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Pro-social Behaviour in Crowdsourcing Systems: Experiences from a field deployment for beach monitoring.

ANDREAS KOMNINOS

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Highlights:

- Openly exposing collected data to participants in CS systems has multiple benefits
- Participation in mobile open data CS systems is strongly driven by altruistic motives
- Financial or personal ethical rewards are not strong drivers of participation
- Altruistic participation safeguards contributed data quality even with anonymity
- Engagement can be boosted by contributing meta-data (reviews) and contextual reminders

Pro-social Behaviour in Crowdsourcing Systems: Experiences from a field deployment for beach monitoring.

ANDREAS KOMNINOS
Computer Engineering & Informatics Department,
University of Patras,
Rio 26504,
Greece
akomninos@ceid.upatras.gr
+30 2620 997525

Abstract. The paper presents experiences from the rapid introduction and deployment of a data crowdsourcing and data sharing system, motivated by an urgent civic need arising due to the appearance of jellyfish in the swimming coastal areas of western Greece during the summer season. The system was tailored for mobile use and although the pressing need for its deployment negated the time for thorough design, a rich set of lessons and findings emerge from its public use by 13,340 users, over a period of 2 months, reporting over 1,800 times on the condition of 189 local beaches, of which 157 were added to the system by the users themselves. This work touches on issues of usability, motivation, data reliability and public utility of mobile participatory systems and demonstrates that effective outcomes for pubic bodies may rise when systems are designed for the immediate benefit of citizens, by openly exposing the collected data. Most importantly, participation in mobile crowdsourced systems where the data is openly shared between participants is found to be strongly driven by altruistic motives and not by financial or ethical awards. Additionally, the altruistic motives behind participation overcome the added difficulty of participating from a purely mobile use context, and safeguard the quality of the contributed data, reducing the need for complex quality monitoring and safeguarding mechanisms. Finally, the paper identifies barriers and opportunities for the opportunistic participation in mobile crowdsourcing systems during leisure time.

Keywords: Crowdsourcing, citizen participation, environmental monitoring, mobile computing, urban computing.

1 Introduction

Crowdsourcing (CS) systems have emerged as a strong alternative to data collection and processing problems in the last two decades (Zamora et al., 2016). With the proliferation of internet-connected mobile devices, any citizen can partake in research and scientific problems, or assist with the governance of their city, with minimal effort. The crowdsourcing approach is useful in overcoming budget, equipment and scale limitations that would otherwise limit the scope of projects in their ability to collect or process data, by offloading the work from researchers and practitioners to members of the general public. Crowdsourcing projects generally fall into three distinct categories: data augmenting, data processing (Garcia-Molina et al., 2016) and innovation generation, e.g (Harding et al., 2015; Mechant et al., 2011). In data augmenting, participants are asked to record and submit information that the project owners would have otherwise been unable to collect. In data processing, the participants are asked to solve small challenges in which humans can excel, for example, classification or identification tasks. Finally, innovation challenges form a process of co-creation, where the public is called upon to contribute ideas or solutions to existing problems, often in a competitive approach that pitches individuals or teams against each other, to find optimal solutions to a problem.

In the framework of smart cities, crowdsourcing often takes the shape of data augmenting problems. Because the hardware sensing infrastructure (sensors, networks etc.) that would otherwise be required to monitor urban areas requires significant investment and maintenance costs, citizens can be called upon to provide information about their environment (Kanhere, 2013). Participation in such projects increases the civic engagement of citizens and provides a powerful data platform for local authorities, which can then analyse the data to inform governance and planning decisions. Although in many cases such projects are initiated and managed by local authorities, it is not uncommon that citizens may self-organise to create and run such projects themselves, particularly where a specific collective need is not being met by the local authorities (Angus et al., 2014).

The paper discusses the experiences with Swymm, a mobile crowdsourced project to monitor and share the conditions in swimming beaches in the Patras and Corinth gulf areas of Western Greece. Contrary to standard scientific practice, the project was designed, developed and released expeditiously to solve an urgent community problem and did not undergo a thorough design and development process. The design and concept was informed only by our background knowledge of CS system literature. Despite the lack of a participation incentivization scheme, the project met striking success. Previous literature reporting on crowdsourcing systems driven by altrustic motives is scarce, and reports only on experiences where the cost to the users is time (i.e. participating from the comfort of their own homes and desktop computers, or at convenient moments via large public displays). These experiences show that framing tasks under altruistic contexts can strongly motivate users in sustained participation without any tangible benefit to themselves.

This work extends the findings of past research and investigates the strength of altruistic motives in a strict mobile usage context. The findings show that these are strong enough to overcome the added cost (time and difficulty) of mobile participation that emerges from the inherent challenges of mobile use (e.g. touchscreen usability, adverse environmental conditions, mobile broadband connectivity issues and charges). The reflection on the collected data and experiences produces several interesting insights, providing thought-provoking evidence relating to some of the key challenges in crowdsourcing systems, as identified by recent literature.

2 Motivation

To give some context to the paper, the motivation for this work is described first. Swimming in coastal areas is a popular past-time in the summer months across the world, and certainly so in Greece. The work relates to the Patras and Corinth gulf areas (Figure 1), where one major urban centre (Patras – 250k inhabitants) and several smaller towns and fishing villages line the coast. Going to the beach often requires considerable preparation (especially if taking young children or pets) and of course making the journey, which, in this area of interest, can take from 10 minutes to over an hour depending on traffic. In late spring 2017, large swarms of jellyfish were spotted at several beach locations in the gulf of Corinth.

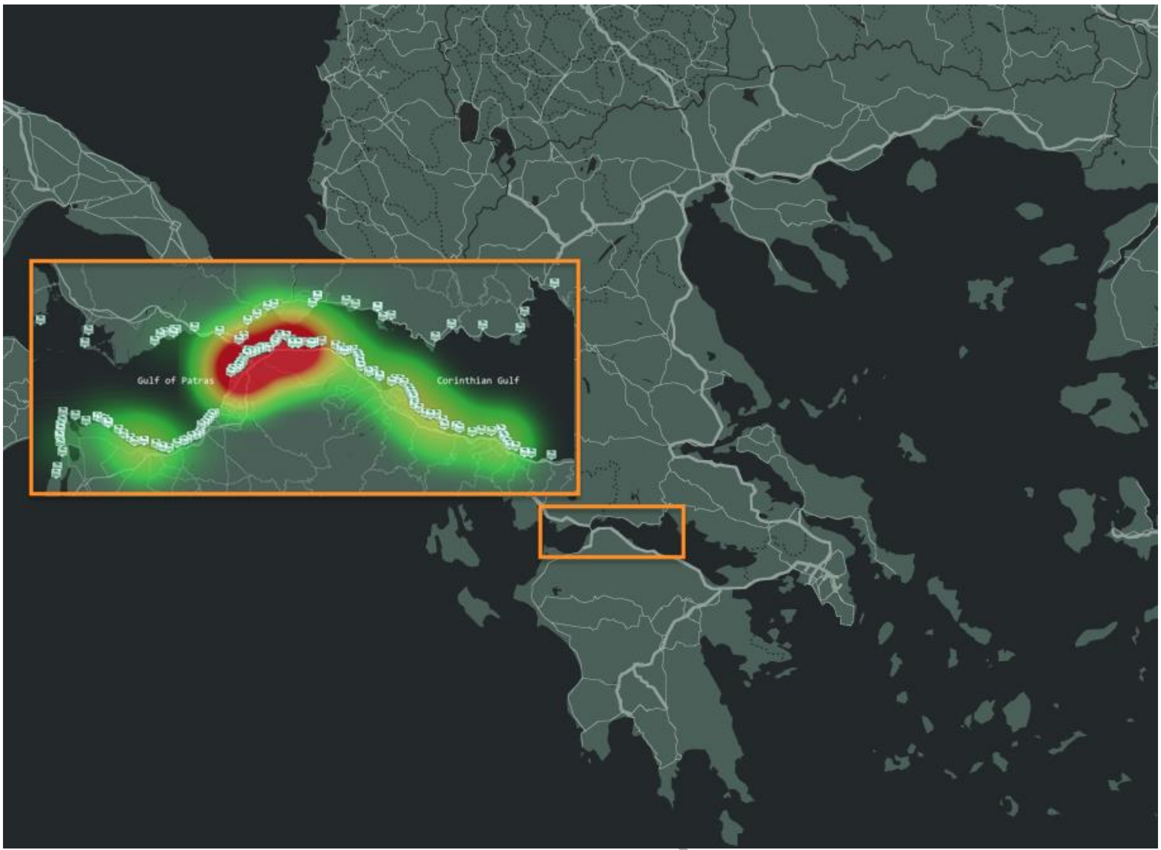

Figure 1. Visualisation of the jellyfish problem areas (Gulf of Patras & Corinthian Gulf, Greece) based on the data captured by our system. Heatmap shows the volume of jellyfish presence reports. Markers show the location of swimming beaches.

The presence of jellyfish largely disrupts bathing and sea-sports leisure activities, since their sting is a rather unpleasant experience, particularly so for small children. In a scientific workshop on the appearance of jellyfish in the area, organised in May 2017 by the "Society for the Protection and Sustainable Development of the Corinthian Gulf" (SPOAK, 2017), it was reported that the phenomenon is cyclically repeated every 8-10 years, lasts for about 2 years and that it is caused by pollution and over-fishing in the area. The workshop concluded there are no immediate interventions that can alleviate the problem, other than long-term measures to reduce the exacerbating causes. Further from the inconvenience caused to beach goers (especially those with families), the issue impacts the economic activity in the affected areas, since many businesses that operate seasonally, are heavily dependent on the volume of beach goers every summer. As June rolled in, the month in which most people in Greece begin going to the beach, the impact was immediately noticed, with several news reports on local and national media discussing the subject. Throughout the summer, news reporting on the problems caused by jellyfish became frequent, as can be seen in Figure 2. This data was obtained by scraping the Google Search results pages, querying News results for the terms "μέδουσες|τσούχτρες" (two synonymous words for jellyfish) and dates 01/04 – 30/09/2017, total 146 discrete stories found.

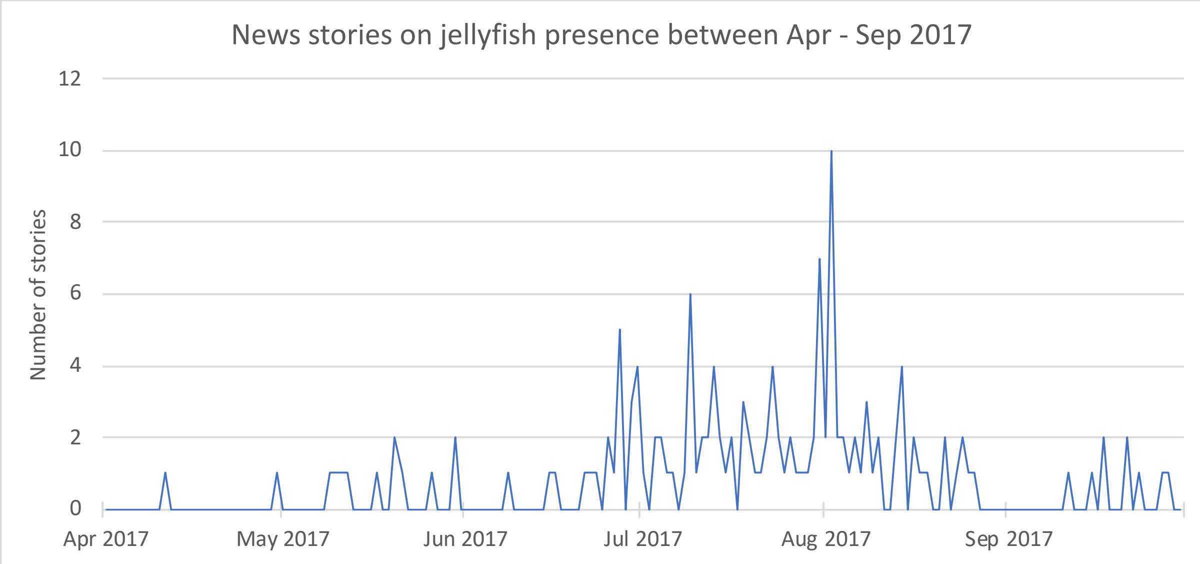

Figure 2. Number of discrete news stories about jellyfish appearing in local and national news portals (source: Google Search).

An inquiry on the matter was even brought to parliament by local MPs. Some rather desperate attempts were made at some beaches to solve the problem by laying miles of fishnets to surround swimming areas, but this was not a scalable solution. An idea for the introduction of schools of dolphins in the area, to prey on the jellyfish population, gained which was a rather unrealistic option. By the end of June, a few Facebook groups for people to report the presence of jellyfish were created, as an effort to coordinate and share knowledge between citizens. Even though these attracted several thousand members, the utility of the groups was low, because the reports were often inaccurate or unspecific (e.g. lacking location details, problem severity or time details), hard to search, and of course, because people needed to be Facebook members to partake in the exchange. After some consideration, I undertook an initiative to intervene and provide a crowdsourced application to help in the exchange of information between citizens. At the same time, and based on personal experiences, this was seen as an opportunity to solve other beach-going related problems that cause disappointment, such as driving for an hour only to find a windy beach, or one that's jam-packed with people.

3 Related Work: Key challenges in developing and deploying CS systems

Crowdsourcing systems are not a novel idea; The concept began in the mid 60s with scientists interested in monitoring wildlife, who decided to involve the help of volunteers in tracking and recording sightings in paper forms. With the advent of Web 2.0 and mobile, connected devices, which also contain sensors, the crowdsourcing movement gained increased momentum, as users were able to participate in real-time reporting systems for crowdsourcing data. Although crowdsourcing can be used in a wide range of applications, from data gathering, predictions, question answering, information processing or innovation (Luz et al., 2015), we are here mostly concerned in the former, namely the collection of primary data that others (the project owners) can later process offline, or even in real-time. This role of a crowdsourcing system is also termed "data augmentation" (Garcia-Molina et al., 2016). By reviewing the literature in crowdsourcing systems (especially state-of-the-art papers), we can draw the following taxonomy of major challenges for the design and operation of a crowdsourcing system, shown in Table 1. Justification for some of these challenges can be self-evident, however, in the next sections, we provide some commentary to highlight what we believe are key salient points from the analysis of this literature. Particular attention of the reader is drawn to section 3.1.2 (user retention and incentivization), as this forms the main focus of our paper.

Table 1. Key challenges in designing crowdsourcing systems.

Challenge	Sub-challenge	Factors
Involving users	User induction	Recruiting (the right type of) users (Luz et al., 2015)(Hetmank, 2013)(Kucherbaev et al., 2016)(Salim and Haque, 2015)(Abecker et al., 2012)(Kettunen et al., 2016)(Conrad and Hilchey, 2011)
		Train the users (Kucherbaev et al., 2016)(Cohn, 2008)(Conrad and Hilchey, 2011)
		Helping users understand their role and value (Brossard et al., 2005)(Bales et al., 2014)
	User retention	Maintain & incentivize user engagement (Malatras and Beslay, 2015)(Luz et al., 2015)(Zambonelli, 2011)(Chen and Shahabi, 2016)(Salim and Haque, 2015)(Bales et al., 2014)(Mechant et al., 2011)(Cohn, 2008)(Micholia et al., 2017)(Guo et al., 2017)
		Draw users attention to the contribution of others (Thiel et al., 2015)(Bales et al., 2014)
Designing Systems	Interaction design	Defining the contributions / tasks (Luz et al., 2015)(Hetmank, 2013)(Abecker et al., 2012)(Kettunen et al., 2016)(Garcia-Molina et al., 2016)
		Define the workflow (Hetmank, 2013)(Abecker et al., 2012)(Garcia-Molina et al., 2016)
	System design	Integrate with other computing environments (Mechant et al., 2011)(Kantarci and Mouftah, 2014)
		Ensure the technology supports opportunistic and horizontal participation (Charitos et al., 2014)(Zambonelli, 2011)
		Allow transparent access to collected data (Charitos et al., 2014)(Harding et al., 2015)(Bales et al., 2014)(Conrad and Hilchey, 2011)
		Ensure privacy (Malatras and Beslay, 2015)(Salim and Haque, 2015)(Bales et al., 2014)(Abecker et al., 2012)(Kanhere, 2013)(Zamora et al., 2016) (Gustarini et al., 2016)
	Data quality	Ensure adequate granularity and uniformity of spatiotemporal data (Maisonneuve et al., 2009)
		Assign task to right users at the right context (Hetmank, 2013)(Chen and Shahabi, 2016)(Sasao et al., 2017)(Niforatos et al., 2017)
		Allow user coordination (Hetmank, 2013)
		Evaluating user performance (Luz et al., 2015)(Hetmank, 2013)(Chen and Shahabi, 2016)(Kantarci and Mouftah, 2014)(Huang et al., 2010)
Managing operation		Manage the workflow (Hetmank, 2013)(Kucherbaev et al., 2016)(Abecker et al., 2012)(Garcia-Molina et al., 2016)
		Maintain project focus (Zhao and Zhu, 2014)(Bales et al., 2014)
		Manage trust between users and project stakeholders (Harding et al., 2015)
Interpreting data		Combining contributions (Luz et al., 2015)(Chen and Shahabi, 2016)
		Evaluate contribution quality (Kucherbaev et al., 2016)(Kamel Boulos et al., 2011)(Chen and Shahabi, 2016)(Angus et al., 2014)(Kanhere, 2013)(Muller et al., 2015)(Conrad and Hilchey, 2011)

3.1 Involving the users

3.1.1 Training users for participation in CS systems.

Crowdsourcing systems are heavily dependent on the ability to recruit users that will contribute data. It is also argued that these users have to be the "right type" of users, in the sense that they should be adequately knowledgeable in being able to use technology to participate in the system and also be able to make value judgments on the observed data and what to submit. Therefore users can either be experts in a domain, or if not, require a modicum of training to ensure their participation in the intended way. This training might include an explanation of the importance of their role in the system and the value of their contributed information. Users often have a focus on their own contributions - being able to draw their attention to the contribution of others can help their understanding of how they fit in as part of a wider whole.

