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A systematic review of app-based and crowdsourcing approaches

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Abstract
Few researches have considered fear of crime as a context-specific experience. This paper reviews a novel methodological approach to operationalizing fear of crime from a place-based perspective. We present a systematic review of published studies that use crowdsourced or app-based measures to explore perceptions of crime, synthesizing reported strengths and limitations from the 27 studies that met our inclusion criteria, to determine key developments and common issues. These are illustrated with data from three studies. We find consensus that app-based and crowdsourcing measures of fear of crime capture more precise spatial and temporal data alongside auxiliary information about the individual and the environment. Practical benefits, such as reduced cost of data collection and implementable outputs that are useful to practitioners are also highlighted. However, limitations around sampling biases, generalizability of findings, and the under-representation of certain areas persist.

Keywords
Fear of crime, environmental criminology, systematic review, Crowdsourcing, open data, mapping, perceived disorder, GIS

Introduction

How does the environment influence the fear of crime? When and where do emotions of fear arise? Which contextual features lead people to perceive some areas as more crime-prone than others? It is important to answer these questions to tackle fear of crime and mitigate its negative individual and societal outcomes. Emotional responses of fear of crime affect psychological wellbeing, ease of access to resources, and, in extreme cases, prevents people from leaving home (Hale, 1996). Fear has a wide societal impact affecting sense of community and punitiveness (Hale, 1996); economic impact affecting housing prices (Ceccato & Wilhelmsson, 2012) and business decisions (Casten & Payne, 2008); and environmental impact through a reduction in walkability leading to increased use of high-emission private transport modes (Foster et al., 2012). Fear of crime is also often considered as an outcome when evaluating interventions such as hotspot policing (Braga et al., 2014), CCTV (Lim &, Wilcox 2017), or 'broken windows' initiatives where neighborhood cleanup and zero-tolerance antisocial behavior policies are implemented. Approaches such as Crime Prevention Through Environmental Design (CPTED) (see Armitage, 2017; Marzbali et al., 2012)) also provide theoretical support for understanding how urban design has an influence on fear of crime.

Yet, many empirical studies of fear of crime focus on individual factors, and much less research has considered fear of crime as a *context-specific experience*. This may be due partially to the dispositional bias in criminology, the tendency to highlight internal factors (personality, attitudes) over the causal role of the immediate environment (Clarke, 1983; Sidebottom & Wortley, 2015). Another explanation may be the lack of available data about fear of crime that describes the environmental context in which these experiences take place, making a place-

based approach difficult to operationalize. To conceptualize the perception of crime and place as a function of the person *and* the environment, it is vital to better understand the contexts in which people experience more or less fear. In response, the last few years have seen several projects employ app-based and crowdsourcing tools in a bid to collect better data on specific experiences of fear of crime (Solymosi & Bowers, 2018). The field is now at a point where these unique studies can be synthesized to create a comprehensive review and inform place-based study of fear of crime.

The aim of this paper is to synthesize key methodological processes from studies using app-based and crowdsourced data collection, in order to promote such tools as a means to operationalize fear of crime and associated constructs from a place-based perspective. We achieve this through two objectives. First, we conduct a systematic review of published studies using these methods, extracting the key strengths and limitations of their research design. Second, we use data from three studies to illustrate key themes. Taken together, the systematic review and the empirical demonstrations provide an overview of this nascent field, and serve to produce guidance to those growing numbers of researchers adopting these techniques.

A place-based approach to fear of crime

It has been recognized that fear of crime is transitory and situational (Fattah & Sacco, 1989), and is influenced by the features of the situations in which people find themselves (Pain, 2000; Rollwagen, 2014). For instance, 'signal crimes' and 'signal disorders' (e.g. graffiti or litter) have been found to communicate a break-down of social order (Innes 2004; Kennedy & Silverman, 1985). Levels of prospect, refuge, and escape in micro-places are associated with

increased fear (Fisher & Nasar, 1992). These situational features interact with person-specific factors known to affect the fear of crime. For example, while women are consistently reported to experience higher levels of fear of crime than men (LaGrange & Ferraro, 1989), in certain situations, it is actually men who show higher fear than women (Moore & Breeze, 2012). Yet most studies of fear of crime still do not address the influence of these contextual factors, possibly due to entrenched issues in fear of crime conceptualization and measurement. The first step to shift fear of crime researchers' focus from the person to the environment is to conceptualize fear of crime as a place-based, context-specific experience. This task cannot be separated from challenges of operationalization, since our understanding of fear of crime is dependent on the measurement instrument (Farrall et al., 1997). Hough (2004), for example, proposed a place-based understanding of fear of crime experiences as 'mental events' (rather than 'mental states' of worry). Similarly, others distinguish between 'concrete' (versus 'formless') fears (Ferraro & LaGrange 1987) or 'state' (versus 'trait') emotional reactions of fear (Gabriel & Greve 2003). However, traditional survey tools make it difficult for respondents to disclose their feelings about particular crimes at particular times and places (Farrall et al. 1997), capturing generalized anxieties instead (formless fears, traits, and mental states) (Gray et al., 2008).

Moreover, traditional survey-based measures have been criticized for failing to capture the behavioral component of fear of crime events (Ferraro & LaGrange, 1987; Gabriel & Greve, 2003). In response to fear of crime, citizens may adopt 'functional' protective behaviors, but also 'dysfunctional' avoidance behaviors. The latter have negative effects on wellbeing but are rarely captured by questionnaire-based measures (Jackson & Gray, 2010).

Evidently, there is a need for a measurement approach to capture behavioral and emotional responses to fear of crime (Solymosi et al., 2015), in a spatially and temporally explicit manner, to reflect the other set of fear of crime conceptualizations, (mental events, concrete fears and states, and behavioral changes due to fear).

In the study of crime, ample spatially and temporally explicit data exist to support a place-based approach focusing on immediate situational conditions that create a criminal opportunity (Wortley & Mazerolle, 2008). Accordingly, the relationship between place and criminal behavior has been the focus of much criminological research producing many problem-solving interventions for crime prevention (Clarke, 1983; Clarke & Bowers, 2017). In order to achieve the same results for fear of crime, a truly place-based measure is needed.

Traditionally, spatial information in surveys has been operationalized as respondents' home address (San Juan et al., 2010), representing where worried people live, rather than where they experience fear events. Although this information may be relevant to study environmental cues associated with fear of some crimes, such as burglary, it is of little use when trying to understand the interface between fear of crime and the environment in public space. Other studies putting fear of crime on the map make use of intensive, mostly qualitative methodologies, for example asking people to map areas they avoid due to fear (Doran & Burgess, 2012), asking about fear in one particular location (Fisher & Nasar, 1992), following participants along a pre-planned route as they narrate their levels of fear (Nasar & Jones, 1997), or asking people about signals in their environment that make them feel unsafe (Innes, 2004). While such studies move towards attributing spatial information to people's perception of safety, none of them collect data on specific instances of fear experienced in day-to-day life

which reflect emotional responses in situ. Rather, by asking people to reflect on general worry, they continue to tap into anxieties like surveys do (Gray et al., 2008).

To remedy this issue, people's experiences need to be captured as and when they happen. One approach is to use mobile applications that implement experience sampling methods (MacKerron, 2011) or to deploy crowdsourcing projects which facilitate the real-time reporting of such experiences (Howe, 2006). Pilot projects evaluating such methods applied to study people's subjective perceptions of their environments and their experiences with fear of crime have begun to emerge. As more of these studies are published, we learn more about the strengths they offer and the challenges they pose. To truly establish this approach as a viable methodological direction for operationalizing fear of crime as a place-and-time-specific experience, the time has come to synthesize these outputs, and establish common directions for further research. By bringing together findings of such pilot studies, place-based fear of crime research can move to rigorous implementation of this methodology to build an evidence base of environmental correlates of fear of crime. Furthermore, the results can inform the use of similar methodologies in other fields measuring emotional reactions to the immediate environment.

