applied sciences

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# Agent-Based Simulation to Measure the Effectiveness of Citizen Sensing Applications—The Case of Missing Children

**Ariadni Michalitsi-Psarrou *, Iason Lazaros Papageorgiou, Christos Ntanos and John Psarras**

School of Electrical & Computer Engineering, National Technical University of Athens, Iroon Polytechniou 9, 15780 Zografou, Greece; iasonlazpap@gmail.com (I.L.P.); cntanos@epu.ntua.gr (C.N.); john@epu.ntua.gr (J.P.)
* Correspondence: amichal@epu.ntua.gr

**Abstract:** Citizen sensing applications need to have a number of users defined that ensures their effectiveness. This is not a straightforward task because neither the relationship between the size of the userbase or its effectiveness is easily quantified, nor is it clear which threshold for the number of users would make the application 'effective'. This paper presents an approach for estimating the number of users needed for location-based crowdsourcing applications to work successfully, depending on the use case, the circumstances, and the criteria of success. It circumvents various issues, ethical or practical, in performing real-world controlled experiments and tackles this challenge by developing an agent-based modelling and simulation framework. This framework is tested on a specific scenario, that of missing children and the search for them. The search is performed with the contribution of citizens being made aware of the disappearance through a mobile application. The result produces an easily reconfigurable testbed for the effectiveness of citizen sensing mobile applications, allowing the study of the marginal utility of new users of the application. The resulting framework aims to be the digital twin of a real urban scenario, and it has been designed to be easily adapted and support decisions on the feasibility, evaluation, and targeting of the deployment of spatial crowdsourcing applications.

**Keywords:** agent-based modelling; human mobility; simulation; urban mobility; citizen sensing; spatial crowdsourcing



**Citation:** Michalitsi-Psarrou, A.; Papageorgiou, I.L.; Ntanos, C.; Psarras, J. Agent-Based Simulation to Measure the Effectiveness of Citizen Sensing Applications—The Case of Missing Children. *Appl. Sci.* **2021**, *11*, 6530. https://doi.org/10.3390/app11146530

Academic Editors: Vicent Botti and Vicente Julian

Received: 9 June 2021
Accepted: 14 July 2021
Published: 15 July 2021



## 1. Introduction

The involvement of citizens in solving real-life problems is not a new idea. Crowdsourcing is an example of this, where an activity is outsourced to the public [1], commonly via the internet. The terminology varies for these applications, depending on where the focus lies. Hence, they can be found as 'citizen sensing' or 'human-centric sensing' when the focus is on the participants and their communities [2,3]. 'Urban sensing' is a term proposed when focusing on people's interaction with their surroundings, such as buildings, other people, and vehicles [4,5]. Spatial crowdsourcing focuses on location-specific sensing tasks, in the sense that the participants should physically be at a specific location to contribute [6]. Participatory versus opportunistic sensing emphasises the active or implicit engagement of users, respectively [7].

Correspondingly, the term 'social sensing' is used to describe the geospatial data generated per individual and the related analyses methods. In social sensing, each individual acts as a sensor, bearing rich information about spatial interactions [8]. On such applications, data collection is strengthened by the human factor by exploiting their mobility, their intelligence, and their flexibility to make complex measurements and deductions, which could not be possible without them physically being there [9].

The availability and growing adoption rates of web-enabled and location-aware mobile devices have boosted the use of these applications that profit from the collection of low-cost, value-added information [10]. The data generated from these devices may then be used for various purposes, such as modelling interactions, recording local conditions, measuring community statistics, stimulating collective awareness, and identifying hidden connections among social and physical phenomena [11]. Therefore, social sensing applications have played a critical role in very diverse application domains, such as environmental protection, urban environment and transportation monitoring, public health surveillance, crisis awareness, disaster recovery, and behavioural epidemiology [9,12–15].

In general, citizen sensing apps are horizontal, real-time, open, accessible to anyone, geo-aware—since local information is more probable to be accurate—and they allow information sharing [15]. In this context, several research challenges regarding citizen sensing applications emerge, such as trust, privacy and data accuracy. Some of the most predominant issues encountered are 'noise' in the data, information overload, bias (propagation of the most famous idea), and misinformation. In that sense, several researchers have been working on those challenges [9]. For instance, in [16], users' contributions are validated by dividing them spatially, temporally, and contextually since an actual event will probably be documented more.

Apart from these critical and widely identified challenges, every discussion on citizen sensing applications should start with the crucial challenge of recruitment. This is especially true for urban sensing or spatial crowdsourcing. In these cases, the coverage of an area, both in time and space, by human sensors for their involvement in data collection and decision making is a key metric [7]. Having human sensors provide high-quality data at scattered locations does not necessarily lead to success. Therefore, the question is whether there exists a minimum number of users, also known as 'critical mass', ensuring the promised experience and objectives. The quantification of this number is neither a straightforward task nor one that produces a concrete number. This paper aims to present a novel approach for estimating the critical mass of users in a citizen sensing application for most cases where it is difficult, unrealistic, or even unethical to run observational studies or controlled experiments on identical settings by only changing the number of users participating.

We focus our solution on a specific problem, the missing children issue, where a mobile application for the general public is developed to involve citizens and volunteers in missing children investigations [17]. The application broadcasts mobile alerts, sharing public information about an active case to all users that have the application installed on their mobile phones. The alerts are activated to those users that are located within a predefined area. The users have then the chance to share any information they have by observing their surroundings.

## 2. Background Knowledge

This section introduces the three pillars on which the current work has been built. In particular, this paper aims to study the critical mass of users needed on spatial crowdsourcing initiatives, where the mobility of citizens, which act as 'human sensors' sensing their environment and sharing information, is exploited. The solution to this research question is given through the development of a simulation framework based on agent-based modelling. Therefore, Section 2.1 examines how the issue of critical mass on collective actions has been studied before, while Section 2.2 introduces the vivid research field of human mobility to showcase that human mobility has already been exploited in many application settings and can be adequately simulated in a city-level. Finally, Section 2.3 presents agent-based modelling as a novel modelling approach for simulating complex systems such as that of a city-scale human mobility simulation.

### 2.1. Critical Mass on Collective Actions

Critical mass has been used as a concept for a long time in social sciences, although the term was adopted later. It was initially met as 'critical density' in the 1970s by Thomas Schelling in his book *Micromotives and Macrobehavior* [18] and strengthened by Mark Granovetter [19], describing the actions and attitudes of a large set of people and events.

Critical mass is applied in many contexts, such as technology, physics, politics, group dynamics, and public opinion.

Critical mass is also frequently met in collective actions [20,21]. Certain products presuppose users' existence and interaction, referring to the data needed to detect people's properties and characteristics [22]. Social networks inherently belong to this category, as also, in this context, citizen sensing applications. There is currently little work in the academic literature regarding the critical mass of participants in social, human-centric sensing applications, possibly due to the significant divergence among the different applications and their purpose. In [23], the authors focus on finding the critical set of people by examining both their speak rates—examining how talkative personalities they are—and their interdependencies. People are evaluated and selected based on their expected contributions' data quality, credibility, and trustworthiness. The topic of source selection in participatory sensing has already created a fair amount of interest in the scientific community [23–25].