3.1.2 User retention and incentivization in CS systems

One very important consideration in the design of a CS system is how to maintain the active participation of users. According to (Hossain, 2012) and their extensive literature review on motivation to participate in CS systems, incentivization can take many forms, leveraging intrinsic, extrinsinc and altruistic motivators. In (Katmada et al., 2016), intrinsic and extrinsic factors are explored to derive design recommendations for four incentivization mechanisms (reputation systems, gamification, social incentive mechanisms and financial/career rewards). Even though some users might commit to a system because of personal interest, others might only participate if motivated financially, or via a gamification system as recommended in literature. However, previous research notes that especially for financial schemes, these may increase participation, but involve a threat to data quality, since users are more interested in contributing a larger volume of data but not as concerned with its quality. It has also been shown that different compensation mechanisms can be to trade quality for the speed (Mao et al., 2013),(Mason and Watts, 2009) and that the level of compensation can be adjusted to predict the number of workers attracted to a task (Horton and Chilton, 2010). In this regard, the authors (Hossain, 2012) do not conclude in definite recommendations as to what the best motivators might be, since they find several examples in literature where intrinsic and extrinsic motivators conflict in CS systems, although (Kaufmann et al., 2011) seem to suggest that intrinsic motivators are more important than many extrinsic ones. In that study payment was the most heavily weighted motivator, although, somewhat ironically, their study was conducted with paid Mechanical Turk workers.

One noteworthy aspect in (Hossain, 2012) is that although the author mentions a third type of motivators, called "altruistic", these seem hardly researched (no reference is offered in the paper). In (Borromeo and Toyama, 2016), it was found that unpaid crowdsourced workers may offer equally good quality contributions compared to paid ones, but in their research the workers performed tasks as a one-off exercise and did not repeatedly engage with the system. More recently, (Katmada et al., 2016) explicitly mention altruism as one of the 7 core motive types for sustained engagement in CS systems, but do not mention any literature discussing this type of motive. It is unclear in (Hossain, 2012) whether altrustic motivators are a subset of intrinsic or extrinsic motivators, or a wholly different construct altogether, although (Katmada et al., 2016) classify altruism as an intrinsic motivator. Previous work referenced here in terms of motivation can, to an extent, fit under the Theory of Self-Determination (Ryan and Deci, 2000). Under this theory, a person's optimal motivation state is, by and large, to be intrinisically motivated, displaying a large degree of self-regulation. To achieve this state, a user needs to fulfill three basic needs: competence, autonomy and relatedness to a task. However, actions motivated by another type of extrinsic motivation, termed "Integrated Regulation", share almost the same qualities as those motivated by intrinsic motivation, even though these actions are performed to achieve a purpose, rather than for the sheer enjoyment of the activity. In this regard, altruistic acts can be seen to closely align to the construct of "Integrated Regulation". Some examples of altruistic tasks in CS systems are found in (Chandler and Kapelner, 2013), who found that framing Mechanical Turk tasks into a meaningful context (i.e. explaining why they might be important for others) both increases the level of participation, the quality of contributions and speed of work. Even though in this case the users were compensated for participation, adding an altruistic dimension clearly had a positive impact on their contributions. In (Goncalves et al., 2013), altruistic framing of the task improved the quality of participation (using public displays instead of participants' own devices), even when no authentication or quality control measures were put in place. Similar findings were obtained by (Rogstadius et al., 2011) using Mechanical Turk workers. It must be noted though that the three previous studies on altruistic framing of CS tasks were all performed by workers at comfortable settings (either a desktop computer in Mechanical Turk, or situated large-screen pervasive displays at opportunistic times, i.e. as the user passed by and had spare time).

3.2 Designing CS systems

3.2.1 Interaction design

Close attention must be paid to the mechanics and architecture of the CS system. Designing the system workflow and users' role in it is a crucial consideration. In particular, carefully designing the tasks that users are going to perform in the system needs special attention, because these tasks must be achievable and easy to perform (considering of course the users' backgrounds and abilities). Because of the varying users' backgrounds, some types of tasks might be suited to a subset of users. Additionally, the changing context of users may also determine the subset of users suitable for performing a task (e.g. because of location). Thus being able to assign the right task to the right users is another consideration for complex CS systems. Task assignment can also be influenced by the need to achieve a uniform granularity of data. For example, users in sparsely populated locations might be burdened with more tasks, while users in heavily populated locations might share the load and receive fewer tasks to individually complete. This introduces a potential need for coordinating users, so that, for example, they might mobilize to address data collection goals that are not achievable with the current dispersal of users. Regardless of the task at hand, the CS systems must support opportunistic and horizontal participation, allowing users to participate when available, but also with any type of equipment available at their disposal. The above recommendations are all supported by literature in Table 1, but they were also the concluding remarks in (Eveleigh et al., 2014), where it was found that despite incentives, most participants in CS systems are "dabblers" (i.e. low volume contributors), and that hence design of CS systems should support solitary, opportunistic, small-scale participation. Further to this, it has been proposed that CS systems should make the data transparently accessible to both users and project owners, so that users can maintain an overview of the state of the project and maintain trust relationships with the project owners. At the same time, privacy must be considered, especially in the case where the data might personally identify participants. Privacy is also an important implication due to the need for CS systems to be interoperable with other systems in many cases (e.g. feeding data into planning or predictive systems).

3.2.2 Usability of CS system user interfaces

Especially for the cases where CS data augmentation projects depend on the manual capture and submission of data by users, we have been mostly unable to find literature that proposes guidelines on how user interfaces for this purpose should be designed. In fact, in (Thiel et al., 2015) we find the following guidelines: Support adding pictures, support the quick generation of a report something and the ability to come back to fill more details later, provide a structure that facilitates easy browsing, use notifications boost engagement, and show project impact in application. Further, in (Harding et al., 2015) we find recommendations that the system should visibly attribute data to users and provide social communication channels for users. However in (Garcia-Molina et al., 2016) it is mentioned that "*A lot more research is needed to understand the available interface choices and their impact on performance and accuracy*."

3.3 Managing the operation of a CS system and interpreting data

During the operation of a CS system, two major challenges are identified in literature. First, managing the trust between project owners and users is important because users need to be assured not just of the privacy of their contributions, but also need to see that the data is actually being used for something which benefits either them directly, or serves a common goal. Secondly, it is noted that project owners need to actively ensure that the project focus is maintained and that users do not inadvertently (or purposely) shift the project focus elsewhere by mostly submitting information that project owners are not primarily interested in.

CS systems are viewed skeptically by many researchers - it is often argued that the quality of the collected data is not sufficient for reliable analyses and indeed this is a serious consideration. User contributed data may suffer from biases and inaccuracies, due to the participants' lack of training and expertise, equipment diversity and malfunctions, or even malevolent use of the system ("trolling" the project owners). Although it is argued that low-quality information might essentially be non-consequential noise in a sea of good quality contributions, assessing the extent of the "noise" problem and placing mitigation strategies in place is essential. Another challenge is the combination of user contributions, which can take place when users perform diverse sub-tasks which, put together, produce knowledge, but also in the case where the data collection is semi-automatic (some data contributed manually by the user and other data gathered automatically by sensors).

3.4 Research questions

The success of crowdsourced systems depends on user participation, and because financial compensation requires a significant investment (not just financial, but also in terms of management) on behalf of the authority (public or private) that manages the system. Other forms of studied incentives (e.g. gamification, or image-related rewards) have a limited appeal that relates to specific types of user personality and profile (e.g. age, gender (Koivisto and Hamari, 2014)) and their effect may fade with use (Cechanowicz et al., 2013)(Koivisto and Hamari, 2014). Thus such methods are likely unsuitable for incentivizing a large part of the population. Gamification also seems to have varying impact the quality of contributed data, with some researchers, e.g. (Cechanowicz et al., 2013) finding no impact, while others, e.g. (Van Berkel et al., 2017) finding positive impact. Bénabou & Tirole (Bénabou and Tirole, 2006) argue that rewards or punishments for pro-social behaviours place doubt on the true motives of people that engage in them, therefore previous studies using such incentives for participation are likely unsuitable for exposing the true motives of participants in such systems. A relatively unexplored form of incentivisation that involves no reward system is the exposure of data to the contributing population, but this has been only mentioned in passing in only a few papers and not throughly evaluated (Charitos et al., 2014)(Harding et al., 2015)(Bales et al., 2014)(Conrad and Hilchey, 2011).

In this work's case, participation can be seen as a pro-social behaviour, because contributing information does not personally benefit the user (although the user expects to benefit from the contributions of others). User who volunteer information to the system do so at a personal cost (time, consumption of data package etc.). Based on the literature review above, exploring the motivation of users for participation in crowdsourcing systems, where incentivisation does not take a form of a reward (e.g. participation in a game, image-related rewards or finacial gains), was particularly interesting. Further to the work of (Rogstadius et al., 2011)(Goncalves et al., 2013),(Chandler and Kapelner, 2013), one aim of this work was to add to the severaly limited literature exploring participation with altruistic motives in CS systems, i.e. contributing data altruistically at a personal cost, for the sake of others, and in the hope that beneficiaries of the contribution will reciprocate by also contributing data. The distinction made in this work is that in these previous studies, the personal cost due to altruism to the user was only their time. In contrast, this paper examines the strength of altruistic motives in CS participation in a *mobile* setting, where significant additional costs and barriers exist (e.g. interaction with touchscreen mobile devices, interaction in natural environmental conditions, mobile broadband connectivity/speed/cost issues). Therefore, the two main aims of this paper are:

a) to expose the motives driving participation in a *mobile* crowdsourcing system when no explicit rewards are offered, and
b) to examine whether the lack of rewards impacts the quality of data contributed to a *mobile* crowdsourcing system.

Additionally, a further aim was to explore the experiences of running of our crowdsource system in relation to the other main challenges outlined by the literature above. To answer the research questions, two types of evidence were examined. First, the paper presents an analysis of the quantitative data that describes the interactions of 13,430 unique users with the system, with particular respect to the levels of participation and quality of contributed data. Secondly, the paper presents an analysis of subjective data emergent from responses to a survey of 94 system users and comment on how they complement the findings from our quantitative analysis. Finally, the paper uses data from this survey to discuss the interaction and user experience aspects of participation in the system.

The paper begins with a description of the implementation of the system (Section 4). A discussion of the quantitative data emergent during system use follows (Section 5). Then, section 6 discusses the analysis of subjective data on the system obtained via survey. A further section (7) discusses the use of the system data for urban planning sections. Finally, the paper draws conclusions and reviews the experience from the operation of the system.

4 Swymm: System Development

As explained in the motivation section, the system was developed expeditiously, because of the pressing need to provide a solution quickly, before the swimming season ended. Following an established development methodology, such as Human-Centered Design or Design Thinking, would simply have taken too long. Furthermore, because of the need for haste and also to be as inclusive as possible, developing a native mobile application was decided against, and instead opted for a web-app front end, effectively a mobile-oriented website, whose main functions are shown in Table 2 and Figure 3. To increase inclusion, the system also did not require a registration and log-in process, making it available for any visitor to use.

Table 2. Main functionality of Swymm user interface.

System section	Functions
Starting page	Overview of recent reports
	Select a beach by drilling down municipality and area menus
	Go to beach details
	Go to add new beach
	Go to Swymm Facebook page
View specific beach	Show map of beach location
	Show meteorological data for beach
	Show 5 most recent reports
	Go to add a new report
Add a new beach	Add a new beach location via map
	Add beach details
	Submit
Add a new report	Fill in report details
	Specify social network sharing options
	Submit
View all beaches	Show map and all beach locations
	Select beach by tapping icon
	Go to beach by tapping infowindow link

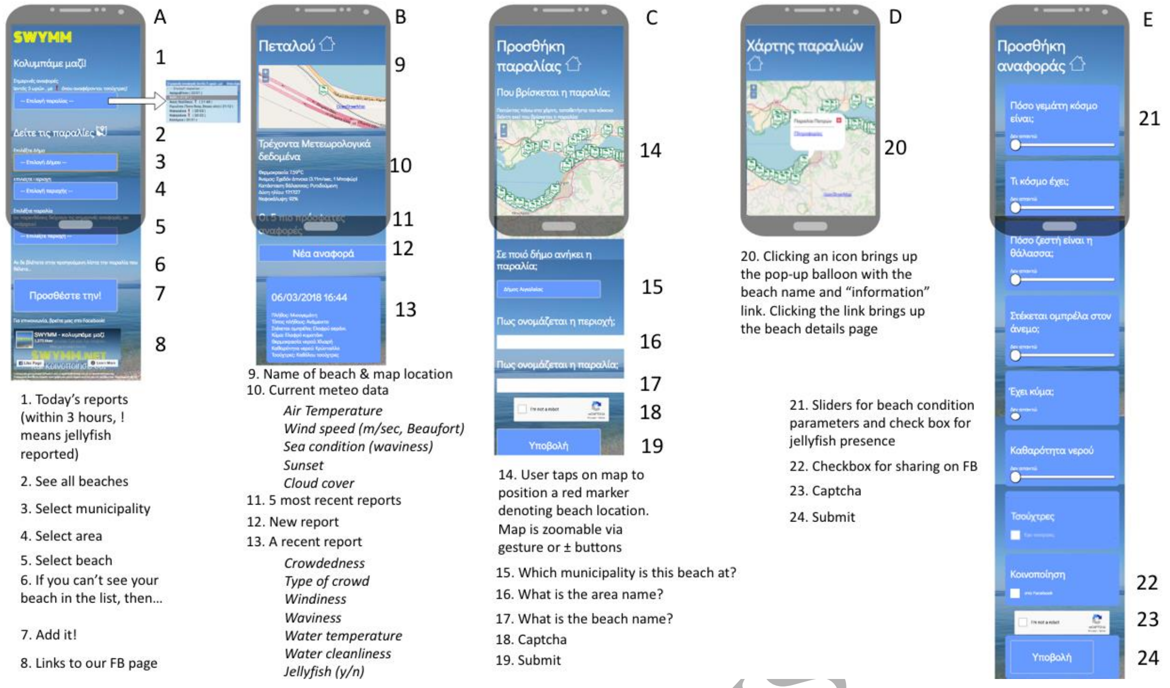

Figure 3. **The application's main sections, Starting page (A), View specific beach (B), Add new beach (C), View all beaches (D), Add a report (E). The device frame represents the approximate "page fold" using a 412x732 screen resolution, corresponding to a Nexus 5X device.**

Responsive or adaptive design was also decided against, because the driving need was to be able to partake in the system from a mobile device (by adding reports) and because the information volume in the system was low, hence there was no real need for a complex desktop-oriented UI. In terms of the UI design choices, these were informed mostly through personal background knowledge and a quick brainstorming exercise to identify and prioritise the user needs, based on the observation of users' expressed concerns on Facebook pages and private discussions. In short, the following basic interaction needs where identified, in this order: 1) See which beaches have jellyfish at a glance, 2) Find a beach and see its current condition, 3) Add a new report for a beach, 4) Add a new beach. To achieve these goals, the screens were designed as follows:

- See which beaches have jellyfish at a glance: Since the starting page was the entry point to the system, the first prioritised need was implemented at the top of that page. This was done with a dropdown menu limited to contain the names of beaches with reports in the last 3 hours. A map was also considered but discarded because of the potential POI occlusion problem (many nearby beaches). Each menu entry was accompanied by a red exlamation mark if the most recent report for that beach indicated the presence of jelly fish.
- Find a beach and see its current condition: In the starting page, the "find" part of the second prioritised need was also implemented, allowing the user to navigate to a specific beach information page by selecting the municipality, area and beach name from dropdown menus (dynamically filled as the user selects each option in sequence), or by navigating to the map overview page, where the user could locate a beach on the map and navigate to its details page by tapping its icon. A search button was also considered, but this was less practical since mobile typing is much more difficult that selecting options from drill-down menus. Seeing a beach's current conditions was done with a dedicated separate page. A small map was placed at the top of the page, to help users verify that the entry in the system also matches their knowledge of the location, or to be able to locate the beach if it was unknown to them. Then, immediately below the information collected by the weather API was placed, since this information was always available even if no reports were added. Then, a button was added to allow users to add reports for that beach, and this was followed by a list of the 5 most recent reports for that particular beach.