Methods

This paper takes a two-pronged approach to synthesizing the recent developments in the application of app-based and crowdsourcing methods to the study of perceptions of crime and place. First, we use a systematic review to identify relevant studies, and extract key strengths

and limitations. Second, where possible, we illustrate these with data made available to the authors by three of these papers. This section discusses each method in turn.

Systematic Review

A systematic review of crowdsourcing and app-based studies analyzing the fear of crime and associated constructs was conducted using a set of a priori searching, inclusion, and selection criteria for deciding eligibility. Our approach is based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA), in line with similar systematic reviews in the domain of criminal justice research (Gravel et al., 2013; Lorenc et al., 2013).

Criteria

Any observational, experimental, feasibility, or case studies employing app-based or crowdsourcing methodologies to collect data about perceptions or emotions of place in terms of safety or crime were eligible for inclusion. In this case, crowdsourcing techniques were defined as those that involve harnessing the information and skills of large crowds of people into one collaborative project (Howe, 2006). Only peer reviewed published literature, including journal articles, books, book chapters and conference papers written in English were examined.

Searching

We used keyword searches in three search engines: BASE (Bielefeld Academic Search Engine), Google Scholar and CORE (COnnecting REpositories). BASE and Google Scholar are two of the most popular multidisciplinary academic search engines, having more than 100 million and around 160 million indexed documents, respectively. CORE aggregates more than 135 million

open access articles. Searches were conducted between December 2017 and March 2018. The search strategy used the following keywords:

((fear of crime) OR (worry about crime) OR *(perceptions of security)* OR *(attitudes towards crime)* OR *(perceived disorder))* AND *((crowdsourcing)* OR *(mobile application)* OR *(web application)* OR *(open data)).*

During this process, Boolean logic was not used to pick up variations on wording. 'Citation chasing' was further used to cross-reference articles from the bibliographies of selected publications (Lorenc et al. 2013). Finally, consultation with members of the research team and the corresponding authors of the selected papers was used to identify additional papers. This search returned 576 papers.

Screening

To select studies from the initial sample (N=576), the abstracts were coded as to whether or not they met the following inclusion criteria:

(a) The paper analyses or discusses app-based or crowdsourcing measures.

(b) The paper focuses on fear of crime, worry about crime, attitudes towards crime, or perception of security or disorder.

Thus, all research analyzing or discussing other quantitative or qualitative measures (mainly survey data) and/or focusing on other social phenomena (e.g., crime, happiness) were excluded. Both studies using primary and secondary data, and publications critically discussing the new approaches, were included. We included any type of study design, as long as it included app-based or crowdsourced data collection. With respect to the object of study, we did not limit our screening to any specific operational definition of fear of crime, worry about crime, attitudes towards crime, perceptions of security or perceived disorder. Papers making use of social media

data such as Facebook or Twitter (e.g., Burnap et al., 2015; Erete et al., 2016; Kim, et al., 2014) were excluded, as they follow different methodologies than those discussed in this paper. Finally, we note that when the same data were analyzed by the same authors in more than one publication, all publications were selected and examined, as long as the publications used the data in meaningfully different ways and presented original contributions. In sum, 27 publications (12 journal articles, 11 conference papers and 4 book chapters) were selected (see Figure I). Those conference presentations published in conference monographs and proceedings are counted as conference papers. Articles include commentaries (3) as well as original research articles (9), as the purpose was to extract critical analysis of strengths and limitations of the method, to which commentaries contribute in substantial ways.

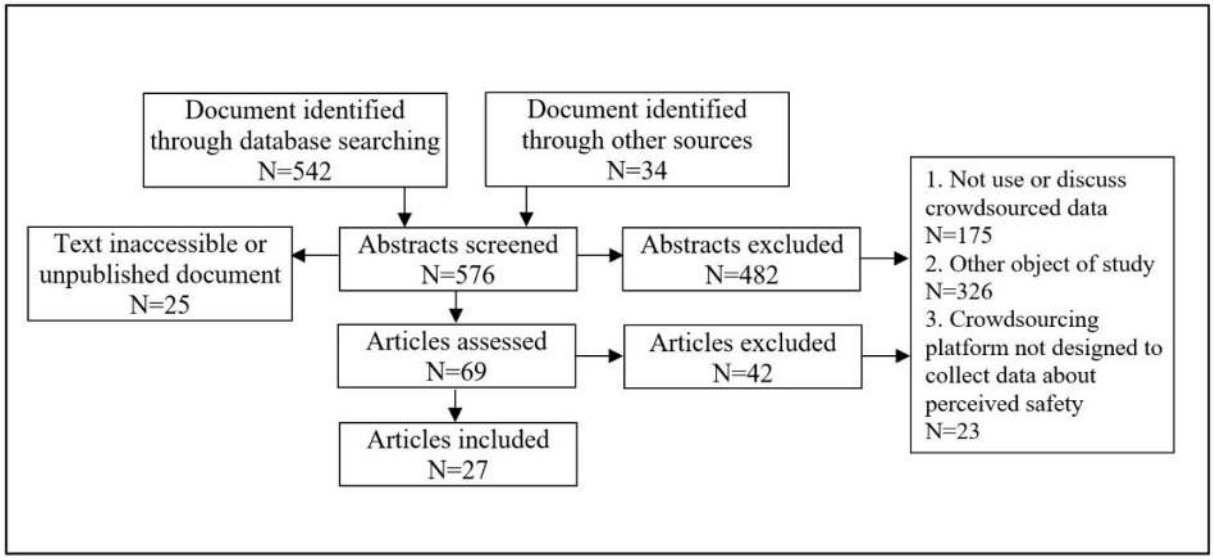

Figure I. Flowchart of literature through the systematic review.

Data extraction and synthesis

Data were extracted from selected articles using a standardized form to record information about authors, methodology, sample, main findings, and conclusions of the research. The extracted data were synthesized and coded into the following categories: substantive topic of study;

measurement of the topic of study; methodological tool used; strengths identified; limitations identified; recommendations and future work; and substantive findings.

Thematic analysis of each publication was conducted to extract a list of the main strengths and weaknesses, which were then coded into subcategories of emerging themes. An intercoder reliability check was carried out where after the initial coding, a second coder assessed the strengths and limitations identified in the paper using the same coding and categorizing protocol (Mouter & Vonk Noordergarf, 2012). The results were that the second coder subsumed four closely related subcategories into one subcategory.

Exploratory Data Analysis

The additional analysis section of a PRISMA review traditionally refers to sensitivity or subgroup analysis. However, here, to supplement the systematic review, we present additional analysis of data from three exemplar studies using exploratory data analysis (see Tukey, 1977). In particular, exploratory spatial data analysis (ESDA) (Bivand 2010) is used to illustrate the extracted themes with empirical data. The three studies (Buil-Gil, 2016; Solymosi et al., 2015; Vozmediano et al., 2017) were selected because the authors had access to the micro data from these. This section will now describe each application.