In [5], the authors acknowledge the necessity of a critical mass of users for a commercially successful citizen sensing application in people's everyday lives. According to them, the sensors' mobility characteristics are vital for the success of the sensing application. They also identify an area's coverage by a mobile sensors' network as a critical issue strongly related to the sensors' mobility characteristics. Their network of human-centric mobile sensors is compared in [4] to a static one to determine the space covered in each case. The sensors' probability to meet, or else 'sense', in space and time, the object of interest is also explored. They ran a simulation to validate their approach, concluding that mobile sensors can cover sensing areas over time, approximating static sensors' coverage with substantially fewer sensors. In this paper, citizens are also used as mobile sensors to cover an area effectively and find the missing child quickly. We also assume that the sensors' mobility characteristics significantly affect this effort. An appropriately configured simulation environment is used to identify the critical mass of participants in such a crowdsensing initiative.

### 2.2. Human Mobility

Over the last few years, the predominance of the internet and subsequent smartphone technology and positioning methods, such as GPS and WiFi, has enabled human mobility data collection. Therefore, academic research and professionals' interest in analysing these data have been stimulated to understand the main laws that drive people's motion and mine patterns within them to boost the development of location-based applications and services [26].

The study of human mobility became an even 'hotter' topic in 2020 due to the COVID-19 pandemic. Many researchers examined the virus's spread based on people's mobility and social interactions and the impact of social distancing policies and other control measures for the virus containment in mobility [27–29]. More research datasets have emerged to facilitate this goal. Key players, such as Google, have supported scientific research in the battle against COVID-19 by providing the aggregated, anonymised mobility insights they use in their products, such as Google Maps, to the public [30].

Human mobility has long been used to study epidemics [31–35], long before the COVID-19 crisis. Analysing and understanding human mobility, however, is vital in many other application domains. Large-scale transportation, mainly served by air and sea, is also studied to better understand global connectivity and migration patterns [36]. On the other side of large-scale mobility, many researchers have attempted to understand the empirical patterns governing pedestrian movement and study emergency evacuation of transport systems, buildings, and public spaces, especially in cases where crowding exists (e.g., religious commemorations, sports events, and festivals) [37]. Applications in that respect may involve many different fields, such as urban planning [38] and simulation [39], public transportation planning [40], and traffic forecasting [41,42].

Over the years, the results of this analysis have shown that human mobility on a macroscale, such as migration, exhibits structural patterns deriving from geographic and socioeconomic factors and constraints. At an individual's level, human mobility also exhibits strong periodic behaviour while influenced by many factors [43]. Former studies had suggested that human mobility follows the random walk model [26,44] to compromise the many obscure factors that stimulate human mobility. However, such abstractions usually fail to reproduce realistic models since social and many other influences differentiate people from random walkers [45]. Certain studies have focused on the role the area of residence plays [46,47], deducing several related parameters, including environmental factors and the effect of population size, the morphology, and the street network's topological structure [43,48] on the travel distances and mobility patterns. For example, Kang et al. [48] have examined the extent to which two urban morphological features, size and compactness, influence intra-urban human mobility. They concluded that individuals' human travel exponents differ based on the city's morphology, despite all following the exponential law.

Several different empirical data types have been used to study both individual and aggregate mobility and help adjust and validate models and their parameters, stemming from census data [49,50], Call Detail Records (CDRs) [51,52], taxicabs exploiting tracking and positioning methods [53], and smartphones using social media, such as Foursquare [54], Twitter [55], Gowalla [43], or their GPS receivers [56]. Analysis and exploitation of the raw mobility data are achieved by using interdisciplinary approaches. Techniques and algorithms of machine learning, data mining, and statistical analysis are used for the deciphering of human movement, the extraction of patterns, and the detection of events affecting this movement [26].

Humans are moving daily to earn their living and carry out their social and leisure activities. The former displays highly periodic behaviour, and the latter introduces a random aspect in individuals' daily trips. According to work by (Cho, Myers, Leskovec, 2011) [43], the three main elements that drive and characterise human mobility are (a) geographic movement, i.e., where we move, (b) temporal dynamics, i.e., how often we move, and (c) social network, i.e., how social relationships affect the movement of an individual. In [57], the authors analysed mobile phone data of 50,000 people over 3 months, concluding a 93% potential predictability in individuals' mobility. On the effect of social relationships, Ref. [43] have shown that social connections can decipher around 10%–30% of all human motion, while periodic behaviour around 50%–70%. To build their Periodic Mobility Model, they assumed that most human movement is periodic, revolving around a limited number of locations. They defined, for simplicity, two 'latent states', as they called them, 'home' and 'work', expecting that an individual, based on the time of the day, will either be in one of these two states or commuting in between them. The patterns extracted from this daily behaviour outline the regularities and recurrence that characterise human lives.

### *2.3. Agent-Based Modelling and Simulation*

Human mobility analysis comes hand in hand with the necessity to generate realistic spatiotemporal trajectories of people's mobility. Concerning the generation of realistic models of human mobility, simulation, specifically agent-based modelling, is probably the most-used in the literature [58]. Agent-based modelling (ABM) is a novel modelling approach when complex systems of independent, interacting agents need to be modelled. ABM can support, through the simulation of an environment's participants' actions and interactions, understanding how one's decisions may affect the whole system. The COVID-19 crisis is also the result of interacting agents. Therefore, apart from studying human mobility, research engineers have extensively used agent-based modelling to understand the COVID-19 crisis and its implications, predict its future outcomes [59–62], and make decisions for measures to be taken, such as social distancing interventions [63], reducing transmission in facilities [64], and comparing different policies [65].

Agents have behaviours and interact with other agents, changing the agents' behaviour, which influences other agents' behaviour in continuous interaction. By this bottom-up modelling approach, where each agent and each interaction are programmed explicitly in the system through rules, new behaviours, patterns, and structures may emerge that were not introduced into the models but ensued from the agents' interaction [66]. An example of a city simulation where ABM can be used for a what-if analysis to unravel new phenomena and test scenarios is the simulation of urban mobility changes after constructing new infrastructures or when alarming events happen, such as terrorist attacks and epidemics [31,67]. In another example, the authors in [68] develop an agent-based data-driven model for urban traffic signal timing, while in [69], the authors use agent-based modelling to model and study future urban land-use scenarios.

ABM can also be used to model interactions with the environment, apart from among individuals. An agent can be anything from a human being to a road or a building in the ABM universe. This adaptability that ABM offers justifies its increasing use as a powerful technique for decision making in entirely diverse areas. The abundance of special-purpose agent tools further proves the significance and wide adoption of ABM by many researchers. These are developed to address the specific requirements for modelling agents, such as Netlogo, StarLogo, Repast, Swarm, Mason, and Anylogic [70,71], allowing scientists to focus on the modelling rather than the visualisation of model progress and outcomes. ABM frameworks have also been built in the most popular software programming languages, such as the Mesa framework in Python [72] and the JABM framework in Java [73].

Space and time are fundamental components of ABM and the base for many modern ABM applications. The range of combined ABM and GIS applications at different temporal and spatial scales is indicative of the usefulness of their functional interconnection. In [74], the author briefly reviews the many and diverse application fields of ABM using GIS, ranging from disease modelling to migration and border security studies. As Andrew Crooks states, 'agent-based simulations serve as artificial laboratories where we can test ideas and hypotheses about phenomena that are not easy to explore in the 'real world'' [74] (p. 71). He mentions the example of pedestrian modelling of an evacuation, where the building cannot, based on logic and ethics, be set on fire to test how people will respond to this. In this work, the investigation for a missing child is examined through the involvement of citizens. This is also a case where it would be impossible and even unethical to actually test different scenarios with unknown results since this would mean testing it directly on individuals already in dire distress. Therefore, as with all simulation systems, ABM provides a way to create an artificial world to test numerous scenarios without running randomised controlled experiments or setting case–control observational studies. The former would be expensive, hazardous, and even immoral. The latter would require the system tested to already be in place and a much broader dataset than the ones fortunately available for missing children's cases.

