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RESEARCH ARTICLE

Highly specialized recreationists contribute the most to the citizen science project eBird

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ABSTRACT

Contributory citizen science projects (hereafter "contributory projects") are a powerful tool for avian conservation science. Large-scale projects such as eBird have produced data that have advanced science and contributed to many conservation applications. These projects also provide a means to engage the public in scientific data collection. A common challenge across contributory projects like eBird is to maintain participation, as some volunteers contribute just a few times before disengaging. To maximize contributions and manage an effective program that has broad appeal, it is useful to better understand factors that influence contribution rates. For projects capitalizing on recreation activities (e.g., birding), differences in contribution levels might be explained by the recreation specialization framework, which describes how recreationists vary in skill, behavior, and motives. We paired data from a survey of birders across the United States and Canada with data on their eBird contributions (n = 28,926) to test whether those who contributed most are more specialized birders. We assigned participants to 4 contribution groups based on eBird checklist submissions and compared groups' specialization levels and motivations. More active contribution groups had higher specialization, yet some specialized birders were not active participants. The most distinguishing feature among groups was the behavioral dimension of specialization, with active eBird participants owning specialized equipment and taking frequent trips away from home to bird. Active participants had the strongest achievement motivations for birding (e.g., keeping a life list), whereas all groups had strong appreciation motivations (e.g., enjoying the sights and sounds of birding). Using recreation specialization to characterize eBird participants can help explain why some do not regularly contribute data. Project managers may be able to promote participation, particularly by those who are specialized but not contributing, by appealing to a broader suite of motivations that includes both appreciation and achievement motivations, and thereby increase data for conservation.

Keywords: birders, citizen science, eBird, engagement, motivations, recreation specialization

LAY SUMMARY

- Contributory science projects have conservation and societal benefits, yet some projects struggle with participant retention.
- Recreation specialization (a framework that describes individuals' degree of engagement in and commitment to an activity) uses three dimensions to classify recreationists: affective (psychological attachment to specific activities), behavioral (frequency of participation, prior experience, and equipment used), and cognitive (knowledge and skill about an activity).
- We used survey data about involvement and preferences of birders in the U.S. and Canada to measure recreation specialization. We then combined these data with respondents' checklist contributions to eBird.
- Individuals who had the highest scores for all three recreation specialization dimensions contributed the most checklists to eBird.
- Participants motivated by achievement contributed more than those not motivated by achievement. Motivation by appreciation did not influence the number of contributions.

Los excursionistas altamente especializados son los que más contribuyen al proyecto de ciencia ciudadana eBird

RESUMEN

Los proyectos de ciencia ciudadana contributiva (en adelante, proyectos contributivos) son una herramienta poderosa para la ciencia de la conservación de las aves. Los proyectos a gran escala como eBird han producido datos que han hecho avanzar la ciencia y han contribuido a muchas aplicaciones de conservación. Estos proyectos también proporcionan un medio para involucrar al público en la recopilación de datos científicos. Un desafío común en los proyectos contributivos como eBird es mantener la participación, ya que algunos voluntarios contribuyen solo unas pocas veces antes de desvincularse. Para maximizar las contribuciones y gestionar un programa efectivo que tenga un amplio atractivo, es útil comprender mejor los factores que influyen en las tasas de contribución. Para los proyectos que capitalizan las actividades recreativas (e.g., observación de aves), las diferencias en los niveles de contribución pueden explicarse por un marco de referencia basado en la especialización recreativa, que describe cómo los excursionistas varían en habilidad, comportamiento y motivos. Combinamos datos de una encuesta de observadores de aves en los Estados Unidos y Canadá con datos sobre sus contribuciones a eBird (n = 28,926) para evaluar si aquellos que contribuían más eran observadores de aves más especializados. Asignamos los participantes a cuatro grupos de contribución según la lista de verificación de envíos a eBird y comparamos los niveles de especialización y las motivaciones de los grupos. Los grupos de contribución más activos tenían una mayor especialización; sin embargo, algunos observadores de aves especializados no eran participantes activos. La característica más distintiva entre los grupos fue la dimensión del comportamiento de la especialización. Los participantes activos de eBird poseían equipos especializados y realizaban viajes frecuentes fuera de casa para observar aves. Los participantes activos tenían las motivaciones de logro más fuertes para la observación de aves (e.g., mantener una lista de vida), mientras que todos los grupos tenían fuertes motivaciones de apreciación (e.g., disfrutar la observación y los sonidos de las aves). El uso de la especialización recreativa para caracterizar a los participantes de eBird puede ayudar a explicar por qué algunos no aportan datos regularmente. Los gestores de proyectos pueden promover la participación, particularmente de aquellos que están especializados pero que no contribuyen, apelando a un conjunto más amplio de motivaciones que incluyen tanto la apreciación como las motivaciones de logro y, por lo tanto, aumentar los datos para la conservación.

Palabras clave: ciencia ciudadana, compromiso, eBird, especialización recreativa, motivaciones observadores de aves

INTRODUCTION

Scientists are challenged to collect large amounts of data across broad geographic scales to address complex, large-scale questions. They are increasingly turning to the public to help collect data as contributory citizen scientists (hereafter "contributory scientists and contributory projects"; see Cooper et al. 2021 for a discussion of usage of this and alternate terms; Dickinson et al. 2010; Bonney et al. 2014). Engagement of contributory scientists in data collection is particularly common for bird research because of the popularity of birding and the ease with which they can be observed, combined with their conspicuous behavior and plumages and ubiquitous nature (Sullivan et al. 2009; Federal, Provincial, and Territorial Governments of Canada 2014; USFWS 2018). There is a long and rich history of members of the public gathering scientific data about birds, dating back to the first Christmas Bird Count in 1900 (Dunn et al. 2005). Bird-related studies have since become some of the most successful contributory projects (Shirk et al. 2012).