- Add a new report: As mentioned, the "add report" button was placed above the recent reports list in the beach details page, to prevent the user from having to scroll through all the information in order to add a report. A separate page opened to allow the initiation of the data entry task. For the data items, sliders that the user could scroll up and down to were chosen, to allow better one-handed use instead of menus, which might be problematic for some phones (thumb reach).
- Add a new beach: Since this was the lowest priority function, we "buried" it a the bottom of the starting page, albeit at a logical place (after the final dropdown with the beach names), so that if a user could not find the beach they wanted, they could immediately begin the process of adding it by pressing on the large "add a beach" button. A new page opened up for this task, with a logical order of selecting a municipality from a drop-down (to ensure entry uniformity), and two free-form text fields so that the user could enter the beach area and name.

Overall, the initial development effort prior to release, and including functional testing and the creation of a social network page on Facebook, took approximately 3 days. The system was released for public use on July 12th 2017 and was advertised on Facebook, and a press release to a popular local news portal. Some modifications and additional functionality to the system were implemented during the usage period, based on the observation of user behaviours and recommendations received through Facebook, from the user base. The system language was set to Greek only, since the region is not particularly popular with tourists and also to increase the inclusion levels. In summary, the data that users could contribute to the system is shown in Table 3.

Table 3. Data manually contributed by users through the Swymm interface.

Type of submission	Variable	Value space
New beach	Crowdedness	Not submitted, empty, calm, half-full, almost full, completely full
	Crowd type	Not submitted, only young people, mostly young people, mixed crowd, mostly families & older people, only families & older people
	Water temperature	Not submitted, cold, relatively cold, mild, warm, very warm
	Windiness	Not submitted, no wind, slight wind, moderate wind, windy, typhoon
	Waviness	Not submitted, smooth, light waves, moderately waves, wavy, tsunami
	Water cleanliness	Not submitted, crystal clear, some bubbles or litter, several bubbles or litter, many bubbles or litter, toxic danger
	Presence of jellyfish	Yes / blank
New report	Municipality	Dropdown list of covered areas
	Area name	Freeform text
	Beach name	Freeform text

5 Analysis of usage quantititative data

Because the system did not require user registration, it cannot be ascertained whether the contributed reports and beach locations were made by a limited number of "enthusiastic" users. Therefore the contribution made by the overall body of users is reported on. The analysis in the next sections is based on data between July 12 and September 15 2017. In the analyses presented throughout sections 5 & 6, the choice of statistical test is based on the distribution of the data (examined using Shapiro-Wilk normality tests).

The rest of this section is organised as follows. First, an overview of usage statistics (5.1) and usage platforms (5.2) from Google Analytics data is presented. This is followed by an analysis of the behaviour of data contributors in terms of adding new beaches (5.3) and beach condition reports (temporal patterns: 5.4, richness and completeness of reports: 5.5). An analysis of the data quality in the submitted reports ensues (5.6) and finally the paper discusses the user engagement via social networks in section 5.7.

5.1 Usage overview

The system included Google Analytics tracking in the service to track the users' behaviour and can hence report some relevant statistics for the period of July 12 until September 30. Overall the system proved quite popular, with over 220,000 page views (>130k unique) (Figure 4). Users spent a short amount of time with each page in the system, approximating 1 minute in duration. Overall, 13,430 users appear reported, carrying out a total of 52,230 sessions. Each session had an average of 4.39 pages viewed, for a total average time of approximately 3m22s. Comparing these numbers to the 1,8k reports received, it appears that our body of users were mostly viewers, with a small number of active contributors, since only approximately 1 in 25 sessions included the submission of a report. However these contributors made a massive impact to the system use: without that contribution of data, other users would have no reason for visiting the system. 74.3% of the users were reported as being returning visitors – people who saw value in the service and returned multiple times to consult it.

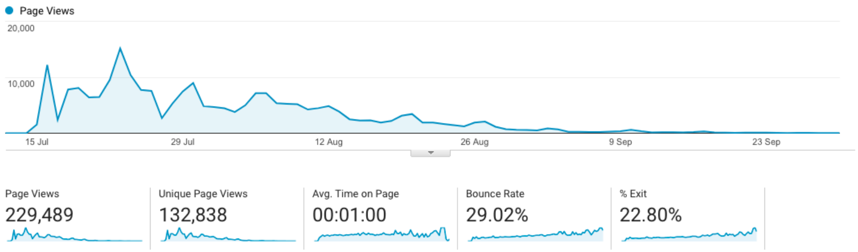

Figure 4. **Google Analytics usage overview, excluding report pages.**

By large the most popular page was the index page, with approximately 130k page views (over half of all traffic). There is a clear explanation for this: because the index page showed a list of recent reports, it was easy for users to check if a particular beach that interested them was reported recently as having problems with jellyfish or not. For the users, this seemed to be the most important bit of information in the system. Interest in the system began to decline after the 2nd week of August. Two interesting dips in the usage data (3rd week of July and 4th week of July, show dates where the weather was rainy and unfavourable for swimming.

5.2 User devices and service utility

The service was visited mostly by mobile users. Android and iOS users made up for 75% of all sessions (60.63% and 14.34% respectively). The remainder of the sessions was made via desktop or laptop computers running Windows (23%) or other desktop computer OS (2%). This non-trivial percentage of users shows that the service was considered in many cases as a tool for planning a visit to the beach, rather than just an ad-hoc consultation service. The fact that the website hadn't been designed for desktop browsers but still achieved high levels of access through those, demonstrates a case for Heckel's Law (Derrett, 2004): The quality of the user interface is relatively unimportant in determining adoption, if the perceived value is high. The same law, to an extent, applies to the mobile-oriented UI.

5.3 Data contributors: Adding new beaches

The service was released with 32 beach locations which were brainstormed across a few colleagues. A function was added to allow users to submit via the service the location and details of beaches that did not exist in the system. The submitted information was manually checked for validity on a daily basis before being allowed to appear to the users. Examples of invalid beaches included a few cases of abuse (e.g. using profane language for the name of a beach), but mostly were duplicates of beaches which already existed in the system. A significant volume of irregularities in the submisson of free-text data (beach names and areas) were noted, such as spelling mistakes, writing in all capitals, or in Greeklish (greek, but using the latin alphabet), which we corrected prior to approval. In the course of the service deployment, users submitted a total of 392 beach locations, and 154 of those were approved, resulting in a final number of 189 beaches displayed in the system.

One interesting observation here is to note that the valid beaches were added mostly on two distinct dates: On July 13th and August 11th, we received 112 and 36 valid beach submissions. On all other dates, we had between 0 and 6 submissions of valid sites only. This leads to the belief that a few enthusiastic users probably undertook a substantial effort on those two dates to submit as much information to the system as they could.

5.4 Data contributors: Temporal patterns in submitting reports

In total, 1,893 reports were received from system users. Out of these, 50 reports were found to contain no data items (blanks) and excluded them from the analysis presented in this section. In analyzing the breakdown of the volume of received reports by weekday, it was noted that user report submission was greater during weekends (Figure 5). This result is logical as more people tend to flock to the beaches on these days, so we would expect the same to apply to our contributor population. A less expected result was that Monday and Wednesday, days on which the city centre shops are closed after lunchtime, had fewer reports than other full-working days, like Tuesday, Thursday and Friday. Empirically it is known that people in the region also flock to the beaches quite heavily on Monday and Wednesday afternoons, so this was a somewhat surprising finding.

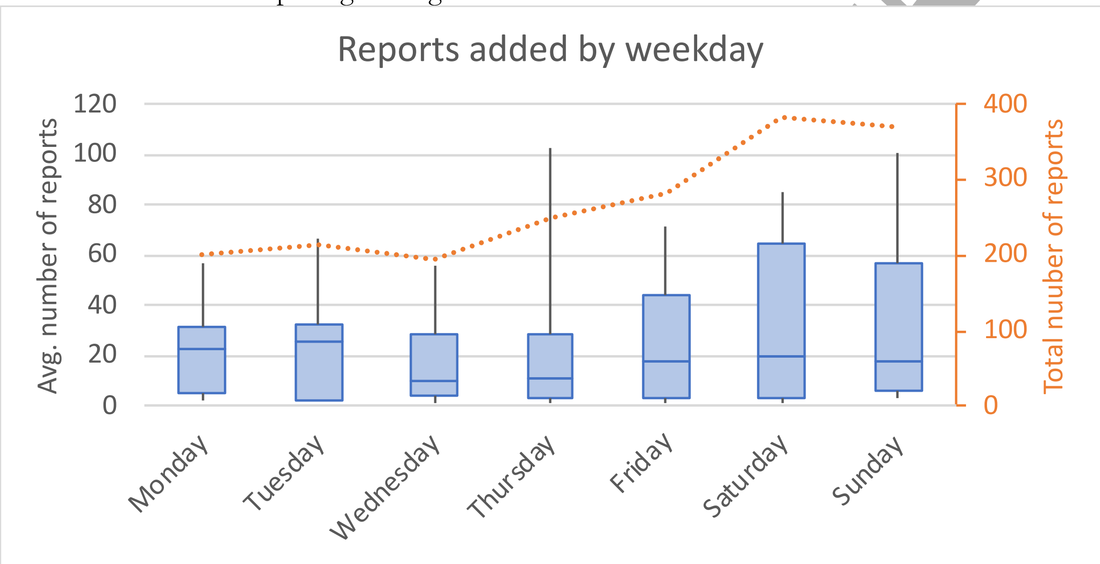

Figure 5. A breakdown of non-blank reports (N=1843) received by day of week (error bars at max/min values). The orange line shows the total number of reports.

Breaking down the reports by hour on which they were received (Figure 6), some behaviour appears reasonable (i.e. most reports received in the daytime), but an interesting pattern emerges from the data. It appears that the reports have two peaks, one at midday (around 12) and then another, smaller peak in the afternoon (16:00 and 17:00). This indicates that the users arrive at the beaches in two distinct crowd waves: one around midday (early swimmers) and another wave in the afternoon (late swimmers). The decline after these peaks is reasonable. Given that the average swimmer will stay at the beach for a few hours, it appears that the users were reporting beach conditions soon after they arrived, but did not further engage with the system before leaving the beach.

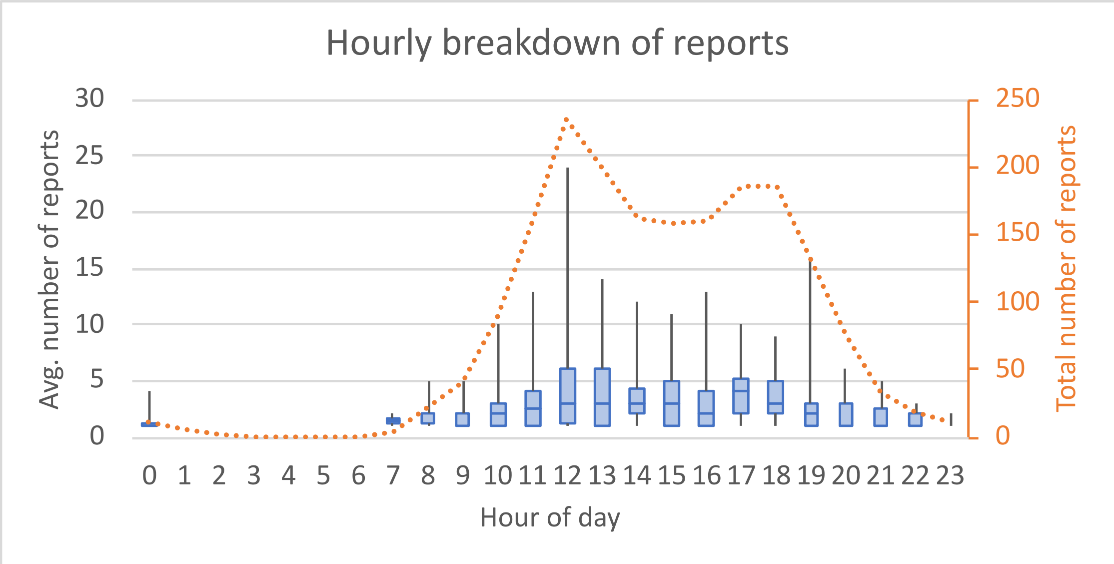

Figure 6. **Hourly breakdown of received non-blank reports (N=1843) for the entire period (error bars at max/min values). The orange line shows the total number of reports.**

Further breaking down the hourly reports by day (Figure 7), also reveals some interesting insights. It appears that the "twin peak" behaviour mostly holds for all days except Saturday and Sunday. On Saturday, the early peak is higher than on weekdays and holds for longer while on Sunday, the early peak is significantly stronger than on any other day. Simply put, on Saturday it appears that the users started flocking to the beach on a continuous flow until early evening, while on Sunday, users flocked to the beaches mostly around lunchtime.

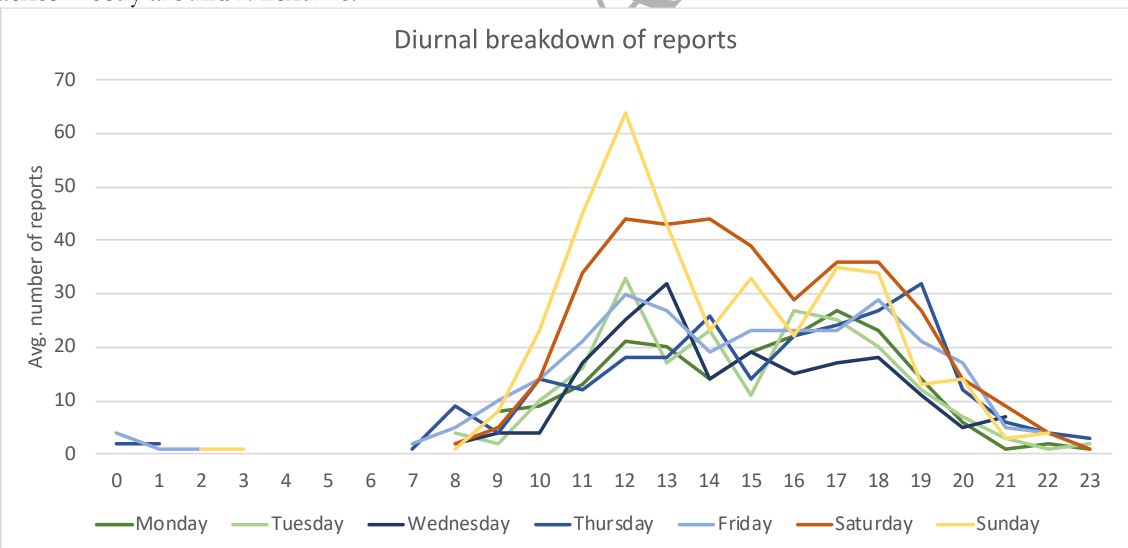

Figure 7. **A diurnal (hourly and by day) breakdown of non-blank reports for the entire period (N=1843). Lines show the total number of reports.**

5.5 Data contributors: richness and completeness of submitted reports

From the reports, a small proportion (50 reports, or 2.6%) contained no data at all, since users were able to submit a report leaving all the sliders to "not submitting" (Figure 8). Therefore this way of "trolling" the system was seldom employed by users. All other reports contained at least one element of observed information. The majority of reports (71.6%) included information for all the other 6 beach state items (excluding jellyfish presence). Therefore it can be concluded that users, when engaging in reporting, mostly took the time to provide all the details, meaning that the number of items asked to report was not excessive, and that users generally found the use of sliders to be a quick and easy way to provide information.

