

# Are We Aware? An Empirical Study on the Privacy and Security Awareness of Smartphone Sensors



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**Abstract** Smartphones are equipped with a wide variety of sensors, which can pose significant security and privacy risks if not properly protected. To assess the privacy and security risks of smartphone sensors, we first systematically reviewed 55 research papers. Driven by the findings of the systematic review, we carried out a follow-up questionnaire-based survey on 23 human end-users. The results reflect that the participants have a varying level of familiarity with smartphone sensors, and there is a noticeable dearth of awareness about the potential threats and preventive measures associated with these sensors. The findings from this study will inform the development of effective solutions for addressing security and privacy in mobile devices and beyond.

**Keywords** Smartphone · Sensor · Attacks · Security · Privacy · Awareness · Perception · Survey · Quantitative · Analysis · Study · Systematic literature review

## 1 Introduction

Smartphones are an indispensable part of our lives, with small and discreet sensors that play the crucial role of functioning and user experience. Many different types of sensors are found in smartphones, each with its unique function [49]. In addition to providing a better user experience, smartphone sensors also have the potential to improve safety and security [5]. For instance, setting a passcode, the inclusion

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of fingerprint scanners, and facial recognition technology on smartphones can help protect against unauthorized access to sensitive information.

In recent years, a variety of studies have been carried out to look at the threats and defense mechanisms of various systems [14, 59]. These investigations, however, have frequently concentrated on well-known system vulnerabilities or network-based risks that result from bad architectural design. The thorough explanation of sensor-based risks has thus far mostly been disregarded. This instigates a high level of risk in terms of security and privacy since these systems can be seriously endangered by sensor-based threats.

The usage of smartphone sensors raises significant concerns about security and privacy. For example, an attacker could use a smartphone's GPS sensor to track a user's location without their knowledge [33]. Similarly, a phone's camera or microphone can be hacked to record an audio or video clip without the user's knowledge [56]. Motion sensors on mobile devices could be exploited to secretly infer the PINs or passwords inputted by users on mobile web applications [53].

While some users may be aware of smartphone sensors' potential security and privacy risks, others may possess less or no awareness of the risks associated with the sensors. Lack of awareness could lead to users unknowingly sharing their sensitive information, resulting in security breaches or loss of privacy. A clear understanding of the present scenario is required to understand this level of risks and awareness. With this level of understanding, individuals and organizations can initiate informed decisions for protection against cyber attacks and data leaks.

Therefore, in this work, we first conduct a systematic review of existing research in the literature on smartphone sensors' security and privacy issues. Later, an end-user survey is conducted to assess user awareness and perception of the privacy and security risks associated with smartphone sensors. In particular, we address the following research questions:

*RQ1:* To what extent are individuals familiar with sensors in smartphones?

*RQ2:* How well are people aware of the existing mobile phone sensor attacks?

*RQ3:* How do people perceive the use of these sensors?

Several works in the past have explored smartphone sensor-based threats including end-user awareness and perception of the threats [10, 16, 19, 26, 37–39, 52, 57]. These earlier studies were conducted either as literature reviews or end-user surveys only. Ours is the first work along this direction taking on wholistic approach combining both a systematic literature review and follow-up end-user survey.

We organize our paper as follows. First, we describe our systematic literature review in Sect. 2. Then, in Sect. 3, we describe our end-user survey, which is designed based on the findings from the systematic literature review. In Sect. 4, we further discuss the results from both the literature review and end-user survey including the threats to validity of the results as well as our plan for future work. Finally, Sect. 5 concludes the paper.

**Table 1** Keywords used for searching relevant papers

Database	Searched keywords
ACM Digital Library	[[‘Smartphone’ OR ‘Mobile’] AND [‘sensor’]] AND [‘security’ OR ‘privacy’ OR ‘awareness’]
ScienceDirect	[[‘Smartphone’ OR ‘Mobile’] AND [‘sensor’ OR ‘sensors’]] AND [‘security’ OR ‘privacy’ OR ‘awareness’]
IEEE Xplore	[[‘Smartphone’ OR ‘Mobile’] AND [‘sensor’ OR ‘sensors’]] AND [‘security’ OR ‘privacy’ OR ‘awareness’] NOT [‘IoT’ OR ‘Wearable’]
Springer	[‘Smartphone’ OR ‘Mobile’] AND [‘sensor’ AND ‘security’ AND ‘privacy’ AND ‘awareness’]
Taylor & Francis	[[‘Smartphone’ OR ‘Mobile’] AND [‘sensor’]] AND [‘security’ OR ‘Sensor privacy’] NOT [‘IoT’ OR ‘Wearable’]
PubMed	[[‘Smartphone’ OR ‘Mobile’] AND [‘sensors’]] AND [‘security’ OR ‘privacy’] NOT [‘IoT’ OR ‘wearable’]
MDPI	[‘Smartphone sensor’ OR ‘Mobile sensor’ AND [‘security’ OR ‘privacy’ OR ‘awareness’]] NOT [‘IoT’ OR ‘wearable’]

