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Martin, V. Y., Smith, L., Bowling, A., Christidis, L., Lloyd, D., & Pecl, G. (2016). Citizens as Scientists: What Influences Public Contributions to Marine Research? *Science Communication, 38*(4), 495-522. doi:10.1177/1075547016656191

Available at http://scx.sagepub.com/content/38/4/495

Citizens as Scientists: What Influences Public Contributions to Marine Research?

Abstract

Public participation in science is bourgeoning, yet little is known about factors which influence potential volunteers. We present results from a national survey of 1145 marine users to uncover the drivers and barriers to sightings-based marine citizen science. Our results show perceptions of control (whether people feel capable and able to contribute) have the strongest influence on intention to participate. Increasing their own or scientific knowledge are strong drivers for participation, while the key barrier is people's belief they have insufficient knowledge of marine species. We discuss implications of beliefs, and make recommendations for marine citizen science projects.

Keywords: citizen science, public participation, science engagement, theory of planned behavior

Introduction

Across the globe, public involvement in research is actively encouraged in many scientific fields. This method of doing 'science by the people' (Silvertown, 2009) is often called *citizen* *science* (although a number of terms exist). The extent of public responsibility, control and involvement reflects a number of different approaches to public participation in scientific research (PPSR), giving rise to typologies of citizen science (Shirk et al., 2012). In what Shirk et al. (2012) describe as c*ontributory* projects, scientists request public assistance often to collect or analyze data. Some projects attempt to answer scientific questions (e.g. the astronomy-based Galaxy Zoo project (www.galaxyzoo.org) asks volunteers to classify images of galaxies to understand how they were formed), while other projects conduct long-term environmental monitoring (e.g. www.reeflifesurvey.com), transcribe historical documents (e.g. www.weatherdetective.net.au), or contribute to scientific databases of life on earth (e.g. www.questagame.com).

Several projects, such as Galaxy Zoo, have had success in attracting large numbers of volunteers, but most achieve more modest levels of public assistance. The number of volunteers needed is dependent on the nature of the activities (e.g. whether volunteers are required to be on site, need training, or simply contribute in an opportunistic way) and the temporal and spatial scale of the project (e.g. whether the project is local, regional, national or global, and whether it is conducted as a single event or as ongoing research). Projects in which contributions are made to existing databases (without volunteer training) can be termed *opportunistic citizen science*. In these projects volunteers contribute data as they encounter the objects of research interest (e.g. birdwatchers are encouraged to send sighting details to the eBird project via www.ebird.org). Opportunistic citizen science has been greatly enabled through technology such as digital cameras and mobile devices. We consider this method of citizen science to present the greatest opportunity to involve large numbers of the public in scientific research, no matter their background. In addition, opportunistic citizen science may gain volunteers who would not normally contribute to scientific research, but may engage through a shared interest outside of science (e.g. fishing). This paper investigates factors which influence public contributions to opportunistic citizen science. Insights into these factors are essential for the design and promotion of citizen science to wider audiences.

The challenge for citizen science projects, particularly those operating at large temporal and spatial scales, is to develop effective ways of recruiting volunteers. This is made more difficult by the lack of information and understanding of the drivers and barriers to public participation, which is essential for the long-term success of citizen science projects (Measham & Barnett, 2008). Recent citizen science studies show volunteer motivations include: making a contribution to scientific research, learning new skills, interaction with others, environmental concern, altruistic reasons, personal satisfaction, public recognition, education of others, or simply that a project aligns with their interests (Crowston & Prestopnik, 2013; Curtis, 2015; Johnson et al., 2014; Land-Zandstra, Devilee, Snik, Buurmeijer, & van den Broek, 2016; Raddick et al., 2013; Thiel et al., 2014). It is difficult to ascertain which of these motivations are most important due to inconsistencies in the research questions and methodologies. One commonality amongst these studies is the respondents; all have volunteered in citizen science. This leaves a gap in our knowledge about the barriers and drivers for potential volunteers in opportunistic citizen science projects, i.e those who have never participated before. Here we apply the Theory of Planned Behavior (TPB; Figure 1) developed by Ajzen (1991) and Fishbein and Ajzen (2010), to explore predictors of Australians’ intentions to contribute to an opportunistic citizen science project. We focused on marine citizen science since it is thought that marine science will inspire the public to become more engaged with science generally, through the strong associations Australians have with the beach and ocean (DIISR, 2010; DIISRTE, 2012).

Specifically, we used TPB measures (explained below) to examine public willingness to submit photographs of uncommon marine species to a hypothetical marine citizen project, which was modelled on Redmap (www.redmap.org.au). Redmap asks Australian marine users (primarily recreational fishers and divers) to 'log' photographs of marine species which are uncommon for a particular area. The information will help determine which species are shifting their normal distribution or range in response to changes occurring in the marine environment (such as warming waters around Australia). According to TPB, a behavior should be defined in terms of four key elements: action, target, context and time. The definition of the behavior we are investigating is: a person *logging* (action) a *sighting* (target) of an *uncommon marine species* (context) sometime in the next *twelve months* (time).

By uncovering factors which influence people's intention to submit a sighting, we can suggest strategies for effective communication and project design likely to result in greater volunteer recruitment. Of particular interest are the beliefs held by the target audience about the behavior, and differences in the strength of these beliefs between people who have contributed in the past, and those who have not. These beliefs and differences identify drivers and barriers for recruitment and retention of volunteers.