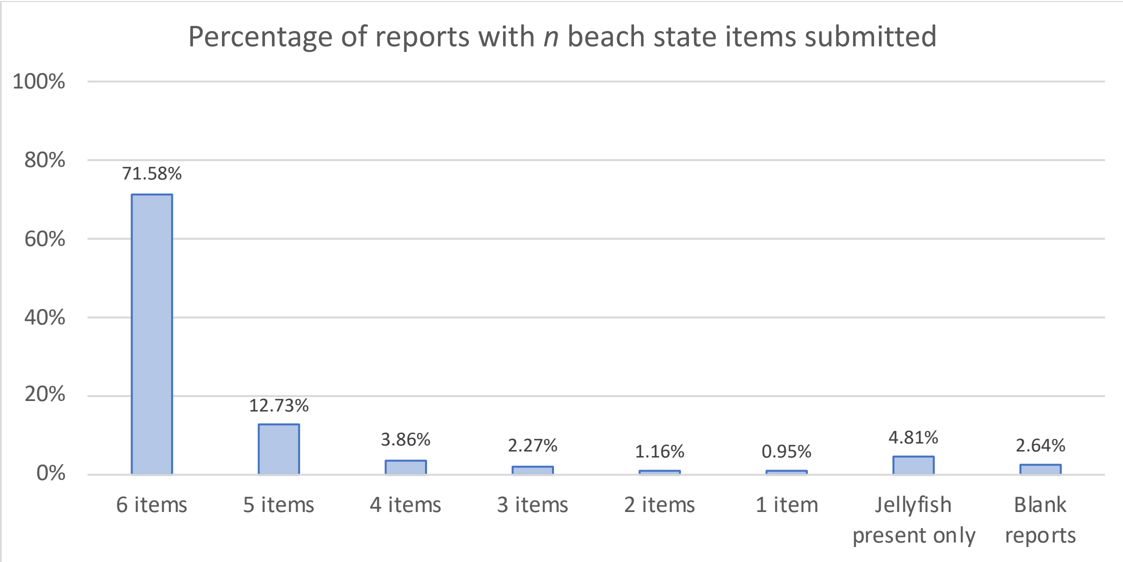

Figure 8. Most reports were received with all 6 data items (except jellyfish) completed (total N=1893).

From there on, since the main motivation for the implementation of the system was to allow users to report the presence of jellyfish, a natural assumption would be that use of the system would be mostly made when this problem was observed and that users would not bother submitting reports when the problem was not present. Contrary to this initial assumption, as can be seen in Figure 8, only 4.8% of reports were submitted with the presence of jellyfish being the only information being provided. If users' only motivation was to report the presence of jellyfish, this figure could have been expected to be much greater. Only 637 reports (33.7%) were found to indicate the presence of jellyfish. One note to make here is that the jellyfish reporting was binary (checkbox), therefore it is unknown whether the 1256 reports that didn't contain information about jellyfish meant that users didn't see any, or weren't aware of the existence of any jellyfish. However, the conclusion is that users saw value in reporting other beach conditions to peers.

5.6 Data contributors: reliability of the crowdsourced data

One of the greatest concerns in crowdsourced data is ensuring the validity of submitted information. Crowdsourced systems are always susceptible to misuse and "trolling" – users who maliciously contribute invalid data. So far, these observations from our system provide some evidence to support the notion that user reported data might actually be mostly reliable. Of course, a level of trolling the system was still encountered. For example, the crowdedness reports for early morning hours show unusually large average crowdedness at the beaches, which defies logic. However, these reports are 0.8% of the total volume received, and while some people do indeed to go swim at night, we should discount this data as probably malicious. This isn't to say that bad data isn't submitted at other times. However, it's a rather small percentage that doesn't affect the overall picture given by the vast majority of submitted reports.

5.6.1 Comparing reported wind intensity with meteorological data

Another way to check the users' attitudes towards submitting valid data would be to compare the reported wind intensity from our users, with the forecasted wind intensity received at the time of the report. From July 24th onwards and after a user's suggestion, a function was added to display meteorological data on the beach detail page, retrieved from the from the OpenWeatherMap.org API (actual intensity). During the ensuing period of use, wind speeds between 0 - 12.3m/sec were recorded, with an average of 2.57m/sec (sd = 1.90m/sec). As can be seen in Figure 9, the average actual wind speed was reported to be higher for each of the category labels in the UI, demonstrating that the users were able to clearly distinguish between different categories of wind speed and provide reports that matched actual conditions.

Some "trolling" of the system was again noted in the "typhoon" category label, where 14 reports were received. The label is humorous and possibly invited such behaviour, but again it represents just 1.2% of all reports. Other categories received 136 (not submitted), 420 (no wind), 417 (slight wind), 142 (moderate wind) and 67 (windy) reports. Excluding "not-submitted" and "typhoon" reported cases, the continuous scale windspeed data was transformed by "binning" according to the Beaufort scale (thereby arranging into an ordinal data set) and a correlation analysis revealed that windspeed is positively correlated to user-reported wind category with statistical significance ($\varrho_{(1608)}$=0.146, p=0.000, Spearman ranked correlation, 2-tailed).

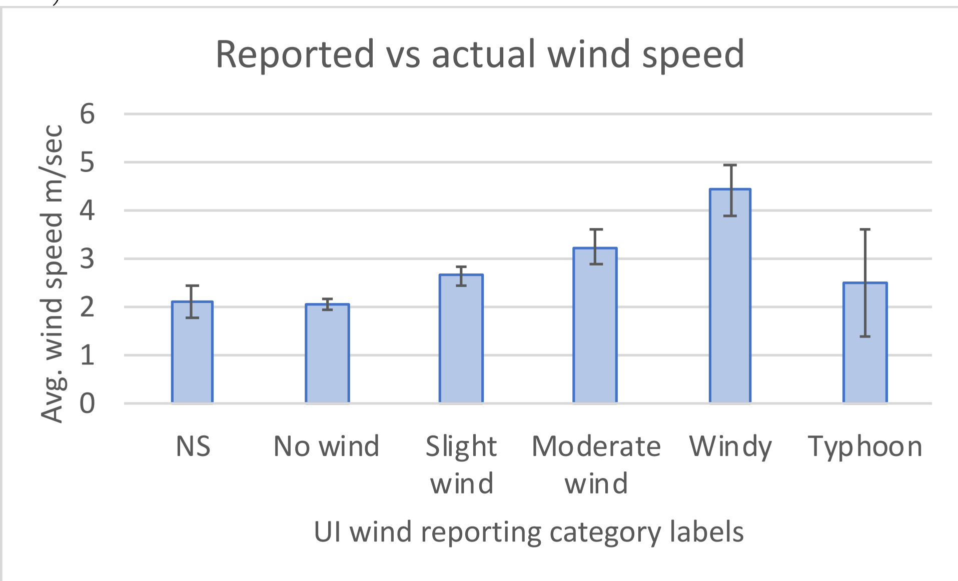

Figure 9. **Reported windiness compared to wind speed data from the meteorological API (total N=1893). Error bars at 95%c.i.**

5.6.2 Comparing reported sea waviness with estimated waviness from meteorological data

Based on the actual windspeed and converting to the Beaufort scale, it is possible to characterise the likely condition of the sea (in terms of its waviness), into several conditions, e.g. "Mirror, Ripples, Small wavelets, Large wavelets" etc ("Beaufort wind force scale - Met Office," n.d.). This calculation was added to the beach details page, while allowing users to report the waviness of the sea. As shown in Figure 10, users reports tend to largely match what is predicted via the OpenWeatherMap API information, so for example, when users reported the sea was "wavy", 53.3% of the reports included a forecast of small wavelets and the percentage of reports where small wavelets was forecasted decreases as the users report more favourable sea conditions.

One should bear in mind here that forecasted sea conditions are not an exact guess, since obviously the condition of the sea depends on the geography and wind direction (e.g. waters in a bay may be rather calm, even if a strong wind is blowing). However these results, and especially the "smooth" reported sea condition column, show that users mostly enter data that matches reasonable predictions. Some "trolling" of the system is again noticed as some users reported on the humorously-labelled maximum "tsunami" condition value. These were only 11 reports (0.9%). Excluding "not-submitted" and "tsunami" reported cases, a correlation analysis reveals here too that reported waviness is positively correlated with the calculated waviness ($\varrho_{(1679)}$=0.081, p=0.001, Spearman ranked correlation, 2-tailed).

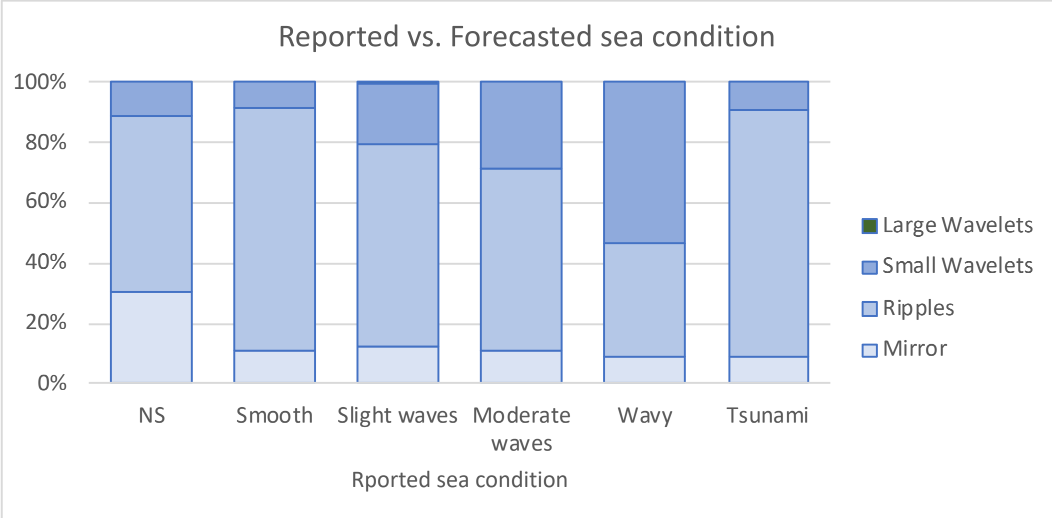

Figure 10. Reported sea waviness against forecasted sea state condition (total N=1893).

5.6.3 Comparing reported crowdedness with report volume

Assuming that the users who contributed data form a reasonably representative sample of the general population, one would expect to see similar patterns emerge in the volume of reports submitted by our users, and the reported crowdedness of beaches. To check if that assumption holds, the crowdedness level reported by our users against the day and time of the report was examined, excluding reports were crowdedness is not submitted (Figure 11). The results of this chart largely match the pattern seen in the number of received reports, except Thursday and Friday, thereby lending a degree of confidence in the reported data.

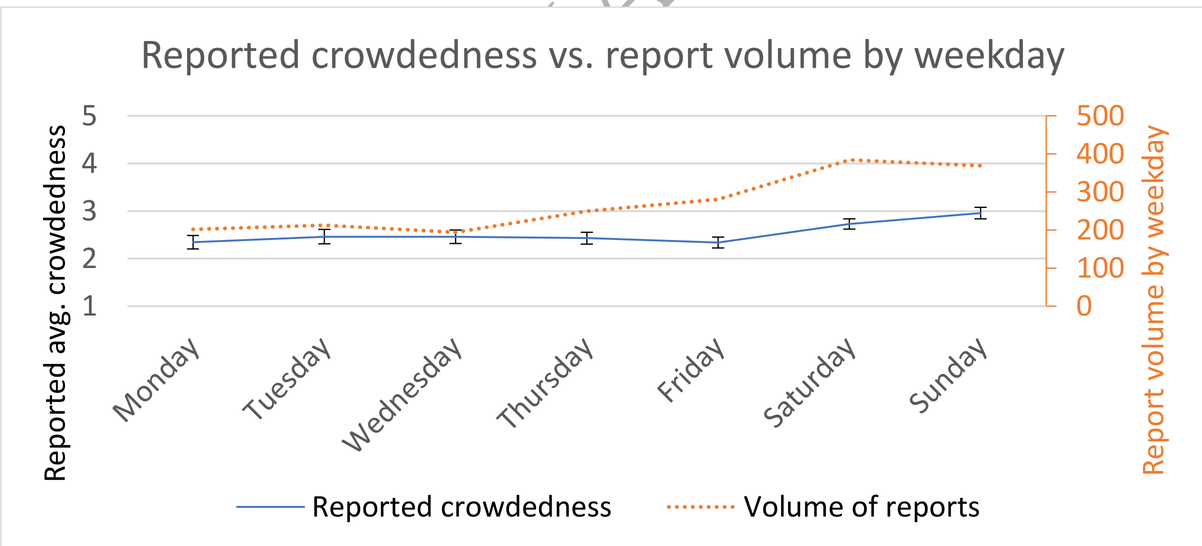

Figure 11. Reported busyness on the beaches by day of the week, according to user non-blank reports (N=1843), vs. volume of reports. Reported crowdedness is on a scale of 1=empty, 5=very busy. Error bars at 95%c.i.

Further, the hourly breakdown of reported crowdedness against report volume was plotted (Figure 12). Excluding those hours where only a few reports were submitted (00:00-09:00 and 21:00-00:00), the reported crowdedness of beaches steadily rises in the morning, while remaining more or less constant throughout the day (orange line). This discrepancy with against the report volume (blue line) is reasonable: The latter shows that the contributor population arrives at the beaches in two distinct "waves" and one might reasonably assume that they will contribute a report only once during their visit, perhaps shortly after arriving. If the general population also arrives in two "waves", as the early swimmers flock to the beach and stay for a few hours, by the time they leave, they are replaced by more swimmers from the second wave. Hence the beach population should be reported to be relatively the same throughout the day, which is exactly what is observed here.

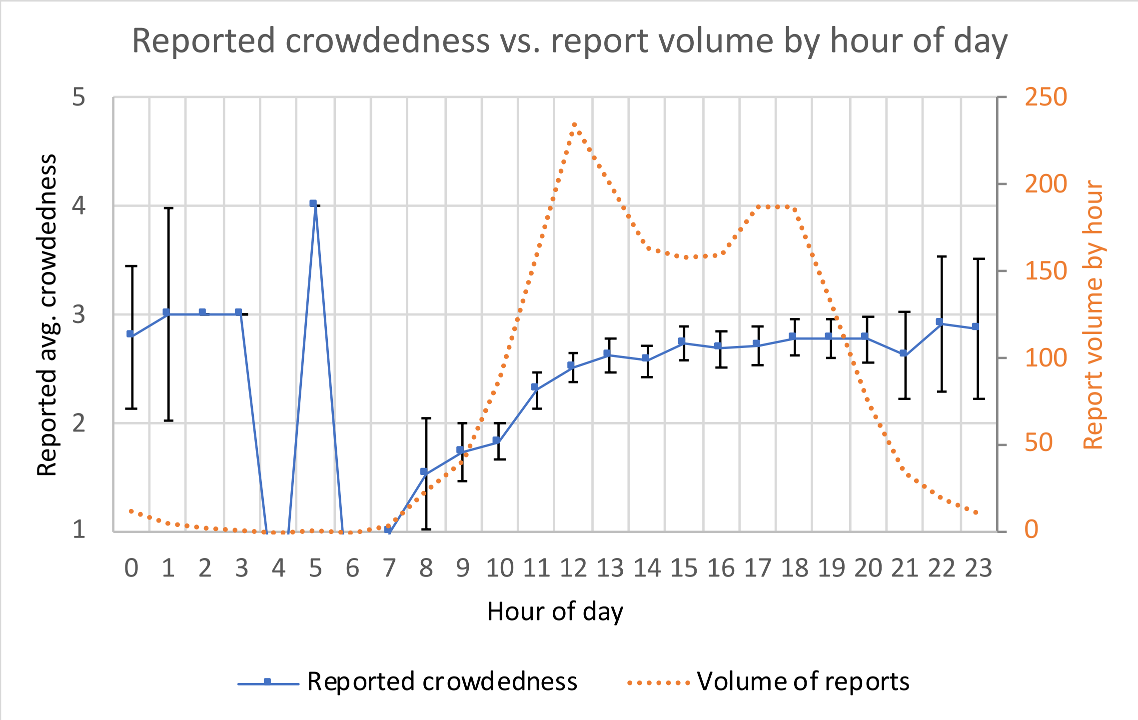

Figure 12. **Busyness of beaches according to reports, by hour, vs. volume of non-blank reports (N=1843). The data for hours 0-9 and 21-00 represent 63 total reports and can be considered as examples of "trolling" the system (bad data). Crowdedness is on a scale of 1=empty, 5=very busy. Error bars at 95%c.i.**

5.7 User engagement via social networks

To accompany the service, a Facebook page was created to assist communication with the users. The Facebook page attracted 1,253 likes and received 13 reviews, for an average rating of 4.8/5 stars. One interesting observation from the community engagement with the posts made on the page, was the nature of some of the comments and the messages that were received. Several users messaged the page to ask whether we could tell them if jellyfish were currently present, or were likely to be present later in the day, in specific locations that they were interested in. In all these cases, there were no reports had been submitted by other users for these locations, and those who messaged the page seemed to believe that the system operators had some way of not only knowing the state of play at every beach, at any time, but also the means to predict the future conditions at any beach. Several other users also posted on the page to let others know that jellyfish were present at their current location, instead of submitting this information via the service.