**Table 2** Inclusion and exclusion criteria

Inclusion criteria	Exclusion criteria
<ul style="list-style-type: none"> <li>● Relevant to smartphone sensors and security or privacy or awareness</li> <li>● Research article</li> <li>● Published between 2010 and 2022</li> <li>● Written in English language</li> </ul>	<ul style="list-style-type: none"> <li>● Irrelevant to smartphone sensors security or privacy or awareness</li> <li>● Book, chapter, reviewed article</li> <li>● Not peer-reviewed papers</li> <li>● Papers not accessible online</li> <li>● Articles related to wearable smart devices and IoT</li> </ul>

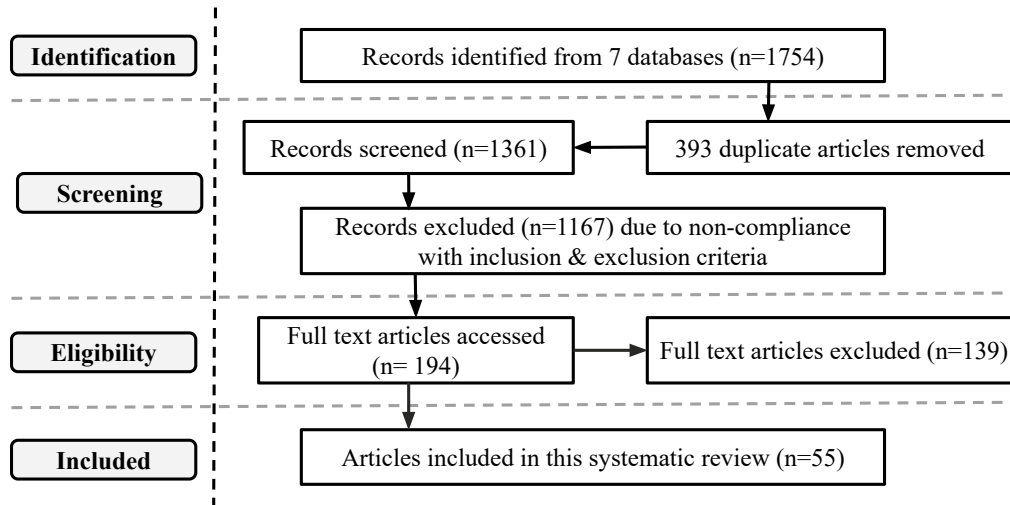
## 2 Systematic Literature Review

### 2.1 Methodology

Our systematic review was carried out using the following four phases:

*Phase-1 (Search of Research Articles):* The seven databases mentioned in Table 1 were chosen for their well-known sources of scholarly research in a wide range of fields to identify relevant research articles. The search for articles to be included in this systematic review began in November 2022 using a keyword-based substring search method. These searched keywords are listed in Table 1.

*Phase-2 (Preliminary Filtering):* Table 2 outlines the specific criteria that have been applied to determine the articles that are included in the review and those that are excluded.



**Fig. 1** States of our work at different stages of PRISMA-P

*Phase-3 (Final Filtering):* The PRISMA-P (Preferred Reporting Items for Systematic Reviews and Meta-Analyses Protocols) [50] guidelines were followed (as shown in Fig. 1) to identify relevant papers, ensuring a systematic and thorough review.

*Phase-4 (Analysis):* The relevant information identified from the reviewed research articles is then further analyzed around the research questions outlined before. This analysis leading to findings is elaborated in the following section (Sect. 2.2).

## 2.2 Analysis and Findings

The searched keywords in Table 1 were used to identify relevant studies published from 2010 to 2022 for the systematic review. The search result yielded 1754 articles among which 393 were duplicate articles. After removing the duplicates, 1361 articles were left for the screening phase. 139 papers were excluded from 194 eligible articles for full-text evaluation. Finally, 55 articles were included in the study. The states of the work at different stages of PRISMA-P [50] are summarized in Fig. 1 and the numbers of articles selected from different sources are listed in Table 3. We thoroughly read all 55 papers and identified various kinds of attacks that can be carried out using smartphone sensors.

### 2.2.1 Sensor-Related Security Threats

We found eight such threats that are most commonly discussed in the literature. These eight common threats are briefly described below.