ABM is commonly used to solve optimisation problems. In classical optimisation approaches, optimisation algorithms are developed as step-by-step processes [75,76]. These algorithms may be either exact if they detect the optimal solution or heuristic if they end up with an acceptable solution that is not necessarily optimal. Lately, agent-based approaches, including ABMs, have been utilised to solve complex optimisation problems when the classical approaches are not applicable [76]. They design the solution either through a 'functional' or a 'physical' scheme. In the first case, the agents are represented as functions with no physical dimension. In the second case, which is also the approach of this paper, agents symbolise physical entities, such as citizens and vehicles [77].

## 3. The ChildRescue Simulation Framework

### 3.1. Methodology

The difficulty of running real-world controlled experiments to identify the number of users needed in a geographical area to have a successful application is further toughened here due to the subject's highly sensitive nature. These experiments would need to be completed during a missing child incident and at the child's expense. Through simulation, the ethical and practical concerns are withdrawn. Different scenarios can run in identical settings for the independent variable, i.e., the number of users of the citizen sensing app.

Current investigations for missing children are supported by missing children response organisations that operate the 116 000 European Hotline for Missing Children, manage the Amber Alert system, and on several occasions exploit their network of certified volunteers and in-field search and rescue teams. They are confronting over a quarter-million cases of missing children every year in the EU alone [78] and around 8 million globally [79]. This is the baseline of our experiment, representing the current situation.

In the context of the EU-funded research project ChildRescue, a citizen sensing mobile application has been developed that alerts its users when they are close to a missing child's incident or other critical locations for the child [80]. The application is already being used in real-life cases and downloaded by more than 20,000 citizens in Greece and Belgium. However, the question raised is how many of these users are needed in an examined geographic area to find a child considered lost there, faster than with the current means, i.e., the baseline, which would enable the claim that the application outperforms the existing systems. To answer this question, we have built a simulation framework that is easily reconfigurable to adapt well to the urban environment in question and its citizens' mobility characteristics. We ran simulations in selected geographic areas to identify the users' critical mass, namely the users' threshold from which point on the application is effective for the specific location in question. The mobility characteristics of these locations must be identified beforehand through appropriate analysis. The insights are translated into specific metrics that are easily fed into the system by the users themselves.

The simulation platform has been built in the GAMA platform, programmed using the GAma Modelling Language (GAML), an agent-oriented programming language [81]. GAMA was selected because its meta-model is designed to facilitate the complex representation of the environment and the creation of multi-level models. It enables the modelling and simulation of spatially explicit agent-based systems through the integration of GIS data. According to the developed framework, a geographic area to be examined should be selected. The geodata of this area are inserted in the system as an OSM file, extracted either directly from Open Street Map or other platforms giving this opportunity (e.g., Extract.BBBike [82]). Therefore, actual data about roads, intersections, and buildings of a certain area are used to develop the simulation environment. The geographic area is modelled through building agents, road agents, and additional geographical information, which is part of the simulation's motion graph. This graph supports the movement of the agents within the simulation. On the created simulated space, citizens, hereby 'people agents', live and work, while at the same time a child is missing.

In GAMA, different types of agents exist with their own behaviour and skills, supported by functions. Our model has the static agents responsible for developing the virtual geographic environment and the mobile agents, consisting of two species: the people and the missing child. The people agents are citizens who move around the city to commute to work, go back home orperform their daily leisure activities. Both species have movement skills, meaning that the movement of agents is simulated along a graph. An interactive visualisation environment in GAMA provides monitoring capabilities to the user.

The people agents' number is the independent variable, editable by the user, to represent the mobile application users in the area in question. Every people agent has a specific apartment of a building as a home and another as a workplace, as in the periodic mobility model of [43]. It is assumed that both buildings are located within the map and are randomly distributed. Each people agent has a daily agenda, different for each day of the week. This agenda involves working, resting and performing leisure activities (e.g., shopping, visiting a friend, going to a restaurant). For the weekdays, as also depicted in Figure 1a, all people agents are assumed to commute to work and perform their leisure activities depending on their agenda, ranging from none to two leisure activities per day, based on the insights for the citizens' daily mobility networks of [83–85]. Thus, at the start of each day and if the day is a working day, each people agent is assigned one of the three agendas depicted in Figure 1a. The agents may: (a) commute only to work and go back home (agenda 0), (b) have one leisure activity during the day, either directly after work or after going home first (agenda 1), or (c) have two leisure activities that they may choose to perform right after work, one after the other, or go back home before the first and/or before the second (agenda 2).