Prior to developing the service, it could be anecdotally observed amongst social network communities, that some users were posting the conditions of the beaches they were at, to let their friends know if they encountered jelly fish, or unfavourable swimming conditions. In several cases, these social posts included invitations to join them at the beach (e.g. "I'm at xxxx beach, the water is perfect, come and find me there if you're doing nothing"). To assist with this behaviour, an option to share a report on Facebook was added to the report submission function. Therefore a user can take advantage of this functionality to let their immediate social circle of the conditions they've encountered, and also disclose their current location. Contrary to expectation, the functionality was little used. Only 53 reports were socially shared on Facebook. Speculating on the lack of use of this function, it is possibly attributable to the privacy implications that this contains. Sharing the report on Facebook lets one's social circle know where a person is (or has recently been) and the type of activity they were involved in (taking some time out for leisure). On the other hand, since the reports viewed in the system are anonymous, users would feel relatively safe in engaging with the system. Having user accounts would allow reports to be submitted with the user's name (or nickname) in the system and that could help with motivation and validity checking (e.g. gamification, adding kudos points to contributors for accurate reports) – however the clear lesson here is that user anonymity should be preserved and that users should be encouraged to use nicknames upon registration. Something that might also help social engagement, would be an option to share the reports of others (for example, to share another user's report with friends on Facebook timelines, or via private message, to tell them that a particular beach they like looks promising, without necessarily meaning that the sharing party is there, or that they intend to go).

5.8 Summary of findings

From the previous analysis of quantitative data, it was found that the active contribution of data volunteered by a critical mass of pro-social users, and the open exposure of this data to every user of the system, resulted in a successful adoption and use of this simple crowdsourcing platform. Although the system did not take specific measures to ensure data quality, there existed compelling indicators that the volunteered data was rich and largely reliable, with abuse of the system remaining at very low levels. However, these findings leave several open questions. What were the motives for volunteering data, or the barriers to volunteering? Why did the system succeed despite the absence of an incentivization scheme? What led to the contribution of valid data? And what else could have been done to encourage further participation? To answer these questions, qualitative data in the form of an e-survey was gathered and analyzed, after the system's period of use. In the next section, the analysis and answers to these questions is described.

6 Subjective aspects of use

Following the summer period in which the system operated, an on-line survey to users of the system was issued. The survey was advertised over 4 weeks in the Facebook page of Swymm, and in the final week the survey was advertised via Facebook, targeting all users residing within a 30km range of the city of Patras. Participation in the survey was incentivized by taking part in a draw for a €50 gift card. Prior to participating, respondents were informed that the survey applied only to users of the system and that participation implied a declaration that they were over 18 years of age and had used the system at least once, whether for the purposes of consuming information or contributing to it. Overall the post reach exceeded 2800 Facebook users and 94 valid (complete) responses to our survey were received. Out of these, 55.3% of respondents (N=52) used Swymm to add a beach condition report, and these participants are termed as "contributors" in the subsequent sections, the remaining users being termed "consumers".

The rest of this section is organised as follows: Participant demographics (6.1) are presented first, followed by their stated purpose of use of the system (6.2) and perceived utility of the system (6.3). Next, the paper discusses the participants behaviour with regard to contributing data (6.4). This discussion begins with the surveying of data consumers about the barriers that prevented them from contributing data (6.4.1). From there on, the motivations of data contributors for supplying reports are discussed and their attitude towards speculative motivators is compared with that of consumers (6.4.2). Further, the contributors' behaviour during the submission of reports is examined (6.4.3), as well as the barriers that prevented them from contributing more systematically (6.4.4). The perceived quality of the contributed data in the system from both consumer and contributor perspectives is discussed in 6.4.5 and this section ends with an exploration of the role of anonymity during participation and contribution. Finally, section 6 ends with an assessment of the overall user experience, using the UEQ standardised questionnaire (Laugwitz et al., 2008).

6.1 Participant Demographics

Respondents were female by majority (67%). The largest age group was people aged between 31-35 (25.5%), followed by ages 36-40 (20.2%), 41-45 (16%) and 26-30 (14.9%). The remainder of participants were very young adults (18-25, 5.3%) and other age groups were 46-50 (7.4%), 51-55 (6.4%) and 55+ (4.3%). Participants were asked if they had participated in crowdsourcing systems similar to Swymm in the past, and 50% of our respondents indicated no previous experience, 36.2% experience of one or more and 13.8% mentioned frequent partipation in similar type systems. When asking about the hardware devices they used to acces Swymm, 61.7% mentioned use exclusively from their mobile device (smartphone or tablet) and 20.2% mostly from their mobile and sometimes from their stationary desktop / laptop device. 10.6% reported mixed mobile / stationary computer user, 6.4% mostly stationary computer use and 1.1% only from their stationary computer. This finding matches the Google Analytics result seen earlier, in which 75% of all sessions were from mobile operating systems, therefore attributing a reasonable first indicator of truthfulness in the responses (and that they may in fact form a reasonable sample of the use population).

6.2 Purpose of use

Participants were asked to chose the reasons for using Swymm, providing 5 choices which related to the main functions of the system, and an open ended choice (to which nobody offered a response). Users could select one or more responses. Out of the options, the largest majority (85.1%) of responses stated using Swymm to consume information that other users provided for planning purposes (see the state of beaches according to other users before going there). The second largest group was using Swymm to add information for beaches (36.2%), followed by checking the automatic meteorological information for beaches for planning purposes (31.9%). Just 9.6% of responses were for using Swymm to add a new beach, and 17% mentioned simple curiosity as their reason for using it. When asking explicitly whether respondents used Swymm to add a report, 55.3% of respondents (N=52) said "yes". From our Google analytics data we note that just 3.6% of sessions included adding a report, therefore this type of user (contributor) seems over-represented in our sample of respondents.

6.3 Perceived utility

Participants were asked to rate the utility of the information that other users provided and of the information that was automatically generated through the meteorology API. Unsurprisingly, the most useful user-provided information was the presence of jellyfish at the beach (96.8%). This was followed by the quality (cleanliness) of the water (75.5%) and the waviness of the sea (68.1%). It is noted here that these items are all directly related with personal safety during a visit to the beach. In terms of the automatically reported data, the most useful information was wind speed (73.4%) and sea waviness (71.3%), followed by ambient air temperature (37.2%).

6.4 Contributing Data

6.4.1 Data consumers - Barriers for not contributing reports

Participants who indicated never contributing reports through Swymm (N=42) were asked to provide the reasons that prevented them from doing so. Eleven multiple-choice options were provided in the survey, along with an open-ended option, to which we received no response. The most frequent response was "because other users had already left a report for the beach I was at" (51.7%). The next most frequent reason was that respondents were "interested in contributing but I kept forgetting to do it" (27.6%).

Following this, the next two reasons related to network connectivity in equal frequency, i.e. "there was no network signal where I was" and "I didn't want to spend my data allowance" (17.2%). Paired to this, a further 13.8% of responses indicated that users were "interested in contributing but didn't understand how to do it". Interestingly, the respondents who indicated the latter fall in a variety of age groups (18-25, 41-45, 46-50 & 51-55). The same amount of responses (13.8%) was given to the option "I was not interested in contributing data" and the last two response groups were "I was interested in contributing but the process seemed too long" (3.4%) and "I didn't want others to know the beach was not crowded, so they would stay away" (3.4%). A further three options received no responses ("I don't have an internet-connected smartphone", "I was interested in contributing but the process seemed too hard" and "I had nothing to gain by contributing").

These results uncover both barriers and opportunities for active participation. Firstly, it appears that users will not engage in contributing a more up-to-date report if a report from another user is available. This indicates a clear opportunity for promoting other types of engagement, e.g. validating the existing report, perhaps by "liking" it, since the users are both interested in contributing and face no other barrier (e.g. network or cognitive difficulty). The most important participation barrier seemed to be forgetting to take action. A reminder/notification mechanism here might be able to remove at least part of this problem, something that is discussed in the following sections about motivation and incentivisation. The next important barrier is network connectivity and concerns over data plan use. For the former a mechanism of caching reports locally and posting them at the next opportunity when the user regains connectivity could be considered, but given the length of stay at a beach which can be several hours, this seems improper (although the system could still gather such reports for data analysis purposes). For the latter, a clearer indication of data consumption (which, in the case of Swymm, is a few kilobytes only), may be effective in removing the participation barrier.

Finally it is noted that no respondents felt that they had nothing to gain from participating in the system. This is particularly encouraging as the concept of "everybody wins if we all pitch in" seems to be clearly communicated by the system, through the exposure of data to all participants.

6.4.2 Data contributors – Motivations for contributing reports

The respondents who indicated contributing reports to the system (N=52) were asked to indicate their reasons for doing so. Seven multiple-choice options were provided along with an open ended option (for which no response was received). The option with the greatest frequency of responses was adding reports "so that all interested citizens can see them" (88.5%). The second most popular option was "because I liked seeing reports from other users and I wanted to contribute too" (63.5%). The third most popular option relates somewhat to the first ("so that my friends and family can see them", 28.8%). The remaining options were selected by small numbers of respondents. The option "so that the local authorities can see them" received 15.4% of responses, although a working relationship with local authorities was never implied in the survey or during operation of the system (or indeed existed). Finally "out of interest in technology" (11.5%), "to pass the time at the beach" (7.7%) and "out of curiosity" (5.8%) were the least selected options.

It seems here that the main driver for contributing reports was an altruistic motive resulting in a pro-social behaviour. Over half of the respondents also indicated that normative beliefs have a role to play in the intention (and behaviour) of contributing since the fact that others were seen to contribute provided motivation for them to do so as well. In (Bénabou and Tirole, 2006) it is discussed that people succumb to the normative peer pressures that attach honour to pro-social actions, but in this case, the reports were anonymous, so no "badges of honour" or other identifiers could attribute the actions to their performers. One cannot discard the possibility that visibly submitting a report while in the company of others (e.g. a group of friends going to the beach together) is not a way to obtain such a recognition from others, but in this case, it appears more plausible that the question fits the scope of caring about one's self-image and identity. In anonymous settings, the importance of self-image has been shown to be a strong influencer of pro-social behaviour (Johansson-Stenman and Martinsson, 2006).

All our participants (N=94) were asked about what might motivate them further to engage with the system. In line with the theory of Self Determination (Ryan and Deci, 2000), the extrinsic motivation types in the self-determination continuum were explored, because the task assignment to participants is not an inherently "interesting" or "enjoyable" activity (indeed, given the length of scrolling and interaction required to submit a report, as per Figure 3, one might argue that it was a rather cumbersome activity). As such, participation in this system is considered to be the result of an extrinsic motivator. The motivation takes the form of an altruistic act under the theory's most internalized regulatory style (Integrated Regulation), when the subject *internalizes* the motivation, through a sense of *relatedness* to others. The aim of this question was to explore how participants might feel towards alternative incentivization schemes found in literature along this self-determination continuum, namely financial gains and ethical rewards, as well as to investigate alternative altruistic incentives. Twelve possible options and user opinion was submitted on a 5-point Likert scale (1="it would completely discourage me" – 5="it would completely encourage me"). Table 4 shows the incentives presented to users, organised in the categories of "Altruistic", "Self-Image", "Public Image" and "Financial". As discussed, altruistic acts are placed under the "Integrated Regulation" style, since they demonstrate increased congruence and awareness through relatedness to the community. Public image falls under "Identified Regulation" since the the user is able to place rationalized and conscious value on their actions, comparing their standing to that of other peers. Self-image falls under “Introjected Regulation” as the user is motivated by ego-enhancing rewards and finally Financial is clearly an “Extenal Regulation” style, since the user is motivated towards compliance by external rewards only. Table 5shows a comparison of the frequecy of received response categories when splitting the respondents between those who were contributors of data and those who were consumers of data.

Table 4. Motives for report submission presented to survey respondents

Behavior	SDT regulatory style	Motive category	Motive
Self-determined	Integrated Regulation	Altruistic	[A1] Receiving notifications to add reports at a beach that doesn’t have current information [A2] Knowing how many users are currently interested in information for the beach I’m at
	Identified Regulation	Public Image	[P1] Having my nickname appear in a public ranked table of active users [P2] Having my real name appear in a public ranked table of active users [P3] Having the Swymm team publicly thank me by nickname in the app or on the Facebook page [P4] Having the Swymm team publicly thank me by my real name in the app or on the Facebook page
	Introjected Regulation	Self-Image	[S1] Being able to see the number of “likes” from other users for the reports I contribute [S2] Being able to see the number of users that saw my reports [S3] Receiving ethical rewards (e.g. contribution certificates) from the Swymm team [S4] Receiving ethical rewards (e.g. contribution certificates) from local pubic authorities (e.g. municipality or prefecture).
Non self-determined	External Regulation	Financial	[F1] Receving small value financial rewards (e.g. discounts or gifts) [F2] Participating in draws for larger financial rewards (e.g. vouchers or gifts)

Table 5. Response frequencies for each report contribution motive (Contributors N=52, Consumers N=42). Majority values are highlighted in bold.

	1=strongly discourage		**2**		**3=indifferent**		**4**		**5=strongly encourage**	
	Contrb.	***Consm.***	**Contrb.**	***Consm.***	**Contrb.**	***Consm.***	**Contrb.**	***Consm.***	**Contrb.**	***Consm.***
A1	1.90%	*9.50%*	11.50%	*4.80%*	19.20%	*38.10%*	**50.00%**	***45.20%***	17.30%	*2.40%*
A2	0.00%	*7.10%*	9.60%	*4.80%*	21.20%	*28.60%*	**36.50%**	***45.20%***	32.70%	*14.30%*
P1	7.70%	*11.90%*	7.70%	*4.80%*	**59.60%**	***61.90%***	15.40%	*11.90%*	9.60%	*9.50%*
P2	15.40%	*23.80%*	19.20%	*14.30%*	**46.20%**	***54.80%***	5.80%	*4.80%*	13.50%	*2.40%*
P3	13.50%	*11.90%*	17.30%	*16.70%*	**46.20%**	***54.80%***	19.20%	*14.30%*	3.80%	*2.40%*
P4	19.20%	*21.40%*	19.20%	*16.70%*	**42.30%**	***52.40%***	13.50%	*7.10%*	5.80%	*2.40%*
S1	5.80%	*11.90%*	11.50%	*4.80%*	**46.20%**	***61.90%***	28.80%	*16.70%*	7.70%	*4.80%*
S2	1.90%	*11.90%*	7.70%	*2.40%*	36.50%	***59.50%***	**42.30%**	*21.40%*	11.50%	*4.80%*
S3	15.40%	*11.90%*	5.80%	*2.40%*	**53.80%**	***64.30%***	17.30%	*9.50%*	7.70%	*11.90%*
S4	13.50%	*14.30%*	5.80%	*9.50%*	**57.70%**	***57.10%***	9.60%	*7.10%*	13.50%	*11.90%*
F1	15.40%	*11.90%*	1.90%	*2.40%*	**36.50%**	***40.50%***	23.10%	*19.00%*	23.10%	*26.20%*
F2	9.60%	*9.50%*	5.80%	*2.40%*	28.80%	***38.10%***	**30.80%**	*23.80%*	25.00%	*26.20%*

In terms of altruistic motivators, both consumer & contributor user types appear to believe they would have a positive effect on persuading them to add data (Figure 13). Mann-Whitney U tests reveal a statistically significant difference in respondent opinion for A1 (notifications), where existing contributors believe that this type of motive will encourage them more to contribute reports ($U=819.50$, $p=0.026$). The other altruistic motive (A2 – knowing the interest of others) is considered positively by both groups at an equal level, since the difference between the two groups is not statistically significant ($U=876.50$, $p=0.085$). There appears to be likely discrepancy between the way these two motives are perceived, and indeed, a Cronbach's α analysis shows values of $\alpha=0.533$ and $\alpha=0.370$ for contributor and consumer groups respectively. These results show that reminders towards sustained engagement might work best for already-motivated users (contributors), while framing the task under an altruistic motive (what is the "need" for information about my current location) could work equally well to encourage sustained use of existing contributors, as well as convert consumers into contributors.