**Table 3** Number of papers selected from different sources

Database	Identification	Eligibility	Included
ScienceDirect	327	25	9
IEEE Xplore	477	79	18
Springer	308	24	10
Taylor & Francis	34	7	1
PubMed	399	12	3
MDPI	26	6	2
ACM Digital Library	183	41	12
Total	1754	194	55

*Keystroke Inference (KIn)*: An attacker can potentially determine the exact keystrokes entered, including sensitive information such as passwords or credit card numbers, by analyzing the subtle vibrations and movements of the device as the user types.

*Location Inference (LIn)*: A LIn attack using smartphone sensors is when data is collected and the physical position of a smartphone user is determined without the user's knowledge or consent.

*Device Fingerprinting (DFP)*: A DFP attack based on smartphone sensor data encompasses creating a unique device profile or 'fingerprint' based on the sensor data, which can then be used to track the device and its user across various applications and services.

*Task Inference (TIn)*: A TIn attack is to infer the user's current activity or task, such as browsing the internet or sending a message without the user's knowledge or consent.

*Eavesdropping (Evd)*: An Evd attack refers to the unauthorized interception and recording of audio using the smartphone's microphone, without the user's awareness or consent.

*Transmitting Malicious Sensor Commands (TMC)*: TMC involves the unauthorized manipulation of sensor data by sending malicious commands to the device's sensors.

*Pin Inference (PinIn)*: A PinIn involves the unauthorized inference or extraction of the user's PIN or password by analyzing the sensor data.

*Physical and Behavioral Activity Recognition (PhBAR)*: An attacker can potentially deduce the user's current activity or behavior by analyzing the patterns and timing of the user's interactions with the device's sensors.

Table 4 identifies the smartphone sensors associated with these threats and the articles in the literature that at least mentioned them. We also identified that 15 sensors are particularly reported susceptible to threats. Based on the type of smartphone's operations these sensors are used for, they are categorized into four groups and presented in Table 5. The literature suggests that environmental sensors, which

**Table 4** Various threats and issues related to smartphone sensors

Threats	#	Research articles	Smartphone sensors
LIn	11	[4, 13, 15, 40, 60–62, 65, 68, 69, 72]	Barometer, Gyroscope, Accelerometer, Speaker, Camera, Magnetometer, Microphone, GPS, Compass, WiFi, NFC
TIn	10	[1, 18, 32, 34, 42, 53, 56, 58, 67, 70]	Gyroscope, Accelerometer, Speaker, Ambient Light Sensor, Magnetometer, Microphone, Biometric Sensors, Camera, GPS, WiFi, Bluetooth, NFC
KIn	6	[2, 6, 20, 22, 54, 64]	Gyroscope, Accelerometer, Speaker, Ambient Light Sensor, Magnetometer, Microphone, Biometric Sensors, Camera, Proximity Sensor, WiFi, Bluetooth, NFC
Evd	8	[3, 7, 11, 25, 29, 31, 41, 67]	Gyroscope, Accelerometer, Speaker, Ambient Light Sensor, Magnetometer, Microphone, Bluetooth
TMC	2	[29, 67]	Ambient Light Sensor, Microphone, WiFi, Bluetooth
DFP	7	[11, 24, 28, 30, 35, 64, 66]	Gyroscope, Accelerometer, Speaker, Microphone, Camera, Biometric Sensors, WiFi, Bluetooth, NFC
PinIn	4	[36, 37, 41, 55]	Biometric Sensor, Gyroscope, Accelerometer, Magnetometer, Barometer, Proximity Sensor, Ambient Light Sensor
PhBAR	13	[12, 13, 27, 40, 47, 48, 56, 60–62, 68, 70, 72]	GPS, Camera, Microphone, Speaker, Biometric Sensor, Gyroscope, Accelerometer, Magnetometer, Barometer, Compass, WiFi

**Table 5** 15 smartphone sensors categorized in groups

Sensor type	Sensors
Identity-related	GPS, Microphone, Speaker, Camera, Biometric
Communicational	WiFi, Bluetooth, Near-field communication (NFC)
Motion	Gyroscope, Accelerometer, Proximity, Magnetometer
Environmental	Ambient Light Sensor, Barometer, Compass

measure factors such as temperature and humidity, are generally less known to users compared to other types of sensors [38, 39].

### 2.2.2 Protection Mechanisms

We also identified various mechanisms that were discussed in the literature for protection against attacks on smartphone sensors. In Table 6, we briefly present the synopsis, performance, and overhead of the security and privacy preserving mechanisms identified.