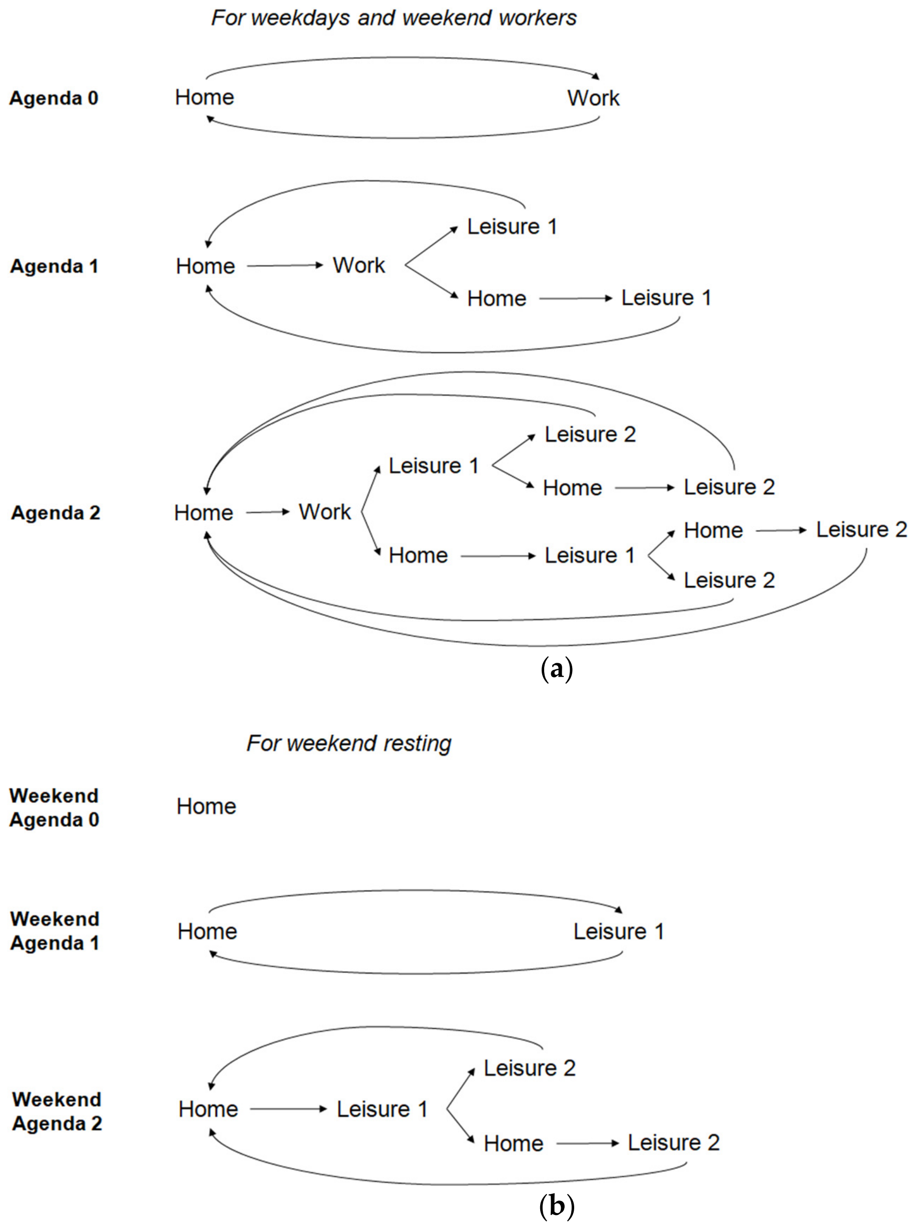


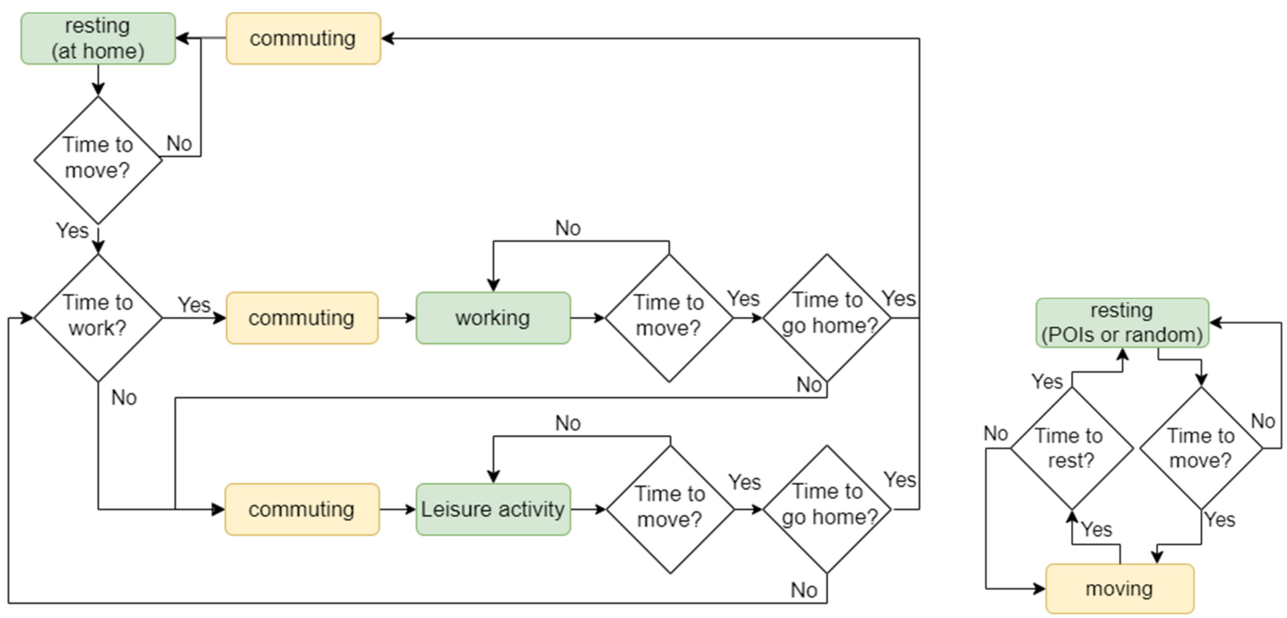

**Figure 1.** The different implemented daily agendas for the people agents in the simulation for (**a**) weekdays, including the weekend workers who have similar behaviour to the one they have on weekdays and (**b**) weekends for all people agents that do not work on weekends.

For the weekends, only 10% of the people agents are assumed to be working. These have the same options for their daily agendas as during the weekdays, shown in Figure 1a. The rest are resting at home or experiencing more prolonged leisure activities, with a maximum of two different leisure activities, as this scenario covers the great majority of cases [83]. The different implemented options for the daily agendas of the people agents for the weekends are depicted in Figure 1b. During weekends, the agent may choose either to stay home without going anywhere (weekend agenda 0), have one leisure activity during the day and return home (weekend agenda 1), or have two leisure activities that may be completed one after the other or mediated by a return to home (weekend agenda 2). All different agendas in Figure 1 aim to be as close to reality as possible and represent and simulate the reasons why a person moves during a day.

People agents move at specific times of the day, different for each person, but within regular working and leisure hours, adjustable during the experiment. They move either on foot or by using means of transport, simulated by giving different speeds to their movement. Every individual's movement has an origin and a destination, following the shortest route within the road network. The framework supports two different modes for the decision on the mobility status of the people agents. The default one is for the agent to walk if the distance to be covered is short (i.e., less than 1 km) and to drive otherwise. The second mode allows the user to run experiments by giving percentages of people agents who move by 'walking' and those 'driving'. This mode is appropriate when demographic data for the area in question are available. The people agents' behaviour can also be represented by their different states and the functions implemented in the system to shift between them, as depicted in Figure 2a. The agents have three static states: working, resting at home, and performing leisure activities. They also implement functions to define the conditions and the timing for these shifts to occur. The day for all people agents starts from the 'home' state; then, they commute to 'work' according to a schedule based on their agendas. They may also go directly to a 'leisure activity' if it is a weekend (Figure 1b). When at 'work' or the location of the 'leisure activity', other functions define the terms for their transition to a new state.

The missing child, on the other hand, moves with a user-adjustable speed depending on age. The location, date, and time that the child was last seen are also parameters of the system initiated by the simulator. The simulator can also enter one or more Points of Interest (POIs) for the child, such as playgrounds, schools, and friends' houses. The missing child then moves either to one of these POIs or a randomly selected location on the map, using a stochastic model, the values of which can be modified by the simulator for each experiment, based on the expected validity of the information they have for the child. It is also assumed that the child will rest for a random period inserted by the simulator, based on the child's age and the data, in each 'shelter' destination, before going to a new destination, as depicted in Figure 2b. These parameters have been co-decided with three missing children response organisations—the Smile of the Child in Greece, Child Focus in Belgium, and the Hellenic Red Cross—along with MCE, being the umbrella organisation of all EU missing children response organisations [86]. These organisations actively participated in validating and testing the developed mobile application and are now its first users. The missing child's parameters in the simulation define the child's disappearance's initial conditions and expected behaviour based on these organisations' and operators' experiences and expertise.

The interaction among the citizens and the missing child is represented by another function, according to which at each simulation cycle, the people agents are looking for whether the missing child is somewhere near them. Even if a citizen comes in easy reach of the child in the simulation, the child is not necessarily considered as found. The citizens may be distracted or may fail to recognise the child from the public pictures distributed through the mobile app, as the academic literature suggests [87,88]. However, we consider this value of destruction less intense than the current situation since the child's picture will be just a click away on their mobile rather than the once-seen picture on an Amber alert.




(**a**) (**b**)

**Figure 2.** Behaviour and states of: (**a**) the people agents and (**b**) the missing child.

The transportation means used by the citizen and the missing child at the meeting time also play a crucial role. They outline the velocity of the citizen and the missing child at their encountering and, consequently, its duration. A probabilistic model of discovery for the missing child has been developed to implement this behaviour in the system, according to which there is a different adjustable probability for the citizens to identify the missing child based on whether they are driving, walking, or resting. Whether the agents are inside or outside a building at the meeting time is also considered in our probabilistic discovery model.

