2015; Wazny, 2017). Community science (a more inclusive term for what is commonly known as citizen science (Cordner, Poudrier, DiValli and Brown, 2019; Eitzel et al., 2017) is generally characterized as an approach whereby members of the public are engaged in the scientific process, taking on various roles to help answer scientific questions, commonly in the fields of conservation biology, ecology, environmental monitoring, and public health (Bonney et al., 2016; Charles et al., 2020). Crowdsourcing is a related approach in which individuals, often as members of an online community, collectively contribute toward a data generation or processing goal — sometimes as one component of a community science program (English et al., 2018; Estellés-Arolas and González-Ladrón-de-Guevara, 2012; See et al., 2016). Enabled by web platforms, mobile applications, and other technology, crowdsourcing has been embraced as a scientific tool in many disciplines, including astronomy, transportation planning, and environmental monitoring (See et al., 2016; Wazny, 2017).

As crowdsourcing and community science approaches begin to appear in outdoor recreation research and monitoring, there are indications that both can help answer questions about recreation use patterns and impacts (Cheung et al., 2022; Wilkins et al., 2021). This study further explores approaches and technologies for implementing community science and crowdsourcing information to help fill gaps in data about recreational use of public lands. We develop and test a method that uses a chatbot to converse with visitors via text messages over short message service (SMS). Our goal is to understand whether this method is cost-effective and flexible, and whether it can support a community science approach that is effective for gathering data, while simultaneously building civic engagement among visitors to public recreation sites. To our knowledge, this is the first study in the field of recreation management to engage visitors through a SMS-based chatbot. In this paper, we place this approach in the context of the community science and crowdsourcing literature, assess participation rates and data accuracy, present a case-study application from a national forest in Washington, USA, and discuss potential future applications.

2. Background

Community science and crowdsourcing are well-established as methods for research and monitoring (Bonney et al., 2016; See et al., 2016; Wazny, 2017). Both methods offer a variety of potential benefits, including increasing the amount of data collected, extending study lifespans, facilitating communication between scientists and the public, and increasing public investment and engagement (Bonney et al., 2016; Conrad and Hilchey, 2011; Kimura and Kinchy, 2016; McKinley et al., 2017; Toomey and Domroese, 2013; Tulloch et al., 2013). The use of new technologies including smartphone applications and open community-science initiatives or platforms such as iNaturalist (iNaturalist 2023) have improved data collection and data validation — two often-noted challenges (Bonney et al., 2009; Bonter and Cooper, 2012; Burgess et al., 2017). Digital data collection and entry allows for data validation during volunteer data contribution, reduces reporting burdens on volunteers, and decreases the need for subsequent data handling and cleaning (Bonney et al., 2009; Bonter and Cooper, 2012). This has increased the viability of crowdsourcing and community science methods in many research fields and improved perceived data reliability and credibility (Burgess et al., 2017).

Participatory structures for community science and crowdsourcing vary (Cooper et al., 2007; See et al., 2016). Community science programs generally focus on specific research tasks (e.g., data collection or curation) but sometimes also involve volunteers in other aspects of research (e.g., study design, interpretation of results) (Charles et al., 2020; English et al., 2018; Shirk et al., 2012). They tend to be geographically or locally focused (e.g., water quality monitoring programs), relying on a local pool of potential volunteers. Many community science programs that are focused on topics of general interest (e.g., pollinator conservation or astronomy) engage individuals or groups that already have specialized knowledge, training, and equipment. Nevertheless, many community science programs include opportunities for volunteers to develop skills and require volunteer training prior to participation (Burgess et al., 2017; Freitag et al., 2016). Programs that require more training have higher incentives to retain experienced volunteers (Dickinson et al., 2010). While training can serve to increase data quality, volunteer engagement, and retention in the program (Bonter and Cooper, 2012), it also has the potential to deter participants because of upfront time investments.

Crowdsourcing programs, on the other hand, rely on opportunistic participation in discrete tasks, requiring fewer technical skills and less specialized inputs, and generally offering fewer opportunities for additional engagement in the scientific process (See et al., 2016; Wazny, 2017). This may lead to less long-term investment or commitment from volunteers, creating potential challenges with retention (Baruch et al., 2016). Yet with fewer training requirements, simpler tasks, and less commitment, crowdsourcing reduces barriers to entry and creates opportunities for one-time as well as repeated participation (Baruch et al., 2016).

Strengths presented by community science and crowdsourcing approaches indicate they would be valuable for supporting outdoor recreation research and monitoring. Outdoor recreation typically occurs in settings where phenomena of interest are easily observable without training (e.g., numbers of visitors) and can be reported by recreationists about themselves (e.g., the purpose of their trip) (Cheung et al., 2022). Successful community science programs often engage groups of enthusiasts with a shared interest. Many outdoor recreationalists are indeed enthusiastic about activities such as hiking and care about the locations where these activities take place. As such, participants may be motivated to regularly contribute valuable observations while they are visiting a site. Easy, low-barrier platforms which allow for contributions from and repeated interaction with visitors, and provide the potential to receive high volumes of data, could be harnessed to fill outdoor recreation data gaps. For these reasons, we sought to test the efficacy of a community science approach alongside a pilot application of a text-messaging chatbot.

3. Methods and application

3.1. Chatbot technology and design

A chatbot can be broadly defined as a computer program designed to interact with human users by simulating conversation (Adamopoulou and Moussiades, 2020; Caldarini et al., 2022; Shumanov and Johnson, 2021). We developed a chatbot to interact with visitors at recreation sites via SMS messages. The chatbot used the Twilio application programming interface (Twilio 2022) to send and receive SMS messages. Upon receipt of a new SMS message, the Twilio service sent the body of the text message along with metadata in JavaScript object notation format to a python application that listened for incoming traffic through a web server. An incoming SMS message prompted the application to store the information, and return programmed SMS responses to the volunteers via Twilio. The application is provided as Supplement 2. Raw data were stored on a secure server, where respondents' phone numbers were anonymized with a cryptographic hash function, and processed by a script written in R which used regular expressions to extract numbers and keyword entities from the body of every text message. The resulting processed data were written in tabular format and then manually examined in order to make any necessary corrections. Any data that were obviously not in response to questions asked by the chatbot were removed.