Theoretical framework

The Theory of Planned Behavior (TPB) is one of the most widely used theories for understanding human behavior (Figure 1). It has been applied in many fields, particularly in health sciences, public safety and for encouraging pro-environmental behavior (Armitage & Conner, 2001; Darnton, 2008; Fishbein & Ajzen, 2010). TPB has also been used in science communication research to understand scientists' willingness to become actively involved in public engagement activities (Poliakoff & Webb, 2007).

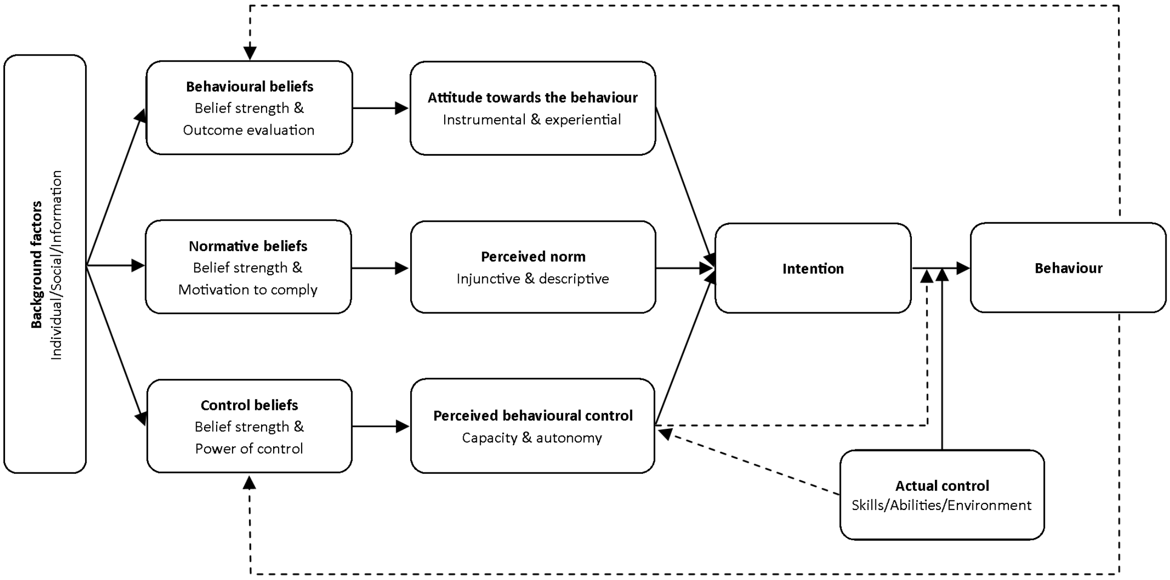

Figure 1. Theory of Planned Behaviour (Ajzen, 1991; Fishbein & Ajzen, 2010)

To illustrate and explain the theory in further detail we provide an example of an environmental communication campaign to encourage recycling at a university food hall (Table 1). According to TPB, a person's intention can predict a specific behavior. The theory acknowledges that a positive intention does not necessarily result in performance of the behavior, and other factors (e.g. infrastructural constraints) may prevent the intended behavior. However, intention has been consistently found to be the strongest predictor of behavior in TPB studies (Armitage & Conner, 2001).

The antecedents to intention are a person's *attitude* towards the behavior, their *perceived norms,* and *perceived behavioral control.* In TPB, attitude is comprised of two types (or subdimensions) of attitude: *instrumental* and *experiential* attitudes. The next antecedent is *perceived norms*, which represent the social pressures to perform the behavior. Pressure may come from people who are considered to be important in a person's life (e.g. family, friends, colleagues), and extends to opinion leaders and celebrities, or in some situations people who are absent. Perceived norms can also be divided into two subdimensions: *descriptive* and *injunctive norms*. The final antecedent to intention in TPB is *perceived behavioral control* (PBC), which is the degree of control a person feels they have over performing the behavior. Like the other antecedents, Fishbein and Ajzen (2010) identify two subdimensions: *capacity* and *autonomy.* The measures of *attitude, perceived norms*, and *PBC* are developed by the researchers using scale items (see Methods and Table 2), and since these measures are asked as direct questions they are referred to as *direct measures*.

The three antecedents to intention (attitude, perceived norms, and PBC) are determined by a person's underlying beliefs (behavioral, normative and control beliefs). The three types of beliefs are measured using two components: the belief itself, and the *strength* of the belief. *Behavioral* beliefs refer to the consequences (positive and negative) of the behavior (called *outcome evaluation*) and the *strength* of the belief in the likelihood of the outcome. *Normative* beliefs refer to the extent that others would approve or disapprove of the behavior (*belief strength*), and how motivated they are to do what these people expect (*motivation to comply*). *Control* beliefs refer to the extent to which the person believes certain factors will facilitate or inhibit their performance of the behavior (*belief strength*) and the power they have to perform the behavior (*power of control*). Belief-based measures are developed using open-ended questions during formative research with a sub-sample of target population, usually through interviews or focus groups.

Researchers assess the effect of attitude, perceived norm and PBC on intention to determine the most important influences on behavior. Once understood, the basic premise of TPB is to look at belief differences between compliers (those who are performing the behavior) and non-compliers (those who are not performing the behavior). This is central to behavior change interventions particularly since past behavior has been found to influence future behavior (Conner & Armitage, 1998; Ouellette & Wood, 1998). From a communication perspective, important beliefs and belief differences can also be instructive for communication strategies.

The goal of our study is to determine factors which influence people's intention to contribute to opportunistic marine citizen science. Using TPB as a framework, key objectives are the identification of: (i) important beliefs, and (ii) belief differences between those who have contributed to a marine citizen science program and those who have not. We aim to use this information to provide an evidence-based approach to the development of effective public engagement strategies for marine citizen science.