In total, 29 parameters are used to calibrate the maps, the missing child's movement, mobility, and probabilities of identifying the child according to the circumstances of the encounter. Apart from the default simulation execution mode, where the simulator supervises the experiment by watching the agents move across the map, a batch experiments' mode has also been implemented. Batch experiments are consecutive experiments performed for multiple iterations until a user-defined condition is met. These experiments aim to test one specific parameter and how its value affects the results. Therefore, in each iteration, only this parameter's value changes. In our case, we aim to explore the impact of the application users' number on the time it takes to find the missing child. In this context, two types of batch experiments have been developed. In both types, only the number of the people agents changes. In the first type, the simulation ends after a selected period to examine the number of times the child was close to other people agents and the number of times these agents identified the child. In the second one, the simulation ends when a people agent identifies the child for the first time.

### *3.2. Forming the Baseline*

To form the baseline of our experiment, the current situation for the missing children issue was captured based on the information provided by the participating organisations mentioned before. Fourteen bilateral meetings and interviews took place, and past resolved cases were collected to set up the experiments' baseline on both their expertise and the data. A dataset of 121 past cases was provided, including a unique case ID for each record and other information about the child and the disappearance conditions, such as gender, age, location last seen, date and time of disappearance, and date and time found. The dataset on which this analysis was based may seem small. However, it well represents the cases that the organisations that provided them have handled in the last 10 years. For the categorisation of the cases, all three organisations have adopted MCE's categorisation system, according to which there are five types of missing children cases, (a) runaways, implying voluntary leave; (b) third-person abductions; (c) parental abductions; (d) missing unaccompanied migrant minors; and (e) lost, injured, or otherwise missing children [89]. Each type demonstrates different characteristics studied a lot by the organisations' social workers and, therefore, different prospects for their successful resolution, as depicted in Table 1 providing summary statistics for the resolved cases of the dataset per missing type. The past cases analysis also showed a statistically significant relation ( $p$-value = $3.796 \times 10^{-1}$) among the missing type and the child's age group when excluding the 'lost, injured, or otherwise missing' category that incorporates all cases with unknown circumstances of disappearance. The Chi-square test of independence was conducted, ensuring that no more than 20% of the cells have an expected frequency lower than five. The Bonferroni-adjusted method was then used as a post hoc test to identify the age groups and missing types responsible for creating a significant relationship. A dependence among runaways and adolescence (age 10 onwards), on the one hand, and parental abductions and early childhood, on the other hand, was identified. Through statistical significance tests, a correlation among the missing type and gender also emerged, indicating that more females than males tend to run away and that there is a higher proportion of male unaccompanied migrant minors.

**Table 1.** Summary statistics (in days) for the resolution of cases per case type from the dataset of missing children's past cases.

| Case Type | Median | Mean | Min | Max | Std |
|---|---|---|---|---|---|
| Lost, injured, or otherwise Missing | 1.35 | 2.89 | 0.45 | 12.58 | 3.64 |
| Missing children in migration | 62 | 175 | 0.396 | 988 | 295.9 |
| Parental abduction | 13.5 | 40.54 | 1.187 | 152 | 63.4 |
| Runaway | 2.92 | 20.01 | 0.25 | 367.7 | 56.7 |

In rough numbers, most of the dataset's disappearances are runaways (52%), which conforms with MCE's annual reports [90]. It is followed by missing unaccompanied migrant minors (31%), a case type not well represented in the official reports. Of the 23 surveyed organisations in 2019, only 47.6% reported that they work on missing children in migration, and only five organisations could provide more detailed information on the time it took before the missing minors were recovered [90] (p. 6). Cases of children in migration take the longest to be solved, if solved at all, as also indicated by Table 1. Thus, it is not the most representative case to work on.

It can be seen in Table 1 that there is significant variation in the data, which renders the determination of a baseline value for the resolution of cases challenging. Each child is unique, and so is each missing child case. Despite their differences, though, there are also commonalities, especially for cases of the same type. Therefore, for the simulation, we have assumed the case of a missing adolescent running away from home. The 'runaway' missing type has been selected as it is the most representative category and the most dependent on the missing child's behaviour rather than external factors (e.g., abductor). It also displays the minimum variance (s = 56.7), with the exception of the 'Lost, injured, or otherwise Missing' type, which denotes unknown reasons and conditions of disappearance and is underrepresented both in the dataset ($n$ = 14) and all cases in Europe (1.3%) [90].

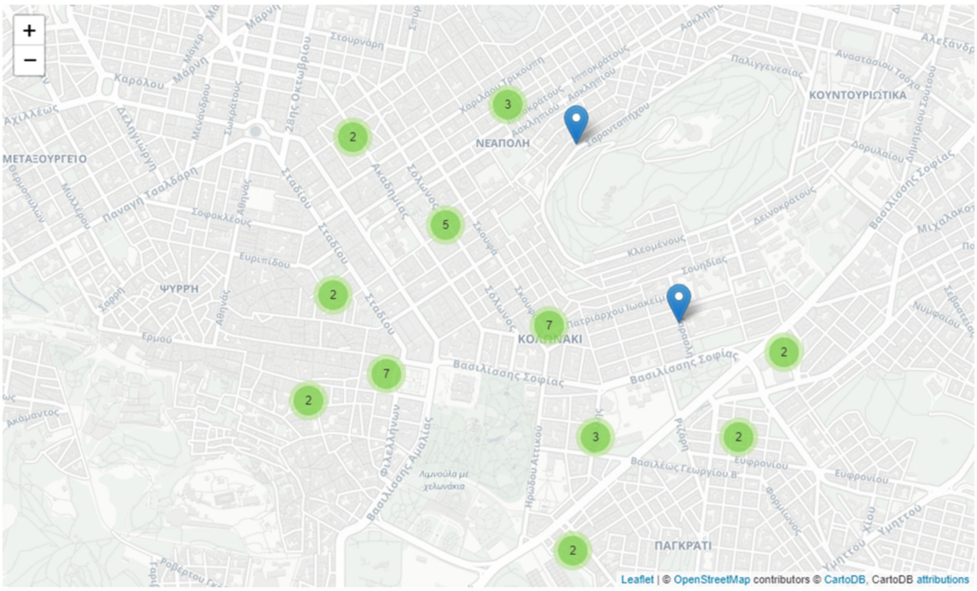
The baseline value was set in agreement with the participating organisations, which would consider the mobile application to be serving its goal if the missing child was to be found in less time than the median value of the examined case type, 'Runaways' (2.92 days). In parallel, confirming the known perception that the first 48 h are crucial for increased odds for the child to be found safe and sound, they highlighted that a case's resolution below that would be the most preferable. Considering this the baseline of our experiment, we aim to show that an intensified, location-based citizen engagement may significantly reduce the time needed to find missing children.