**Table 6** Security and privacy preserving mechanisms identified

Mechanisms	Synopsis	Performance
SemaDroid [63]	<ul style="list-style-type: none"> <li>• Android sensor management system</li> <li>• Uses simulated data to evaluate the potential risks of apps</li> <li>• Offers users the ability to customize sensor policies to their liking</li> </ul>	100% accurate against sensor-based malware
AWare [43]	<ul style="list-style-type: none"> <li>• An authorization framework</li> <li>• Allows users to authorize sensitive sensor operations</li> <li>• Binds application operation requests to the corresponding user input events</li> </ul>	Successful compatibility and usability test with 1000 most downloaded Android apps
EnTrust [45]	<ul style="list-style-type: none"> <li>• Android Sensor authorization framework</li> <li>• Generates authorization queries in response to input occurrences from complying programs and delegation graphs</li> </ul>	Low overhead in Android smartphones
6thSense [51]	<ul style="list-style-type: none"> <li>• An intrusion detection system</li> <li>• Employs sensor data to comprehend the context of the user's activity</li> <li>• Identifies malicious activity on the device</li> </ul>	Achieved 96% accuracy against many sensor-based threats with minimal overhead
LocPPM [44]	<ul style="list-style-type: none"> <li>• Employs Synthetic data to mimic real data</li> <li>• Uses targeted movements to combine real and synthetic sensor data</li> </ul>	Decreases the likelihood of a white-box attack by 3%
AuDroid [46]	<ul style="list-style-type: none"> <li>• A trust evaluation framework</li> <li>• Scrutinizes app demands for sensor access and decides whether the access is legit</li> <li>• Detects instances of over-privilege and defend sensors from unauthorized access</li> </ul>	High accuracy tested with 17 mobile applications on an Android smartphone
SensorSafe [8, 9]	<ul style="list-style-type: none"> <li>• Based on trusted remote data stores and a broker who arbitrates access to the data stores of the users</li> </ul>	Prevents unauthorized access to sensed data of workers' identity and position
Perceptual Assistant [71]	<ul style="list-style-type: none"> <li>• A privacy protection system</li> <li>• Allows modification of personalized sensor policy for all third-party sensing apps</li> </ul>	Less than 7.6% overhead and high adaptability
Android Extension [17, 21]	<ul style="list-style-type: none"> <li>• Manages information and stops malicious applications</li> <li>• Uses semantically rich context models (Xposed framework)</li> </ul>	Effectively enforces privacy over sensed and contextual data without scalability issues

### 3 End User Survey

Now, we want to understand three aspects: (a) to what extent the smartphone end-users are familiar with the 15 smartphone sensors (classified in four categories) that are identified (from literature survey) as susceptible to attacks or data leaks.

(b) To what extent the end-users are aware of the smartphone sensor-related security threats and the identified mechanisms identified from the literature survey. (c) How the end-users perceive the use of the 15 smartphone sensors. Aspects (a), (b), and (c) are respectively addressed in research questions RQ1, RQ2, and RQ3 outlined in Sect. 1. We, therefore, carried out a questionnaire based survey on smartphone end-users as described below.

### 3.1 Survey Procedure

#### 3.1.1 Questionnaire

The questionnaire we used for the survey is briefly presented in Table 7. The Likert-scale questions (i.e., 12, 14, 15, and 17) about familiarity, the participants had the followings five options to choose from: extremely, moderately, somewhat, slightly, and not at all. Along with the questionnaire, a set of three appendices were also provided to the participants. The appendices included brief description of the 15 sensors, the sensor-based attacks, and the security mechanisms against the sensor-based attacks.

**Table 7** Survey questionnaire

1.	Age? (15–19, 20–24, 25–29, 30–34, 35–39, 40 years or more)
2.	Gender? (Male, Female, Other)
3.	What is the highest educational level you have attained? (High School, College, Bachelors, Masters, Doctoral)
4.	What is your profession?
5.	Ethnicity? (Caucasian, African American, Asian, Hispanic, Other)
6.	Time spent on the internet per day in hours? (>2, 2–5, 6–10, <10)
7.	What do you use the internet for? Check all that apply. (Social Media, Research, Education, Entertainment, Financial Purpose, Others)
8.	How many hours per day do you spend browsing the internet?
9.	Average number of hours spent using smartphone apps per day?
10.	How long have you been using a smartphone (in years)?
11.	Operating system of your smartphone (Android, iOS, or Windows)?
12.	What is your level of concern (in Likert scale) about unauthorized access to data?
13.	Have you personally experienced privacy or security issues while using a smartphone? Check all that apply (options in Table 10).
14.	Familiarity with 15 smartphone sensors (Table 5) in Likert scale?
15.	Awareness about the security threats (Table 4) in Likert scale?
16.	Perception of 15 smartphone sensors (Table 5) with respect to the security threats (Table 4), (i.e., sensor $\times$ threats)?
17.	Familiarity with the security mechanism (Table 6) in Likert scale?