Table 1. Illustration of the Theory of Planned Behaviour

Context of example:	An environmental communication campaign to encourage recycling at a university food hall	
Desired behavior:	Staff and students sort their rubbish into the recycle bins during term	
TPB dimensions	**TPB sub-dimension**	**Example/explanation**
Intention	n/a	The intended behavior. In our example, this is the intention to sort rubbish into the appropriate recycle bin
Attitude towards the behavior	Instrumental attitude	*Instrumental attitude* is distinguished by the cognitive nature of the construct. Instrumental attitudes reflect a person's thoughts on whether the behavior is a good (or wise, valuable etc.) thing to do. For example, a student may think that sorting their rubbish into the correct bin is a good thing for environmental health.
	Experiential attitude	*Experiential attitudes* are more *affective* in nature, that is, they reflect the person's evaluation of the experience of performing the behavior. Such attitudes may be described by terms such as painful, exciting, unpleasant, or fun. Note: It is possible for instrumental and experiential attitudes to be inversely correlated. E.g. although people think sorting rubbish is a good thing (positive instrumental attitude), they may also think it will be unpleasant removing their food scraps and placing them into a smelly compost bin (negative experiential attitude).
Perceived norms	Descriptive norms	*Descriptive norms* refer to what others do in the same circumstance, e.g. piles of rubbish left lying around the food hall may lead to the perception that 'everyone else' litters.

	Injunctive norms	*Injunctive norms* refer to a person's perception of what behaviors others approve of, e.g. 'most people think I should sort my recycling into the correct bin.'
Perceived behavioral control	Capacity	*Capacity* refers to the ease or difficulty a person expects in performing the behavior, e.g. 'it is easy for me to sort my rubbish into the correct recycling bins.'
	Autonomy	*Autonomy* relates to the person's perceived degree of control over performing the behavior i.e. to what extent the decision to perform the behavior rests with them (and not others, or other factors). E.g. if there are no recycling bins provided people would be unable to recycle. In this example, the degree of autonomy would be very low.
Behavioral beliefs	Belief strength & Outcome Evaluation	Refer to the consequences of the behavior. E.g. a person might believe their recycling efforts would result in a tidier campus, but that recycling does not actually have a positive impact on environmental health.
Normative beliefs	Belief strength & Motivation to Comply	Beliefs about the expectations and behavior of others in relation to the behavior. E.g. students may believe that staff would approve of their recycling efforts, but other students do not care.
Control beliefs	Belief strength & Power of control	Beliefs about the resources and opportunities to perform the behavior. E.g. the provision of more recycling bins in convenient locations may help increase recycling, or the signage may be inadequate for determining what types of rubbish can be recycled.

Methods

Our research comprised two phases for the application of TPB: (i) a qualitative phase to uncover salient beliefs using face-to-face interviews; and (ii) the quantitative phase during which a national survey was conducted and analyzed to determine important influences on people's intention to contribute to marine citizen science. The national survey asked respondents a broad range of questions, of which the TPB questions formed one section (albeit a substantial section). This paper reports on the TPB results from second phase, while the first phase is reported elsewhere (Martin, Christidis, Lloyd, & Pecl, 2016).

National survey development and recruitment

Our TPB questions were developed according to Fishbein and Ajzen (2010). In phase one, belief-based measures arose from face-to-face interviews with 110 marine users in four regions of Australia. Responses to the open-ended questions on behavioral, normative and control beliefs were coded into the key themes, checked for inter-coder reliability between three coders, then used as the belief items in the national survey (Table 2). The most salient behavioral beliefs about participation in marine citizen science were that it would increase knowledge (either scientific or their own), provide information and raise awareness for the community, and help to protect/manage the marine environment. The most salient control beliefs (i.e. things which would help them to log a sighting) were an easy and user-friendly website/mobile app, having better knowledge of marine species, and having more free time.

During the interviews, we also tested the direct measures for use in phase two. It became evident that descriptive norms were problematic. To apply TPB correctly in our study, we attempted to ask respondents about the behavior of others who have observed an uncommon species. Very few interviewees knew someone who had seen an uncommon species and those who had assumed the others did not log a photograph. This problem raised the issue of relevance of the descriptive norm questions since this is not a commonly observed behavior and therefore has little influence on behavior. For this reason, descriptive norms were removed from the national survey questions.

We assessed the validity of the remaining direct measure scales (Table 2) by means of a confirmatory factor analysis in SPSS Amos 22.0. The results indicated that one PBC (autonomy) item (*It is mostly up to me whether I log an uncommon marine species on the website/mobile app*) had a low factor loading (.34), so this item was removed, leaving five PBC measures.

The national survey in phase two included questions on demographics and the quantitative TPB measures developed through the earlier phase. Demographic questions were based on the most recent population census (2011) by the Australian Bureau of Statistics (retrieved from www.abs.gov.au). They included age, gender, Australian state residence, and education variables. All TPB measures used a 7 point scale, which were presented as either unipolar scales (1 to 7) or bipolar scales (-3 to +3), where appropriate (a bipolar scale was used for items with negatively-worded responses, then converted to unipolar for the analysis).

The questions were entered into the Qualitrics online survey platform and pre-tested by 12 people in different locations across the country on a variety of devices. This resulted in some minor changes to wording for clarity. To promote the survey nationally we used a multi-pronged communication campaign via mainstream and social media, and direct email to relevant groups around the country. The method for recruiting respondents is further described in Martin, Christidis, and Pecl (2016).