3.2. Study sites

We deployed the chatbot at 14 recreation destinations within the Mt. Baker-Snoqualmie National Forest (MBSNF) between June 2018 and November 2019. The MBSNF is located on the western side of the Cascade Range in Washington, USA and stretches from the Canadian border to Mt. Rainier National Park in the south. The MBSNF covers 688,000 ha of temperate coniferous forests and includes alpine meadows, numerous lakes, rivers, and peaks, which provide visitors myriad recreation opportunities. Some of the most popular recreation activities include hiking, backpacking, and camping, although motorized recreation is also popular. Recreational use on the MBSNF occurs year-round, though the majority of use at our study sites occurs between June and October.

The selected trailheads were a subset of sites used in previous studies of recreational visitation done in collaboration with USDA Forest Service researchers and recreation managers (Fisher et al., 2018). The sites represented a range of use levels (visitation rates), parking lot sizes, mobile phone coverage, and accessibility from nearby towns and cities (Table 1). Trail use levels were estimated a priori by MBSNF staff as part of the USDA Forest Service National Visitor Use Monitoring Program (Zarnoch et al., 2011). Cellular service (yes or no) was determined based on whether service was available on cellular devices carried by the researchers, using AT&T, T-Mobile, and Verizon as carriers. Remote sites were generally outside the range of towers that provide connectivity, so when sites lacked signal from one carrier, they typically lacked signal from all carriers. Researchers also approximated parking lot vehicle capacity, including capacity of the overflow parking areas at each site.

3.3. Visitation rates

We used automated methods to count the number of visitors using each trail and the number of vehicles parked at trailheads. To count the number of visitors to each trail, we deployed infrared pedestrian counters that enumerated daily hiker traffic (Fisher et al., 2018). Sensors were tested and calibrated as detailed by Fisher et al. (2018). To monitor the number of vehicles in parking lots, we deployed cameras at three sites where it was possible to capture a complete view of the parking area. Cameras captured one image every five minutes during daylight hours, for comparison with vehicle count data provided by volunteers at the same location and time.

3.4. Chatbot deployment

At each study site, signs encouraged visitors to volunteer and “Help Your Forest” by counting the number of vehicles in the parking lot, and then report the data to the chatbot via a text message to a site-specific local phone number. All signs contained the same information, aside from a photograph or satellite image of the specific parking lot and the unique phone number (Fig. S1). Each sign provided instructions about the specific area in which to count vehicles, as well as a sentence explaining why the data were valuable, that participation was voluntary and anonymous, and contact information for the researchers. The signs, which were color, 8.5 in″ x 11 in″, and laminated, were posted on the official USDA Forest Service trailhead information board. Information boards were located near or at the beginning of the trail and included other information about trail routes, permit requirements, and regulations. The exact location of the trailhead information board varied by site. We chose vehicle counts as the initial question because it was a simple and understandable request that provided valuable data for estimating visitation rates.

Since all the instructions needed to participate were provided by the recruitment sign, no volunteer training was necessary, nor was additional advertising done to recruit volunteers, as we were interested in engaging any individuals who were already present at the specific recreation sites. Our volunteer pool included any visitor at the trailhead who observed and read our sign, had access to a mobile phone, and decided to participate. After volunteers submitted the parking lot vehicle count data, the chatbot responded via SMS with a message asking if volunteers were willing to contribute additional information. The first follow-up question from the chatbot asked volunteers what time they counted vehicles. If this question received a response from the volunteer, then the chatbot continued to ask additional questions related to the visitor’s trip and demographics (Table 2). Volunteers were only asked the “How Long” question if they indicated they were returning from their hike. Repeat volunteers were not asked the demographic questions if they had already answered them in a prior conversation with the chatbot. Visitors could contribute information from multiple participating sites or on multiple visits to the same site. Volunteers were not required to complete the entire survey and could stop interacting with the chatbot at any time; the chatbot only continued to ask questions as long as the volunteer responded.

3.5. Analysis

We addressed three research questions in order to evaluate the chatbot as a tool for recreation monitoring and data collection: (i) do site characteristics influence volunteer participation, (ii) who are the

Table 1
Study sites and their relative attributes ordered by vehicle capacity of the parking lot. Ranger District is an administrative designation assigned by the USDA Forest Service. Participation rates show the percentage of visitor parties interacting with the chatbot at each study site.

Site name	Ranger district	Lot capacity	Lot size	Use level	Cellular service	Chatbot participation (SE)
Neiderprum	Darrington	10	Small	Medium	Yes	12.12% (1.53%)
Lost Creek	Darrington	21	Small	Low	No	6.44% (1.66%)
Goat Mountain	Mt. Baker	24	Small	Low	Yes	4.96% (0.65%)
Dingford Creek	Snoqualmie	40	Small	Medium	No	9.67% (1.27%)
Tunnel Creek	Skykomish	60	Medium	Low	Yes	2.87% (0.43%)
Snoqualmie Lake	Snoqualmie	80	Medium	Medium	No	2.26% (0.25%)
Summit Lake	Snoqualmie	125	Medium	High	No	4.25% (0.29%)
Picture Lake	Mt. Baker	133	Medium	Very high	Yes	0.26% (0.04%)
Skyline Divide	Mt. Baker	150	Medium	High	Yes	3.16% (0.23%)
Dorothy Lake	Skykomish	150	Medium	High	No	2.67% (0.28%)
Tomyhoi	Mt. Baker	150	Medium	Medium	No	2.43% (0.20%)
Lake Serene	Skykomish	200	Large	Very high	Yes	1.48% (0.10%)
Ira Spring	Snoqualmie	265	Large	Very high	Yes	1.87% (0.19%)
Snow Lake	Snoqualmie	550	Large	Very high	Yes	0.27% (0.06%)

Table 2
Questions asked by the chatbot via SMS and relative response rates for each question. Response rates represent the percentage of volunteers who answered a given question after submitting a parking lot vehicle count in response to the prompt on the sign. Note that "ZIP Code" and "Year Born" were only asked once of volunteers who sent data on multiple occasions. "How Long" was conditionally asked only to volunteers who indicated they were returning from their visit.