Contributory projects provide individual and societal benefits by increasing scientific knowledge (e.g., Jordan et al. 2011; Phillips et al. 2018), increasing pro-environmental behavior among participants (e.g., Oberhauser and Prysby 2008; Tanner and Ernst 2013; Toomey and Domroese 2013), encouraging the learning of new skills (e.g., Bela et al. 2016; Haywood et al. 2016; Phillips et al. 2019), informing public policy (e.g., Couvet et al. 2008; McKinley et al. 2017), and leading to a variety of other conservation outcomes (e.g., Sullivan et al. 2017). Sustained contribution is necessary to achieve both scientific and societal benefits, yet many large-scale contributory projects (e.g., eBird, iNaturalist, Map of Life) struggle with participant retention. For most projects, the bulk of the contributions come from a relatively small number of dedicated individuals, with most participants contributing only a few times before disengaging with a project (Eveleigh et al. 2014; Sauermann and Franzoni 2015; Tiago et al. 2017; Fischer et al. 2021). Lack of sustained contribution can negatively impact the scientific goals of projects because participants become more skilled over time, increasing the quality of their data (Jiguet 2009; Schmeller et al. 2009; Stylinski et al. 2020). Ongoing participation in contributory science also promotes its broader societal benefits, such as learning new skills and science content (Kelling et al. 2015; Masters et al. 2016). Understanding factors that influence contribution rates can help contributory projects achieve their desired societal, scientific, and conservation outcomes.

Recreation Specialization

Recreation specialization offers a framework to explore what influences participation in contributory science when it is associated with a recreational activity (e.g., birding). Bryan (1979) proposed recreation specialization to describe a process whereby individuals are more or less involved with an activity along a continuum of low to high commitment (Figure 1). Specialization includes three dimensions: affective (psychological attachment to specific activities), behavioral (frequency of participation, prior experiences, and equipment used), and cognitive (knowledge and skill about an activity) (McIntyre and Pigram 1992). Recreationists with high levels of specialization are more psychologically attached to the activity, spend more time performing the activity, and have more activity-related knowledge and skills than do recreationists with lower levels of specialization. Previous studies have used recreation specialization to segment birders into distinct groups on a continuum of low to high specialization (e.g., generalist, intermediate, specialist; McFarlane 1994, 1996; Martin 1997; Hvenegaard 2002; Scott and Thigpen 2003; Scott et al. 2005; Vas 2017). Categorizing birders into groups allows researchers to capture different characteristics among birders and the amount of specialization for all three dimensions, which then allows for understanding differences among the groups.

Researchers have used the recreation specialization groups to understand differences in birders in a variety of contexts, such as attendance at birding festivals (Scott and Thigpen 2003), participation in bird-related tourism (Hvenegaard 2002), membership in birding associations (Glowinski and Moore 2014), and purchasing Migratory Bird Hunting and Conservation (Duck) Stamps (Shipley et al. 2018). However, the framework has rarely been applied in the context of participation in contributory science projects, with one notable exception. Randler (2021) found that participants in Ornitho.de (www.ornitho.de; a German contributory science project) were more highly specialized birders than non-participants and that highly specialized birders contributed more data than less specialized birders.

Motivations for Contribution

Studying motivations related to contributory science participation is also important to understand differences in contribution rates (Nov et al. 2011; Alender 2016). Previous studies identified a relationship between motivations and the extent of contributions to contributory science projects (e.g., Eveleigh et al. 2014; Wald et al. 2016). Intrinsic motivational factors (i.e. the desire to do something out of interest, pleasure, or joy; Ryan and Deci 2000) can have a strong influence on the extent of an individual's contribution to a project (e.g., Tiago et al. 2017; Jones et al. 2018). Intrinsic motivation due to an interest in the study subject can be a key driver of contribution (Clary and Snyder 1999), especially when the project employs a recreational activity that an individual already pursues (e.g., birding; Rotman et al. 2014).

Decker et al. (1987) proposed that motivations related to participation in a recreational activity (but not specifically contributory science) could be categorized as achievement-orientated (performing the activity to realize a specific goal), appreciation-orientated (performing the activity to receive mental well-being), and affiliation-orientated (performing the activity primarily to accompany another person or group). Achievement-oriented and appreciation-oriented motivations can strongly influence people's engagement in birding (e.g., McFarlane 1994, 1996; Scott and Thigpen 2003; Glowinski and Moore 2014), whereas affiliation-orientated motivations are not as predictive (McFarlane 1994). McFarlane (1994) found that active birders were primarily motivated by achievement, whereas casual birders were primarily motivated by appreciation. Thus, achievement-oriented and appreciation-oriented motivations may be useful, along with recreation specialization, to explain contribution patterns in birding-focused contributory projects.

eBird

In this study, we focus on the avian contributory project eBird to explore how recreation specialization and motivations explain contribution patterns. eBird is the world's largest biodiversity-related contributory science project (Sullivan et al. 2009). As of 2020, there were over 600,000 registered users who annually submit over 100 million bird sightings worldwide, with participation rates growing at an average of 20% per year (www.ebird.org). The vast quantity of data available across such a large geography makes eBird a powerful tool for avian research and conservation (Sullivan et al. 2017). Participant contributions to eBird have allowed researchers to map species distributions (e.g., Fink et al. 2014; Dallas et al. 2017; Fournier et al. 2017), track migratory patterns (e.g., La Sorte et al. 2013; Laughlin et al. 2013; Supp et al. 2015; Horton et al. 2019), detect changes in population trends (e.g., Kamp et al. 2016; Horns et al. 2018), and identify landscape-occupancy relationships (e.g., Zuckerberg et al. 2016; Muller et al. 2018; Rosenblatt and Bonter 2018). The eBird dataset has also been used in studies to advance statistics and computer science (e.g., Fink et al. 2010; Kelling et al. 2013). In addition to these benefits to science and conservation (see Sullivan et al. 2017 for further details), eBird also provides birders with resources to enhance their birding experiences, such as the ability to find birding hotspots, keep lists of birds seen, and view real-time species distribution maps (Sullivan et al. 2009).