The survey was open for 8 weeks from February to April 2015. During this time, 1375 people commenced the questions, of which 1145 were determined to be fully complete and valid after data cleaning and hence could be included in the final analysis. This represents a completion rate of 83.3%. Respondents took approximately 30 minutes to complete the survey. The survey was designed to ask the TPB questions only if the respondent had access to technology that would allow them to take digital photos and load them on the internet, or through a smartphone app. This reduced the number of respondents for the TPB questions to 1076. Any negatively worded questions were reworded and reverse coded to facilitate comparisons of the results.

Table 2. Survey item mean scores, standard deviations and reliability of scales

Item label	Survey question	Response (all on 7 point scales)	Mean	SD	Correlation with direct measure composite	Cronbach's alpha
	BEHAVIOURAL BELIEFS: Belief strength	1 = unlikely, 7 = likely			.509, p = .000	n/a
	How likely do you think the following will be if you log an uncommon marine species in the [website/mobile app]?					
IABS1	• it will increase scientific knowledge		5.84	1.08		
IABS2	• it will increase my own knowledge of marine species		6.10	1.03		
IABS3	• it will provide information for the greater good/everyone		5.85	1.02		
IABS4	• it increase public awareness of the marine environment		5.63	1.15		
IABS5	• it will help to protect/manage the marine environment		5.75	1.19		
	BEHAVIOURAL BELIEFS: Outcome evaluation	1 = a very bad thing,				
	How good (positive) or bad (negative) do you think the following things are?	7 = a very good thing				
IAOE1	• Increasing scientific knowledge is:		6.79	0.55		
IAOE2	• Increasing my own knowledge of marine species is:		6.54	0.71		
IAOE3	• Providing information for the greater good/everyone is:		6.47	0.80		
IAOE4	• Increasing public awareness of the marine environment is:		6.65	0.68		
IAOE5	• Helping to protect/manage the marine environment is:		6.69	0.72		
	ATTITUDE TOWARDS BEHAVIOUR: Instrumental and experiential	(scale shown in question)				.934
	For me, logging a sighting of an uncommon marine species onto the [website/mobile app] would be:					
DAIN1	• worthless : 1 : 2 : 3 : 4 : 5 : 6 : 7 :valuable		6.20	1.15		
DAIN2	• unimportant : 1 : 2 : 3 : 4 : 5 : 6 : 7 : important		6.21	1.10		
DAIN3	• unproductive : 1 : 2 : 3 : 4 : 5 : 6 : 7 : productive		6.13	1.14		
DAEX1	• boring : 1 : 2 : 3 : 4 : 5 : 6 : 7 : interesting		6.16	1.19		
DAEX2	• unenjoyable : 1 : 2 : 3 : 4 : 5 : 6 : 7 : enjoyable		5.90	1.23		
DAEX3	• aggravating: 1 : 2 : 3 : 4 : 5 : 6 : 7 : satisfying		6.23	1.11		

	NORMATIVE BELIEFS: Motivation to comply* If your ____ think you should/should not log uncommon species, how much do you want to please them by doing what they think you should do?	1 = not at all, 7 = a great deal				n/a
INMC1	• family		2.37	1.72		
INMC2	• close friends		2.22	1.64		
INMC3	• recreational peers (i.e. other people, not close friends, who do your favorite marine activities with you)		2.15	1.62		
	PERCEIVED (INJUNCTIVE) NORM How much would your____ approve or disapprove of you logging uncommon marine species?	1 = strongly disapprove, 7 = strongly approve				.85
DNIN1	• family		6.32	1.04		
DNIN2	• close friends		6.24	1.06		
DNIN3	• recreational peers		6.12	1.11		
	CONTROL BELIEFS: Belief strength	1 = strongly disagree,			.398,	n/a
ICBS1	• An easy and user-friendly website/app will enable me to log an uncommon marine species	7 = strongly agree	6.63	0.77	p = .000	
ICBS2	• Having better knowledge of marine species would help me to log an uncommon species		6.42	1.03		
ICBS3	• Having more free time will enable me to log uncommon marine species		5.62	1.62		
	CONTROL BELIEFS: Power of control	1 = very unlikely,				
ICPC1	• I expect the [website/ mobile app] will be easy and user-friendly	7 = very likely	6.19	0.97		
ICPC2	• I will have enough knowledge of marine species to log an uncommon species		5.29	1.51		
ICPC3	• I will have enough time to be able to log uncommon marine species		5.72	1.29		

	PERCEIVED BEHAVIOURAL CONTROL: Autonomy**				.769
DCAU1	• The number of events outside of my control which would prevent me from logging an uncommon marine species on the [website/mobile app] are:	1= numerous, 7 = very few	5.53	1.53	
DCAU2	• How much control do you have over whether you would log an uncommon marine species on the [website/mobile app] or not:	1 = no control, 7 = complete control	6.45	0.93	
	PERCEIVED BEHAVIOURAL CONTROL: Capacity				
DCCA1	• For me to log an uncommon marine species on the [website/mobile app] would be:	1 = very difficult, 7 = very easy	6.22	1.14	
DCCA2	• If I see an uncommon marine species, I am certain that I can log it on the [website/mobile app]:	1 = strongly disagree, 7 = strongly agree	6.10	1.20	
DPCA3	• How capable do you think you are to log an uncommon marine species on the [website/mobile app]?	1 = very incapable, 7 = very capable	6.51	0.85	
	INTENTION				.879
INT1	• If you saw an uncommon marine species, how likely is it (realistically) you would log it on the [website/mob. app]?	1 = very unlikely, 7 = very likely	6.09	1.12	
INT2	• I intend to log any uncommon marine species I may see in the next 12 months on the [website/mobile app]	1 = definitely not, 7 = definitely will	6.07	1.13	
INT3	• I am willing to log any uncommon marine species I may see on the [website/mobile app]	1 = strongly disagree, 7 = strongly agree	6.43	0.91	
INT4	• I want to log any uncommon marine species I may see in the next 12 months on the [website/mobile app]	1 = strongly disagree, 7 = strongly agree	6.29	0.97	

*Indirect measures were removed from the analysis following our concerns with potential measurement issues outlined in the Method section.