SMS Chatbot questions & response rates		
Question ID	Full question	Response rate
Vehicle count	How many vehicles are in the parking lot right now? (Hook question on sign)	100%
Count time	What time did you count vehicles?	88%
Party size	How many people (adults and children) are in your party today?	81%
Party vehicles	How many vehicles did your party bring to the trailhead today?	79%
In vs. Out	Are you leaving for your hike, or returning from your hike?	77%
Trail visits	How many times have you visited this trail in the last 12 months, including today?	76%
Info source	How did you get information about this trail site?	74%
How long	How long did you spend on this trail? (Only asked to volunteers who responded "returning" to question "In vs. Out"	73%
ZIP code	What is your home ZIP code? (Only asked to new volunteers)	68%
Year born	In what year were you born? (Only asked to new volunteers)	28%

volunteers, and (iii) do volunteers collect accurate data?

To understand volunteer engagement, we calculated participation rates for each site where we deployed the chatbot. First, we calculated the average party size across all sites using the responses to the "Party Size" question. We then used this value to convert the number of visitors per day (recorded by the infrared pedestrian counters) into the number of parties per day. Assuming that only one person would submit data from a given visitor party, and thus each SMS conversation represented a unique party, we then summed the total number of volunteer parties who submitted data and divided it by the total number of parties who used each trail, according to the infrared counters, on dates when we could confirm that the recruitment sign was present at the trailhead. In order to establish when the sign was present, we recorded the date that each sign was posted, and if the sign was still present when we returned to the site we assumed it was posted the entire time. If the sign was missing when we returned, we assumed it remained posted until the most recent SMS message received from a volunteer. All dates following the most recent data submission, until the date when a new sign was posted, were removed from the participation rate calculation.

We examined several site attributes to determine whether they influenced volunteer participation rates. In particular, we compared participation rates to relative use level of the trail (ranging from low to very high), whether or not there was cellular service at the site, and the estimated size of the parking lot. We categorized parking lots as large (>150 vehicle capacity), medium (between 60 – 150 vehicles), or small (<60 vehicles; Table 1). To test whether participation rates varied by site attributes, we performed a one-way analysis of variance (ANOVA) for each of the three attributes, followed by a Tukey's test of differences among levels for attributes where the effect was statistically significant.

To evaluate who was volunteering, we asked visitors to provide their birth year and home ZIP code. We converted the "Year Born" data submitted by volunteers to approximate age by subtracting "Year Born" from the year the data was collected. Volunteer ZIP Codes were summarized by state and metropolitan area.

To assess whether volunteers collected accurate data, we compared parking lot vehicle counts submitted by volunteers to the number of vehicles in images captured by time-lapse videos of the same parking lots. At the three sites with cameras, we extracted the time-lapse image that corresponded with the time that a volunteer reported a parking lot vehicle count (within five minutes), and then manually counted the number of vehicles present in the image. Since timelapse videos were only taken during daylight hours, our analysis evaluates daytime activity.

4. Results

4.1. Participation and response rates

Between June 2018 and November 2019, at our 14 study sites, 1,618 visitors sent 12,550 messages to the chatbot. Most volunteers submitted data on one occasion (1,475 participants), although 143 volunteers submitted information on two or more dates. After a volunteer submitted the initial information (i.e., the number of vehicles in the parking lot), 88% of volunteers answered one or more follow-up questions. Response rates for individual questions declined as the chatbot continued to ask follow-up questions (Table 2).

Participation rates varied substantially between sites, ranging from under 1% to over 12% of recreating parties (Table 1, Fig. S2). We found that some of this variability could be explained by the attributes of the sites in our study. Specifically, parking lot capacity influenced volunteer participation rates ($F = 14.9$, $p < 0.001$), with significantly higher participation rates at sites with smaller parking lots than at sites with medium or large parking lots (Fig. 1; Tukey's HSD $p < 0.001$). There was no significant difference between participation rates at medium and large lots. Very high-use sites tended to have lower participation rates than sites with high, medium, or low estimated use (Fig. 2), however, the differences were not statistically significant ($F = 2.602$, $p = 0.11$). Estimated use levels and parking lot size were closely related to one another (Table 1). The presence of cell service had no statistically significant influence on participation rates (F value $= 0.432$, $p = 0.52$; Fig. 3).

4.2. Volunteer age and ZIP code

We received data from volunteers spanning a range of ages and home locations. The average age of volunteers was 42 years, and ages ranged from 18 to 78 years (Fig. 4). Volunteers originated from 300 unique ZIP codes. Most respondents (91%) reported that they lived in Washington and the majority of reported ZIP codes (86%) were associated with the Seattle metropolitan area.

The origins of our volunteers were consistent with the USDA Forest Service (2015) estimate that 55% of visits to the MBSNF are by visitors who live within 75 miles of their recreation destination, and that the bulk of visitors live in the Seattle metropolitan areaUSDA Forest Service, ND. Similarly, the age distribution of volunteer participants was consistent with USDA Forest Service (2015) estimates for the MBSNF that 1) visitors in their 20s are the most common age group, 2) the majority of visitors are between 20 and 60 years old, and 3) visitors over the age of 70 account for a relatively small share of visits. Finally, the average party size (2.49 people) of our volunteers compared well to the USDA Forest Service estimate for the MBSNF (2.52 people) based on the 2015 visitor intercept surveys.

4.3. Volunteer accuracy

We found that visitors submitted accurate vehicle counts to the chatbot (Fig. 5). Vehicle counts submitted by visitors were highly correlated with manual counts of vehicles in camera images of the same parking lots at the visitor-reported count times (Pearson's $r = 0.98$).