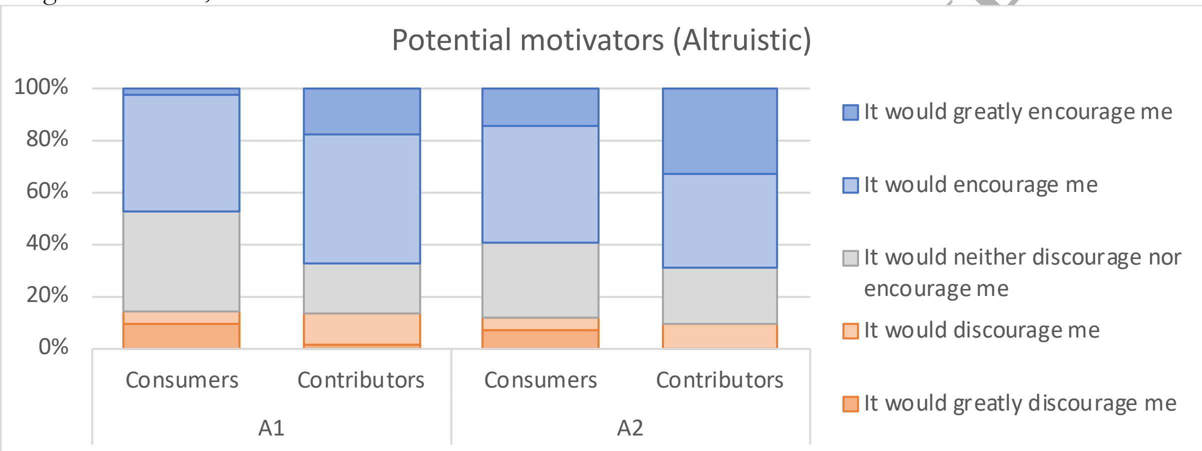

Figure 13. Response frequencies for altruistic motivators: [A1] Receiving notifications to add reports at a beach that doesn't have current information, [A2] Knowing how many users are currently interested in information for the beach I'm at (Contributors N=52, Consumers N=42).

Participants seem to be largely indifferent to the public-image motivators (Figure 14). Positive and negative responses are mostly equally distributed except in P2 (consumers) and P4 (consumers) where the negative opinion outweighs the positive. Comparing between the user types, there exists no statistically significant differences in opinions for any of the motivators (Mann-Whitney U tests; P1 $U=1046.00$, $p=0.692$; P2 $U=943.00$, $p=0.224$; P3 $U=1063.00$, $p=0.812$; P4 $U=1019.00$, $p=0.554$). Cronbach's α values for consumer ($\alpha=0.865$) and contributor ($\alpha=0.913$) show these motive types are seen to reliably measure the construct of identified regulation.

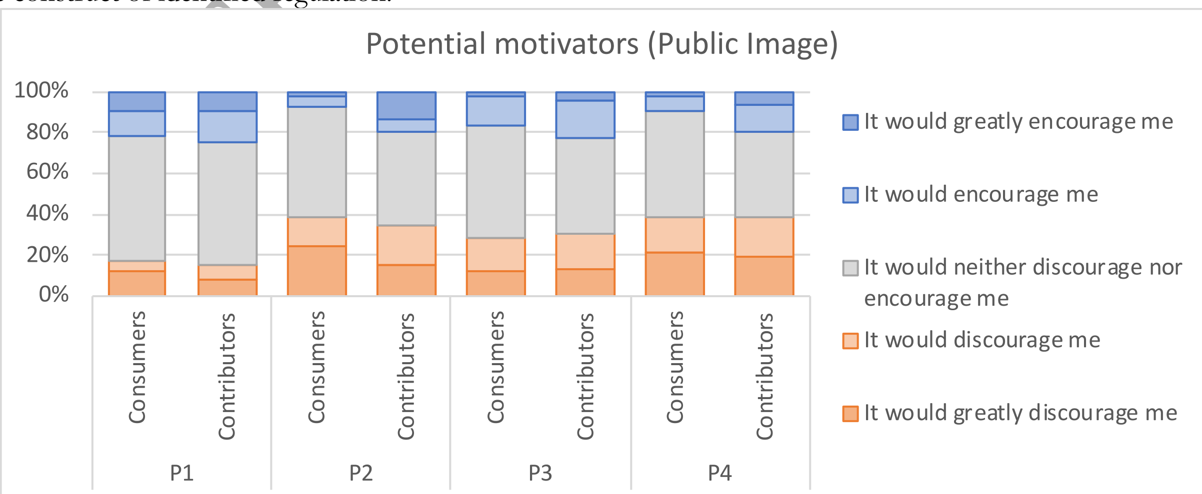

Figure 14. Response frequencies for public image motivators: [P1] Having my nickname appear in a public ranked table of active users, [P2] Having my real name appear in a public ranked table of active users, [P3] Having the Swymm team publicly thank me by nickname in the app or on the Facebook page, [P4] Having the Swymm team publicly thank me by my real name in the app or on the Facebook page (Contributors N=52, Consumers N=42).

Regarding the self-image motivators, respondents seem largely indifferent, with perhaps the exception of S1 (contributors) and S2 (contributors) where positive opinion is a sizable proportion of responses (Figure 15). Comparing between the two user type groups, a statistically significant difference in opinion exists only for S2 (Mann-Whitney U tests; U=781.00, p=0.011). Other motivators have no statistically significant difference (Mann-Whitney U tests; S1 U=949.00, p=0.234; S3 U=1055.00, p=0.755; S4 U=1025.00, p=0.570). Cronbach's α values for consumer (α=0.749) and contributor (α=0.818) show these motive types are seen to reliably measure the construct of introjected regulation.

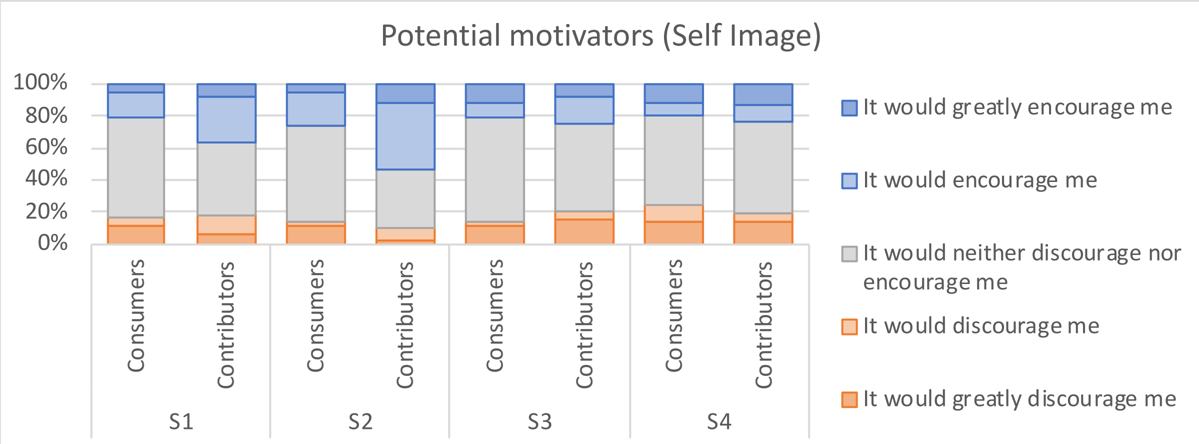

Figure 15. Response frequencies for self-image motivators: [S1] Being able to see the number of "likes" from other users for the reports I contribute, [S2] Being able to see the number of users that saw my reports, [S3] Receiving ethical rewards (e.g. contribution certificates) from the Swymm team, [S4] Receiving ethical rewards (e.g. contribution certificates) from local pubic authorities (e.g. municipality or prefecture) (Contributors N=52, Consumers N=42).

Finally, in terms of financial motivators, respondents seem to be generally either positively inclined or indifferent to these (Figure 16). There is no statistically significant difference in opinion between the consumers and contributor user types (Mann-Whitney U tests; F1 U=1063.00, p=0.818; F2 U=1075.00, p=0.893). Cronbach's α values for consumer (α=0.959) and contributor (α=0.968) show these motive types are seen to reliably measure the construct of external regulation.

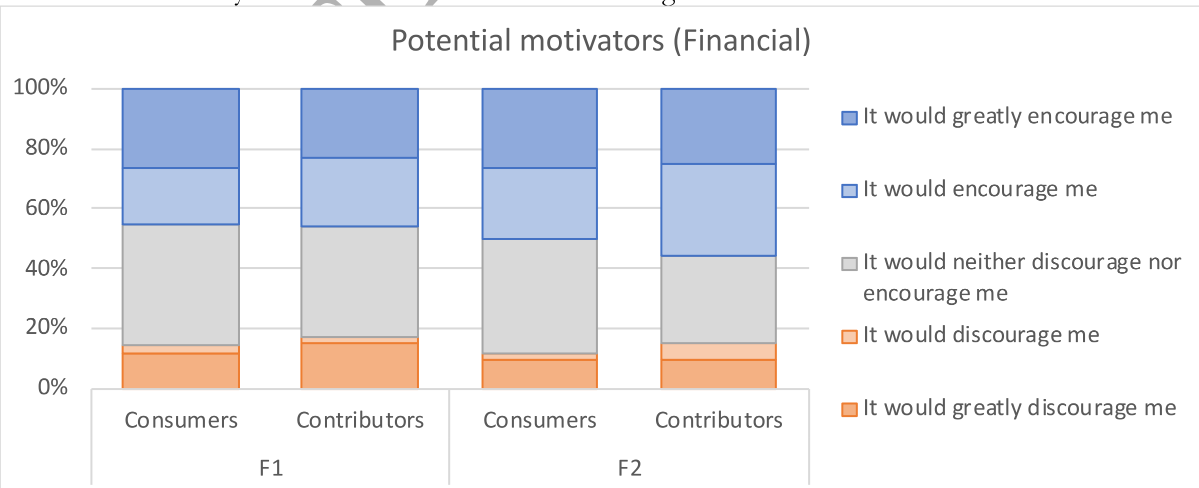

Figure 16. Response frequencies for financial motivators: [F1] Receving small value financial rewards (e.g. discounts or gifts), [F2] Participating in draws for larger financial rewards (e.g. vouchers or gifts) (Contributors N=52, Consumers N=42).

As a final step in analyzing this data, it is noted that altruistic and financial rewards seemed to resonate better with users in order to increase contributions, compared to self-image and public-image motivators.

To gauge whether these differences were statistically significant, appropriate tests were carried out between each factor in these categories and all the factors in the public & self-image categories (Wilcoxon signed-rank, with Bonferroni correction resulting in a p-value threshold of 0.00625). Table 6 shows the results of the statistical tests.

Table 6. Statistical test outcomes for differences between contribution motivators. Post-hoc Bonferroni-corrected statisically significant differences (p<0.00625) are highlighted in bold.

		Consumer (N=42)				**Contributor (N=52)**			
Motivators		**A1**	**A2**	**F1**	**F2**	**A1**	**A2**	**F1**	**F2**
P1	Z	-1.594	-2.537	-2.043	-2.653	**-2.987**	**-3.953**	-1.053	-2.390
	p	*0.111*	*0.011*	*0.041*	*0.008*	*0.003*	*0.000*	*0.293*	*0.017*
P2	Z	**-3.875**	**-4.365**	**-4.071**	**-4.155**	**-3.962**	**-4.328**	-2.086	**-3.227**
	p	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.037*	*0.001*
P3	Z	-2.430	**-3.407**	**-3.524**	**-3.771**	**-3.996**	**-4.694**	-2.646	**-3.696**
	p	*0.015*	*0.001*	*0.000*	*0.000*	*0.000*	*0.000*	*0.008*	*0.000*
P4	Z	**-3.644**	**-4.190**	**-4.088**	**-4.191**	**-4.306**	**-4.629**	**-3.191**	**-4.038**
	p	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.001*	*0.000*
S1	Z	-1.595	**-3.617**	-2.298	-2.608	**-2.821**	**-4.013**	-1.036	-2.261
	p	*0.111*	*0.000*	*0.022*	*0.009*	*0.005*	*0.000*	*0.300*	*0.024*
S2	Z	-1.397	**-3.749**	-1.732	-2.059	-.873	**-3.094**	-.953	-.196
	p	*0.162*	*0.000*	*0.083*	*0.039*	*0.383*	*0.002*	*0.341*	*0.844*
S3	Z	-1.395	**-2.740**	-2.505	**-2.777**	**-3.254**	**-4.422**	**-2.883**	**-4.151**
	p	*0.163*	*0.006*	*0.012*	*0.005*	*0.001*	*0.000*	*0.004*	*0.000*
S4	Z	-1.700	**-3.036**	**-3.086**	**-3.331**	**-3.128**	**-4.032**	-2.561	**-3.901**
	p	*0.089*	*0.002*	*0.002*	*0.001*	*0.002*	*0.000*	*0.010*	*0.000*

These results demonstrate the differences in what might motivate the two types of users. Regarding altruistic motivators, for consumers of data, notifications to contribute (A1) are no more important than other public or self-image indicators, with the exception of P2 & P4 which rate lower. On the other hand, knowing how many people are interested in the beach they are at (A2) provides a better motivator than all other public & self-image motivators, with the exception of P1. In the contributor group, these altruistic motivators are clearly more important than public or self-image motivators (with the exception of A1-S2). Regarding financial motivators, it is noted that both groups believe the participation in a draw (F2) to be more important than public & self-image motivators with the exceptions of P1, S1 & S2. This finding must be taken with a "pinch of salt" however, since some of the respondents might the type of people who are likely motivated by participating in draws (after all, participation in our survey was rewarded with a draw). With regard to winning gifts of small value (F1), the two groups behaviour differed. For consumers of data, this was a better motivator than half of the public and self-image motivators (P2, P3, P4 & S4), while for contributors of data this was found to be a better motivator for than just two (P4, S3). In a sense, the findings for F1 are not surprising. For contributors of data, it is already shown that they are largely motivated by altruistic factors. For consumers of data, previous research indicates that Greek non-student populations (reflective of our own sample) are generally more inclined to prefer the certainty of a small reward than participation in a draw for a larger reward (Drichoutis and Koundouri, 2011).

6.4.3 Data contributors – Behaviour during contributing reports

In section 5.6.3 the plausible assumption was made that data contributors would submit a report once per beach visit, thereby explaining the hourly temporal patterns in reported crowdedness and report volume. Participants were asked about when they submitted their reports in relation to their arrival time at a beach (on arrival, after some time had passed, on leaving, after having left). Responses were on a 5-point Likert scale (1=never, 5=always) (Figure 17).

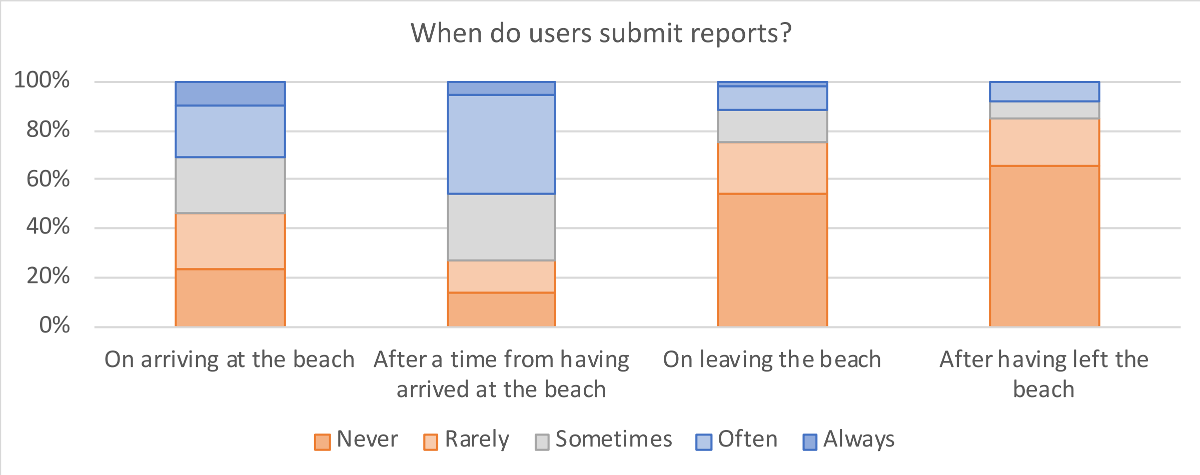

Figure 17. Temporality of report contribution relevant to arrival at a beach location (Contributors N=52, Consumers N=42).

A Friedman test on the responses revealed a statistically significant difference ($\chi^2_{(3)}$ = 48.458, p=0.000). Post-hoc Bonferroni-corrected pairwise Wilcoxon tests (resulting in a significance value of p≤ 0.008), indicated that the response differences were statistically significant between conditions on-leaving-beach & on-beach-arrival (Z=-3.258, p=0.001), after-leaving-beach & on-beach-arrival (Z=-3.819, p=0.000), on-leaving-beach and after-beach-arrival (Z=-4.687, p=0.000) and after-leaving-beach & after-beach-arrival (Z=-4.793, p=0.000). The results indicate that user typical behaviour is to add reports when they arrive, or after some time has passed from their arrival at the beach. This finding adds further credibility to the data quality, as users' typical behaviour was to complete the process in-situ rather than from memory (stale data).