Analysis

The analysis of the TPB questions from the survey proceeded in four steps: (i) assessment of direct measure scale reliability (ii) computation of composite scores and correlations between direct and indirect measures, (iii) structural equation modelling of direct measures and their influence on intention, and (iv) computation of differences in belief measures between past contributors and non-contributors. SPSS 22 was used for steps (i), (ii) and (iv) and SPSS AMOS 22 for step (iii). The first two steps are assessments of the data, while the third and fourth steps produce results.

The first step in the analysis examined the scale reliability of the direct measures using Cronbach's alpha (Table 2). All scales exceeded the minimum reliability coefficient of .70 (Pallant, 2013). This means the scales were reliable measures of the direct measure construct.

In the second step, we computed composite scores for the direct and indirect measures. Items in each of the direct measures (attitude, injunctive norm and PBC) were summed. This resulted in the following maximum composite scores: 42 for attitude (6 items x 7 points on scale), 21 for injunctive norms (3 items x 7 points on scale), and 35 for PBC (5 items x 7 points on scale).

The indirect measure composite scores were calculated for behavioral and control beliefs. Behavioral beliefs were determined by multiplying the outcome evaluation by the strength of each belief (maximum score = 49 from the two 7-point scales), and the resulting 5 belief scores were summed to create the composite score with a maximum of 245 (49 x 5). Similarly, control beliefs were calculated by multiplying the power of control by the strength of each belief (maximum score = 49 from the two 7-point scales) and the resulting 3 scores summed to generate the composite score with maximum = 147 (49 x 3).

Composite scores were checked for any differences in direct and indirect measure correlations arising from use of bipolar scoring (-3 to +3) or unipolar scoring (1 to 7). (Fishbein & Ajzen, 2010) recommend selecting the scale which results in the strongest correlation. There was little difference in the correlations between attitude and behavioral belief composites (Spearman's rho = .568 for unipolar scale, and .557 for bipolar scale, $p<.001$ for both correlations), and between PBC and control belief composites (Spearman's rho = .363 for unipolar scale, and .347 for bipolar scale, $p <. 001$ for both correlations) so the unipolar scale was maintained throughout the analysis.

The resultant composite scores were used to check for correlations between: (i) behavioral beliefs and attitude towards the behavior, and (ii) control beliefs and PBC to ensure the underlying beliefs are a function of the direct measures (Table 2). The correlation coefficients indicate (i) large, and (ii) moderate effects, respectively (Field, 2013). A composite score for intention was calculated by summing the scores from the four intention items.

The third step in the analysis was the structural equation model. To assess the model, we used a two-step procedure as outlined in Byrne (2010). Since our data are multivariate non-normal (most scales were negatively skewed which impacts on the reliability of the model, and in particular may result in an inflated χ^2 likelihood ratio test of model fit) we used bootstrapping procedures with 1000 samples during the analysis. First, we examined the validity of scores using a second-order confirmatory factor analysis (CFA), which was performed in SPSS AMOS 22. According to Hagger and Chatzisarantis (2005), incorporating the sub-dimensions of the higher order TPB factors into the CFA model enables distinctions to be made at the sub-dimension level. The model was assessed using the following model fit indices, all of which fell into acceptable parameters (Byrne, 2010; Hu & Bentler, 1999): $\chi^2 = 447.111$, $df = 125$, $p < .001$, RMSEA = .049, CFI = .975, SRMR = .0347.

The factors in the CFA were examined for convergent and discriminant validity using the following measures, all of which fell into acceptable parameters (Hair, Black, Babin, & Anderson, 2010): composite reliability (CR) were all > .7, average variance extracted (AVE) were all > .5, maximum shared variance (MSV) and the average shared variance (ASV) for all factors were less than the AVE for corresponding factors, and the square root of AVE was greater than inter-construct correlations.

Reliability of the model was examined for common method bias using the common latent factor (CLF) method (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003) which showed no large differences between the model with a CLF and the model without a CLF (the largest difference was .02 which is well below the standard cut-off of .2). Measurement model invariance was also tested for configural and metric invariance. The model passed the configural variance test using two groups (males and females) to test for differences in model fit. For the metric invariance test, which relies on the χ^2, the sample size had to be reduced to a random sample of 400 (200 in each of two groups) due to the sensitivity of χ^2 to large sample sizes. This test showed the two models being compared were invariant. In summary, the CFA confirmed we could proceed with the structural model without modification. The structural model (presented below) was also assessed for validity and reliability using the same measures, and was found to pass all of the tests.

The fourth and final step in the analysis was to investigate belief differences between compliers and non-compliers. For this, we used several questions to identify those who had participated in an opportunistic marine citizen science project in the past. First, we asked whether people were aware of any projects similar to the hypothetical project, and we asked them to name the project if they could. Redmap is the only citizen science project in Australia asking people to log sightings of uncommon marine species, and matches our definition of the behavior. Next, we asked: *Have you ever contributed observations, data or photos to any of the projects you mentioned?* People who said they: (i) had made a contribution, and (ii) mentioned Redmap specifically were recoded into a group called 'contributors' (N = 88, or 8% of the sample), while those who had not made a contribution in the past were coded as 'non-contributors' (N = 988).