Fear of Crime Application (FOCA; Solymosi et al., 2015)

FOCA is a purpose-built mobile application that employs an experience sampling design asking participants about their perception of safety. Responses are recorded along with coordinates and a time stamp from the phone's inbuilt sensors. The application allows for retrospective annotation through the option of locating the area of interest on a map manually, once the participants have removed themselves from the dangerous location. Figure II shows the mobile

app visual flowchart that represents the users' interaction flow with the application. In this study, we access data from 76 users who submitted 1344 reports between 1st August 2013 to 2nd September 2013 (pilot) and 20th June 2014 to 15th March 2015 (main study). Of these, 1220 reports were "Not at all worried" (90.8%), 87 "Not very worried" (6.5%), 29 "Fairly worried" (2.1%) and 8 "Very worried" (0.6%).

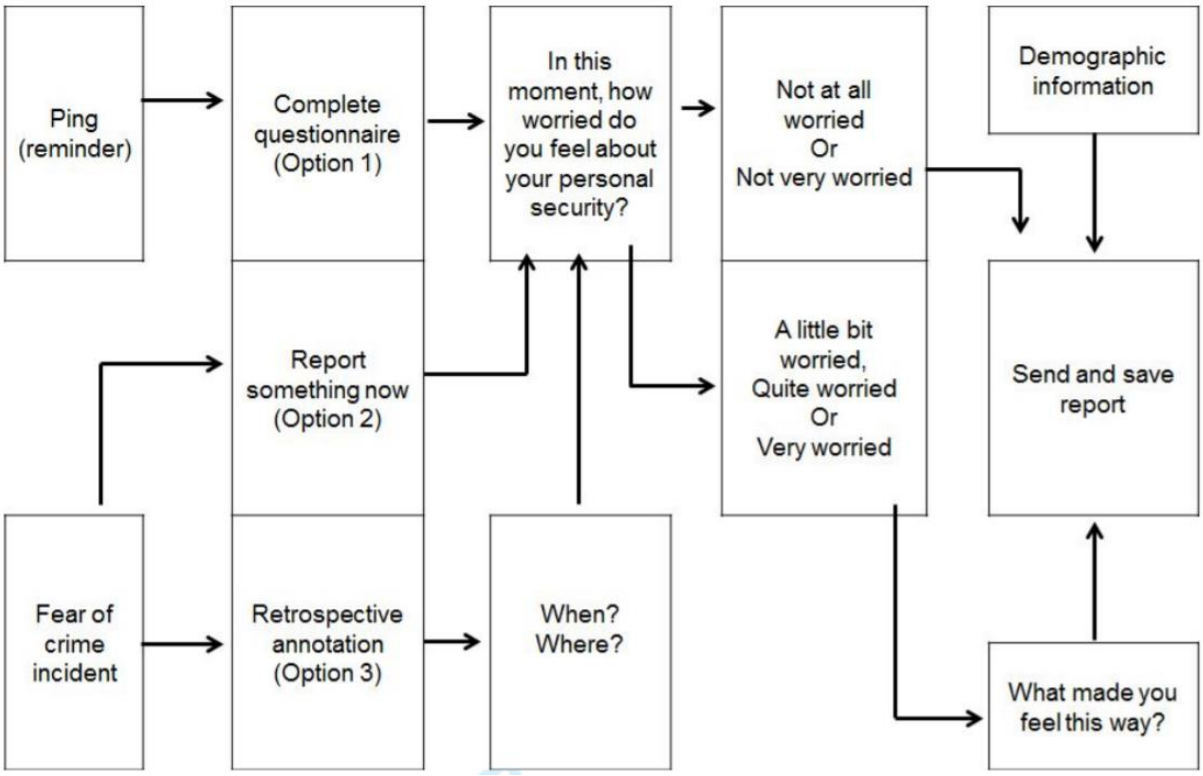

Figure II. FOCA visual flowchart.

InseguridApp (Buil-Gil, 2016)

InseguridApp is an Android application built by researchers at Crimina Research Centre of Miguel Hernandez University. It was deployed in Elche, Spain, and is available in Spanish language. It follows a similar structure and approach to FOCA, allowing users to self-report their fear of crime. InseguridApp did not include a retrospective map for reporting historic

events. Figure III shows screenshots of this application. Data were collected from 32 users, who submitted 439 reports (315 “Not at all fearful” (71.7%), 100 “Not very fearful” (22.8%), 17 “Fairly fearful” (3.9%) and 7 “Very fearful” (1.6%)) between 1st April 2016 and 31st May 2016.

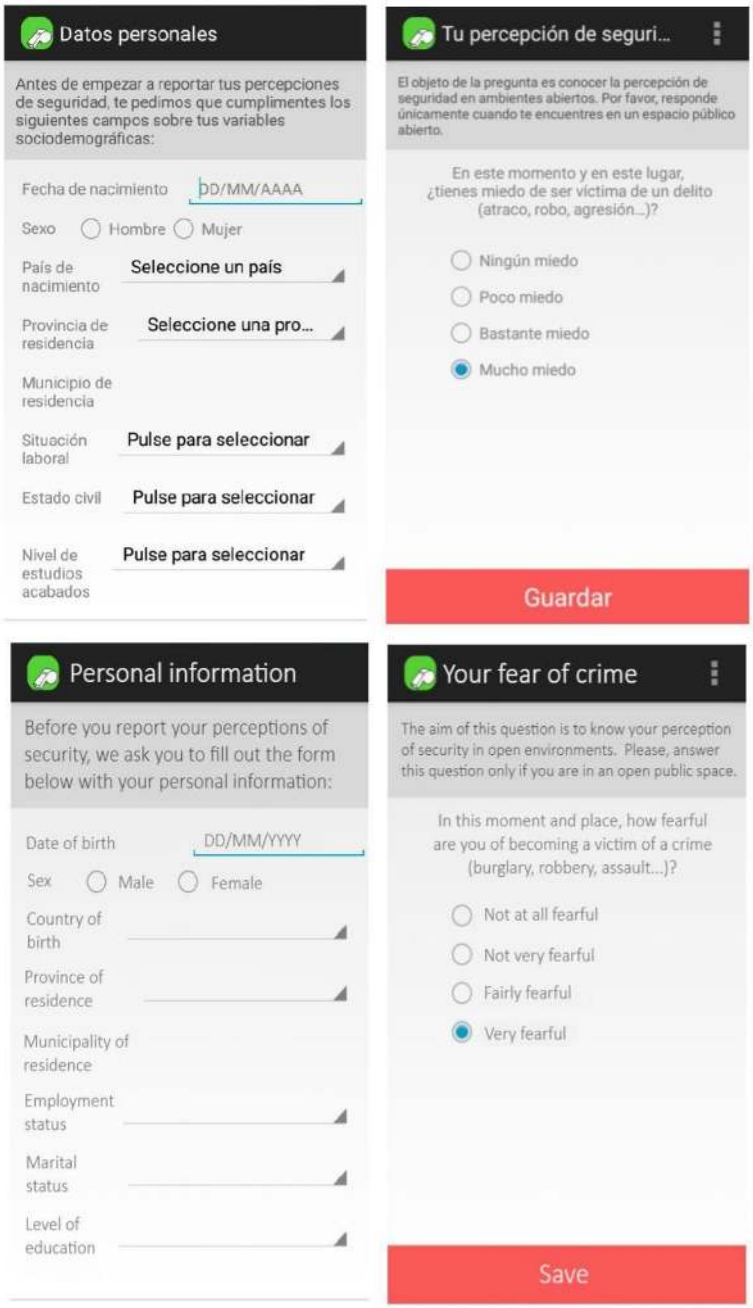

Figure III. Menus 1 and 2 of InseguridApp app and its translation to English.