## 4. Experimental Evaluation

### *4.1. The Data*

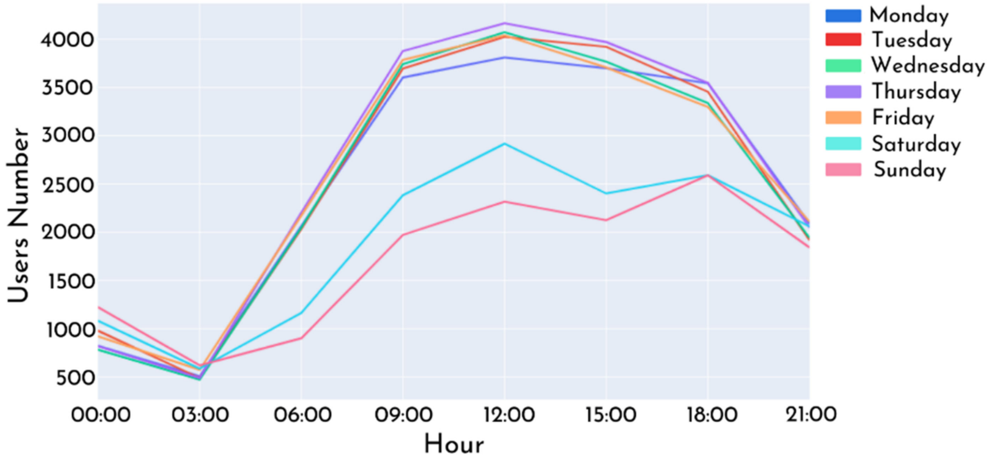
Empirical data from mobile phones were collected to analyse mobility in Athens, Greece's capital city, encompassing spatiotemporal information for citizens at an aggregate level. Telecom provider-collected data were analysed to study human mobility. The dataset originates from one of Greece's top three largest mobile operators, with more than 4.4 million active subscribers, translated into around 15–25% of mobile telephony subscribers in Greece. It contains users' volume information for 39 cell sites in the Athens centre for every 3 hours for 1week (6 September 2019–12 September 2019). The provider selected the 3-hour timeframe because the connection with a mobile device is observed and updated every time the device initiates an activity (e.g., phone call, SMS) or every 3 hours if the device is idle. Therefore, information about the devices' connection with cell towers is logged at least every 3 hours, even if they are in 'standby' mode, not displaying an activity.

Figure 3 shows the 39 cell sites' locations and the total number of connected users per hour and weekday for all the participating cell towers. Athens centre being a commercial district, its dataset allowed examining the effects of commuting to workplaces and leisure activities, such as shopping. The datasets also enabled the approximation of the citizens' number commuting there and the identification of users' density maps and, consequently, patterns for the centre of Athens. The derived maps show the mobile phone users' distributions, indicating the total population distribution. Linear regression models have been proposed to extract total population numbers and distribution [91].




**(a)**

**Figure 3.** *Cont.*




(**b**)

**Figure 3.** (**a**) The location of the 39 cell sites participating in the analysis. Blue markers show the exact location of a cell site, while green circles represent marker clusters with a number showing the number of cell sites in the vicinity of the circle's location. Marker clusters group markers at varying zoom levels. (**b**) The mobile phone users' number per hour and weekday.

## *4.2. Results*

The previous analysis was used to study the mobility in Athens and adapt the model accordingly. For example, the time to start work was based on the insights from the data, setting the minimum value at 03:00 and the maximum at 09:00. Other parameters of the simulation framework were fed with statistical information from governmental and European Commission reports. For instance, the percentage of people walking in the simulation was set to 42%, following the percentage of citizens who most often use walking as their mode of transport in Athens, based on the 2016 State of European cities report [92]. The maximum driving speed was adapted to the maximum driving speed in the Athens centre, which is 50 km/h. Realistic default values were also used for some parameters to apply to all simulations, such as the minimum driving speed, which was set to 10 km/h, and the minimum and maximum walking speed for people agents, set to 3 and 6 km/h, respectively [93]. Some random value selections had to be made, such as the starting position for the missing child and the POIs to search for.

In general, all simulation parameters can be easily adapted to the specificities of a particular city or neighbourhood when there are data available or statistics for the people's mobility there (e.g., car use, traffic hours). They can also take values from probability distributions when, based on the available data, the empirical distributions for the simulation parameters fit well on specific distributions (e.g., gauss, gamma), having the least Sum of Square Error (SSE) among the examined distributions.

In the simulation, we explore two different indicators, how much time has passed for the missing child to be found by one of the people agents, i.e., citizens of the simulated city, and the number of times the missing child was found in 2 days to explore the impact that the number of mobile application users, denoted as *nb_people* in the simulation framework, have over the simulations' result. The *nb_people* is the independent variable that we aim to explore to investigate the critical mass of application users. The 2 days' timeframe was selected since this was decided to be the threshold below which a missing child should be found with the new mobile application, as indicated and explained in Section 3.2. The simulation step is set at one second, as a quite small step that can enable realistic representation of the motion of both people agents and the missing child, not affecting the accuracy of the results. The aim is to run many simulations using the same conditions and analyse the impact of the number of engaged citizens on the time needed for the missing child to be found. In addition, different values for the probabilities of the probabilistic discovery model, discussed in Section 3.1, are explored to examine the impact of stochasticity on the simulation results. We launch ten (10) simulations for each experiment examining a different number of people agents and display the indicators' mean and standard deviation values, keeping the seed values constant for the random number generators among the experiments. The variable *nb_people* took values from 50 to 2200 with a step of 20 to examine a great range of people agents' numbers in the simulation. The batch experiments were conducted twice, one for each indicator explored. For each batch experiment, each different *nb_people* value ran 10 times, as mentioned above, leading to 2160 simulations.

For each experiment of an increment of 20 users added, the number of iterations was set to 10. The variation in the results using this amount of simulations is small enough and straightforward so as to produce a clear curve, as shown in Figure 4b. More simulations are not expected to alter in any significant way the shape of the curve, which is what the aim of the experiment is.

Figure 4a provides a screenshot from the simulation framework during an experiment where there are 600 users at the simulated centre of Athens and the missing child. The experiments conducted for the Athens centre highlighted how this simulation framework could be used to examine the necessary adoption rates of such a citizen sensing mobile application per area to be successful. The results for the first indicator, days for the child to be found, are shown in Figure 4b,c. A horizontal dashed line at days equal to 2 has been added to show the baseline value of the experiment. It can be seen in Figure 4b that the median values of the days for the missing child to be found for the different number of users create a curve resembling a hyperbola. Indeed, fitting the data through nonlinear regression to different curves, the best fit, by using nonlinear least-squares minimisation, was found to be:

$$f(x) = \frac{a}{x}, \text{ where } \quad a = 466.18 \tag{1}$$

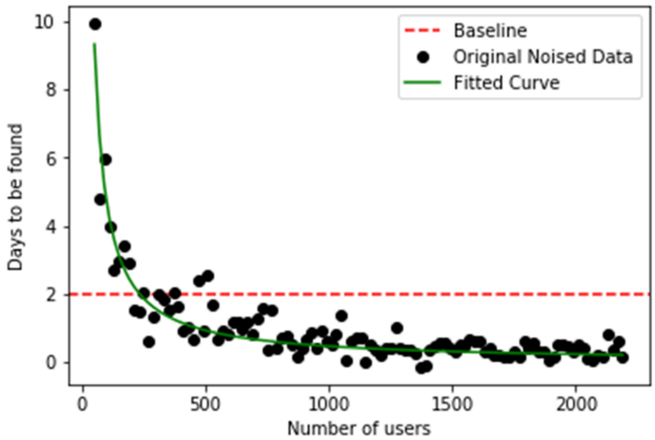
The optimal value for parameter $a$ was determined so that the sum of the squared residuals (SSR) of $f(x) - y_{data}$ is minimised, namely, the minimum of:

$$SSR = \sum_{i=1}^{108} (f(x_i) - y_i)^2, \tag{2}$$

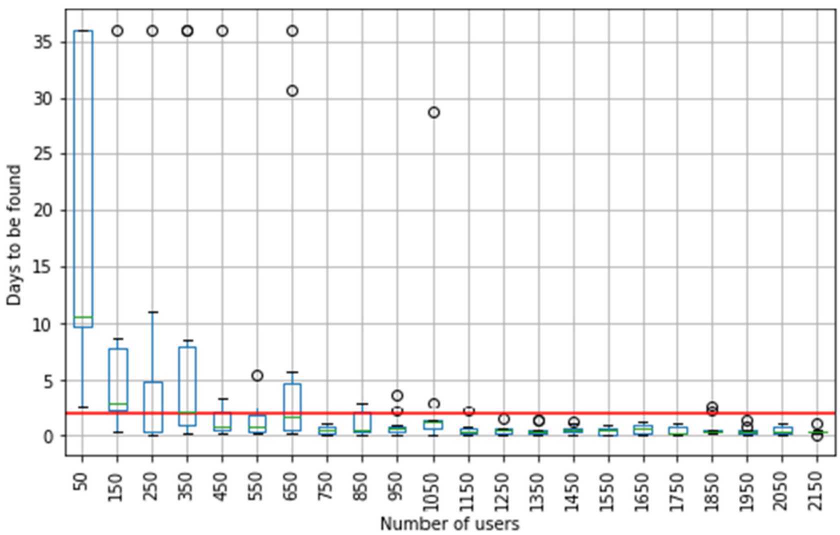
where $y_i$ is the $i$th value of the sample, $f(x_i)$ is the predicted value of $y_i$, and $x_i$ is the $i$th value of the independent variable (i.e., *nb_people*). The fitted curve over the original data is also depicted in Figure 4b. The resulting fitted curve can then be used in decision-making as it can be considered a utility function that quantifies the marginal utility of the users for the citizen sensing application in question. In other words, a diminishing marginal utility [94]—which is a concept also used lately in a broader sense than its original economics scope [95,96]—can be observed in Figure 4b as its first users yield more utility than the subsequent ones, with a continuous decline for more users. Therefore, the decision-makers—the missing children organisations in that case—will be able to determine the expected benefit from the acquisition of new users of the mobile application to adapt their marketing strategies and compare this solution over their other approaches for engaging the public.

According to the data, the median value for the 'days to be found' falls below the baseline for the first time at *nb_people* = 210. After 500 users, a horizontalisation of the curve appears, approaching a horizontal asymptote. Therefore, while the critical mass cannot be an exact number, it can be claimed that around 500 users of the mobile application are needed in the examined geographical area to outperform the current situation and have significantly better results. Less than 500 users mean that the area is not yet sufficiently covered, and, thus, each new user offers significance to the investigation. More than 500 users would increase the effectiveness, but with diminishing returns per new user. An ANOVA test also concurred that until they reach 500, more users would make a significant difference. In particular, the differences between the results for the time needed to find the child with *nb_people* = 50 and with *nb_people* = 550 are statistically significant ($p$-value = 0.0016), while for *nb_people* = 550 and *nb_people* = 1050, they are not ($p$-value = 0.394).


(**a**)

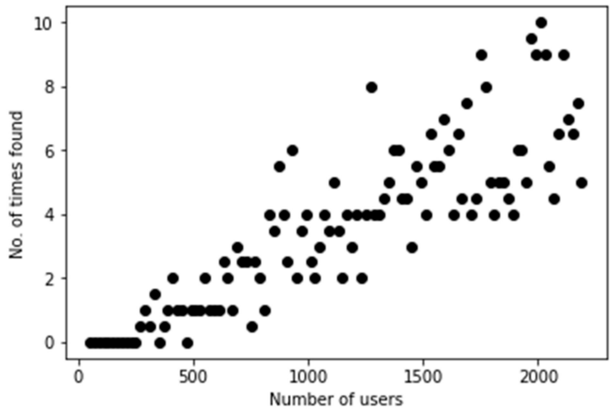



(**b**)




(**c**)

**Figure 4.** *Cont.*




(**d**)

**Figure 4.** (**a**) Screenshot from the simulation for the Athens centre with the missing child (red dot) and 600 users (blue dots) (**b**), (**c**), (**d**) Results of simulation runs: (**b**) median value for the days needed for the missing child to be found, removing outliers using a z-score with a ±3 standard deviations threshold. (**c**) Simulation results using boxplots for *nb_people* mod 50 = 0. (**d**) Median value for the number of times the missing child is found in a 2-day simulation for different numbers of users.

The simulated area is the centre of the city of Athens, Greece and is around 2.5 $km^2$. Overall, the average population density for the entire city is 7381 people/$km^2$ [97], while for its centre, it reaches more than 25,000 people/$km^2$. This is also close to the estimation from the mobile operator's data ($\mu$ = 27,340 people/$km^2$ considering a 24.5% market share for the operator [98]). A total of 500 users of the application represent 0.8% of the 62,500 people considered to be living in the area ($2.5 \times 25,000$), down to 0.7% of the 68,350 people, if using the mobile operator's density estimation. This means that for the characteristics of the centre of Athens, the user density required for effective investigations should be more than around 200 users/$km^2$, representing a little less than 0.7–0.8% of the population for that area.

This estimation cannot be accurately extended to the entire city, for example, by calculating the average population density of the entire city, because this will lead to unfounded generalisations. The morphology and street layout greatly affect the citizens' movement and, thus, the circumstances and chances for a missing child to be found. Other parameters, such as if the area is a commercial or residential one, need also to be taken into consideration, and affect human mobility. Nevertheless, it can still be used for crude estimates and ballpark figures in the absence of more accurate information.

Figure 4c reveals much variation in the data for each number of users examined, though reduced as we test for more users. This is expected since there is more uncertainty, because a successful encounter of the missing child is less likely to happen at any given moment. This variation is reduced the more agents are added to the experiment, as is the average time until an encounter with the missing child takes place. Using ten (10) test runs for each scenario reduces this uncertainty in the results, but at the same time, emphasises the fact that this greater upwards variation for low numbers of users translates into even more pronounced risks for the safety of the missing child. In other words, there are two categories of outcomes for missing children: they are either found in good health or not. A larger upwards variation in the time needed to locate each missing child will inevitably lead to fewer children ending up being found in good health. More users aware of the disappearance reduce the uncertainty and make the discovery not only timelier but also more predictable.

Figure 4c also confirms our initial assumption that the critical mass of users cannot be a precise number. Nevertheless, for the selected area of the centre of Athens, we found that if the Amber Alert system was not in place, we would need at least 233 moving users to achieve the same result of less than 48 h until a missing runaway is located. In a scenario such as this, where multiple unpredictable parameters affect the turn of events, the aim is to reduce the uncertainty as much as possible or needed, to maximise the utility of the application. In the end, the resulting estimation of more than 200 users/km$^2$ for the centre of this city cannot be decoupled from the reduction of the variance achieved in larger numbers of users when considering real cases of missing children. The real-world situation confirms that the variation that the simulation results illustrate aligns with the data from actual cases. As shown in Table 1, presenting data for the resolution of past cases, even cases of the same type are resolved at very different times, even though the same search and rescue mechanisms are activated. In other words, if most children are found within a couple of hours, that one which will be found a couple of days later will face greater risks. Reducing this variance with more users in the citizen sensing application, i.e., reducing this uncertainty, also reduces the number of deviant cases, and hence those extreme situations where luck, or lack thereof, may cost a life.

The second indicator, depicted in Figure 4d, shows the number of times a child has been located if the simulation does not end when they are found the first time, and the experiment runs for 2 simulation days. The interpretation of the graph is that the more users are aware of the disappearance, the more times they will recognise the child in the street during a period of 2 days. The variance of the number of times the child is located is increased as the users are increased at a lower rate than its ratio, showing again that the unpredictability in locating the missing children is reduced. A significant result is also the large number of cases where with a small number of users, the child is never encountered by a user in these critical first 2 days. Nevertheless, when considering the cases where the child is encountered more than once, a scenario where this is applicable is the case where agents fail to recognise the child, as seen before [87], and multiple sightings may be required for a positive identification to take place.