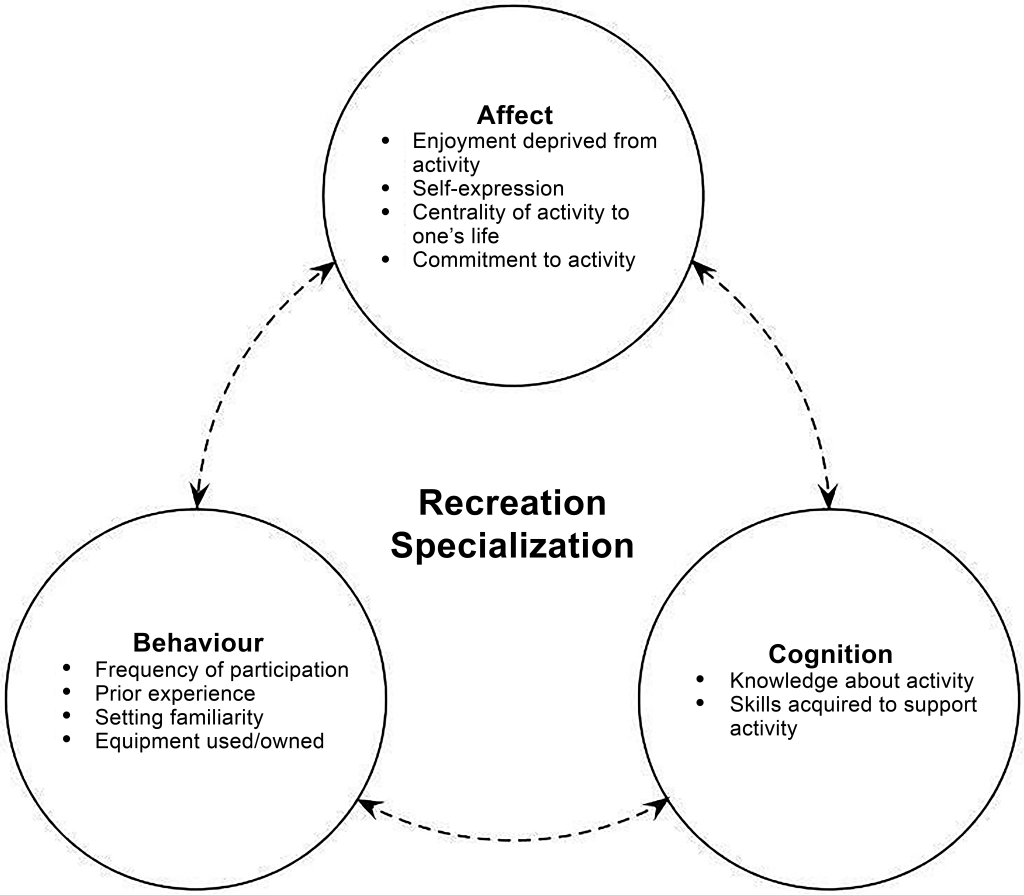

FIGURE 1. Recreation specialization is a multi-dimensional construct that consists of affect, behavior, and cognition related to involvement in a recreational activity. Measuring a recreationist's relationship to an activity on these three dimensions allows for classification along a continuum from low to high specialization.

In this study, we paired data from a survey of birders from the U.S. and Canada with data about their eBird contributions, using the recreation specialization framework and Decker et al.'s (1987) recreational motivations framework to examine differences in eBird contribution rates. We had 3 objectives: 1 to create groups of eBird participants based on contribution levels; 2 to compare scores for the three specialization dimensions (affective, behavioral, and cognitive), as well as achievement and appreciation motivations, among the eBird contribution groups constructed in the first objective; and 3 to identify individuals who belong to the most specialized group of birders and then compare specialization dimensions and motivations among those participants.

For our first objective, we hypothesized that eBird participants would fall into distinct groups based on variables related to eBird behavior (e.g., number of checklists submitted, number of unique days with checklists submitted). These groups would range from occasional contributors to frequent contributors (Wood et al. 2011). For the second objective, we hypothesized that the group that contributed the most to eBird would have the highest scores across specialization dimensions. We further hypothesized that the group that contributed the most to eBird would have the highest scores for achievement motivations, whereas the group with the lowest contribution level would have the highest scores for appreciation motivations (McFarlane 1994; Glowinski and Moore 2014). For the final objective, we hypothesized that achievement motivations would be highest among the highly specialized birders who frequently contributed to eBird, as previous research suggests that those who contribute most to online contributory projects are motivated by achievement (Jay et al. 2016).

METHODS

Survey

The dataset for this study came from a survey developed by the North American Waterfowl Management Plan's (NAWMP) Human Dimensions Working Group (6 of the

10 authors of this paper are members), the National Flyway Council, and affiliated governmental and non-governmental agencies (Harshaw 2018; Slagle and Dietsch 2018). The survey was designed to understand behavior and preferences of birders in the U.S. and Canada. Survey questions measured demographic characteristics of birders, motivations for birding, and levels of specialization according to affective, behavioral, and cognitive dimensions (see Supplementary Material for complete survey). The University of Minnesota organized and implemented survey and data collection, which was not conducted on behalf of the U.S. Geological Survey. The survey included questions that measured components of specialization based on previous literature about recreation specialization in outdoor recreationists (e.g., Lee and Scott 2004; Kyle et al. 2007; Needham et al. 2009; Schroeder et al. 2013). Survey questions related to specialization dimensions, motivations, and behaviors were measured on a five-level interval scale from "strongly disagree" to "strongly agree". For demographic characteristics, age was a continuous variable, sex was a binary variable (male/female), education was a categorical variable with 6 levels, and income was a categorical variable with 10 levels (see Supplementary Material for detail). The University of Alberta's Research Ethics Board approved the Canadian component of this study (Pro00054255), the data analysis by the lead author, and the pairing of the survey data with eBird observations. The University of Minnesota Institutional Review Board determined that the U.S. component of the survey did not meet the definition of human subjects research and did not require approval.

The survey in the U.S. was administered by the University of Minnesota between November 16, 2016 and March 23, 2017 and in Canada between August 1, 2017 and September 1, 2017. The survey sample included individuals who were registered for eBird as of October 13, 2016 and had logged into their account at least once since January 1, 2012 (n = 138,303). Researchers sent up to 5 email invitations for U.S. respondents and up to 3 email invitations for Canada respondents, following the recommendations of Dillman et al. (2014). A total of 37,096 respondents at least partially completed the survey, resulting in a response rate of 26.8%.

A non-response assessment was randomly administered to 16,000 U.S. and 2,000 Canada non-respondents from the original survey to assess the representativeness of the sample. These non-respondents received a shortened version of the original survey, which 23% of U.S. and 34% of Canada respondents completed. This non-response survey contained questions about birding experiences, identity, and demographics, and determined whether there were substantive differences between the original survey respondents and non-respondents. Compared to respondents, a greater proportion of U.S. non-respondents were female (63% vs. 55%) and white (99% vs. 95%), and they also had a slightly higher average age (60.3 vs. 58.5). Canada non-respondents were more likely than respondents to be male (47% vs. 45%) and had a higher average age (59.9 vs. 55.1). Both the U.S. and Canada non-response surveys suggested that non-respondents were slightly less specialized than respondents. The demographic characteristics of the sample were generally consistent with those of birders sampled by the U.S. Fish and Wildlife Service in 2016, although differences were statistically significant (see Rutter et al. 2021 for further details about the representativeness of the sample). Despite the statistical significance of the differences between the full and non-response samples in both countries, effect sizes were generally small. We therefore did not apply weights to our data to correct for non-response bias. Because our sample was not fully representative of all eBird participants, our results only reflect the proportion of participants who responded to the survey.

eBird Data

Users submit data to eBird in the form of checklists, through which individuals record counts of different bird species observed, along with data to describe the birding effort, such as date, start time, end time, distance traveled while birding, and location (see Sullivan et al. 2014 for further details on eBird). Users can also submit optional additional data about breeding and other behavioral observations. We paired survey data with the eBird Basic Dataset (EBD), which is the complete set of all checklist data submitted to eBird worldwide (downloaded 15 May 2019). Within the EBD, we used the Sampling Event Data (SED) to obtain eBird checklist contribution information for each survey respondent (eBird Basic Dataset 2019). The SED file contained information about each checklist (i.e. userID, date of checklist, location of checklist), rather than information on individual species recorded. This pairing allowed us to combine survey responses with data on eBird contribution behavior, which to some degree provided information on birding behavior.