Walkcap (Vozmediano et al., 2017)

Walking capturer, or 'Walkcap', is an Android application designed by researchers of the University of the Basque Country, Spain. Walkcap is available in Spanish, but multilingual support was included. The app was designed to capture walking routes: it detects when the users start walking and when they stop, collecting GPS points and time prints through the walk, mapping urban mobility of the participants. Once a day (time of the day can be chosen) the app prompts users to answer questions about a randomly selected recorded route from that day. Resulting data is of routes labelled with information about the age and gender of the person, the purpose of the route, if the participant walked alone, perceived levels of safety, perceived beauty of the urban landscape, and reason for making the decision to walk. Figure IV shows screenshots of the application. Access was provided to data from 90 routes, but given that participants were asked to evaluate one random route daily, only 34 of them included data about safety perceptions.

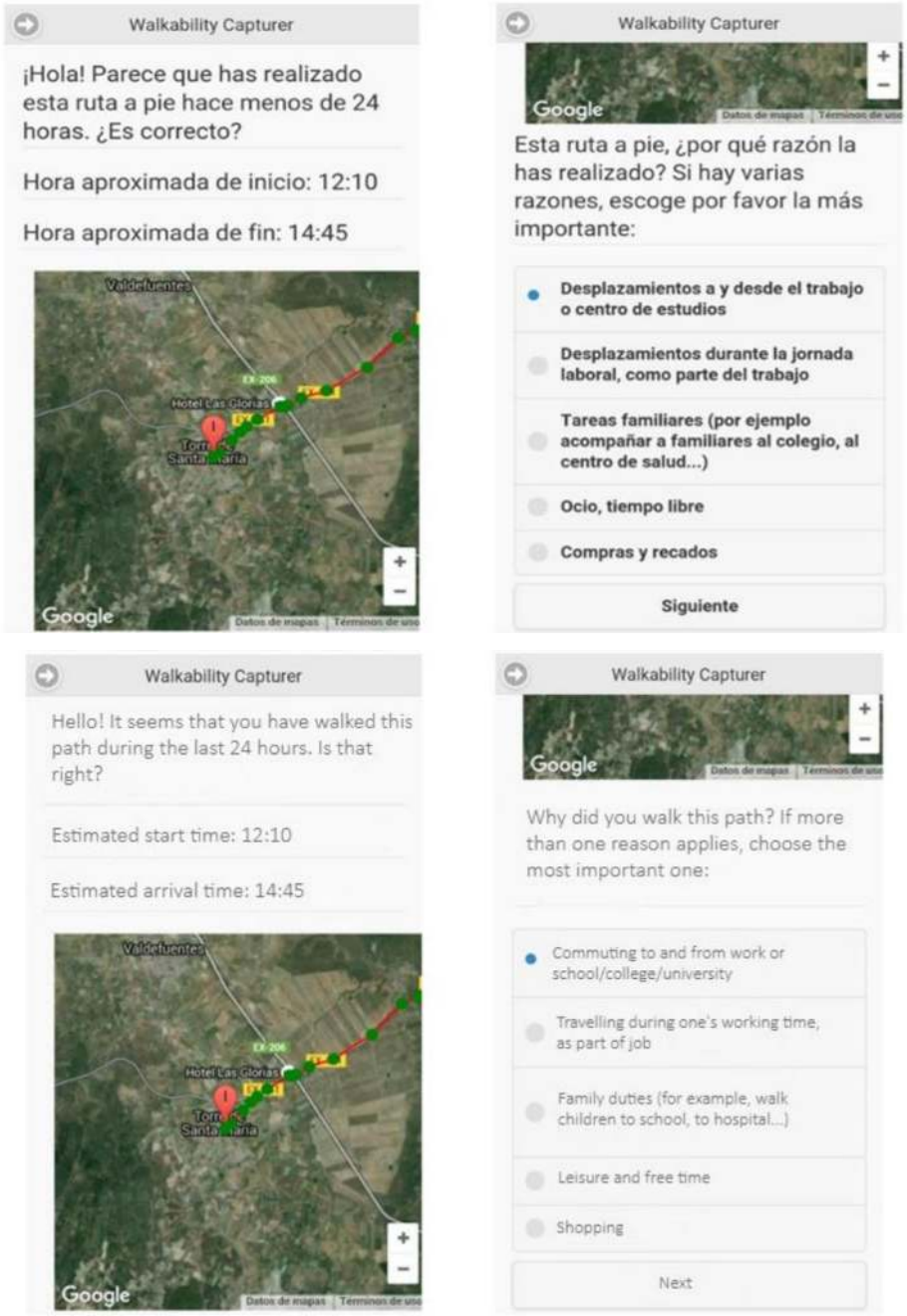

Figure IV. Two menus on Walkcap - confirmation of the detected route and purpose - and its translation to English.

Results

Descriptive Landscape of Studies

Table 1 details the 27 studies included in our systematic review. Publications date from 2010 to 2018 and cover research in eleven countries. Each paper has been assigned a number in the first column of Table 1 which is used to refer to it in text.

Six papers discuss data recorded from self-built mobile applications (1, 2, 4, 7, 11, 23), eleven inspect crowdsourced data from a self-built online platform (3, 5, 6, 12, 17, 18, 19, 20, 22, 26, 27), three discuss data recorded from an already existing mobile application (9, 10, 13), and six analyze data from already existing online platforms (8, 14, 15, 16, 21, 24). One (25) analyses secondary data from both methods.

Eighteen studies focus on 'perceived security' (1, 2, 3, 5, 6, 7, 8, 12, 14, 15, 16, 17, 18, 19, 21, 22, 26, 27), eight analyze 'fear of crime' (4, 9, 10, 11, 13, 20, 23, 25), and four studies examine 'perceived disorder' (4, 17, 24, 25). Three studies tackle both fear of crime and at least one type of perceived disorder (4, 17, 25). Interestingly, the approaches to operationalizing these concepts vary widely between researchers (see Table 1). The distinct approaches to wording in the measurement of fear and perception ranges from questions originating from past survey-based fear of crime research (4, 23, 25) to asking people to rank places (3, 5, 14, 15, 16, 21, 22), or asking about annoyance (17). This is important to consider, as the way that fear of crime is operationalized affects results (Farrall et al., 1997; Gabriel & Greve, 2003).

Table 1. Characteristics of the article included in the systematic literature review.