5. Discussion

The SMS-based chatbot developed in this study demonstrates the

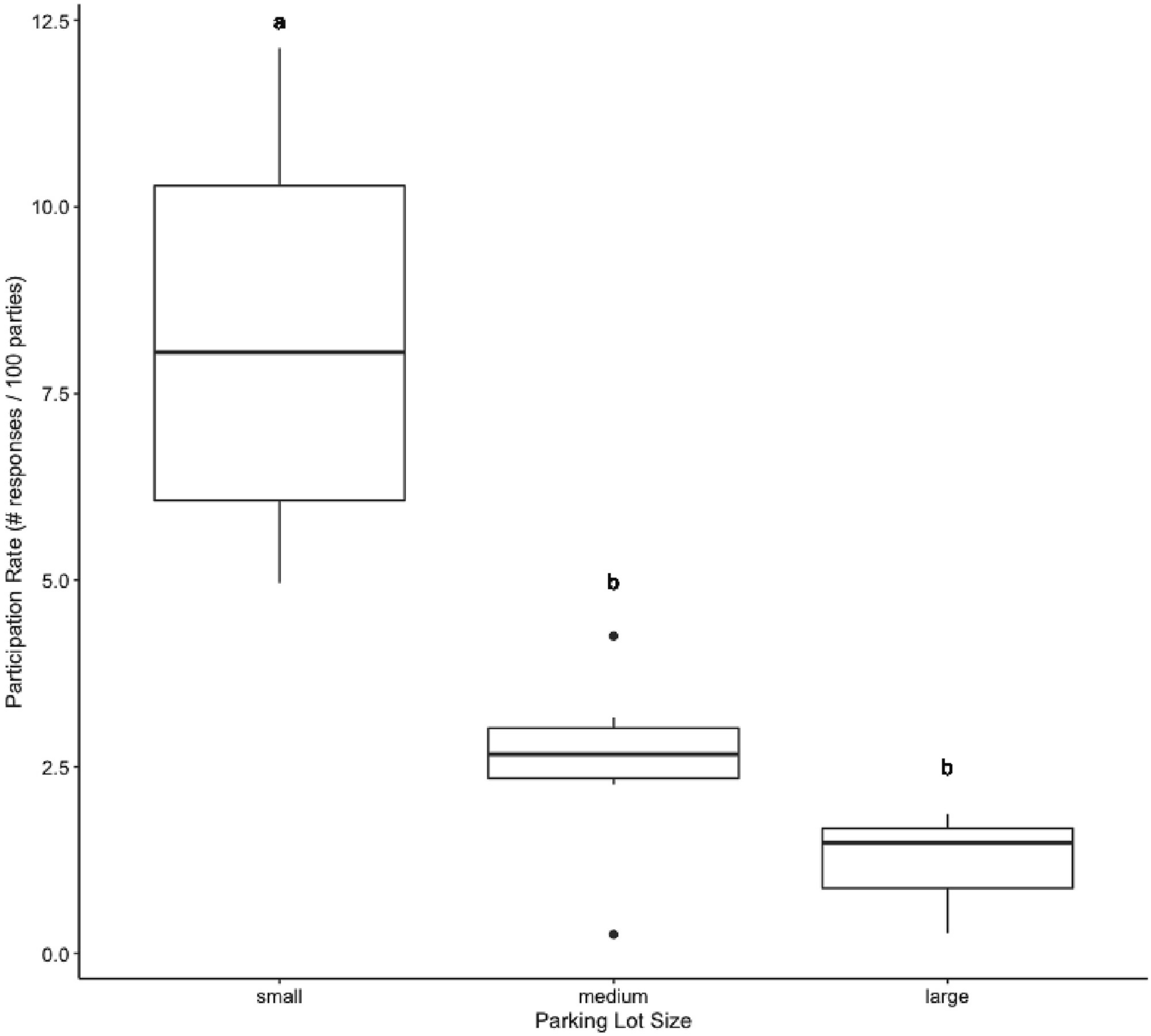

Fig. 1. Volunteer participation rates at sites grouped by parking lot size (small, medium, and large). Participation rates were statistically significantly higher at sites with small parking lots (a) compared to medium and large lots (b). There was no significant difference in participation rates between sites with large- and medium-sized parking lots (b).

potential for novel technologies to facilitate crowdsourced data collection in remote outdoor settings. Visitor-contributed counts of vehicles at trailhead parking lots were consistent with controlled observations across sites that varied in popularity. Furthermore, the origin and age of volunteers compared well with independent estimates of visitor demographics derived from a separate, systematic, on-site recreation monitoring program. Volunteers provided data from every study site, although we found that participation rates were greater at sites with smaller parking lots. Additionally, and importantly, the presence versus absence of cellular connectivity did not influence participation rates. These findings support other recent research indicating that chatbots are an effective method for collecting survey data (Kim et al., 2019). It is also possible that the conversational method employed by the chatbot produced higher quality information and created a more favorable experience for users, compared to a traditional web-based questionnaire (Celino and Calegari, 2020; Xiao et al., 2020, but see Zarouali et al., 2023), but this supposition would need to be evaluated through further research.

Our pilot implementation of a SMS-based chatbot indicates that in addition to producing reliable information, the method could feasibly be scaled-up to support a community science effort at a large number of sites. With very few barriers to participation for visitors, volunteers do not need prior training or tools (beyond access to a SMS-enabled mobile phone) to participate. Signs posted on trailhead information boards are simple and inexpensive to create, and require relatively little effort to deploy and maintain. The chatbot application does require a cloud computing instance or other computer that is configured to accept incoming data. However, once the application is deployed, cost per site is relatively low when compared to traditional methods of collecting similar data. During the course of this study, the cost to send and receive SMS messages was under $0.01 USD per message and each phone number cost $0.75 USD per month.