We encountered further issues with the questions on normative beliefs, primarily on the *motivation to comply* items, which obtained low mean scores (averaging 2.25 on the 7-point scale). This means respondents felt other people cannot significantly influence their behavior. While we acknowledge that, in this context, it is possible respondents could have a low desire to 'do what others think I should do', we suspect this result may be due more to the social desirability to say 'no one can influence my behavior'. Yet, if an important other (say, a child) is particularly enthusiastic about sending a photograph of an uncommon species to marine scientists, it is likely the child will be able to persuade their parent to log the sighting. We also acknowledge the considerable problems identified in behavioral research when it comes to measuring norms accurately (Armitage & Conner, 2001; Manning, 2009, 2011; Osborne & Waters, 2002; Rivis & Sheeran, 2003). Recognizing that our results for perceived norm may be inaccurate, we have removed indirect normative beliefs from further analysis, and highlight this topic as an area requiring more research.

Due to the difference in sample size and variance of composite behavioral and control belief scores for contributors and non-contributors, a Mann-Whitney U Test was used to determine whether there were significant differences in the mean composite scores (Field, 2013; Pallant, 2013).

Results

Demographics of respondents

Although our survey was not intended to be representative of the Australian population, it is nevertheless useful to compare our sample with census data to understand the types of people who responded. A detailed description of the respondents is provided in Martin, Christidis, and Pecl (2016); however for the purposes of this article we summarize the background of respondents.

Survey responses came from every state and mainland territory of Australia, differing from the census by no more than 4% except for an overrepresentation from the state of New South Wales (41.3% compared to 32.0% in the census) and underrepresentation from Victoria (8.3% compared to 24.9% in the census). The sample represented a broad range of age groups between 15-84 years, the two-thirds of which fell between 25 – 54 years. Compared to the census data (49.8% males, 50.2% females) we had a slight overrepresentation of males (54.1%) and fewer females (45.9%). The most striking difference between our sample and the census population was the level of higher education. A little over one fifth of our sample (22.4%) had attained postgraduate degrees, compared to 5.2% of the general population.

Intention

The majority of respondents indicated a strong intention to log a sighting of an uncommon marine species if they see one. All mean scores for the four intention measurement items are greater than 6 on the 7-point scales used (Table 2). A Mann-Whitney U Test revealed that past contributors to Redmap have stronger intentions to contribute sightings than those who had not contributed. The composite intention scores for past contributors (Md = 27.00, n = 88) is higher than for those who have not contributed (Md = 26.00, n = 988), U = 33,619, z = -3.593, $p < .001$, however the magnitude of the differences in the means was relatively small at r = .11 (Pallant, 2013).

The mean item scores for the antecedents to intention (attitude, injunctive norms, and PBC) were all above 5.50 and most above 6.00 (Table 2). This means respondents have a positive attitude towards submitting a sighting of an uncommon marine species, and feel that they have a strong degree of control over whether they do so or not. In addition, important people in their lives (family, friends and other recreational peers) would support their decision to log a sighting.

The structural equation model of the antecedents and their influence on intention (Figure 2) was found to be acceptable (χ^2 = 447.111, *df* = 125, RMSEA = .049, CFI = .975, SRMR= .0347). The three predictor variables attitude, injunctive norms, and PBC explain 69% of the variance in behavioral intention. Perceived behavioral control (β = .495) plays the greatest role in determining intention, followed by attitude (β = .374), and to a lesser extent, injunctive norms (β = .138; all β are the standardized regression weights after bootstrapping). All of the regression coefficients are significant at p < .01 using the bias-corrected percentile method. In addition, the three predictors moderately correlate with each other between .39 and .50.