We matched email addresses from all survey respondents with eBird userIDs corresponding to that email address to join the two data files. We discarded survey responses from 1,713 respondents (4.6% of sample) because they did not have an eBird userID. Initial inspection of the data revealed some participants had multiple eBird userIDs corresponding to the same email address, which happens when participants create multiple accounts either intentionally (e.g., to enter historical records for other participants) or unintentionally (e.g., they forgot they had an account and created a new one). We performed a match to

identify all existing userIDs associated with an individual survey email address. A total of 8,770 email addresses had multiple userIDs (25% of sample). To match a participant's eBird SED with the survey responses when the participant had multiple eBird accounts, we selected the account with the greatest number of checklists as it was most likely the primary account for the participant and thus better captured the participant's eBird behavior.

We used the package *auk* (Strimas-Mackey 2019) in program R version 3.5.1 (R Core Development Team 2019) to perform a join on the EBD to be able to extract all SED for our list of userIDs. We only included checklists for observations dated after January 1, 2002 (corresponding to the formal public launch of eBird), and before December 31, 2017 (the end date for participants to return their surveys). A total of 34,975 participants submitted at least one checklist during that time period. We excluded survey responses with missing information on any questions needed to measure recreation specialization (see below), which reduced our sample to 28,926 participants.

We used the *kmeans* function in R to perform *k*-means cluster analysis to classify participants into different eBird contribution groups. *K*-means cluster analysis partitions observations in a dataset into a small number of distinct groups (clusters), where each observation is assigned to a group such that the sum of squared distance between each observation and the arithmetic mean of all other observation in that group are minimized (Kanungo et al. 2002). We used the following variables from the eBird SED to create groups: total number of checklists submitted, number of unique birding locations visited, number of unique counties with submitted checklists, and total number of days spent birding (described as days where the participant submitted at least one checklist). Because there was great variation in values of all four variables and a heavy positive-skew, we log transformed all variables before performing the *k*-means cluster analysis. We determined the optimal number of clusters through visual inspection of a scree plot with both the elbow method (Bholowalia and Kumar 2014) and silhouette method (Rousseeuw 1987) to compare weighted sum of squares.

We hypothesized that participants would be classified into distinct groups that differed in the extent of contributions to eBird. Our initial *k*-means clustering produced an unequal distribution as one group contained over half of the participants (the low-contribution group). This result occurred because nearly 20% of total participants submitted exactly one checklist (n = 5,566). We addressed this unequal distribution by assigning these participants to their own unique group (hereafter referred to as non-retained) and removing them from the subsequent cluster analysis. We then performed the *k*-means cluster analysis again on the remaining 23,360 participants who submitted more than one checklist. We ran our *k*-means analysis for 100 iterations, which was sufficient for convergence.

Recreation Specialization and Motivations

We included 10 variables from the NAWMP survey instrument to measure recreation specialization (Table 1). We used 4 variables to measure the affective dimension, 3 variables for the behavioral dimension, and 3 variables for the cognitive dimension, based on previous literature that measured specialization of outdoor recreationists (e.g., Lee and Scott 2004; Kyle et al. 2007; see Harshaw et al. 2020 for a more comprehensive description of the operationalization of our recreation specialization construct). We used second-order confirmatory factor analysis to confirm the structure, reliability, and validity of these measures of recreation specialization. Second-order confirmatory factor analysis describes the relationships between measured variables on a multi-level scale and latent factors (unobserved variables inferred from other variables), and tests whether the latent factor adequately captures the information described by the measured variables (Kline 2011). We used comparative fit index (CFI; values ≥ 0.90 indicate good fit), root mean squared error of approximation (RMSEA; values < 0.08 indicate good fit), Tucker-Lewis index (TLI; values ≥ 0.95 indicate good fit), and standardized root mean square residual (SRMR; values < 0.08 indicate good fit) to assess the fit of the construct. As the multi-dimensional structure of recreation specialization was confirmed, we used *k*-means cluster analysis on the 10 variables to group participants into 3 specialization groups that represented different degrees of specialization in birding (Oh and Ditton 2006). We used Cronbach's alpha (α) to measure the internal consistency of survey questions used to construct each dimension (Table 1). Cronbach's alpha assesses the extent to which all items in a scale measure the same concept, with values ≥0.70 indicating adequate internal consistency (Kline 2011). We used the selected survey items to create scales for each dimension of recreation specialization and added them together to create a single continuous scale for overall recreation specialization. These scales produced continuous scores, which are relative values that indicate the degree of specialization, with higher scores indicating a greater degree than lower scores.

We constructed 2 latent variables for appreciation and achievement motivations based on several items from the NAWMP survey instrument (Table 2). We performed second-order confirmatory factor analysis to test the structure of the relationships between variables and latent constructs. We used the fit statistics CFI, RMSEA, TLI, and SRMR to assess the fit of these variables and used Cronbach's alpha (α) to measure internal consistency of included survey items.

TABLE 1. We used ten survey items to construct a measure of recreation specialization according to affective, behavioral, and cognitive dimensions. Cronbach's alpha (α) values ≥ 0.70 indicated acceptable internal validity for the affective and cognitive dimensions, but suggested inadequate fit for the behavioral dimension.

Dimension	Survey items
Affective dimension (α = 0.824)	Birdwatching is one of the most enjoyable activities I do.
	Birdwatching has a central role in my life.
	A lot of my life is organized around birdwatching.
	If I couldn't go birdwatching, I am not sure what I would do instead.
Behavioral dimension (α = 0.600)	In the past 12 months, how many trips at least 1.6 km (1 mile) from your home did you take primarily for birdwatching?
	Do you have any of the following equipment that you own primarily for birdwatching? [3 items: binoculars, cameras, spotting scopes]
	I tend to just watch birds without using any special equipment.
Cognitive dimension (α = 0.792)	How would you rate your own ability to observe and identify birds?
	I can identify most birds I see in the field.
	I can readily identify many birds in the field by sound.