For many US federal agencies that manage recreation, such as the USDA Forest Service and the Bureau of Land Management, most recreation visits occur at relatively low-use sites that are dispersed across large remote areas. Traditional, on-site approaches to collecting information about recreation and visitor characteristics at low-use and remote sites are often costly and can yield limited data. For instance, in

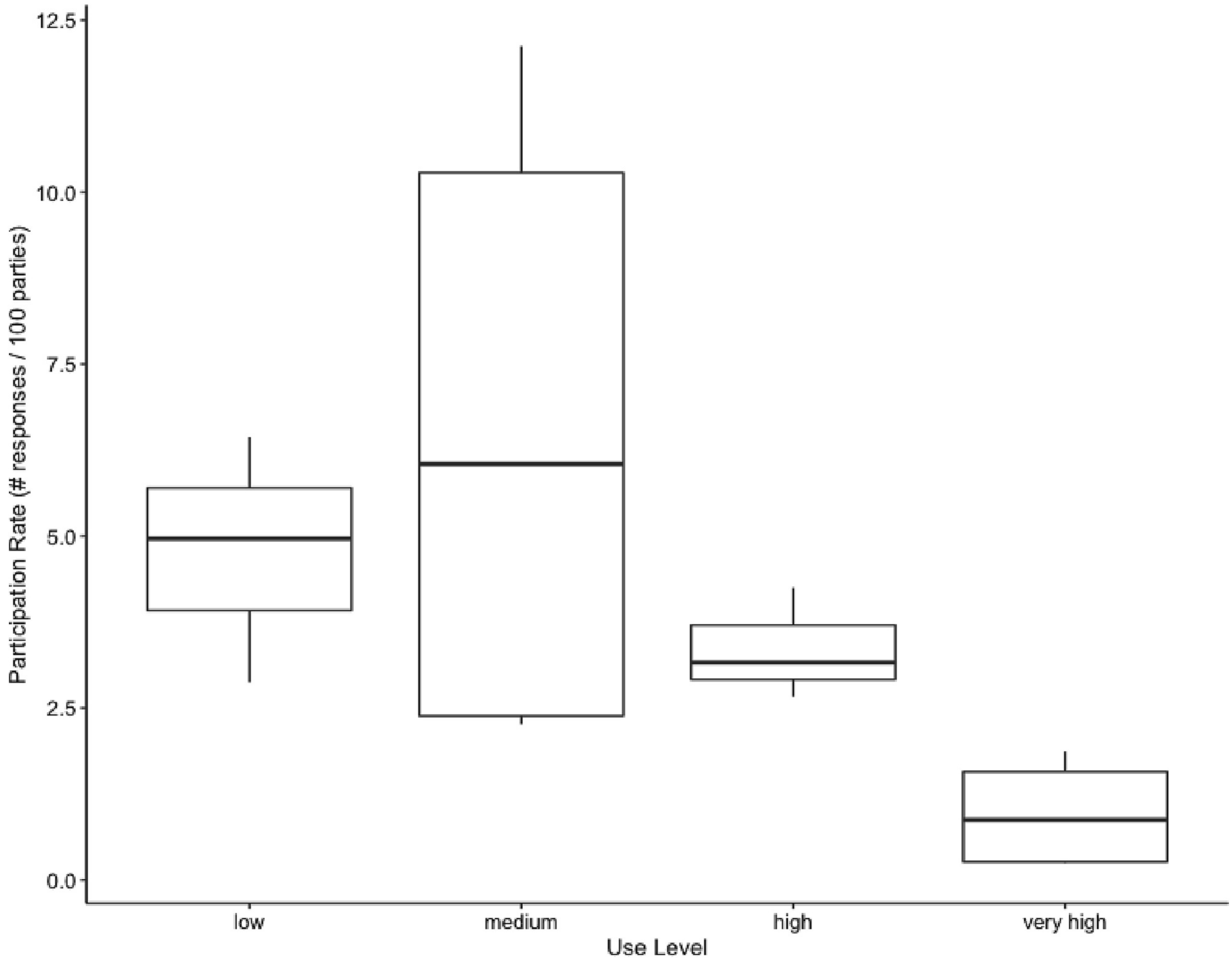

Fig. 2. Volunteer participation rates at sites grouped by use level (low, medium, high, and very high) — a factor assigned by recreation managers. While participation rates tended to be lowest at very highly used sites, there were no statistically significant differences in participation rate by use level.

2015 the USDA Forest Service dedicated 47 field days to collecting counts of recreation traffic and doing visitor interviews at dispersed, low-use recreation sites in MBSNF — more field days than any other type of recreation site. At an approximate cost of $450 USD per field day, the agency spent $21,150 USD to obtain 47, 6-hr counts of non-motorized recreation traffic and 44 interviews of recreation visitors. If the agency paired on-site surveys with a SMS-based chatbot method, such as the one that we implemented in this study, then additional information could be collected at these types of recreation sites.

In order to scale-up the crowdsourcing method that we tested, technical improvements would be required to enhance the accuracy and reliability of the SMS-based chatbot. One key opportunity lies in improving the capacity of the chatbot to recognize the intent of volunteer messages. Currently, the chatbot simply receives and stores a message, then replies with the next question in the predetermined series. Since the chatbot does not interpret users' intents, it cannot respond coherently when users attempt to interact with it in novel ways — for instance by asking a question of the chatbot or correcting a prior response — and this can result in disjointed conversations for some volunteers. Furthermore, in these situations where the incoming data that are provided by the volunteers do not align with the questions that the chatbot is asking, data are miscategorized. Although some of these data errors can be corrected with automated data cleaning, most require a manual data review by a human. The time that is required for this step presents a challenge when scaling up the use of the chatbot to a greater number of sites. Large language models and natural language processing have thepotential to improve the conversational abilities of the chatbot (Adamopoulou and Moussiades, 2020; Caldarini et al., 2022), by automating data parsing and allowing for data validation to happen during the conversation, which could help prevent data loss.

While our results suggest that the lack of cellular service and visitor age are not barriers to participation, respondents are nonetheless a self-selecting sample. Only some visitors, for example, read trailhead information boards (Davis and Thompson, 2011), and not all of them will see the recruitment sign. Then, only a subset of those visitors will choose to use their mobile phone and contribute data. Consequently, volunteers represent a convenience sample that may differ in important ways from a sample generated using a systematic sampling process, although we did not see evidence of this in our comparisons of demographics of community scientists versus respondents from a systematic survey in the same national forest. Future research on how to correct for biases of different data generation processes is necessary before these novel methods can be used to accurately describe characteristics of visitors and their trips to public lands.