	Paper	Country of institution	Substantive topic	Operationalisation of topic	Methodological tool
1	Birenboim (2015)	Netherlands	Sense of security	Evaluate the momentary sense of security from 1 to 5	Self-built mobile app
2	Blom et al. (2010)	India	Feeling of security	Green or red tag to indicate locations where they feel comfortable or uncomfortable	Self-built mobile app
3	Candeia et al. (2017)	Brazil	Perceived safety	Choose "which place looks safer?" from two images	Self-built website or online platform
4	Chataway et al. (2017)	Australia	Fear of crime / perceived disorder	Frequency of worry: scale between 1 (Not once in the last month) to 4 (Everyday) /	Self-built mobile app
5	Dubey et al. (2016)	India	Perceived safety	Perceived disorder: how much of a problem certain conditions (e.g. vandalism/graffiti, rubbish, drinking) are in the immediate area, between 1 and 4	Self-built website or online platform
6	Gómez et al. (2016)	Colombia	Perception of security	Choose "which place looks safer?" from two images	Self-built website or online platform
7	Hamilton et al. (2011)	Australia	Perceived safety	Trace a polygonal area on a map and quantify the level of risk and uncertainty between 0 and 10	Self-built mobile app
8	Harvey et al. (2015)	USA	Perceived safety	Choose between two scared/safe emoticons	Website or online platform
9	Innes (2015)	UK	Fear of crime	Choose "which place looks safer?" from two images	Mobile app
10	Jackson and Gouseti (2015)	UK	Fear of crime	"In this moment, how worried are you about becoming a victim of crime?"	Mobile app
11	Jones et al. (2011)	UK	Fear of crime	"In this moment, how worried are you about becoming a victim of crime?"	Self-built mobile app
12	Kyttä et al. (2014)	Finland	Perceived safety	Note level of immediate happiness in relation to personal safety, between 1 and 4	Self-built website or online platform
13	Leitner and Kounadi (2015)	USA	Fear of crime	Locate on a map all possible fearful places and danger locations	Mobile app
14	Li et al. (2015)	USA	Perceived safety	"In this moment, how worried are you about becoming a victim of crime?"	Website or online platform
15	Naik et al. (2014)	USA	Perceived safety	Choose "which place looks safer?" from two images	Website or online platform
16	Ordonez and Berg (2014)	USA	Perceived safety	Choose "which place looks safer?" from two images	Website or online platform
17	Pánek et al. (2017a)	Czech Republic	Perceived criminality / Perceived noise	Choose "which place looks safer?" from two images	Self-built website or online platform
18, 19	Pánek et al. (2017b, 2018)	Czech Republic	Perceived safety	Trace a polygonal area, line or point on a map and quantify the level of annoyance between 1 and 6	Self-built website or online platform
20	Pődör et al. (2016)	Hungary	Fear of crime	"Mark places where you feel unsafe during the night-time / day-time"	Self-built website or online platform
21	Porzi et al. (2015)	Italy	Perceived safety	"Indicate [with polygons on a map] those places where you feel fear of crime"	Website or online platform
22	Salesses et al. (2013)	USA	Perceived safety	Choose "which place looks safer?" from two images	Self-built website or online platform
23	Solymosi et al. (2015)	UK	Fear of crime	Choose "which place looks safer?" from two images	Self-built mobile app
24	Solymosi et al. (2017)	UK	Perceived disorder	"In this moment, how worried are you about becoming a victim of crime?"	Website or online platform
25	Solymosi and Bowers (2018)	UK	Fear of crime / perceived disorder	Report a problem (e.g. graffiti, litter) on an online map.	Self-built mobile app / Website or online platform
26, 27	Traunmueller et al. (2015, 2016)	UK	Perceived safety	Fear of crime: "In this moment, how worried are you about becoming a victim of crime?" /	Self-built website or online platform

Eighteen studies focus on 'perceived security' (1, 2, 3, 5, 6, 7, 8, 12, 14, 15, 16, 17, 18, 19, 21, 22, 26, 27), eight analyze 'fear of crime' (4, 9, 10, 11, 13, 20, 23, 25), and four studies examine 'perceived disorder' (4, 17, 24, 25). Three studies tackle both fear of crime and at least one type of perceived disorder (4, 17, 25). Interestingly, the approaches to operationalizing these concepts vary widely between researchers (see Table 1). The distinct approaches to wording in the measurement of fear and perception ranges from questions originating from past survey-based fear of crime research (4, 23, 25) to asking people to rank places (3, 5, 14, 15, 16, 21, 22), or asking about annoyance (17). This is important to consider, as the way that fear of crime is operationalized affects results (Farrall et al., 1997; Gabriel & Greve, 2003).

All publications recorded geographical information, creating spatially explicit data about people's experiences with fear of crime, supporting a place-based approach to evaluating emotions about crime. Three different approximations were used to record spatial information. Mobile phone GPS signal was used by nine publications to geocode users' locations (1, 2, 7, 9, 10, 11, 13, 23, 25). Ten papers requested participants to assess their safety perceptions for specific images, which were geocoded by researchers (3, 5, 8, 14, 15, 16, 21, 22, 26, 27). Finally, ten studies asked users to trace or point out on an online map places where they felt unsafe or perceived signs of disorder (4, 6, 12, 17, 18, 19, 20, 23, 24, 25). Some applications allowed two approaches, for example Solymosi et al. (2015) allowed both real-time reports using GPS and retrospective reporting using a map. The temporal dimension (day and exact time) of each report was also recorded and analyzed in seven cases (1, 2, 4, 11, 23, 24, 25).

Identified strengths and limitations

To learn from these diverse applications and advance current discourse, the key strengths and limitations identified by each paper were coded and synthesized.

Strengths

Our systematic review identified five strengths associated with this approach (Table 2). The most commonly identified strength is the ability to capture the transitory and geographically-specific nature of fear of crime. Coded as "*Capture the spatial-temporal specific nature of attitudes and emotions towards crime*", this theme was mentioned by twenty-three publications. For example, Birenboim (2016) (1), who developed a mobile phone application to measure perceptions of security during a music festival in Jerusalem, noted that mobile technologies allow for a more granular resolution in terms of spatial and temporal precision. Such precision might be used to map real-time experiences in its exact location, at the smallest possible spatial scale (Kyttä et al., 2014 (12); Gómez et al., 2016) (6), allowing researchers to "un-erroneously associate them with elements of the environmental backcloth such as incivilities, crime, and disorder" (Solymosi et al. 2015:198) (23). Such granular data allows employing techniques like Kernel density estimation to identify hotspots of fear, and explore the environmental context associated with these (1, 17, 18, 19, 25). This is the key strength and innovation of these methods, which allows for the framing of fear of crime as a situation-specific experience and reveals within-neighborhood variation of experiences of fear. To demonstrate this, Figure V shows a map of points of fear of crime reports made in London using FOCA, and Figure VI a similar map from the results of InseguridApp in Elche.

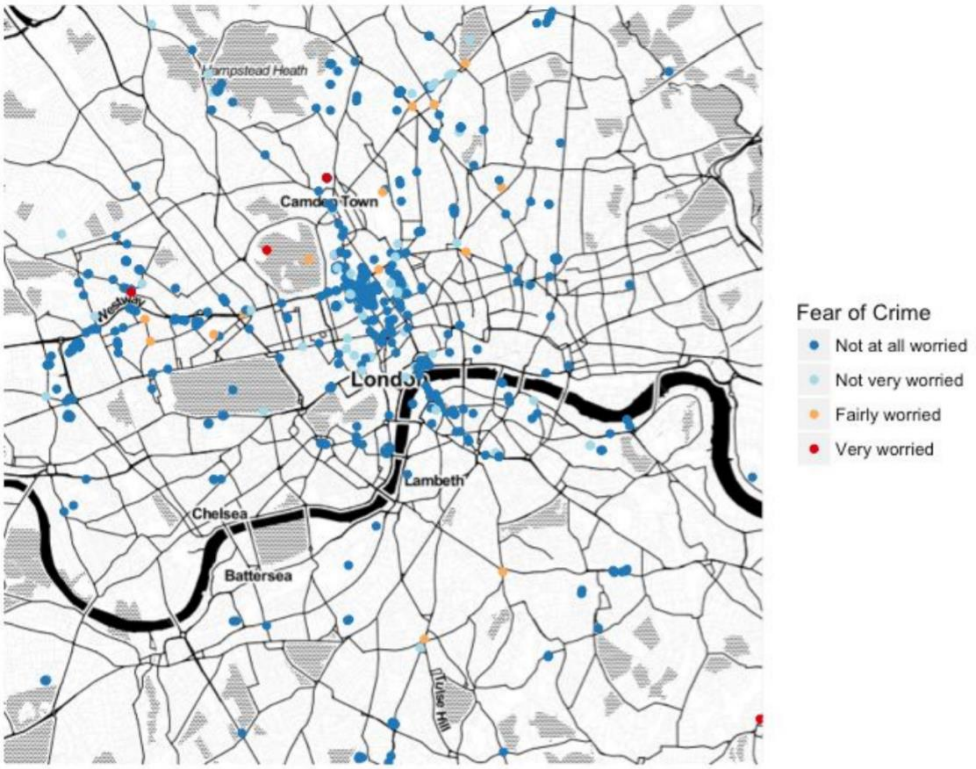

Figure V. Reports of fear of crime in London by FOCA users.