TABLE 2. We used survey items used to construct the two latent variables of appreciative and achievement motivations. Cronbach's alpha (α) values used to measure internal consistency of survey items.

Motivation	Survey items
Appreciative Motivation (α = 0.776)	Being in nature is an important part of birding.
	The sights and sounds of nature are important.
	Getting to enjoy the natural environment through birding is important.
Achievement Motivation (α = 0.760)	Developing skills and abilities is important.
	Getting a chance to add a new bird to my life list is important.
	Using techniques, technology, and equipment is important.
	Challenging my birding skills is important.

We used one-way Kruskal–Wallis tests to compare mean specialization and motivation scores among eBird contribution groups. We then performed multiple pairwise comparisons among the different groups. We considered differences to be significant if $P < 0.05$, and used the Benjamini–Hochberg correction to adjust P-values for multiple comparisons. For each specialization dimension and motivation type, we performed a Kruskal–Wallis H-test to calculate eta-squared (η^2) as a measure of effect size, using the Kruskal–Wallis χ^2 value obtained from the initial Kruskal–Wallis test (Cohen 2008). Because large sample sizes can lead to small differences in mean scores being statistically significant, we focused on η^2 values to identify meaningful effect sizes. We considered an η^2 value less than 0.06 to indicate a small effect size, an η^2 value between 0.06 and 0.14 to indicate a medium effect size, and an η^2 value greater than 0.14 to indicate a large effect size (Miles and Shevlin 2001).

Our final objective sought to compare differences in specialization dimensions and motivations scores among the most highly specialized birders across the different eBird contribution groups. To achieve this objective, we performed one-way Kruskal–Wallis tests and calculated η^2 to compare effect sizes for the different recreation specialization dimensions and motivation types.

RESULTS

eBird Contribution Groups

We found a total of four eBird contribution groups, which supported our hypothesis (see Table 3). Hereafter we refer to these four contribution groups, in increasing order of contribution frequency, as non-retained (n = 5,566), occasional (n = 12,594), moderate (n = 5,645), and active (n = 5,121). The groups all differed in terms of the number of checklists, number of birding locations, number of birding counties, and number of days birded, with all variables increasing from non-retained to active contribution groups (Table 3). Members of all groups tended to be in their late 50s to early 60s, had attained a bachelor's degree, and possessed incomes greater than $50,000/year (Table 4). eBird participants were older (median age of 56 vs. 43) and included fewer females (56% vs. 64%) compared to participants across other participatory projects, but otherwise were demographically similar (National Academy of Sciences, Engineering, and Medicine 2018). Despite statistically significant differences in demographics between the four groups, effect sizes were small (Table 4). All groups contained more females than males except for the active group, which was majority male; however, the effect size was small for this variable (η^2 = 0.043).

TABLE 3. We identified 4 eBird contribution groups through *k*-means cluster analysis on participants in our sample (n = 28,926) that differed in the amount of contribution according to checklists, eBirding locations, eBirding counties, and days spent eBirding. Values for all variables increased from non-retained to active contribution groups. Mean values ± standard deviations are presented (mean ± SD).

Group	Group size	Mean number of checklists	Mean number of eBirding locations	Mean number of eBirding counties	Mean number of days eBirded
Non-retained	5,566	1 ± 0	1 ± 0	1 ± 0	1 ± 0
Occasional	12,594	7 ± 6	2 ± 2	1 ± 1	6 ± 5
Moderate	5,645	94 ± 132	28 ± 25	8 ± 7	71 ± 109
Active	5,121	1,544 ± 2,745	439 ± 622	69 ± 70	732 ± 712

TABLE 4. Differences in demographic variables between the four eBird contribution groups had small effect sizes ($\eta^2 \leq 0.06$). We made pairwise comparisons between the group means via pairwise Wilcox tests with Benjamimi–Hochberg corrections to adjust the *P*-value for multiple comparisons. Any two means with different superscripts are significantly different ($P < 0.05$).

Variable	Non-retained	Occasional	Moderate	Active	η^2
Age[a]	59.70*	60.20†	56.50‡	55.00§	0.02
Sex[b]	1.61*	1.64†	1.53‡	1.35§	0.04
Education[c]	5.00*	5.03†	5.14‡	5.20§	0.00
Income[d]	3.62*	3.55†	3.52‡	3.62§	0.00

[a] Continuous variable.
[b] Dichotomous variable; 1 = male, 2 = female.
[c] Categorical variable; 6 levels.
[d] Categorical variable; 10 levels.

Recreation Specialization and Motivations

Fit statistics for the recreation specialization confirmatory factor analysis suggested a good fit of the construct (CFI = 0.975; RMSEA = 0.053; TLI = 0.965; SRMR = 0.027). First-order factor analysis revealed that all dimensions represented specialization well (affective = 0.82; behavioral = 0.88; cognitive = 0.73), and factor loadings were significant ($P < 0.001$). Measures of Cronbach's alpha confirmed acceptable reliability for the affective (α = 0.824) and cognitive (α = 0.792) dimensions, but were relatively poor for the behavioral dimension (α = 0.600). Our *k*-means cluster analysis for specialization produced three categories of birders, referred to as generalists, intermediates, and specialists (Figure 2). Specialist birders had the highest mean scores for all specialization dimensions (affective, behavioral, cognitive), generalists had the lowest mean scores, and intermediate birders were in between (Figure 2). These differences were significant at $P < 0.05$ and η^2 values indicated large effect size (Figure 2).

As hypothesized, specialization scores for all three dimensions increased among eBird contribution groups from non-retained to active participants (Figure 3A). The effect sizes between groups were large for all dimensions, with the effect size for the behavioral dimensions (η^2 = 0.270) almost twice as big as the effect sizes for the affective (η^2 = 0.150) and cognitive (η^2 = 0.150) dimensions.

Our hypothesis that the active contribution group would have a higher achievement motivation, while the non-retained group would have a higher mean score for appreciation motivation was partially supported. Scores for both measures of motivation tended to increase with the amount of contribution across the different groups. Fit statistics indicated a good fit of the two latent variables we created to measure appreciation and achievement motivations (CFI = 0.989; RMSEA = 0.042; TLI = 0.983; SRMR = 0.023). First-order factors ranged from 0.511 to 0.812 and were significant at $P < 0.001$. Cronbach's alpha values indicated acceptable reliability for both appreciation motivations (α = 0.776) and achievement motivations (α = 0.760) (Figure 3A). There was a large effect size for achievement motivations (η^2 = 0.141) and a small effect size for appreciative motivations (η^2 = 0.048).