### 3.1.2 Participant Recruitment

First, we recruited 15 student participants from a computer science class at the Idaho State University. Then additional eight participants were recruited for the study from the entire institution. Out of the total 23 participants, 14 completed the survey in person, while the remaining nine participants completed it online via Google Forms. More than half of the participants are Asians, and none are African Americans. Out of the 23 participants recruited, seven are females and 16 are males with ages between 20 and 40 years, with the majority (13) falling in the age range of 20–24.

Among these participants, nine (39.13%) have a bachelor's degree, eight (34.78%) have a college degree, five (21.74%) have a graduate degree, and one (4.35%) have a high school degree. Among the 23 participants, 13 use iOS and the rest use Android. Most of the participants have good technical knowledge, either as students or from a work environment. The amount of time spent per day on the internet, using apps, and the duration of smartphone ownership on average are 3.33 hours per day, 2.42 hours per day, and 11.8 years respectively. The details of the participants' internet and smartphone usage is shown in Table 8.

### 3.1.3 Participants' Response Analysis

After collecting the questionnaire responses from all the participants, a thorough analysis was performed on these collected data. To gain insight into the participants' perception of smartphone sensors, we identify True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) in participants responses. Then, we compute precision ( $\rho$ ) and recall ( $\mathcal{R}$ ) for the responses.

**Table 8** Participants' usage of internet and smartphones

Age range	#	Internet usage (in hours/day)	App usage (in hours/day)	Owning smartphone (in years)
20–24	13	3.23	2.69	8.38
25–29	6	3.83	3.00	8.33
30–34	2	3.50	2.00	11.50
35–40	2	2.75	2.00	19.00

## 3.2 Survey Outcome

### 3.2.1 Familiarity (RQ1)

The participants are found the most familiar with the camera and least familiar with the magnetometer. The ranking of the smartphone sensors' familiarity among the participants based on the responses to the survey questionnaire is listed in Table 9. From the systematic review part, it was found that environmental sensors are not well-known to users [38, 39]. However, this is not reflected in the results of our survey, as the participants are found to be least familiar with motion sensors.

Table 10 presents the percentage of participants who reported to have first-hand experience of facing privacy and security issues when using a smartphone in given different scenarios. When questioned about their experiences with privacy and security threats, 13 (57%) participants reported having experienced at least one attack, while six (26%) reported experiencing two or more attacks. Their response to the

**Table 9** Participants' familiarity with smartphone sensors

Rank*	Sensors	Rank*	Sensors
1	Camera	09	Ambient light sensor
2	Microphone	10	NFC
3	Speaker	11	Gyroscope
4	WiFi	12	Accelerometer
5	GPS	13	Proximity sensor
6	Bluetooth	14	Barometer
7	Compass	15	Magnetometer
8	Biometrics	(*Rank 1 indicates the most familiar)	

**Table 10** Security/privacy issues faced by the participants

Privacy and security issues	Faced (%)
The smartphone had a virus or other harmful software installed	26
Passwords or other account information for banking, email, social networking, or other personal accounts were stolen and exploited	35
Was misled to pay for or use a service that turned out to be a scam	17
Personal or private information was posted on the Internet on social networks or online forums without permission	10
Nothing suspicious was ever noticed	43
Other	10

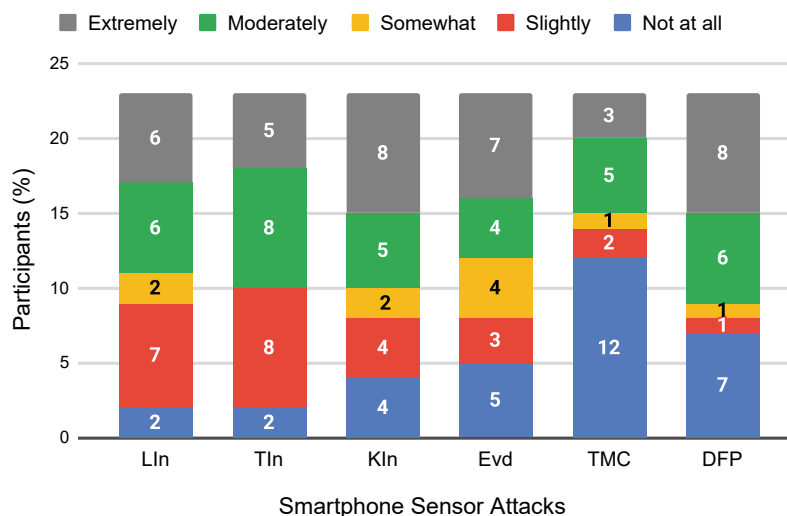
possibility of facing privacy and security issues while using a smartphone is shown in Table 10. Furthermore, among participants who used internet for more than 10 hours per day, 18 (80%) reported being exposed to at least one attack. This implies that heavy internet users may be particularly vulnerable to these types of attacks. We derive the answer to RQ1 as follows:

*Ans. to RQ1: Identity-related sensors are the most familiar, while motion sensors are the least familiar to the end-users.*

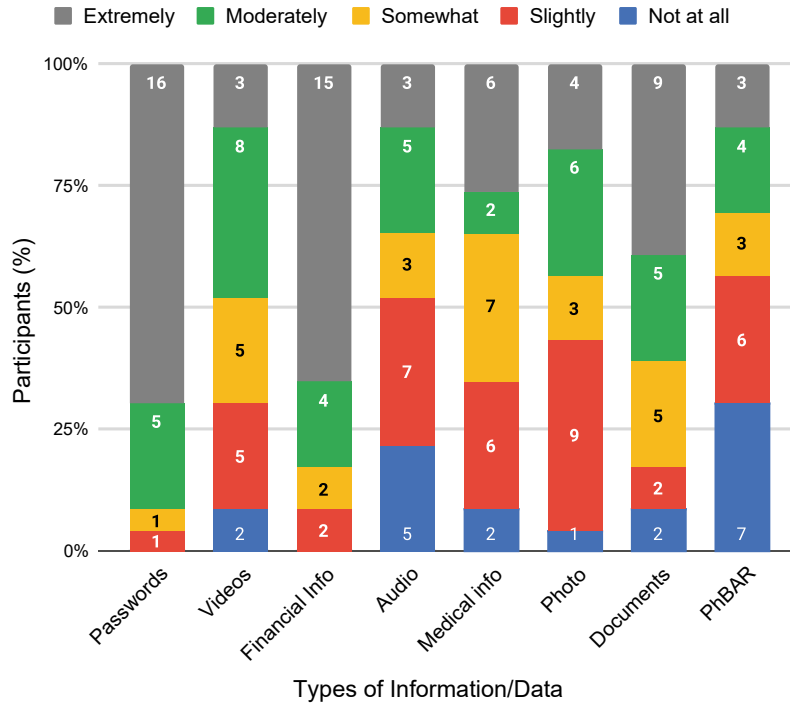
### 3.2.2 Awareness (RQ2)

On average, the participants are aware of the six sensor attacks mentioned in the survey. However, the participants are least aware of TMC and most aware of DFP and KIn. Figure 2 provides a visual representation of the level of awareness associated with all the attacks. The majority of the participants exhibit the most concern about the security of their passwords and financial information in response to unauthorized access. In contrast, only a small number of participants expressed concern about the potential for PhBAR to be used to access their information without their permission.

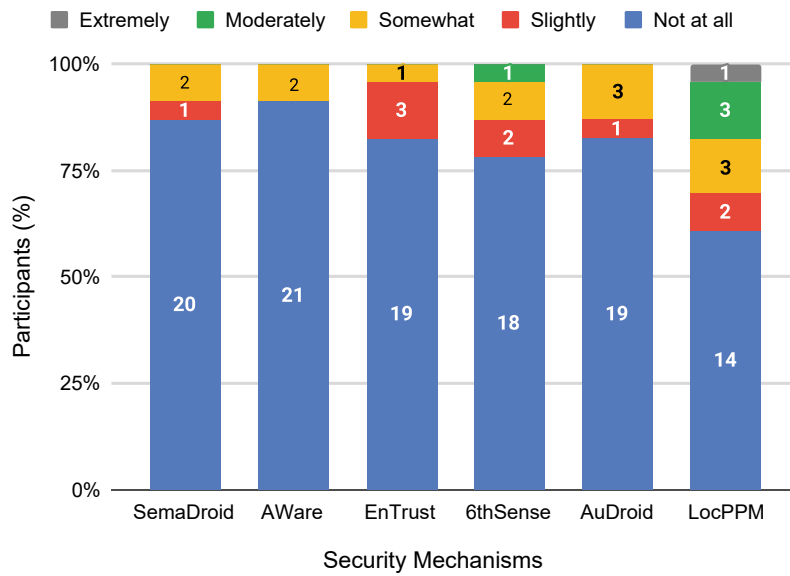
The level of concern for each aspect of unauthorized access is illustrated in Fig. 3. However, the majority of the participants in the study are not at all aware of the security mechanism’s capabilities for protecting against sensor attacks, with only a small number being somewhat familiar, and only one individual being extremely familiar with one of the mechanisms. Familiarity of the participants with the available security preserving mechanisms is presented in Fig. 4. We, therefore, formulate the answer to RQ2 as follows:



**Fig. 2** Participants’ awareness of smartphone sensor-based attacks



**Fig. 3** Participants' levels of concern about unauthorized access



**Fig. 4** Participants' familiarity with existing security mechanisms

**Ans. to RQ2:** Participants are the least aware of TMC threat. The majority of the participants are not aware of the security mechanisms against sensor attacks.

### 3.2.3 Perception (RQ3)

To measure participants' perception of smartphone sensors and sensor attacks, a survey question (i.e., question 16) asked them to identify which attacks are possible for which of the 15 sensors. The seven columns from the left in Table 11 shows the participants' perceptions of sensor-related threats as well as the facts drawn from the literature review as well as the computed TP, TN, FP, FN, precision ( $\rho$ ), and recall ( $\mathcal{R}$ ). Here, a reddish-colored cell indicates that the literature identified corresponding sensor *susceptible* to the corresponding security threat. For example, according to the literature, the camera can potentially cause LIn, TIn, KIn, and DFP threats. A white/colorless cell indicates that literature identified corresponding sensor *not* susceptible to the corresponding security threat. For example, according to the literature, the camera is not vulnerable to Evd or TMC attacks.

A value in a cell reports the number of survey participants reported to believe/perceive the corresponding sensor susceptible to the corresponding security threat. For example, 11 participants correctly perceived that camera is susceptible to the LIn attack. But five participants incorrectly thought that the camera is vulnerable to Evd. Five participants incorrectly also thought that the camera is vulnerable to TMC.

**Table 11** Perception of the threats associated with smartphone sensors

Sensors	LIn	TIn	KIn	Evd	TMC	DFP	TP	TN	FP	FN	$\rho$	$\mathcal{R}$
Camera	11	4	2	5	5	3	20	48	10	60	0.67	0.25
Microphone	3	10	2	18	4	4	41	0	0	97	1.00	0.30
Speaker	2	8	2	11	3	5	28	20	3	87	0.90	0.24
WiFi	8	9	2	3	7	5	34	0	0	104	1.00	0.25
GPS	17	3	3	1	2	3	20	83	9	26	0.67	0.43
Bluetooth	3	10	3	6	8	5	32	20	3	83	0.91	0.28
Compass	14	2	1	0	3	4	14	105	10	9	0.58	0.61
Biometrics	1	3	1	0	8	10	14	60	9	55	0.67	0.20
Ambient Light Sensor	0	7	1	1	9	2	18	44	2	74	0.90	0.20
NFC	2	6	1	2	9	5	14	35	11	78	0.56	0.15
Gyroscope	12	7	1	0	4	3	23	19	4	92	0.85	0.20
Accelerometer	14	4	3	2	7	2	25	16	7	90	0.78	0.22
Proximity Sensor	8	3	2	2	10	5	2	87	28	21	0.07	0.09
Barometer	1	1	0	5	4	7	14	104	11	16	0.39	0.30
Magnetometer	8	7	5	0	6	1	21	17	6	94	0.78	0.18

That is why the FP value for the camera is 10, while TP is 20 as a total of 20 participants correctly identified the LIn (11 participants), TIn (four participants), KIn (two participants), and DFP (three participants) threats posed by the camera. We see that the proximity sensor has the lowest precision and recall values. This indicates that participants have the most incorrect perceptions about the proximity sensor. In contrast, their perceptions of the WiFi and microphone sensors are more accurate. Based on the precision ( $\rho$ ) and recall ( $\mathcal{R}$ ) values, it can be concluded that participants have relatively accurate perceptions of the other surveyed sensors in smartphones. We derive the answer to RQ3 as follows:

*Ans. to RQ3: Participants' perceptions of the proximity sensor are the most inaccurate, whereas their views of the WiFi and microphone sensors are the most precise.*

## 4 Discussion

While a systematic literature review identifies the gaps in the current state of the art, a follow-up end-user study complements with a comprehensive understanding of the topic with new insights, as accomplished in our work. In our study, the survey result demonstrates that the participants are less familiar with motion sensors, which differs from the findings of our systematic review where environmental sensors were the least familiar [38]. In terms of sensor attacks, there is a conflicting familiarity with device fingerprinting, with some users being extremely knowledgeable and others having no knowledge at all. Additionally, the participants are not familiar with security and privacy-preserving mechanisms against smartphone sensor attacks. This lack of familiarity may make participants more vulnerable to sensor-based attacks, as they may not be aware of the potential risks or know how to protect themselves from these types of attacks.