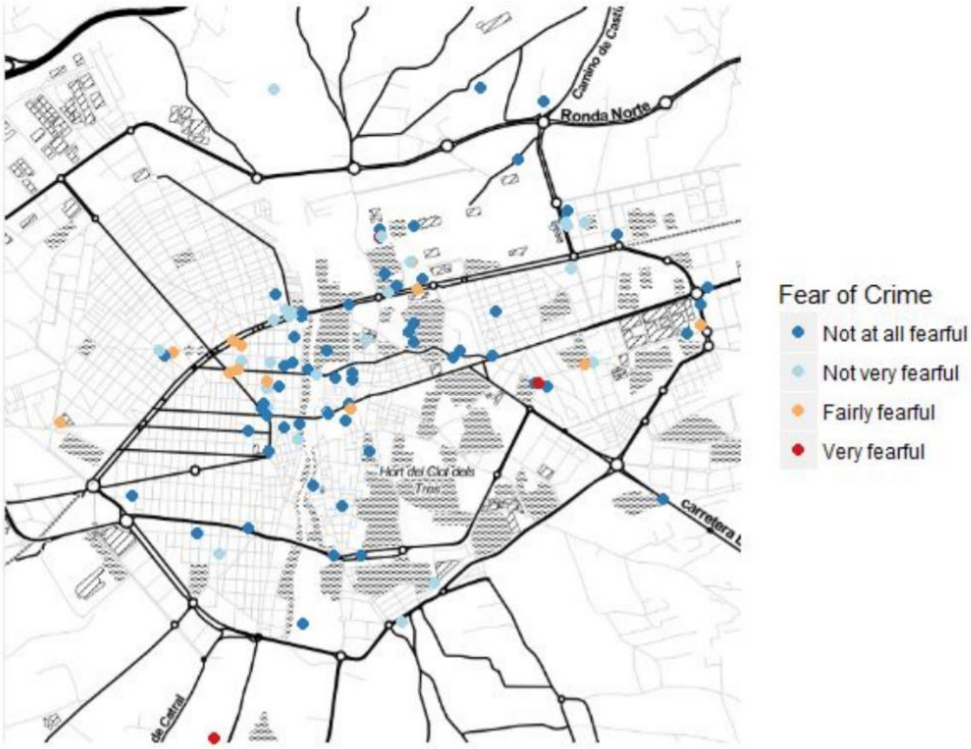

Figure VI. Reports of fear of crime in Elche by InseguridApp users.

Coded as the ability to "r*ecord data on individual variables and specific types of fear/disorder",* twelve papers note that crowdsourcing applications may also record data on socio-demographic variables of users, such as age, gender, place of residence and income. While this feature is present in traditional measures, a particular strength of its application here was identified by five papers (4, 6, 12, 24, 25) whereby it is possible to pair these with more dynamic and context-specific information, providing granularity in contextual knowledge around the fear event. For example, in FOCA (23), the demographic variable 'home neighborhood' was used to code whether each fear event occurred in a familiar or unfamiliar place to the individual. This variable shows the odds of reporting worry while outside home postcode area (non-familiarity) to be 3 times the odds of reporting worry inside familiar areas (odds ratio = 3.33, 95% confidence interval = 1.2 - 10.6, p = 0.025, AIC = 164.41, χ^2 = 0.018, likelihood ratio R^2 = 0.034). This effect holds when adding control variables to the model to account for time of day and day of the week (odds ratio = 3.31, 95% confidence interval = 1.2 - 10.6, p = 0.028, AIC = 163.45, χ^2= 0.008, likelihood ratio R^2= 0.124). Evidently, collecting such data allows exploration of the dynamic interaction of person and situation-specific variables that affect fear.

The strength ability to "*record data on architectural features"* was mentioned by twenty papers, as a way for providing further context to people's experiences and better understand the role of the built environment. To illustrate, architectural features of six high-fear locations (where users of InseguridApp reported feeling unsafe) were coded from photos. Features identified were: narrow alleys with limited visibility (four locations), three contained places where potential offenders could conceal themselves, two were closed-in pathways or dead ends, three were poorly lit at night, two contained observed cues of physical disorder, and three had

a scarce presence of neighbors and passersby. Figure VII shows daytime and nighttime photos of two of these locations. This information motivate testing hypotheses of relationships between such environmental features and fear of crime in larger sample sizes.

Figure VII. Daytime and nighttime photos of two locations reported as unsafe by InseguridApp users.

A technical consideration, the *"reduced cost of data collection"*, was mentioned by eleven papers, claiming that crowdsourcing methodologies reduce data collection costs while generating large sample sizes. For example, Salesses et al. (2013) (22) asked volunteers to choose which place looks safer from two Google Street View images on an online platform, reaching 208,738 reports from participants across 91 countries. Dubey et al. (2016) (5) analyzed more than 1,150,000 pairwise comparisons. The FixMyStreet dataset used by papers 24 and 25 contained more than 275,000 entries. These sorts of sample sizes are costly to obtain using traditional, survey-based or experience-sampling methodologies.

Finally, twenty-one papers argue that policy makers and security planners can use precise geocoded data to design environments less likely to produce fear (coded as "*Oriented to evidence-based policy making/urban planning"*). For example, Candeia et al. (2017:143) (3) argue that crowdsourced geocoded data can be used by urban planners to "understand what interventions may be applied to areas perceived as less pleasant or safe". Some applications, such as FixMyStreet, generate impact directly by submitting users' reports to local authorities to address the issue being reported (Solymosi et al., 2017).

Table 2. Summary table of crowdsourced data in fear of crime research's strengths.

Strength	N	Papers
Capture the spatial-temporal specific nature of attitudes and emotions towards crime.	23	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 16, 18, 19, 20, 21, 22, 23, 24, 25.
Record data on individual variables and specific types of fear/disorder.	12	3, 9, 12, 13, 17, 18, 19, 20, 22, 24, 26, 27.
Record data on architectural features.	20	1, 2, 3, 4, 5, 8, 11, 12, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 26, 27.
Reduced cost of data collection.	11	3, 4, 6, 11, 14, 16, 21, 23, 24, 25, 26.
Oriented to evidence-based policy making/urban planning.	21	2, 3, 4, 5, 6, 7, 8, 9, 11, 12, 14, 15, 16, 17, 18, 19, 20, 22, 23, 24, 25.

Limitations

Just as knowing the advantages of a method is important, the limitations identified by early adopters are vital for setting research agendas for methodological improvement and providing tales of caution. Table 3 lists the themes into which the limitations extracted from each paper were coded.

Many of the limitations identified by our systematic review can be subsumed into the overarching category of issues around sampling. While it is a common and widely researched problem with sample surveys, this issue is revisited each time a new platform for collecting data is introduced (e.g., Bethlehem & Biffignandi, 2012; Elliott & Valliant, 2017). Therefore, it is no surprise that sampling issues are the most common limitation identified.

Perhaps the most unique issue to crowdsourced data collection is *participation inequality*, noted by thirteen publications. This can be split into two issues. One is self-selection bias of participants: for example, males tend to be more represented than females, and young citizens are overrepresented compared to older groups, as "certain demographics of crowdworkers [are] not reached" (Traunmueller et al., 2015:132). As noted by Chataway et al. (2017), even established sampling techniques struggle to reduce the bias arising from self-selection in crowdsourcing projects. However, Jones et al. (2011) tested their mobile app with senior citizens and argued that new methodological approaches should not be a major barrier to record data from various demographic groups; and Salesses et al. (2013) argue that results obtained from analyzing the Place Pulse 1.0 dataset are not driven by biases from gender, age or country of residence.