Specialist Birders

The three-cluster solution for recreation specialization classified 7,893 participants as specialist birders (Figure 4) who have strong birding skills and devote a higher portion of their lives to birding. All eBird contribution groups included specialist birders (Figure 4). The active contribution group was the only group where the majority of members were specialists (Figure 4). We hypothesized that specialist birders in the active contribution group would have stronger achievement motivations than specialist birders in the non-retained group. This hypothesis was not supported, as there was a small effect size for achievement motivations (η^2 = 0.016; Figure 3B), and a similarly small effect size for appreciation motivations (η^2 = 0.000). We found that the only specialization dimension with a medium or

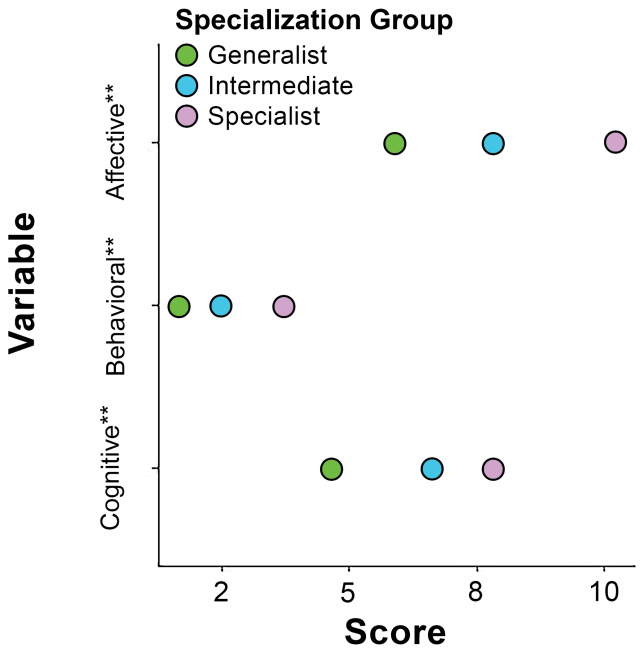

FIGURE 2. Participants in our sample could be classified into 3 recreation specialization groups that differed in their mean scores for affective (psychological attachment), behavioral (frequency of engagement), and cognitive (knowledge and skill) dimensions, with specialists having the highest mean scores for all dimensions and generalists having the lowest mean scores. Scores indicate the extent of specialization, with higher scores indicating a greater degree of specialization than lower scores. We performed *k*-means cluster analysis on 10 variables to construct these different groups (n = 28,926). The effect sizes were large for all dimensions ($\eta^2 \geq 0.14$); affective ($\eta^2 = 0.63$), behavioral ($\eta^2 = 0.44$), and cognitive ($\eta^2 = 0.57$).

large effect size was the behavioral dimension ($\eta^2 = 0.145$), with small effect sizes for the affective ($\eta^2 = 0.003$) and cognitive ($\eta^2 = 0.029$) dimensions (Figure 3B).

DISCUSSION

The Role of Recreation Specialization in Contributory Project Contribution Rates

The results confirmed our hypothesis that participants could be classified according to recreation specialization into distinct groups that differed in the extent of contribution (Table 3). The most frequent eBird contributors in our sample were also the most specialized across all three dimensions of recreation specialization (Figure 3A). Our results corroborate those of Randler (2021) that highly specialized birders contribute more data than less specialized birders. Active participants comprised 17.7% of survey responses and submitted the majority of checklists (93%), echoing the Pareto curve trend in contribution rates found in previous studies of eBird participants (Wood et al. 2011) and contributory scientists more generally (Sauermann and Franzoni 2015; Tiago et al. 2017; Parrish et al. 2019). There were relatively few specialist birders in the non-retained or occasional contribution groups (Figure 4). The finding of most specialist birders being active eBird participants could be due to the fact that specialist birders may view eBird as a way to enhance their overall hobby of birding. Wright et al. (2015) found that opportunities to engage in an already enjoyable recreation activity may be a strong motivation for contribution to a contributory project. High scores for the affective dimension of specialization among the most specialized group further suggest that the participants who enjoyed birding the most also contributed to eBird the most, which further suggests intrinsic motivations could potentially be important factors that influence contribution (Ryan and Deci 2000).

Active eBird participants had the highest mean scores for all specialization dimensions, with a decreasing trend towards non-retained participants (Figure 3A). This confirmed our hypothesis that the groups that contributed the most would be the most specialized across all three specialization dimensions, and further confirms the results of Randler (2021) that birders who participate in contributory science are more specialized than birders who do not. The effect size for the behavioral dimension (including owning/using specialized equipment and taking trips away from home to bird) was nearly twice as large as the effect size for the affective and cognitive dimensions. This suggests that differences in the behavioral dimension of specialization were the most distinguishing characteristic among specialists from the different eBird contribution groups. Because specialist birders had higher scores for the cognitive dimension of specialization than did generalist and intermediate birders, it suggests that the majority of eBird data is submitted by birders who perceive themselves to be highly skilled, as was found in other contributory science projects (Tiago et al. 2017) and in a study examining contribution to the avian focused contributory science project Ornitho.de (Randler 2021). Scott et al. (2005) found that self-classification of birding skill is generally an accurate measure of level of expertise. While our study inferred skill from self-reported survey items, these results can supplement other observed behavior approaches, such as species accumulation curves (as described in Johnston et. al. 2018).