Participation rates and representativeness of the volunteers may be related to our recruitment strategies and chatbot design decisions. The placement of the recruitment sign and signboard, as well as the language and graphic design of the sign, are all likely factors affecting whether visitors read signage, as well as their engagement or compliance with the content (Hall et al., 2010; Rice et al., 2023). Similarly, the order, wording, and tone of questions asked by the chatbot may be influencing the likelihood that volunteers will continue to respond (Kim et al., 2019;

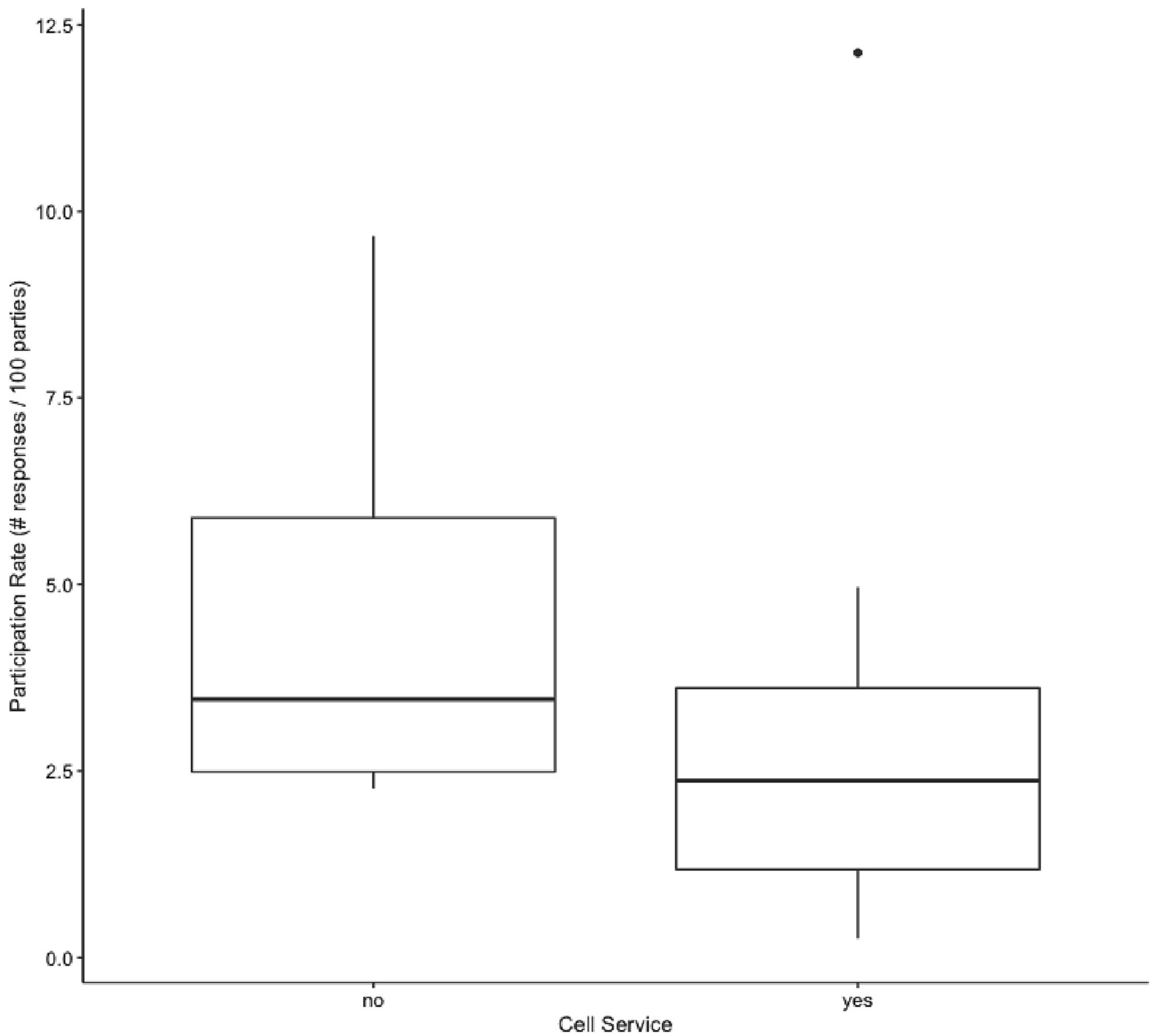

Fig. 3. Volunteer participation rates at sites with and without cellular service. There was no significant difference in participation rate with cellular service.

Shumanov and Johnson, 2021). Chatbots which use anthropomorphic design cues such as empathy, small talk, and a self identifying name or pronoun typically improve user engagement and compliance with requests (Adam et al., 2021), although we did not implement these techniques. Because chatbot technology facilitates large-scale experimentation, it presents opportunities for future research to test hypotheses about how participation is influenced by aspects such as wording, order, or speed at which questions are asked. These factors could be easily manipulated in randomized experiments with multiple respondents. Future studies could also test whether recruitment signage and questions in languages other than English increase participation and the demographic representation of participants, or whether participation rates are related to other factors such as the visitors' activity types, motivations for visiting, or affinities to the location, among other factors that potentially influence participation.

Understanding the motivations of community scientists who contribute to collective efforts for scientific advancement could offer valuable insights for the design of future community science efforts (Baruch et al., 2016; Domroese and Johnson, 2017; Land-Zandstra, Devilee, Snik, Buurmeijer and van den Broek, 2016; Wright, Underhill, Keene and Knight, 2015). Although this study does not directly measure participants' motivations for contributing, we hypothesize that their interest in maintaining the quality of the recreation resource plays a large role. Recreationists may have personal interests in contributing data that helps protect places that are special to them — perhaps similar to interests that motivate participation in environmental monitoring community science projects (Halliwell et al., 2022). If this is true, further communicating the value of vehicle counts and other recreation data could help motivate additional participation. While our approach engages visitors only in data collection, our findings indicate there is potential to use this tool to support a more robust community science program in which volunteers are engaged in the design and implementation of recreation monitoring and its management applications. Given that participation in community science improves scientific literacy and understanding of the effects of policy and management actions (Kimura and Kinchy, 2016), and that it can foster a deeper connection to place and engagement with environmental stewardship (Dean et al., 2018; Halliwell et al., 2022), we propose that if recreation managers and visitors collaboratively designed both data collection and purposes of the data, then there would be more public support for management plans or actions (Cooper et al., 2007).