A concerning factor the survey demonstrated is that a majority of participants reported experiencing at least one attack during the usage of a smartphone. It is noticed that those who spend a significant amount of time online are at a higher risk of experiencing privacy and security issues while using their smartphones. Individuals need to educate themselves about smartphone sensor attacks to protect themselves.

Passwords or PINs are an essential barrier to preventing unauthorized access. Participants show the highest level of concern for password protection for their personal information. However, participants have the least concern about the risks associated with PhBAR. But they do not understand that this collects a large amount of data about a person's activity, location, speed, duration of the activity, and even stress level. These data can be accessed by unauthorized parties and lead to sensitive personal information being exposed to third parties. Then this information can be used for a variety of nefarious purposes, such as targeted marketing, information selling, disclosing classified data, and inferring and manipulating user habits [23].

By understanding the different ways in which sensors can be exploited, they can take steps to prevent these attacks and protect their sensitive information.

The survey illustrates that the participants have the highest number of incorrect perceptions about the proximity sensor, as indicated by its low precision and recall values. Moreover, the familiarity of sensors is somewhat in line with the participant perception level, except for the magnetometer. The participant's perception of this sensor is moderately clear with 78% precision, even though it is the least familiar one. The survey findings suggest that familiarity with a sensor may not necessarily correlate with participant perception.

#### ***4.1 Threats to Validity***

We recognize that our participant group is not very diverse and consists primarily of individuals with a technical background. While analyzing the survey responses, we did not take into account whether the participants used iOS or Android smartphones. Analyzing this aspect could have revealed some interesting findings. From the systematic literature review, we identified eight sensor attacks (listed in Table 4), from which we chose six sensors for the survey. We identified nine security measures (Table 6) from the literature review. In our survey, we chose the recently reported six security measures. This may be argued as a limitation of our work.

To conduct the survey, we provide our participants with a brief overview of the smartphone sensors, sensor-based attacks, and the security measures in three appendices. The purpose of this is to provide uniform briefing and the same set of instructions to the participants. However, this method of informing users still might have fallen short to ensure equity as it is possible that some of the participants might not have fully understood the descriptions provided while others did.

A limitation of our end-user survey is that it relies only on self-reported responses to the questionnaire, which may be subject to exaggeration or other biases. It would have been more informative to conduct a live interview with the participants to get a more accurate understanding of their perceptions. This could have provided a more in-depth understanding of their views and experiences.

#### ***4.2 Future Work***

By addressing these limitations, we gain a better understanding of the human impact of this rapidly advancing technology and provide reliable recommendations. Therefore, we plan to first increase diversity by reaching out to a varied demographic groups, communities, and/or organizations. The inclusion of participants with little to no technical knowledge would provide a more comprehensive picture of the actual situation. Secondly, we aim to analyze the survey responses based on the smartphone's two major operating systems (i.e. Android and iOS). Thirdly, we want

to further extend this work by including sensors of wearable devices such as smart watches and smart glasses. Finally, we plan to develop a deeper understanding by combining both quantitative and qualitative approaches for collecting participants' responses and analyzing them in depth.

## 5 Conclusion

Smartphone sensor awareness is a crucial kind of literacy required to secure individual's confidential information to avoid breach or cyber attack. The utmost goal of this research was to investigate individuals' familiarity, their level of awareness and perception on smartphone sensors. To achieve this goal, in this study, we analyzed the privacy, security, and awareness concerns of smartphone sensors involving an extensive systematic review and a subsequent questionnaire-based survey conducted both online and in person.

The systematic literature review highlights the complex and multifaceted nature of smartphone technology, with both benefits and risks to consider. We conducted the descriptive investigation to establish the foundation for the research, to identify interesting phenomena, and developed the research questions to analyze further. The results from the end-user survey revealed that identity-related sensors are the most familiar to the participants, while motion sensors are the least familiar. Furthermore, participants have a distorted perception of the proximity sensor and are unaware of the security mechanisms available to protect against various sensor-related attacks.

These findings emphasize the importance of users being aware of the potential risks and taking steps to protect their data and privacy. In future, we plan to address the limitations identified in Sect. 4.1 and extend this work for further research on the vulnerabilities and attacks associated with different types of smartphone sensors.

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