Motivations for Contribution

The large effect size for achievement motivations, with active participants having significantly higher scores, confirmed our hypothesis that active participants would have the highest mean score for achievement motivations. Given that eBird promotes "healthy competition" through rewards and recognition (Sullivan et al. 2009, pg. 2285), it is not surprising that those who contribute frequently would have higher achievement-oriented motives as they relate to birding. Several features of eBird use achievement to encourage contribution, such as Top 100 rankings, where

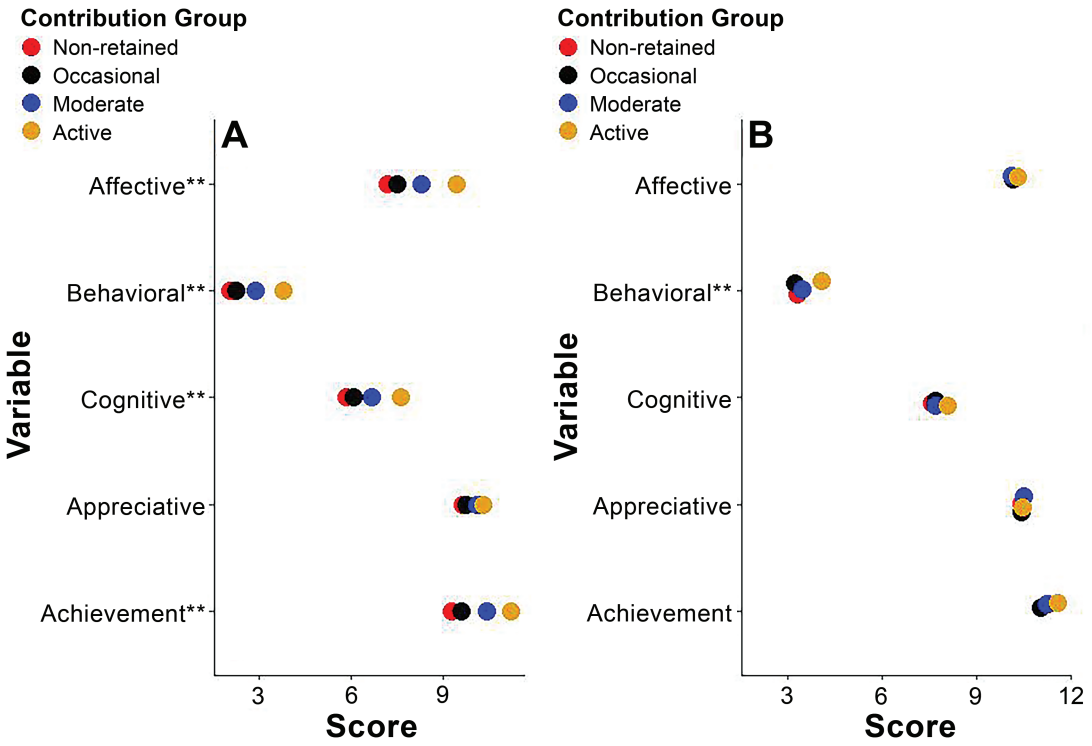

FIGURE 3. Active eBird participants had the highest mean scores for the affective (psychological attachment), behavioral (frequency of engagement), and cognitive (knowledge and skill) dimensions of recreation specialization, as well as for appreciative and achievement motivations. Scores indicate the extent of specialization, with higher scores indicating a greater degree of specialization than lower scores. Due to different scales of construction, the 3 specialization dimensions cannot be directly compared against the two types of motivations. (A) Contribution groups constructed via *k*-means cluster analysis on all participants in our sample (n = 28,926). The effect sizes were large ($\eta^2 \geq 0.14$) for the affective dimension ($\eta^2 = 0.15$), behavioral dimension ($\eta^2 = 0.27$), cognitive dimension ($\eta^2 = 0.15$), and achievement motivations ($\eta^2 = 0.14$), whereas the effect size was small ($\eta^2 \leq 0.06$) for appreciative motivations ($\eta^2 = 0.05$). (B) Contribution groups with only participants classified as specialist birders according to our recreation specialization construct are presented (n = 7,893). Effect sizes were small for the affective dimension ($\eta^2 = 0.00$), cognitive dimension ($\eta^2 = 0.03$), appreciative motivations ($\eta^2 = 0.00$), and achievement motivations ($\eta^2 = 0.02$), whereas the effect size was large for the behavioral dimension ($\eta^2 = 0.15$). Points on the graph are jittered to help show overlapping mean scores.

birders can view the top participants in a region based on number of species seen or number of checklists submitted (www.ebird.org). It is common for online contributory science projects to promote competition and achievement to increase contributions (Wiggins and Crowston 2011; August et al. 2019). Although this gamification can be effective for promoting participant engagement (Jay et al. 2016), it may deter those who are not driven by achievement but rather by appreciation motivations (Duffy and Kornienko 2010; Robson 2012; Bowser et al. 2014). Our result that achievement was a weaker motivation for birding for non-retained participants than it was for active participants could influence decisions to discontinue contributing to eBird.

In contrast to achievement motivations, all contribution groups had a high level of appreciation motivation, with minimal differences between groups. This finding was counter to our hypothesis that appreciation motivations would be highest among non-retained participants and lowest among active participants. Appreciation of the natural world has broadly been shown to be an important motivational factor for participation in biodiversity-related contributory projects (e.g., Guiney and Oberhauser 2009; Hobbs and White 2012; Merenlender et al. 2016; Ganzevoort et al. 2017; Martin and Greig 2019). Our results specifically show that appreciation motivations drive all birders in our sample. eBird could build on this shared appreciation by linking birding hotspots to scenic areas by showcasing photos of natural scenery at birding hotspots, in addition to the types of bird species found there. Scott and Thigpen (2003) found that casual birders were often interested in pairing birding with other activities that facilitated appreciation of the natural world such as fishing and attending environmental education events. Designing contributory projects that appeal to recreationists with both achievement and appreciation motivations could make a project more effective by appealing to a broader audience (Larson et al. 2020), thereby providing more data to support conservation.