In a more connected information system, our chatbot participants would be able to use the information generated from their collective data contributions to inform their own future recreation activities, making them both participants in and beneficiaries of the community science monitoring program (Connors et al., 2012). By providing data

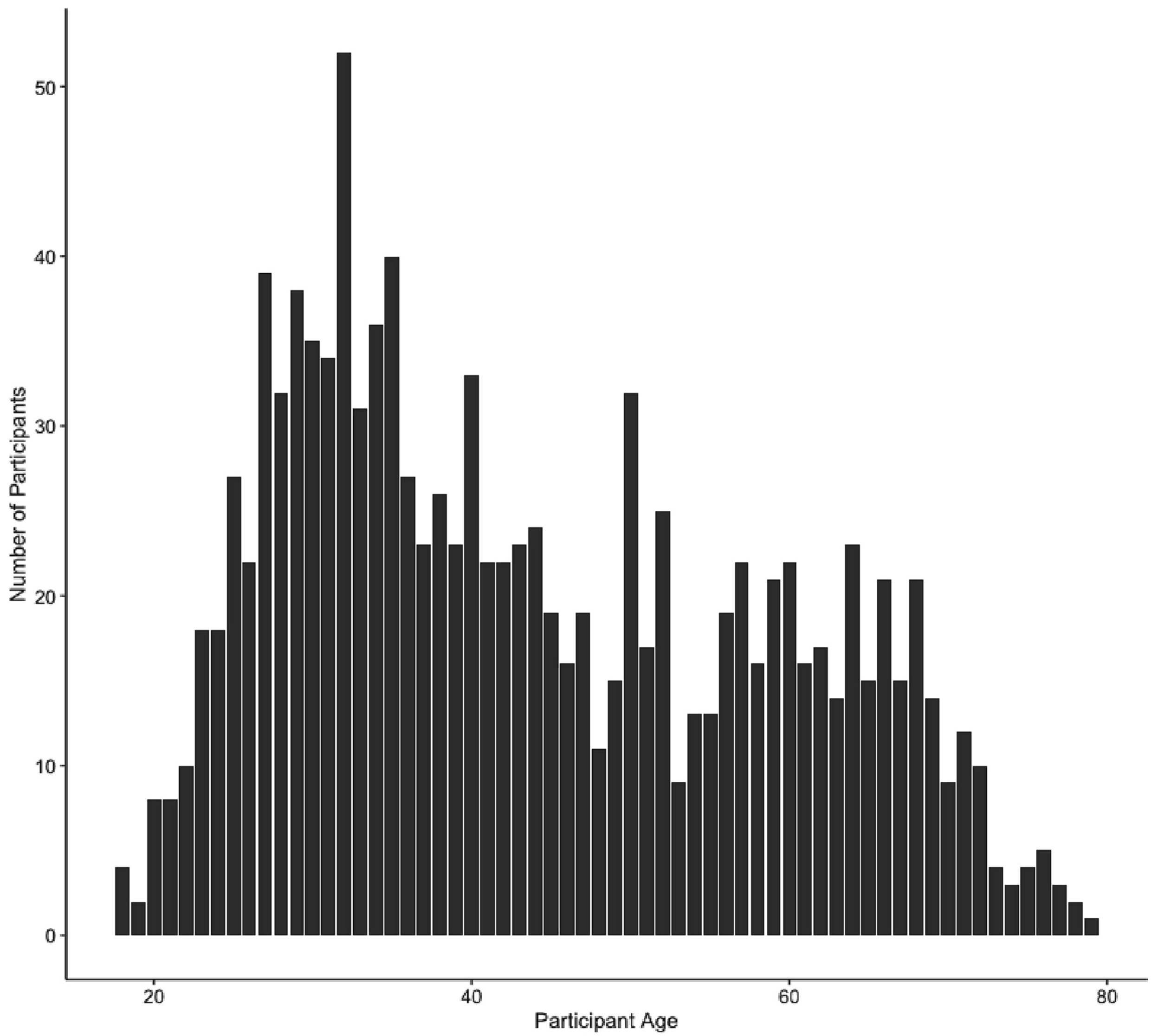

Fig. 4. The self-reported age distribution of volunteers. Volunteer age spanned a wide range from 18 to 78 years old, with the mean being 42 years.

visualizations through web-based dashboard interfaces, for instance, researchers and practitioners could not only demonstrate the value of volunteer contributions but provide a useful educational tool for visitors, similar to other successful programs such as eBird or iNaturalist (Connors et al., 2012). Furthermore, chatbot communications could be used to provide real-time, tailored information in response to data submissions; for example, a similar chatbot could be designed to provide recreation managers with a new way to deliver messaging about desired recreation behavior or information on current conditions such as fire restrictions.

Tools such as our SMS-based chatbot have the potential to transform recreation monitoring through creative but simple ways that allow visitors to contribute to the stewardship of the places where they recreate. Importantly, though, recreation monitoring involves considerations that set it apart from other community science or crowdsourcing contexts. Instead of participants reporting observations of birds or pollinators or other natural phenomena (Bonter and Cooper, 2012; Dickinson et al., 2012; Domroese and Johnson, 2017), people are reporting on themselves or their group, or observing other people (or vehicles as proxies for people). While in typical recreation monitoring, the visitor is the "subject" when responding to a survey or being counted by a sensor, within the context of a community science program, the participant is being asked to be both the subject and the observer. These dual roles have the potential to expand the definition of community science and crowdsourcing, by considering the multiple roles of people in the social-ecological systems under study (Cheung et al., 2022; Haklay et al., 2021). The successful deployment of a chatbot enabling the crowd-sourced collection of dispersed recreation data suggests there is potential for other programs that build civic engagement through new ways of contributing to environmental stewardship. Crowdsourcing has not typically operated in this arena, so this presents a conceptual and practical expansion of methods.