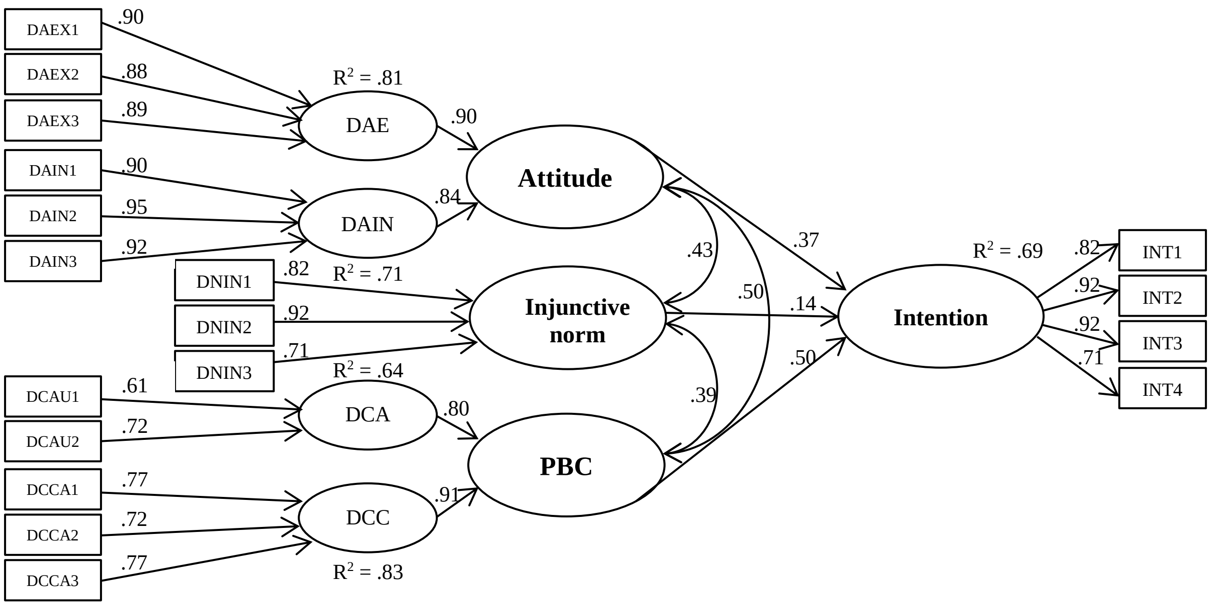

Figure 2. Structural equation model results

Beliefs

The respondents' beliefs about logging an uncommon marine species are (in descending order of importance) that it would: (i) increase their own knowledge, (ii) increase scientific knowledge, (iii) help to protect/manage the marine environment, (iv) provide information for the greater good/everyone, and (v) increase public awareness of the marine environment

(Table 3). The most prominent control belief was that website/mobile app would be easy and user-friendly and this would help them to log a sighting. This belief received a much higher score than the other two (better knowledge of marine species, and having more free time).

Table 3. Composite belief scores

		Overall (*N* = 1076)			Contributor (*N* = 88)		Non-contributor (*N* = 988)	
		Max	Mean	SD	Mean	SD	Mean	SD
BEHAVIOURAL BELIEFS								
BB1	increase scientific knowledge	49	39.78	8.42	40.88	8.42	39.68	8.41
BB2	increase my own knowledge	49	40.20	9.09	40.41	9.00	40.18	9.10
BB3	provide information for the greater good/everyone	49	38.27	9.28	38.28	8.68	38.27	9.34
BB4	increase public awareness of the marine environment	49	37.68	9.27	37.28	9.17	37.71	9.29
BB5	help to protect/manage the marine environment	49	38.77	9.64	37.36	9.22	38.90	9.67
CONTROL BELIEFS								
CB1	Easy and user-friendly website/app	49	41.23	8.64	42.52	7.55	41.11	8.73
CB2	Better knowledge of marine species*	49	33.79	11.56	37.66	10.00	33.45	11.08
CB3	More free time	49	31.51	11.00	33.33	9.92	31.35	11.08

*differences between contributors and non-contributors belief scores are statistically significant, $p < .001$

The Mann-Whitney U Test revealed the only significant difference in beliefs between past Redmap contributors and non-contributors is one control belief CB2: *better knowledge of marine species*. Past contributors to Redmap believe more strongly that they have enough knowledge of marine species to be able to submit a sighting compared to the beliefs of non-contributors (contributors Md = 42.00, n = 88; non-contributors contributors Md = 35.00, n = 988; U = 33,065.50, z = -3.76, p < .001), although the effect size is small (r = .12).

Discussion

The results highlight important considerations for the design and communication of marine citizen science projects, particularly those which are opportunistic in nature. Below we discuss influences on people's intention to participate, and examine underlying beliefs about participation. Finally, we consider how marine citizen science projects can use this information for enhancing volunteer engagement.

Influences on intention

The SEM showed the strongest influence on intention is their perception of control over submitting a sighting. The stronger their feelings of control, the higher the likelihood they will log a sighting. However, the majority of marine users in our survey feel they have capacity and autonomy to submit sightings if they choose to do so.

Perceived behavioral control has also been found to be a strong predictor of intention and/or behavior in studies of pro-environmental behaviors (de Leeuw, Valois, Ajzen, & Schmidt, 2015; Howell, Shaw, & Alvarez, 2015; Le, Yamasue, Okumura, & Ishihara, 2013). In many ways, contributing to a citizen science project could be considered a pro-environmental behavior which, in essence, is behavior which minimizes environmental impacts, or benefits environmental health (Steg & Vlek, 2009). Most marine citizen science projects are concerned about negative impacts and aim to improve the health of the marine environment either through provision of data for science and management or directly through volunteer restoration work. Our results emphasize the important role that contextualized 'control' factors play in encouraging people to act pro-environmentally.

The second factor influencing participation is attitude towards the behavior, that is, the more positive a person's attitude about logging a sighting with the marine citizen science project, the higher their intention to do so. Overall, marine users in this survey have a favorable attitude towards our hypothetical project, considering it to be a worthwhile and positive experience. These results likely reflect the generally positive attitude towards science in the Australian community (DBI, 2012; Searle, 2014). When combined with the high social value of marine environments in Australia (DIISRTE, 2012; Tobin et al., 2014; Voyer, Gollan, Barclay, & Gladstone, 2015), it is appears likely there are many potential volunteers for marine citizen science. Our results indicate supportive attitudes are already in place for future participation in marine citizen science. They may also help to explain why Brossard, Lewenstein, and Bonney (2005) found no change in citizen scientists' attitudes towards science and the environment, since the types of people most likely to contribute to citizen science already hold these attitudes in a positive light.

The third factor (injunctive norms) plays a minor role in determining a person's intention to contribute, despite people feeling they would be well supported by others (family, friends etc.) As mentioned earlier, measurement issues arose for the normative questions, so it remains to be seen whether this result is valid in this particular context. We suspect that, in a 'real life' scenario, social norms will play a more significant role in encouraging people to submit sightings than our results suggest, particularly as there is recognition in the behavioral literature of the important role social influence has on environmental behavior (Abrahamse & Steg, 2013). This issue may become more relevant in the future as the number of marine citizen science projects increase and the behavior becomes more frequent amongst marine users. Some citizen science projects (e.g. Redmap and QuestaGame) already encourage social norms through promotion of submitted sightings in social media and their websites.