Related to the temporality of reports, participants were asked if they would add more than one reports for the beach they were at, if considerable time had passed from their arrival at that location. Responses were on a 5-point Likert scale (1=never, 5=always). The most frequent response type was "Never" (46.2%), followed by "Sometimes" (30.8%), and "Rarely" (19.2%). This result indicates the level of voluntary engagement with the system, thus a typical user can be assumed to feel that they have done their "duty" by submitting one report. However, the considerable percentage that indicated adding further reports "sometimes" or "rarely" means that it is likely that users might be persuaded to repeatedly contribute for the same location, if motivated accordingly. The findings about these temporal aspects of data contribution link back and confirm to our previous assumption (section 5.6.3) that users may typically only report data once per beach visit, and typically shortly after having arrived there, thereby supporting our previous argument that the temporal (hourly) patterns exhibited in reported crowdedness and report volume are indicative of accurate reporting by data contributors.

Finally, participants were asked to explain the previous observation that most reports contained entries for practically all items in the report. We provided 3 multiple-choice options and an open ended option (for which we received no response). The most frequent response was "Because I felt this information would be useful to others" (75%). This was followed by "It was quick and easy to do so" (57.7%) and "It appeard to be compulsory to fill in all the items" (15.4%). The results show that even though a significant proportion of respondents did not feel that the process was "quick and easy" (as they didn't select that option), they still went through the trouble of submitting full reports, because of the perceived benefit this would have for others.

6.4.4 Data contributors – Barriers for systematically contributing reports

The contributor participants were asked if there were cases where they didn't contribute any reports. Five multiple-choice options were provided, along with an open ended options (for which we received 4 responses). In this case, 65.4% of respondents mentioned that they wouldn't do so if there already existed a report by another user. A further 53.8% mentioned forgetting to do so as a reason. These results match well with the explanations given by those who never contributed a report and support the identification of the two most important participation barriers identified above. Other reasons ("I didn't think this location is of interest to others" and "I didn't want others to know the beach was not crowded, so they would stay away") received 3.8% and 1.9% of responses. Interestingly 3 other responses at a frequency of 1.9% each were added by participants, all relating to connectivity issues ("no data allowance left", "could not connect", "slow connection") and one participant indicated "[the process] might take too long".

6.4.5 Quality of contributed data

All participants were asked to rate the accuracy of the information they could find in the system (reports and meteorological data) by reporting their level of agreement on the statement of whether that information was accurate, using a Likert scale (1=completely disagree, 5=completely agree). For meteorological data, 78.8% of respondents agreed or completely agreed that it was accurate, 15.9% neither agreed or disagreed and 5.3% disagreed or completely disagreed. A similar picture emerges for user-contributed reports, for which 68.1% of respondents agreed or completely agreed that it was accurate, 24.5% neither agreed or disagreed and 7.5% disagreed or completely disagreed.

The data was separated by user type (consumers or contributors) and further by origin (automatically generated meteorological data, or user-contributed data), to see if being a contributor had an effect on the perceived accuracy between the two types of data. Consumers of data in this case exhibited greater confidence in the automatically generated data ($Z=-2.500$, $p=0.012$, Wilcoxon signed rank test), while contributors of data did not show a statistically significant difference in the two types of data ($Z=-0.200$, $p=0.842$, Wilcoxon signed rank test). This result indicates that consumers of data were more skeptical about the accuracy of the contributed information, but those that engaged in providing information themselves considered that the reports contributed by others were at least as accurate as the highly accurate data reported by an independent third-party system, thereby placing more trust in the system and in the other users that form a part of it.

In psychology, the false-consensus effect is well known cognitive bias that leads people towards the belief that their own behaviour is typical to those of others (Ross et al., 1977). If this bias does exist in contributing users, then it would explain that contributor users considered the contributions of others to be as highly accurate as the data retrieved from the meteorology API, only if these users themselves behaved in a way as to provide accurate data. Asking these users to state their level of agreement with the statement "I was very careful to ensure that the data I reported was accurate", the responses were 96.2% agree or strongly agree (59.6% strongly agree). This accounts for the perception that contributing users had about the data offered by others being highly trustworthy, but it also confirms our quantitative validation of the accuracy of data submitted (comparing wind speed and sea waviness).

6.4.6 Data contributors – the effect of anonymity on participation and data quality

Since the system did not support user accounts and all reports were anonymous, contributors were asked about the role of anonymity in the system. For the question "It is important that I remain anonymous while contributing reports", user opinion tended towards a preference for anonymity (answers on a 5-point Likert scale, completely disagree=1.9%, disagree = 26.9%, neutral=28.8%, agree=28.8%, completely agree=13.5%). However, participants seemed to believe that "anonymity encourages the submission of inaccurate reports" (completely disagree=11.5%, disagree = 13.5%, neutral=32.7%, agree=23.1%, completely agree=19.2%). It seems a balance has to be struck here between maintaining anonymity while also ensuring data quality, and a possible solution might be a validation mechanism (confirming other users' reports).

As seen in section 5.7, users rarely shared the reports they submitted with their immedate social circle on Facebook. Participants were asked how difficult they thought this function was, and a high proportion (32%) stated they never used it. It would be plausible to attribute this to user difficulty in engaging with this function, since sharing requires the additional cognitive and usability burden of engaging in the process of logging in to Facebook via the phone's browser. However, the majority of users stated that they found the function easy or very easy to use (46%) and just 9.5% found it was difficult or very difficult to accomplish the task of sharing. These results confirm the earlier assumption that lack of social engagement signifies a preference towards anonymous participation, which has to do with the users' location and current activity (leisure time at the beach).

6.5 Assessing the user experience

The final item in the survey was a UEQ questionnaire (Laugwitz et al., 2008). The questionnaire measures participant responses in 26 questions arranged into 6 scales. Comparing the responses of the two user types (Mann-Whitney U test), we found no statistically significant differences in any of the scales (Attractiveness U=1073.50, p=0.888; Perspicuity U=1020.00, p=0.581; Efficiency U=1019.00, p=0.577; Dependability U=1047.00, p=0.731; Stimulation U=1008.50, p=0.523; and Novelty U= 1052.50, p=0.762). Hence we report the findings for the whole body of users. Overall, the system was rated positively across all 6 scales (Figure 18).

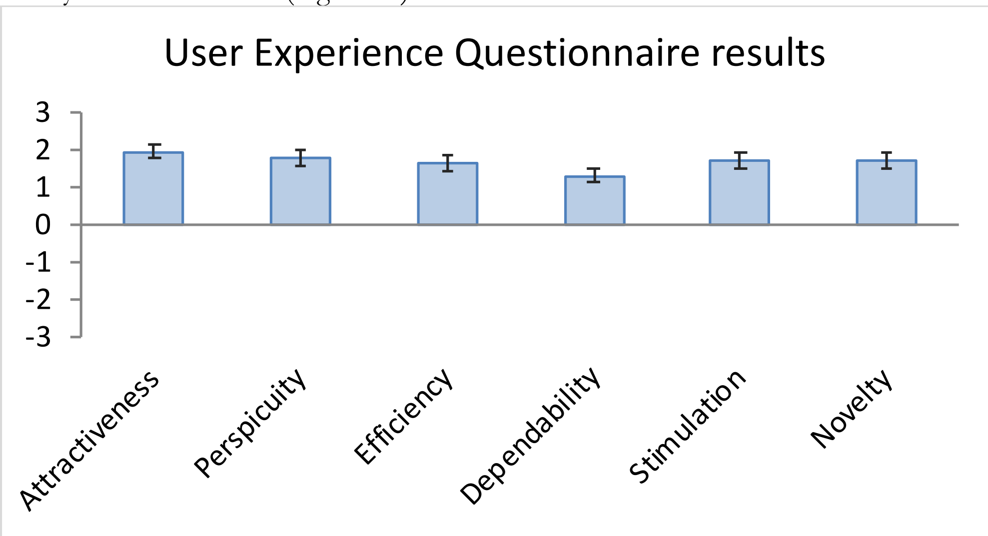

Figure 18. Outcomes of the UEQ questionnaire for all respondents (Contributors N=52, Consumers N=42). Error bars at 95%c.i. Background colouring as per Laugwitz et al. (2008).

The scales bring the system a positive rating in Attractiveness (1.99), Pragmatic Quality (1.61) and Hedonic Quality (1.72). Internal consistency of the responses was generally high or very high, with the exception of Dependability (Cronbach's α_{Attr}=0.84; αPersp=0.80; α_{Effic}=0.82; α_{Dep}=0.48; α_{Stim}=0.80; α_{Nov}=0.72), so perhaps this item needs revisiting since it is possible that either respondents did not interpret the questions related to this scale correctly under the context of the application. Swymm also rates favourably in the UEQ benchmark from 246 studies (Attractiveness=Excellent; Perspicuity=Good; Efficiency=Good; Dependability=Above Avg.; Stimulation=Excellent; and Novelty=Excellent).

7 Crowdsourced data for urban planning and recommendations

A crowdsourced system such as Swymm primarily offers value to the users of the system (i.e. the public at large). However, the collected data is not only personally relevant to individuals, but its aggregation can provide tangible benefits and uses for other interested parties, e.g. to inform urban planning and policy decisions. In the next section, and based on the evidence that the data contributed to the system is largely reliable, a few such use-cases for the collected data are highlighted. The findings are also relevant to the challenge of achieving uniformity in the granularity of spatiotemporal data, as identified from the literature.

7.1 Examining the extent of the jellyfish problem and water quality in the region

Starting off with the main motivation for this work, one can examine the extent of the jellyfish problem in the region. Figure 19 depicts the severity of the problem in terms of reported frequencies of jellyfish appearances in beaches. Markers are more transparent in beaches were a smaller percentage of reports mentions the appearance of jellyfish. Thefore the collected data allows the visualisation of not just the extent of the problem (the number of locations where jellyfish were spotted), but also its severity (the frequency of appearance of jellyfish) and to establish confidence levels (by limiting reporting to locations with at least *n* reports over the period).

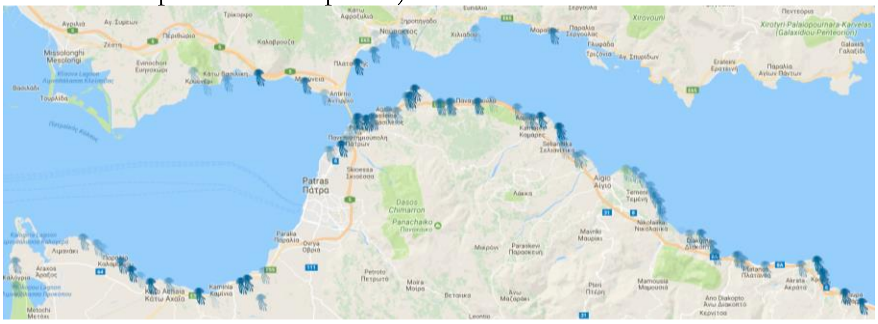

Figure 19. **The extent of the jellyfish problem in the region, based on averege frequency of appearances, according to user reports (beaches with >5 reports shown).**

7.2 Data granularity and uniformity - Understanding the popularity of swimming locations

Next, the crowdedness of beaches in terms of frequency of reports, requests for information and reported busyness is examined. Figure 20 shows the number of reports received for each beach. This follows a power-law distribution, with 31.5% of beaches representing 80% of all reports received. Based on this distribution, the data can be separated in three frequency buckets, red: [9%, 2%), yellow: [2%, 1%) and green [1%, 0%). Spatial visualisation (Figure 21) shows where users were most active in reporting. The opacity of the markers further distinguishes the frequency of reports received for each beach (the most opaque marker of each category has the most reports in that category).

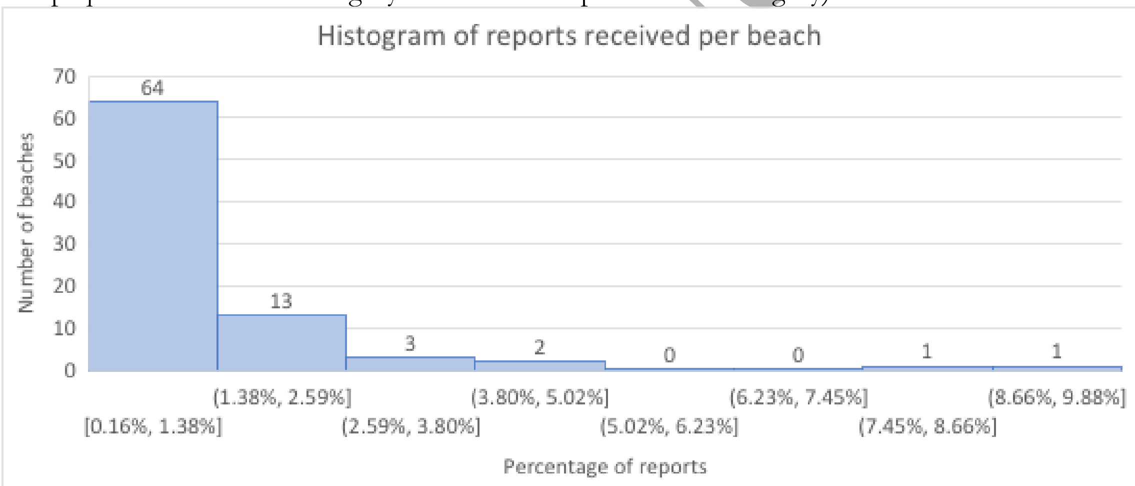

Figure 20. **Distribution of received reports per beach (N=1843). The two beaches closest to the largest urban center (Patras) received most reports.**

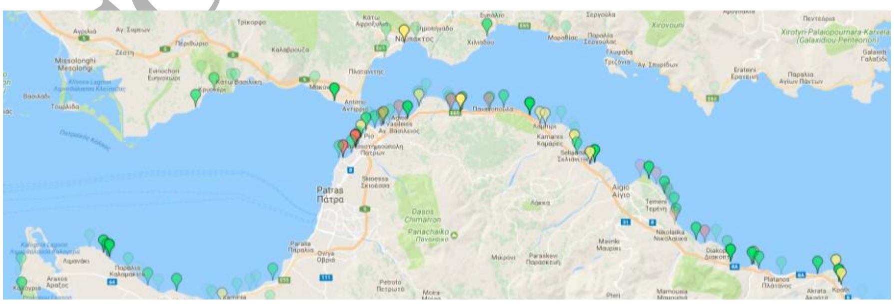

Figure 21. **The map overview showing the frequency of reports received per beach.**

Another interesting measure is the frequency of information requests for each location (i.e. the number of beach detail page views for each location). It is noted that the distribution of page views follows a power-law shape (Figure 22), where the top 24.7% of beaches in terms of page views make for 79.7% of all page views. Based on this distribution the beaches can be divided into three popularity brackets, namely red: [9%, 2%), yellow: [2%, 1%), green: [1%, 0%) and spatially visualised as before (Figure 23). The opacity shows how popular each beach is, within its own category of popularity.

One interesting observation here is that there exists a strong and statistically significant correlation between the reports percentages made on the beaches and the percentage of information requests per beach (beach detail page views) (Spearman's $R=0.9201$, $p<0.01$). At this time it can be assumed that this is because some beaches are (for a number of reasons, such as proximity to urban centers) more popular than others, hence attract a larger crowd that includes reporting users, and also attract interest for information. However it would be interesting in the future to examine the possibility of causal effects, i.e. how much the existence (and frequency) of reports for a beach also increases the number of information requests for it.