6. Conclusion

This study presents a novel community science approach for interacting with visitors at recreation destinations via a SMS-based chatbot, and demonstrates that this new approach creates simple and effective ways to engage visitors and collect management-relevant information for a relatively low cost. The approach allows researchers and managers to bridge data gaps that are otherwise expensive to fill because sites are numerous, widely dispersed, and can be logistically difficult and expensive to access. Our evaluation of the approach on a national forest in Washington indicates that visitors will participate regardless of their age and cellular connectivity at the site, and they are willing to volunteer information about the site, their visit, themselves, and their party.

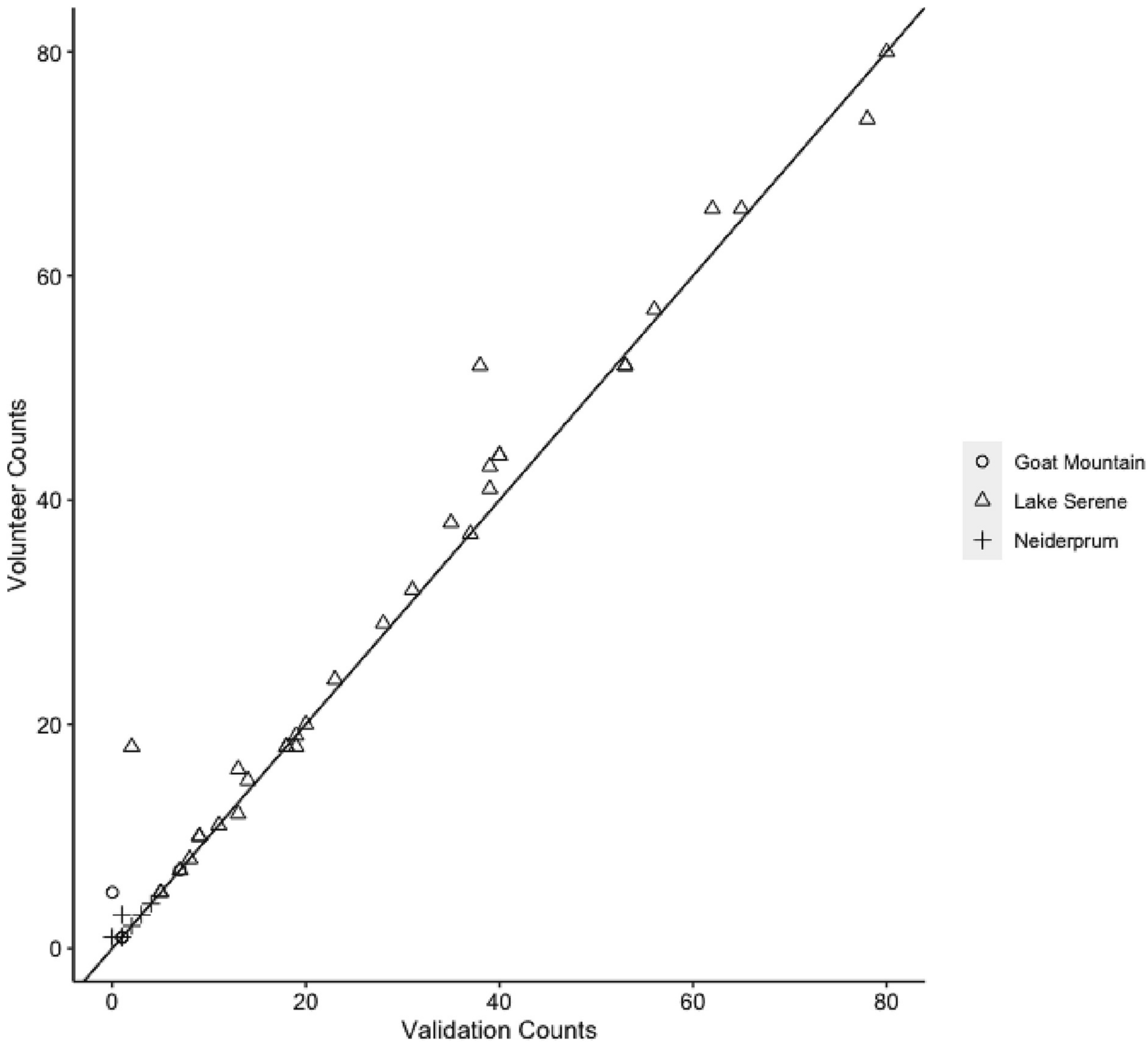

Fig. 5. Volunteered parking lot vehicle counts plotted against counts by researchers at the same time with a 1:1 line. Shapes represent three distinct parking lots where calibration counts were collected via cameras. Counts submitted by volunteers were highly correlated with counts by researchers (Pearson's $r = 0.98$).

To our knowledge this is the first study to use a text-messaging chatbot as part of a recreation monitoring program and to demonstrate the promise for recreation-focused community science programs designed to involve visitors more deeply in stewardship and monitoring. While there are several potential limitations to using the chatbot tool, we suggest that these limitations can be resolved through improved design, and this study should inspire the development of the next generation of recreation monitoring technology.

CRediT authorship contribution statement

Emilia H. Lia: Conceptualization, Methodology, Data curation, Formal analysis, Visualization, Writing – original draft, Writing – review & editing. **Monika M. Derrien:** Writing – original draft, Writing – review & editing. **Eric M. White:** Conceptualization, Visualization, Writing – original draft, Writing – review & editing. **Samantha G. Winder:** Conceptualization, Formal analysis, Writing – original draft, Writing – review & editing. **Spencer A. Wood:** Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors have none.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.diggeo.2023.100059.

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