Beliefs about participation

This study found respondents' belief about their knowledge of marine species is the most influential barrier to citizen science participation. Changing this belief amongst potential (rather than current) volunteers could increase public contributions to marine citizen science. People who are already contributing to marine citizen science feel more confident in their knowledge, and have higher intentions to submit sightings, than those who have never contributed. This may be a consequence of past experience in citizen science, which has been shown to have a positive effect on volunteer knowledge in other contexts (Bonney, Phillips, Ballard, & Enck, 2015; Brossard et al., 2005; Crall et al., 2013).

There were no other significant belief differences between contributors and non-contributors. Nevertheless, it is useful to look at other underlying beliefs of all respondents to understand important considerations for volunteer engagement. These issues emphasize best practice for project design, communication and recruitment of volunteers. For instance, while time considerations are less of a barrier than species knowledge, this may be an issue for newcomers to opportunistic citizen science. Unless it is well communicated, many may not be aware of the actual time commitment (which is often minimal). Logging an observation with Redmap for example, takes approximately two minutes.

The behavioral belief results highlight potential volunteers' expectations that participation will bring about increases in: (i) the individuals' knowledge of marine species, and (ii) scientific knowledge. In other words, marine citizen science volunteers expect they will learn something, and will be able to make a tangible contribution to scientific understanding of the marine environment. Studies on the motivations of citizen scientists have also found contributing to science is an important reason behind volunteer effort (Curtis, 2015; Haywood, 2015; Land-Zandstra et al., 2016; Raddick et al., 2013). While this is also an important expectation for our respondents, our study shows they believe a more likely outcome is they will learn more about marine species. With this in mind, it is important to remember that volunteer motivations are likely to change over time as they continue to make contributions to the project (Rotman et al., 2014).

Many respondents also believe their contributions may help to protect or manage the marine environment or increase public awareness about the marine environment. These may also be important drivers for participation, particularly for divers, who tend to have a strong desire to assist conservation outcomes (Hammerton, Dimmock, Hahn, Dalton, & Smith, 2012). The results from the additional beliefs (beyond simply the motivation to contribute to science) increase our understanding of reasons why people are likely to assist marine research in the future.

The study shows the most important control belief is the user-friendly design of websites or apps. This was also a key issue for marine users in our interviews (Martin, Christidis, Lloyd, et al., 2016). Most Australians are very familiar and comfortable with using digital and mobile technology, and have high levels of access to the internet (Internet World Stats, 2015). This means they are likely to have experienced good and poor design of websites and apps, and understand the value of user-friendly design which is quick, simple and free from errors. Since potential volunteers feel that this is an important issue, and expect good design, citizen science projects should not underestimate the value of developing these interfaces with end users in mind.

Implications for citizen science projects

This study found many people are in favor of making contributions to marine citizen science, despite the fact 92% of the respondents had never participated in a project similar to the one we described. The barriers to participation appear to be relatively minimal, although this will depend on good project design and thoughtful communication aimed at targeting the beliefs held by marine users in relation to their potential contributions.

The most important interventions likely to lead to new volunteers submitting sightings are those which increase people's perception they have enough knowledge of marine species to be able to do so. We recommend project managers implement mechanisms within their project to build volunteer knowledge (such as ID charts, running workshops, providing training materials etc.), and clearly communicate the level of knowledge required to participate (which may be less than volunteers presume since many projects do not require in-depth knowledge). The findings in this study suggest that doing so will help marine users overcome the hurdle of uncertainty in their ability to participate, and increase the number of sightings reported.

The responses to other belief questions also provide valuable information on important elements of project design from volunteers' perspectives, which form the basis for our additional recommendations below. Although many of these issues should be part of any effective engagement strategy (such as user-friendly design of websites and apps) our observation is that some projects deal with these issues better than others, and some do not consider them at all.

Our next recommendation is to make sure potential volunteers understand the time commitment required, especially since a lot of opportunistic citizen science projects take very little time to submit a sighting (often a matter of minutes). Many projects we have looked at make no mention of the time it takes to add a record.

Given volunteers expect they will learn something, we suggest that project managers communicate stories about actual participants to demonstrate this is a realistic outcome. Additionally, volunteers want to see their contributions have real impact on scientific knowledge or conservation. Demonstrating these outcomes in a public space (such as on a website, through newsletters etc.) will confirm and strengthen the beliefs of potential volunteers.

Engaging volunteers also requires effective website and mobile app design. Most importantly, design of these interfaces needs to be done in consultation with end user groups. Failure to provide digital solutions which are quick, simple to use, and free from errors will likely result in low uptake of the project amongst volunteers, and will discourage repeat contributions – a known problem in large-scale collaborative projects (Crowston, Jullien, & Ortega, 2013). Our observation is that some opportunistic projects are much better designed than others. The difficult platforms appear to be set up more for the end user of the data rather than considering the contributors' ease of use. We recommend project planners work with IT specialists in this area, who not only develop user-friendly designs, but may have existing technologies and experience in citizen science. It may also be possible to partner with existing apps which already process large volumes of digital information.

Finally, we encourage citizen science practitioners to conduct further research on their target audience since certain beliefs are likely to differ in other contexts. We have demonstrated the usefulness of a theory-based approach to understanding drivers and barriers of public contributions to opportunistic marine citizen science. The insights provide guidance for recruiting more volunteers, through strengthening their knowledge of marine species, and for effective engagement strategies which align with participants' expectations. The value in growing the number of productive collaborations between marine scientists and the public is the increased speed and scale of data collection. This information is urgently needed to increase understanding of the considerable changes occurring in our oceans now and into the future.

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