Another issue, however, is around the participation inequality *within* the sample; a small group of participants are often responsible for most reports (2, 23, 24, 25). For example, with FixMyStreet data, one fourth of all reports were produced by one percent of users, while 73% of people in the sample contributed only once (Solymosi et al., 2017). One way to address this is at the data collection stage: in order to reduce the bias in crowdsourced data, four papers (1, 4, 23, 25) suggest implementing Experience Sampling Method (ESM) or Ecological Momentary Assessment (EMA) (see Csikszentmihalyi, 2014) as sampling design approaches. By making use of ESM/EMA sampling techniques, the bias arising from unequal participation and the subjective decision about when and where to report might be reduced (Chataway et al., 2017).

Another methodological approach to overcome this source of bias is to combine crowdsourcing and machine learning tools which train computational algorithms to reproduce patterns captured by human participation at unreported or underreported geographical areas (3,

5, 15, 16, 21, 22). However, computational modeling approaches might be limited to predicting perceived safety in these areas with similar architectural styles and urban planning of the areas for which crowdsourced data is available (Candeia et al., 2017; Harvey et al., 2015; Naik et al., 2014).

A sampling issue specific to any study design that requires ongoing participation is *sample attrition* over time. While only one study in this review highlighted the issue (2), it was also observed in the data collected by InseguridApp (Figure VIII). Blom et al. (2010) found that the number of data points collected was especially high during the first days after launching the crowdsourcing application. Participation then decreased progressively during the following weeks. Thus, the decision about when to start the data collection might bias the final results due to seasonal variation associated with the time of launch.

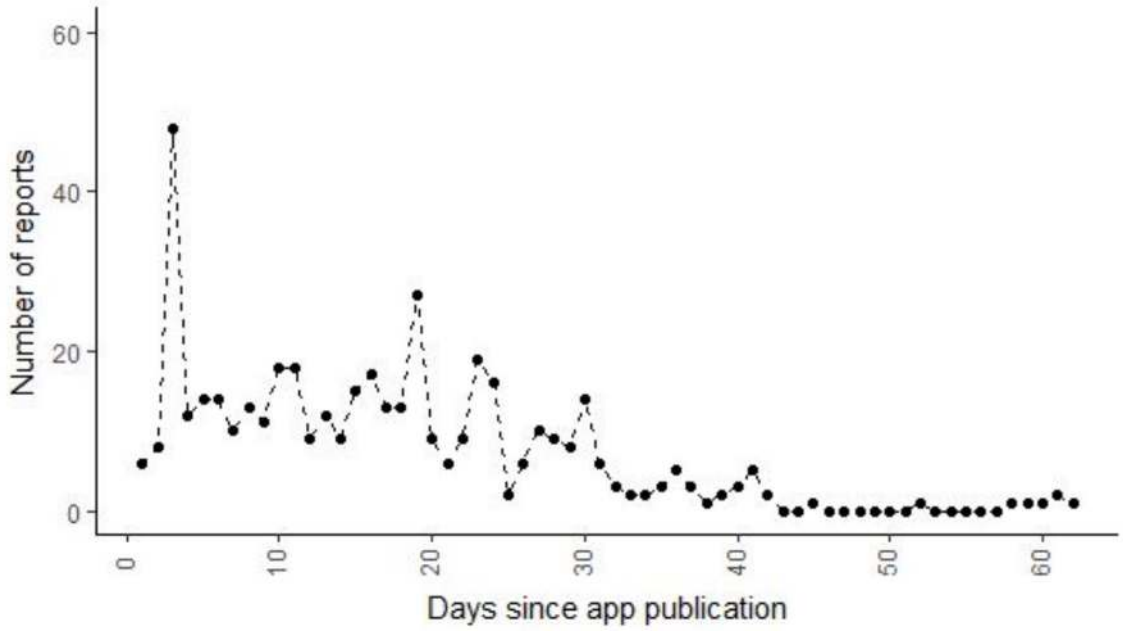

Figure VIII. Participation decrease over time observed at InseguridApp.

Three papers (3, 4, 8) identified that some crowdsourcing platforms do not include screening questions about variables that might bias the final results such as the users' previous experiences with crime. It is therefore recommended that self-built applications consider implementing pre-participation questionnaires to control for important variables.

Finally, while one of the key strengths identified by many papers was the ease with which large sample sizes can be acquired, some self-built mobile phone and website apps experienced *small sample sizes and low response rates.* Many of these studies experienced issues in recruiting large samples, possibly due to a lack of incentives offered to participants, something which platforms such as FixMyStreet clearly offer (Solymosi et al., 2017). Pletikosa Cvijijk et al. (2015) found that participants' main motivations to contribute to platforms by sharing information were that the application had helped them in the past (e.g. by providing crime prevention advice), and concern about neighborhood safety. These findings could be utilized to incentivize participation in other app-based research. Similarly, in light of the large sample sizes of anonymous websites, Pánek, Pászto et al., (2017) suggest that building platforms which do not require registration may help to engage more people.

The limitation '*under-representation of certain areas and times'* relates to bias arising from unplanned sampling designs in which users decide when and where to report, a limitation cited by ten publications. Innes (2015:217) argues that citizens "avoid those locations that they think might expose them to a source" of fear, which might result in the under-representations of those areas perceived to be more dangerous. With respect to the under-representation of certain times, Blom et al. (2010) note that reports are five times higher at noon, while participation during the night is almost zero. While the unequal participation by time reflects people's routine activity patterns, it also results in a systematically biased selection of routes. In order to address this

limitation, Walkcap records multiple journeys of every participant every day, and then asks participants about their perceived safety in one randomly-selected journey.. Applying random sampling of journeys stratified by time and place allows recording information about night-time routes as well as journeys crossing specific areas of interest (Figure IX).

Figure IX. Routes captured by Walkcap are overlaid on top of Google Maps by connecting the registered GPS points. Orange routes belong to females and green ones to males.

The walkcap approach also aims to better diagnose avoidance behaviors. If used by a large sample of citizens in a given community, mobility data would allow researchers to detect avoided areas -both in general or by specific groups (e.g. women, older people) or in certain moments (nights, weekends), as well as to verify if the smaller group of people walking by these areas rate them as more dangerous than usual.

While contextual data collected by app-based platforms allow some association of people's experience of fear with environmental factors, twelve papers highlight the *difficulty to*

interpret results arising from the lack of ability to hold variables constant in real-world environments, leading to difficulty in interpreting the concrete reasons why fear increases in specific areas. Limitations for interpreting results are also found by researchers using crowdsourced data from websites where images are assessed by users. For example, by asking users to report which place looks safer from two images taken from Google Street View, researchers can extract features, such as the presence of trees or gardens, the prevalence of residential houses, the number of people on the street or the street width (e.g. 3, 8, 14, 21), and even the images' brightness and contrast (14). Nevertheless, these platforms do not record data about other sensory elements that might affect safety perceptions, such as noise, smell, temperature and weather conditions (8, 27). As stated by Traunmueller et al. (2016:76), "we experience a city not just through single images one by one, but through movement, developing a sense of place over time".