## 5. Discussion

In this paper, we have built a stochastic, bottom-up simulation framework for citizen sensing crowdsourcing applications, together with a proof of concept on the investigation of missing children. It shows that the effectiveness of such applications is a function of the number of users they have, which in turn can be approximated and studied. This can be completed if the simulation model is scalable, allowing for heterogeneity in individual characteristics (e.g., agendas, working hours, travel speed, missing child's movement). This framework relies on geographical and aggregated demographic data. Since the simulations aim to approximate, rather than predict, cases of investigations for missing children, demographic aggregates are enough for the required granularity of the test runs. As the real cases are random events in a fluid, but probabilistically predictable environment, so are the simulated ones. This leads us to conclude that the simulations do not need to replicate the real world, but rather provide statistical results that are comparable with it. Further refinement of the model is easily achievable, with the use of more data on human mobility in an area, and of course, allow the simulations to run for other locations, but for the scenario investigated in this paper, more data will not significantly alter the statistical results of the simulations. In the end, the goal of this framework is to provide a decision support tool for organisations that need to predict the effectiveness of the collective awareness mobile tools they provide to form a strategy for reaching the market penetration they need to have.

Agent-based modelling and simulation have been primarily used in many applications to analyse the relation of different variables and their mutual influences in a spatiotemporal context. They intended to unfold valuable insights for the spatial dynamics developed when simulating a complex system such as that of the natural world by simulating people's bottom-up behaviour [99,100]. Our model is built on the knowledge the academic literature has acquired to develop a new urban simulation of human mobility able to answer complicated questions, opening up capabilities for other applications. In particular, considering the use of the adapted simulation model on any similar citizen sensing mobile application as a decision support tool, the quantified marginal utility of new engaged users can be compared with the cost of obtaining them. This can lead to an estimation, for example, of a metric that takes the form of average minutes saved per dollar spent on promotion. Obviously, this is not a real-life metric, but it can certainly guide business decisions by calculating a form of Return on Investment (ROI) based on it, to decide on the appropriate amount to be spent for promotion, or decide on the duration of promotional activities, depending on the size of the userbase achieved. Moreover, the use of the simulation tool in different geographical areas of interest can help to better target promotional campaigns in locations that lack engagement in order to maximise the impact of the investment.

In the case of missing children, the simulation framework demonstrates the improvement margin that public engagement may bring through crowdsourcing initiatives to reduce the principal period between the moment a child is declared missing and the one when it is found. Public engagement in these investigations has already proven to be particularly helpful. From 2018 to 2019, there was an 18% increase in cases resolved with citizens' help, probably signifying that public engagement is rising [90]. The criticism, though, that the Amber Alert system and publicity appeals receive regarding their success in achieving public participation [101,102] suggests that there is still room for new applications that call for public engagement with better success measuring mechanisms and evidence-based targeting of citizens recruitment. For example, our calculations show that for a specific area, there can be defined a comparison between the existing system (Amber Alert) and the alternative through the use of a mobile app, in terms of probability of a sighting and a positive identification of the missing child, depending on the number of people moving and having received the mobile notification with the details of the missing child.

Of course, this system, as any other simulation model, is not above limitations. First, the simulation model is highly dependent on the initial conditions and the decisions taken for its many parameters. A change in one or more of these parameters may give different results for the critical mass of users. Therefore, especially for data that may be noisy to begin with, careful selection of the appropriate variables needs to take place. Where sensitive factors may heavily impact the results of the simulation, the related variables need to be based on more or more carefully selected data. For example, although deviations in the average walking/driving speed in an area does not seem to affect the results a lot, the amount of time the missing child rests before moving to another location, or the probability of a positive identification when a chance encounter with an app user takes place seem to have greater impact.

A limitation we have identified is that the coverage of an area is dependent on both the number of users as well as their distribution. Our simulation framework examines only the former, while it considers the users uniformly distributed. In that view, simulation of large areas, such as a city, would be less accurate, and the need arises to split that area into smaller ones. The model is parameterised on a generic level, and the indications on the users' number apply uniformly to the whole area without considering neighbourhood-level specificities. Splitting the large area into many smaller ones partially solves the problem but significantly increase the computational complexity and presents a challenge as to the criteria and configuration for this split. On the other side, extrapolating the results of a small region to larger areas, such as a city, would also involve risks. The micro-geography of a region, namely, the small scale of detail on its geography and street structure, affects how people are moving within it. What is more, the actual micro-geography of any geographic area, such as a city, is still overall unexplored [74] (p. 77), which may also impact the results' accuracy.

A proposed method to circumvent these issues for larger areas is instead of applying a uniform two-dimensional distribution for the starting locations of the agents in each simulation, namely, the people's homes, to apply a nonlinear distribution of probabilities that the starting location (the home) of a user is in each point in the map. This probability distribution can be derived from mobile user data with more granularity, point population densities per municipality, averaging the points between them, or other similar methods.

This would mean that the geographic user density in a set of simulations will match that of the population.

Additionally, some challenges remain for ABM in general, which also apply here, regarding the difficulty to validate the resulting model. These were the challenges that led us to use simulation in the first place. However, as mentioned before, collecting data from the actual implementation of ChildRescue is a potential source of data to validate the system. The actual adoption of the ChildRescue mobile application by missing children organisations and the public in Greece and Belgium is ongoing. The platform has already been used in more than 85 real-life cases (March 2021). Therefore, our next steps involve validating the simulation results with the actual ones leveraging the growing adoption rates in these two countries.

Furthermore, we had to make several assumptions and simplifications about the citizens and the missing child to build the model. We aimed to simulate the case while continuously refining our model to bring it closer to reality. Our next steps regarding the development of the simulation involve further advancements, including (a) the integration of traffic information and its impact on the agents' mobility, (b) the addition of POIs for the citizens as well, since the distribution of citizen sensor observations is also quite critical, (c) the creation of profiles for the people agents, as in [103], such as teenagers, working people, and seniors, (d) the addition of a new travelling mode, namely, the use of public transport, that follows different routes and movement speeds, and (e) the creation of the 'outside' agent, to represent all the cases where the working or home place is outside of the simulation.

Having mentioned these future modifications for the simulation model, we note that a simulation's role is not to create an accurate copy of any system or environment but to help explore various contingencies' consequences. The suggested future modifications hold the risk for system overload without a corresponding increase in accuracy and reliability. Therefore, the presented model, using agent-based modelling and building on its scientific robustness, provides an adequate approximation to reality for the intended purposes and serves as a testbed helping answer several research questions.

**Author Contributions:** Conceptualisation, A.M.-P. and C.N.; Data curation, A.M.-P. and I.L.P.; Formal analysis, A.M.-P.; Funding acquisition, C.N. and J.P.; Investigation, A.M.-P.; Methodology, A.M.-P. and I.L.P.; Project administration, J.P.; Software, A.M.-P. and I.L.P.; Supervision, A.M.-P.; Validation, A.M.-P.; Visualisation, A.M.-P.; Writing—Original draft, A.M.-P.; Writing—Review and editing, A.M.-P., I.L.P., C.N., and J.P. All authors have read and agreed to the published version of the manuscript.

**Funding:** This work has been co-funded from the European Union's Horizon 2020 research and innovation programme under the ChildRescue project 'Collective Awareness Platform for Missing Children Investigation and Rescue', grant agreement No 780938.

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** The datasets that concern the results of the simulation runs conducted during the current study are available in GitHub at https://github.com/ariamichal/Missing_Child_Simulation (accessed on 2 July 2021). The mobile phone users' volume data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to data privacy restrictions.

**Conflicts of Interest:** The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

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