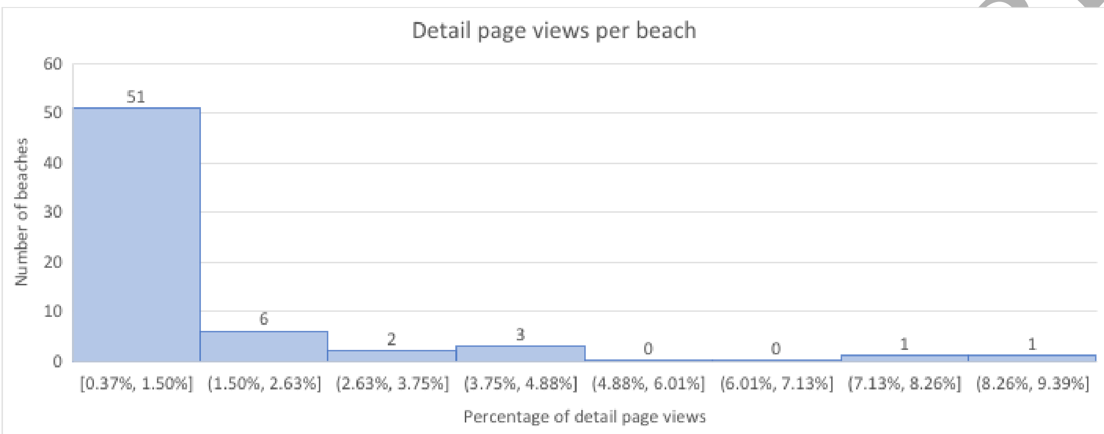

Figure 22. **Frequency of beach detail requests per beach (N=96,948). The two beaches closest to the largest urban center in the region (Patras) draw the most attention.**

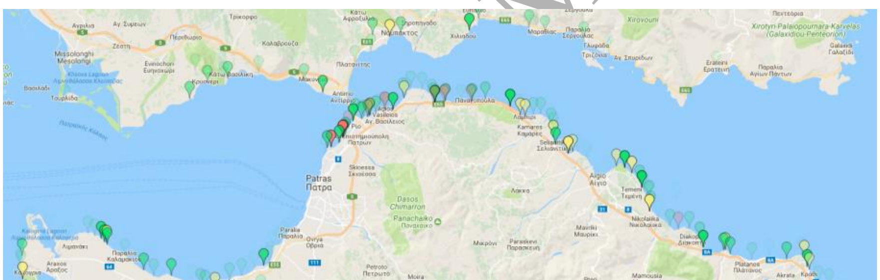

Figure 23. **Map overview of information requests per beach.**

In this simple analysis, the temporal variations in the interest shown in beaches is not considered, although it is trivially easy to add such a filter, allowing the breakdown of popularity by weekday and/or hour of day. All of this information is useful for public planning. Local authorities can examine it to understand where sanitation and facility management efforts should be concentrated, or to manage the allocation of coast guard and lifeguard personnel at the various locations under their jurisdiction. Furthermore, planning for business permits is made easier by identifying the demand at the various swimming locations, so that new permits can be issued in line with demand, or managed (e.g. setting the levels of permit fees or issuing season-end rebates) based on the popularity of locations and the impact of disruptive phenomena, such as the emergence of jelly fish or bad bathing water quality.

A further extension of this information can affect the design and behaviour of the user-facing application. Knowing in advance the locations for which there is likely to be a surge for demand for information and the time of these surges, means that the system can proactively nudge users to remember to provide that information when they are on location. Further motivation to these users could be to expose the size of the audience that might benefit from this information, as we suggested to users with motivator A2 (e.g. "There is currently a great demand for information at your location. Providing a report now will likely help X thousands of users interested currently in this beach"). These suggestions are indeed feasible using data from the current system.

7.3 Distribution of different population types at swimming locations

Another type of analysis allows the classification of beaches based on the type of crowd that prefers them. As can be seen in Figure 24, it's relatively easy to see that some beaches are designated as mixed crowd, while others are dominated mostly by young swimmers or older adults. This simple visualisation doesn't take into consideration time variations, but again this is a trivial addition. As shown in Figure 25, temporal changes are easily spotted. In this example of two beaches adjacent to the urban area of Patras, it can be seen that the older adults tend to flock the beaches in the earlier hours of the day, while in the afternoon, the crowd synthesis changes to include more young adults. Based on empirical local knowledge of the area, this is an accurate representation of what takes places at these locations. This information, paired with the information of interest and busyness at each location, can further inform public authorities' ability to manage sanitation, policing and lifeguard allocations. The latter is a crucial public safety issue as every year in Greece there are over 300 incidents of drowning, mostly affecting those aged over 55[1]. Sadly, just in the area of Patras, there were 7 reported drownings in 2017.

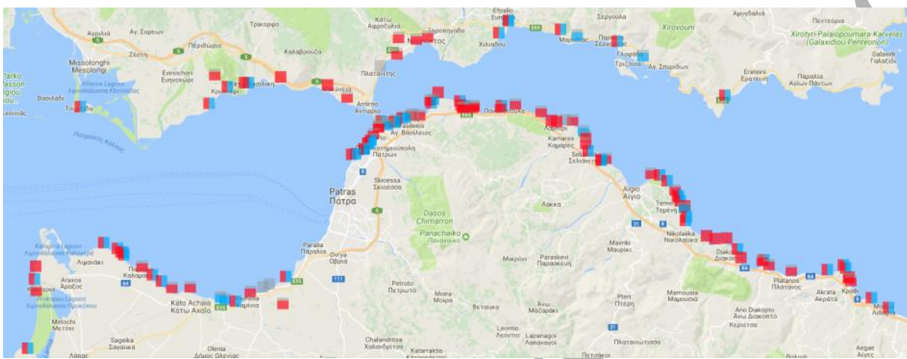

Figure 24. Map overview showing the crowd composition in all beaches. Blue = older adults & families, red = young adults. Half-filled boxes mean "mostly [young/old&families]. Mixed boxes (red-blue) show a mixed crowd.

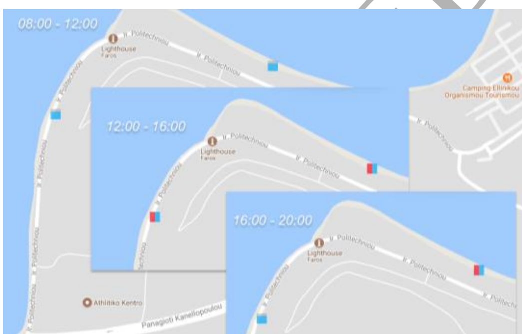

Figure 25. Temporal changes in the crowd composition of two beaches.

8 Reflection and Design Recommendations for Mobile Crowdsourcing Systems

Data augmentation crowdsourcing projects need to be designed with a range of considerations in mind, as recommended by existing literature on the experience of designing and deploying such systems. In the case of Swymm, a mobile hybrid CS data augmentation / data sharing system was designed and deployed in extreme haste, due to the pressing circumstances and lack of available time to engage in a thorough human-centered system development methodology. The experience with running the system over a period of approximately 2 months, provides valuable insights and design recommendations, with

[1] Hellenic Centre for Disease Control & Prevention http://www2.keelpno.gr/blog/?p=4195

respect to the main challenges identified by the literature, which are discussed next, starting with the paper's main focus, i.e. the emergent challenges in participation and data quality, in the absence of reward schemes.

8.1 Designing mobile CS systems in the absence of reward schemes

8.1.1 Motives driving participation in the absence of a reward scheme

Swymm did not follow the established practices of encouraging participation through financial rewards or a gamification system. The idea was to leverage pro-social behaviour and motivate participants to engage with the application by openly exposing the collected data to all users. In contrast also to previous research, where the cost of altruistic behaviour was simply the user's time, in this case users had to face additional participation costs that are inherent to mobile use, such as interaction difficulty and network-related barriers. The analysis shows that even though the proportion of participants that volunteered information was small compared to the whole body of users, the information that they provided was valuable and pivotal to the success of the system in terms of use. For those users who participated in the contribution of information, the main drivers were indeed altruistic and they were strong enough to overcome the added difficulty of mobile use context. Altruistic behaviour promoted via notifications was also found to be a likely strong motivator for contributing data for the body of users who did not originally contribute. A financial reward scheme was also found to be a possible strong motivator that could be used in the future, however, it was striking to see that public and self-image rewards, which are critical components of gamification schemes, were largely considered to be ineffective. Gamification schemes can also be linked to financial rewards, but further from this cost, they are a non-trivial development effort, as they require the implementation and balancing of game mechanics and appropriate code, graphics and support infrastructure. In contrast with literature such as (Salim and Haque, 2015) where gamification is a strongly recommended option for maintaining participation, we believe that open exposure of data might be a stronger driver for crowdsourced systems. The recommendation therefore is that crowdsourcing systems aiming for increased participations should strongly consider the open exposure of data to participants, and work on supporting and encouraging pro-social behaviour (contribution) in the system by leveraging altruistic motives, rather than relying on self or public-image motivators. If gamification systems are to be included, then they are most likely to be successful if they are linked to a financial reward scheme. However, the experience from Swymm shows that it is possible to motivate a critical mass of contributing users just by leveraging their propensity for altruistic, pro-social behaviour, thereby avoiding the costs of developing gamification systems, or including financial rewards.

8.1.2 Data quality in the absence of a reward scheme

Even though Swymm was open to many forms of exploitation, the quality of the received data was very good. Although some "trolling" in the submission of new beaches and beach reports was noted, this had a negligible impact on the overall quality of the data we received. This is demonstrated not only by the direct analysis and correlation of the crowdsourced data with objective data, but also by the self-reported behaviour of the users themselves and the perceived utility of the system and the data it contained.

It is logical to link this phenomenon with the fact that the main motivators for use were altruistic. As can be expected, a propensity towards pro-social behaviour should result in the contribution of good quality data. Here, it is plausible that the transparent access to the information collected by the system acted as a strong safeguard and encouraged the users towards contributing good quality data. Being able to see the information submitted by others and thus being helped by it, also helped the users understand the value of contributing to the system themselves and becoming more active in engaging with it. Increasing the stake of contributors in the project and also regularly exposing information about how our system was being used in general over Facebook, had a strong preventative effect to the problem of "trolling".

In this sense, and while the argument for complex quality assurance algorithms remains valid, experience draws the conclusion that transparent access to the data and providing a real stake for system users is a priority for ensuring data quality in such systems, which can then be supplemented by further technical measures. These supplemental measures should also, ideally, be primarily focused on assisting users in assembling high-quality information *before* it is submitted, rather than acting post-hoc to discard submitted data. For example, Swymm could have checked the user's location, or strongly suggested default values for windiness and waviness based on the meteorological data, or compiled a "trustworthiness" assessment to present to users prior to the submission of reports, to encourage contributing good quality data.

8.2 Reflection on the main challenges of CS systems

In Table 1 the main challenges in CS systems that arise from literature were identified. With respect to these, the following lessons learned through the deployment and operation of Swymm are presented.

8.2.1 Involving users

Regarding recruitment, no specific tactics were employed, other than word-of-mouth dissemination of the platform on Facebook and an article in a local news portal. Contrary to literature recommendations, users were not vetted or evaluated for their contribution, neither were they trained on using Swymm. Despite this, the system was widely used because it offered a solution to a problem affecting many people. The altruistic motives that drove data contribution were sufficient to ensure good quality data contributions. Careful design to ensure a logical flow in the process of finding and submitting information supported the will of motivated users to provide good quality data. In openly exposing the contributed data to the public, the users' attention was drawn to the contribution of others (thus motivating them to engage or further contribute) and helped users understand their role and value in the system. Open exposure of the data therefore is considered to have played a pivotal part in user involvement.

8.2.2 Designing systems

Swymm was primarily designed for mobile use, but this didn't stop a significant percentage of users from accessing it through their desktop computers, thereby ensuring both horizontal access and opportunistic participation. The decision to proceed with a web-based app rather than a mobile app was appropriate and supported this challenge.

In Swymm, the workflow, tasks and contributions were clearly defined and communicated to users through the application design. Although a uniform granularity of the collected data was not achieved, in this case, it didn't really matter, as the aim was not to collect data that can scientifically describe a phenomenon (e.g. the presence of jellyfish, or the crowdedness of beaches). Despite this, as shown, the collected data could still be useful for planning or analysis purposes especially for sites that were locally important. Better granularity and homogeneity might be ensured if Swymm supported user coordination or assigning tasks to appropriate users as literature recommends, but this is left as future work to investigate. However, evidence emerged that "nudging" users to contribute at opportune times is a likely motivator that might strongly contribute towards this goal. Such measures might also work well towards maintaining engagement, where no evidence to support a gamification scheme was found (unless linked to financial rewards). Instead, design should focus on leveraging more of the altruistic pro-social motives that already led to Swymm's success.

The critical element of Swymm's success centered on the open access to collected data, so that users might benefit from the contributions of others. This has been discussed this extensively in the paper, but here the impact of anonymity and privacy should be elaborated. In previous work, such as (Gustarini et al., 2016), it was found that in the domain of mobile crowdsourcing, data is shared more often when collected anonymously, and that sharing data with others on Facebook is much more unlikely than sharing anonymously via some an application server. Though this research related to content types of information about the user themselves, the results are quite close to the experience from Swymm. Users avoided sharing their reports on Facebook, thereby indicating that anonymity of action is desirable. This is supported by responses to the survey, where users tended to indicate that anonymity is preferable. Anonymity also was considered as ineffectual to the quality of submitted data. It is thus concluded that while open access to data is crucial, anonymity of the contributors (both in terms of their personal information and also in terms of their current location and activities) should be carefully managed and preserved in CS systems.

8.2.3 Managing the operation of CS systems

Existing literature briefly comments on the need to manage the workflow, maintain project focus and manage the trust between users and project stakeholders. In this case, commentary can be made on the project focus, which initally was the reporting of the jellyfish problem. While most users found this to be the most useful service offered, notably, much of the other data in the system was considered highly useful, particulary those pieces that related to the safety during beach visits. In a sense, the focus of the system might have somewhat shifted towards a broader sense of safety, which still included the original focus. The conclusion is that CS systems should be carefully monitored (e.g. via qualitative studies) and adapted after deployment, because the bottom-up appropriation of technology can often lead to unintended uses which are legitimate (Nan, 2011) and should be supported to encourage continued engagement. Sadly this aspect is entirely missing from current CS literature and needs to be investigated further.

8.2.4 Interpreting data

Most literature in this challenge relates to the evaluation of the contribution quality and combining contributions. In the case of Swymm, even though no safeguards were implemented, data quality remained high, somethat that can be attributed to the altruistic pro-social motives that drove contribution. The simultaneous collection of independent data (meteorological API) can serve as an excellent tool for post-hoc evaluations of contribution quality and, given the comparative assessment of the two sources of data, a recommendation can be made that independent data be used to filter contributions at the time of generation (rather than discarding data post-submission). However, such prevantative safeguard mechanisms should only be deployed after the independent data has been checked for reliability and correlation with user-contributed data.

8.3 Other considerations and lessons learned

The approach in Swymm was widely inclusive – users were neither vetted nor trained to use the system. Simple navigation, non-technical language and user interface control options allowed most users to quickly familiarise themselves with the system and to engage in submitting information. The users' performance in terms of being able to successfully complete tasks was not evaluated so as to exclude participation. However, the statistics from our questions on why reports were typically fully completed, show that even when faced with difficulty, users would persevere with the system because they believed that the contributed data offered value to others.

Swymm presented contributors with two simple tasks: adding a new beach, or adding a report. By considering how to facilitate the entry of data, the task flows were designed to be, quick, logically mapped to a rational cognitive process, easy to carry out and also horizontally accessible - any user with a connected smartphone could participate in an opportunistic manner, without the need to employ sensors (e.g. location). The 25% of users who accessed the system via desktop computers also shows the value of supporting horizontal access. The lack of user accounts and optionality for sharing on Facebook helped maintain users' privacy, and to ensure that adequate trust between the contributors and us could be maintained, but on the other hand, it prevented the system from allowing user coordination, or assigning tasks to contextually relevant users (e.g. by location and time of day). The success of the system both in terms of submitted reports and general information access use indicates that the maintenance of privacy is a more significant concern over the system's ability to better coordinate its operation.

As can be seen from our statistics, because of this, it was not possible to achieve a uniform granularity of the spatiotemporal data, which is reasonable because some locations are inherently more populous and attract more interest than others. This outcome had positive and negative aspects. On one hand, the non-uniform granularity served most users well - they could typically find information about the locations that they cared most about, resulting in a high perceived value and use of the system as an information source.

On the other hand, in terms of use of the data as a scientific planning and analysis basis, reasonable evidence emerged that this non-uniform data can still serve to draw useful conclusions and develop valuable tools and systems for authorities, though more rigorous analysis, e.g. creating statistical or machine-learning forecasting models, remains as future work.

On a final note, a comment should be made on the continuous engagement of the users. Clearly in this case there existed no incentivization scheme. The enthusiastic use of the system and its success must be attributed to the volunteering spirit shown by a small subset of users who contributed reports. Here, transparent access to the information collected by the system arguably played the biggest role in incentivizing the users. Being able to see the information submitted by others and thus being helped by it, also helped the users understand the value of contributing to the system themselves and becoming more active in engaging with it. There is still a number of users who wanted to engage but failed to completely grasp the concept of how a crowdsourced data-sharing system works, though this was a very small minority.

The inclusion of automatically generated data also played a strong role in encouraging use of the system - even in the cases where no user reports were available for a location, the user could at least glimpse some meteorological information, something that offers unique value and also helped maintain the project focus on the original scope: Providing information to swimmers and beach-goers.

8.4 Final thoughts

Swymm served as a useful exercise in validating, or disputing several of the identified challenges in the deployment and operation of CS systems. Through this experience, it became possible to identify future avenues of research not previously mentioned in literature, such as the investigation of system appropriation and unintended use. In anticipation for the coming swimming season, further improvements will be made to Swymm, based on the guidelines from literature but also from the experiences in running the project. Most importantly, a pressing question is to investigate how maintaining users privacy can impact the participation in the project, by introducing user accounts. This addition will also the investigation of how to best mobilize users under context to provide information as and where needed, e.g. via notifications and calls to action.

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