Seven papers identified *limitations to generalize results.* Publications 2, 3, 5, 14, 15, 21 and 27 suggest that it is unclear if results obtained from studies using crowdsourced data can be generalized to other local jurisdictions and countries, which might be characterized by different architectural and urbanistic styles, land use types, crime levels, or cultural values. To address these two limitations (i.e., difficulty to interpret results and limitations to generalize results), some papers suggest that follow-up interviews would be helpful to interpret results obtained from crowdsourced data (2, 11, 20, 23, 26). Others (11, 24) suggest taking advantage of built-in cameras available in most smartphones to provide further visual information. Leitner and Kounadi (2015), for example, suggest that mobile apps may incorporate new functionalities to ask participants further information about the number and type of people that are present when

they report their emotions about crime, or asking participants to wear wristband sensors to measure fear at the same time that data is recorded from direct participation.

The limitation whereby *repeatedly asking about fear might increase/cause fear* has implications not only in terms of the mere measurement effect, where simply by asking about a concept we affect it (Morwitz & Fitzsimons, 2004), but also ethical concerns around possibly increasing fear and causing distress in study participants. Five publications argue that mobile phone applications that seek to capture the fear of crime might affect the emotions themselves (7, 10, 13, 23, 25), as these "invite individuals to think about the personal relevance of crime, [...] framed in terms of personal risk and threat" (Jackson and Gouseti 2015:212). Then, if the application sensitizes users to think about crime by increasing psychological proximity, the method itself might be artificially increasing fear emotions. Hamilton et al. (2011) also recognize that ethnographic research and surveys are needed to analyze the effect of mobile applications in changing human perceptions. Conversely, Blom et al. (2010:1850) argue that mobile apps might work as safety inducing services "that highlight the positive aspects of the urban spaces while ignoring the dark side". Finally, only seven studies collected temporally-explicit data about people's experiences, and many of those that did not mentioned this in their limitations, recognizing a *lack of temporal variability in some web-based measures.* Five publications note specifically how pictures of different places struggle to capture the temporal variability of fear of crime (3, 4, 8, 16, 25). Harvey et al. (2015) argue that crowdsourcing websites, such as Place Pulse, ask respondents to assess their perceived security at a snapshot in time without chronological and contextual knowledge, and do not analyze the temporal dimension of perceptions. On the other hand, temporal information is recorded by mobile phone

applications (1, 2, 4, 7, 11, 23, 25), and some websites distinguish between perceived safety "when it is dark" and "when there is a light" (17, 18, 19) or record the exact day and time (24).

Table 3. Summary table of limitations.

Limitation		N	Papers
Sample issues	Participation inequality.	13	2, 4, 8, 13, 17, 18, 19, 20, 23, 24, 25, 26, 27.
	No screening questions.	3	3, 4, 8.
	Participation decrease	1	2.
	Small sample sizes and low response rates.	8	2, 4, 11, 12, 13, 20, 23, 25.
Under-representation of certain areas and times.		10	2, 5, 8, 9, 13, 14, 17, 23, 24, 25.
Difficult to interpret results.		12	1, 5, 7, 8, 12, 13, 15, 16, 18, 20, 22, 27.
Limitations to generalise results.		7	2, 3, 5, 14, 15, 21, 27.
Repeatedly asking about fear might increase/cause fear.		5	7, 10, 13, 23, 25.
Lack of temporal variability in some web-based measures.		5	3, 4, 8, 16, 25.

Discussion

Our systematic review identified 576 papers that mention the use of app-based or crowdsourced data collection and allude to the fear of crime or associated constructs, of which 27 met our inclusion criteria. These papers were synthesized to consolidate the strengths and limitations they identified, to establish good practice and map the route for future work in developing app-based and crowdsourcing data collection as a robust methodological approach to study fear of crime as a place-based, context-specific experience. Specifically, we have consolidated a list of suggestions and highlighted areas for further development and research for those using app-based and crowdsourced data to operationalize the fear of crime.

The main strength and motivator for using app-based measures is the ability to collect precise spatial and temporal data, which situates fear of crime events in their precise physical

place, linking them to valuable auxiliary information about environmental features. Alongside technical advantages over traditional survey methodologies, such as reduced costs and the ease to apply results to policy and practice, this strength of location-based data collection promotes a methodological approach to operationalize fear of crime that can be used by researchers looking to explore empirically a place-based approach to mental events of fear of crime. App-based measures can therefore address this long-standing limitation of survey tools to capture the emotion-based fear with suitable rigor.

Beyond using app-based measures to self-report, these methodologies further hold the promise to link with sensors to capture physiological indicators of emotional fear responses (galvanic skin response, heart rate measure, etc.) (Warr, 2000). Researchers working in controlled experimental settings have explored these avenues recently (e.g., Castro-Toledo et al., 2017; De Silva et al., 2016), and further work can see how to link these with app-based methodologies.

Further, there is a promise that app-based and crowdsourcing projects may provide insights into participants' behavioral responses to fear of crime. The functionalities made available by these methods could be used to inform and capture changing behaviors due to fear of crime (e.g., app-based approaches may record changes in citizens' everyday journeys and time spent at home). App-based projects focused on the use of public space (walking, biking, public transportation systems and so on), if broadly used by a significant number of citizens in a neighborhood or city, would allow to locate less used areas, therefore pointing to possible avoidance due to fear. This was one of the aims when designing the Walkcap app. The hypothesis about the fear-related motivation for avoidance could be informed by the safety ratings of the limited number of users of those areas. Similar apps could explore intentions to

avoid areas in the future, after reporting about a route being perceived as dangerous. Similarly, app-based projects may include new functionalities to ask participants about the use of protective measures such as alarm systems, guard dogs or security fences, but this was not deployed by examined projects.

Limitations synthesized in our review identified a need to improve the reliability, validity, and generalizability of these measures. The most prominent theme was around issues with sampling bias and generalizability. We propose a few avenues for research to address these issues identified in this review, such as to explore participation motivation, the use of sensors, or interviews or follow-up questionnaires. Another avenue suggested in studies in our review is the use of statistical or computational modeling approaches to mitigate bias. Regarding the under-representation of areas due to avoidance, one possible approach is asking users to report retrospectively about a randomly selected route from a sample collected from them that day, as suggested by Walkcap. The issues introduced by sampling are multifaceted, and a variety of approaches to fully explore and to eventually account for them should be a key focus of research in this area.

Research on the contextual elements that trigger fear of crime may benefit from the increased use of eye tracking techniques (Crosby & Hermens, 2019; Guedes et al., 2014; Kim et al,. 2014) to help address the 'difficulty to interpret results' limitation.

Finally, we must emphasize the importance of thorough ethical review for such studies. As the limitation '*repeatedly asking about fear might increase/cause fear'* suggests, it is important to maintain discussions around the ethical implications of such methodologies. This is an issue that should be explored further in order to create discussion and establish the mechanisms through which the mere-measurement effect may influence data gathered in this

way. It is further possible that there are other risks associated with this emerging method, such as considerations around data security and risk of participants' identification (Jones et al., 2011; Solymosi & Bowers, 2018), and researchers have a duty to consider these as they develop. Questions regarding sampling rate of GPS points and the type of information to be recorded, amongst others, are also important to consider. In our review, only 2 out of the 27 papers reported obtaining ethical approval from their organizations (26, 27). We recommend this be a criterion for all such work.

Concluding Comments

Overall, the papers in this review all share an approach that allows the understanding of fear of crime as a place-based, contextually specific event, captured in people's emotional and behavioral responses, that may lend itself to problem-solving approaches. Much like a place-based approach for crime, applying these methodologies to fear of crime make possible its operationalization in a way that allows such exploration. By building on the strengths and working to address the limitations discussed in this review, we can explore fear of crime as a function of people's experiences in their immediate environments, and inform evidence-based policy making and urban planning for safer places.

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