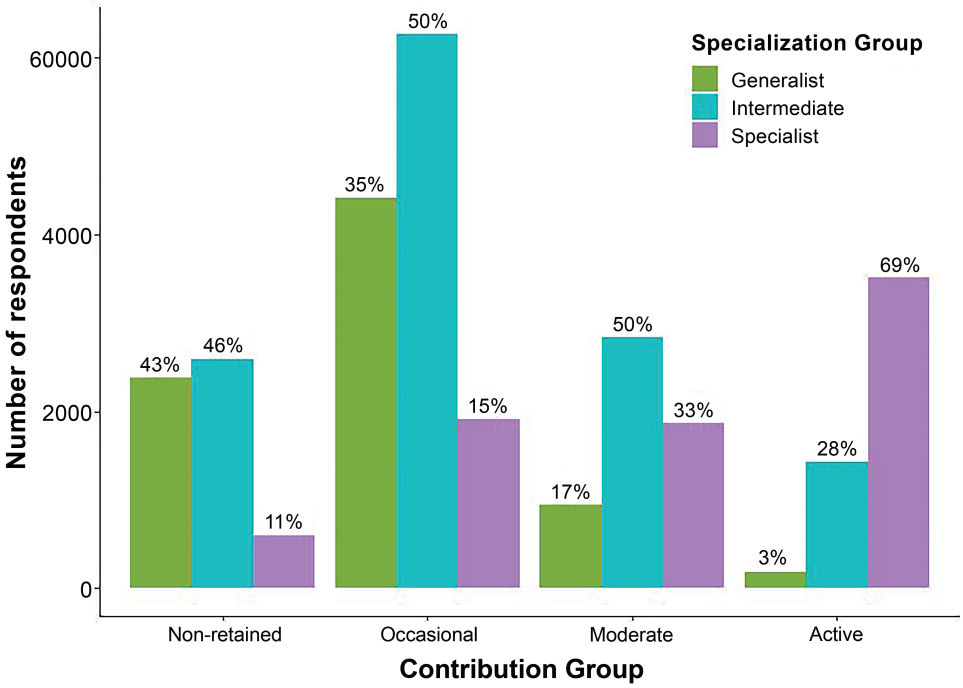

FIGURE 4. Majority of the active eBird contribution group comprised specialist birders (69%) while generalist birders made up a small portion of the active contribution group (3%). Specialist birders constituted a smaller percentage of the group as the amount of contribution decreased from active to non-retained, whereas generalist birders made up a larger percentage of the contribution group as contribution decreased from active to non-retained. We used *k*-means cluster analysis to assign participants to 1 of 3 specialization groups and then to 1 of 4 contribution groups ($n = 28{,}926$). Percent of the contribution group each specialization group composes are indicated above vertical bars.

Because motivations for contributing to a contributory project (e.g., Iacovides et al. 2014; Rotman et al. 2014) as well as for birding (Glowinski and Moore 2014) may change over time, appealing to a variety of motivations is important for promoting sustained contribution and long-term retention (Jackson et al. 2015).

Differences Among Specialist Birders

Specialist birders did not differ in either achievement or appreciation motivations, and the only large difference was in the behavioral dimension of specialization. This indicates that non-retained specialists take fewer birding trips away from home and could primarily be backyard birders. Such a pattern in contribution could be explained by the multi-dimensional aspect of specialization; that is, over time some aspects of engagement are more likely to change than others (Oh et al. 2011). For example, Backlund and Kuentzel (2013) presented the life-course event hypothesis, whereby over time, behaviors related to an activity may change, but cognitions and attitudes towards the activity are relatively stable. Birders in the non-retained group could be at stages of their life where eBird and birding are not possible for them to do as frequently due to caretaking obligations for young children, or, for older individuals, health or mobility constraints.

Limitations and Future Directions

One of our greatest limitations was that we did not have information on "non-participants" who never created an eBird account or submitted a checklist. While our non-retained participants only submitted one checklist and are likely similar to those who never submitted a checklist, there may be further differences to consider among those who never submitted a checklist. For example, Randler (2021) found birders who did not participate in Ornitho.de were significantly less specialized than those who did participate. Given the need to additionally study motivations and other distinguishing characteristics of non-participants in contributory citizen science projects to improve recruitment (Martin et al. 2016; Hermoso et al. 2019), future work could seek to directly study birders who have never submitted an eBird checklist.

Another limitation was that we did not directly ask participants about their motivations for using eBird, and instead only had information about their motivations for birding more generally. While birding is the central recreational activity that eBird harnesses, recreationists may differ with respect to their engagement purely for pleasure vs. for contributory science, the latter of which may be influenced by motivations to contribute to science and research (Hermoso et al. 2019). A future study that directly

explores non-retained participants' reasons for not submitting to eBird would allow for a more focused evaluation of the types of motivations among eBird participants and non-participants. Additionally, our results are limited in regards to what they describe about the similarities and differences between contribution groups. Our data came from a survey aimed at measuring recreation specialization of birders and was not designed with the aim of classifying recreationists into contribution groups per se. We suggest more research to understand differences among the various eBird contribution groups, such as life stage and other motivational factors (i.e., those specific to eBird rather than birding generally), that could further explain differences in contribution.

Conservation Implications

We found that eBird participants are not a homogeneous group and that most non-retained and occasional participants were generalist or intermediate birders (Figure 4). Understanding contributory science participants as recreationists offers managers insights as to how to structure programs to increase retention and thereby increase contributions to conservation. Bird-focused contributory projects could increase retention through marketing and promotional strategies that specifically target generalist and intermediate birders. This strategy might include providing educational materials and highlighting other non-bird aspects of the birding experience, such as visiting scenic natural areas (Scott and Thigpen 2003; Glowinski and Moore 2014). Increasing retention could improve bird conservation efforts in several ways. As these individuals are retained and continue to contribute over time, their skill levels may increase and they may contribute higher quality data (Kelling et al. 2015). Although eBird is already a large and growing project, smaller projects at local scales may lack the quality and quantity of data needed to achieve their conservation goals without such expansion of skilled participants. Maximizing the societal benefits to participants may also contribute to conservation. Individual interest and motivation in conservation increases with continued participation in contributory science (Larson et al. 2020) and can lead to individuals taking more conservation actions in their own lives (Evans et al. 2005; Toomey and Domroese 2013; Merenlender et al. 2016). High dropout rates for projects thus represent a lost opportunity to foster conservation behaviors and attitudes in lapsed participants.

Additionally, we found some highly specialized birders who did not actively contribute contributory science data. Ensuring that a project appeals to recreationists with achievement-oriented motivations and appreciation-oriented motivations could help build a larger, more actively contributing participant pool for recreation-based contributory projects. With contributory projects often struggling to encourage sustained contribution from a variety of participants, the findings of this study suggest that having multiple strategies for drawing in participants and maintaining appeal over the long-term may be an effective way to facilitate social benefits of project engagement among participants while improving the data available for conservation science.

SUPPLEMENTARY MATERIAL

Supplementary material is available at *Ornithological Applications* online.

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Ethics statement: The University of Alberta's Research Ethics Board approved the Canadian part of this study (Pro00054255); however, the University of Minnesota Institutional Review Board determined that the survey did not meet the definition of human subjects research, and did not require approval.

Author contributions: A.D., C.R., D.F., H.H., A.R. conceived the idea, design, and experiment. D.F., H.H. collected the data. C.R., A.D., J.D., T.P., J.R., C.W., N.C., H.H., D.F. wrote the paper. C.R., A.D., D.F., H.H., A.R., J.D., C.W. developed the methods. C.R., A.D., H.H. analyzed the data. C.W. contributed substantial materials.

Data depository: The eBird data are available at https://ebird.org/data/download. The survey data are not available to be shared or disseminated. The informed consent information provided to research participants indicated that "[I]ndividual responses will not be made available to anyone outside the research team."

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