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WristSense framework: Exploring the forensic potential of wrist-wear devices through case studies ☆

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ABSTRACT

Wrist devices have revolutionized our interaction with technology, monitoring various aspects of our activities and making them valuable in digital forensic investigations. Previous research has explored specific wrist device operating systems, often concentrating on devices from particular manufacturers. However, the broader market of wrist-worn devices, which includes a wide range of manufacturers, remains less explored. This oversight presents challenges in retrieving and analyzing data from wrist devices with different operating systems. Additionally, there has been limited exploration of utilizing health data from wrist devices in digital investigations. To address these gaps, this study presents a framework called "WristSense," which systematically extracts health-related data from heterogeneous sources of wrist devices. The framework has been evaluated through case studies involving Huawei, Amazfit, Xiaomi, and Samsung wrist devices. The WristSense ensures compatibility with devices from different vendors and analyzes health data such as sleep patterns, heart rate, blood oxygen saturation, activities, and stress levels. The research uncovers potential circumstantial evidence applicable to law enforcement and introduces a wrist-wear device artifact catalog, which also serves as a taxonomy, enabling practitioners to codify and leverage their forensic collective knowledge. The findings demonstrate the effectiveness of the WristSense framework in extracting and analyzing data from various vendors, providing valuable insights for forensic investigations. However, challenges such as encryption mechanisms on certain devices present areas that require further investigation. This research provides a comprehensive overview of suspect or victim health data, empowering digital forensic investigators to reconstruct detailed timelines and gather crucial evidence in criminal investigations involving wrist devices.

1. Introduction

Wearable devices refer to a category of technology designed to be worn or attached to the skin, allowing for continuous monitoring of an individual's behavior while preserving their freedom of movement (Gao et al., 2016). Wrist devices, including smartwatches and wristbands, have achieved mainstream status within the extensive selection of wearable devices (de Arriba-Pérez et al., 2016). In 2022, the wrist-wear segment dominated global revenue, holding the largest market share and representing over 49.45% of the total revenue (Market.us, 2023).

As the popularity of wrist devices continues to soar, it is essential to explore their potential implications in the field of digital forensics. Digital forensics involves the extraction, preservation, and analysis of electronic evidence for investigative purposes (Pande and Prasad, 2016). Traditionally, this field has focused on the examination of computers, smartphones, and other conventional digital devices. However, with the proliferation of wearable devices, specifically wrist devices, a new

☆ Abbreviations: IoT, Internet of Things; DF, Digital Forensics; DFRIR, Digital Forensic Readiness Intelligence Repository ; DFI, Digital Forensic investigators; PCE, Potential Circumstantial Evidence; SFCRT, Sensor-Feature Cross-Reference Table; HRV, Heart Rate Variability

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frontier for digital forensics has emerged, presenting unique challenges and opportunities. Although several forensic frameworks and techniques have been proposed over the years to facilitate the investigation of IoT networks and devices, finding a perfect solution that covers the diversity of IoT devices and networks remains a significant research challenge (Mahmood et al., 2024).

Previous research has explored specific wrist device operating systems, such as Android OS, Garmin OS, and Tizen OS, often concentrating on devices from particular manufacturers. However, the broader market of wrist-worn devices, which includes a wide range of manufacturers like Apple, Samsung, Xiaomi, and Huawei, remains less explored. This focus on specific systems, while beneficial, may inadvertently limit the scope of data retrieval and analysis in forensic investigations. Although the desired files may be discovered, they are often difficult to view and understand (MacDermott et al., 2019). This research gap in wrist device operating systems and file systems can lead to the omission of valuable information for criminal investigations.

Another challenge is the limited research examining how health data from wrist devices can be utilized in digital investigations. For example, Heart Rate Variability (HRV), which measures the variation in the time interval between successive heartbeats, can serve as an indicator of an individual's stress or relaxed state. High HRV might indicate a person is in a relaxed state, while low HRV might suggest a person has a less adaptable cardiovascular system and is therefore in a stressed state (Shaffer and Ginsberg, 2017). Exploring the utilization of health data like HRV in digital investigations remains relatively scarce in the literature.

This research introduces a novel framework called "WristSense" designed to systematically extract health-related data from a wide range of wrist devices, encompassing various vendors and operating systems. WristSense empowers investigators to effectively navigate through the wrist devices present at a crime scene, providing circumstantial evidence. The circumstantial evidence relies on indirect indications or established facts to infer the existence of another fact (Direct and Circumstantial Evidence, 2019). Legally, there is no differentiation in weight or significance between circumstantial evidence and direct evidence, as both can sufficiently fulfill the burden of proof required in a case (Direct and Circumstantial Evidence Defined, 2023).

This article addresses the following research questions:

1. What artifacts can be recovered from wrist-worn devices for digital forensic investigations?
2. What potential circumstantial evidence (PCE) exists in wrist-worn devices?
3. To what extent can the WristSense framework extract and analyze PCE from different wrist-wear device vendors?

To evaluate its capability in extracting valuable evidence from health-related data, the proposed framework undergoes a comprehensive evaluation using a diverse set of case studies involving wrist devices from vendors such as Huawei, Amazfit, Xiaomi, and Samsung.

Our primary objective is to equip digital forensic investigators (DFIs) with a comprehensive understanding of biological data pertaining to both suspects and victims. This will enable them to reconstruct a detailed timeline of events and individuals involved in a given crime scene. To address existing gaps in the field, we have made significant contributions:

- WristSense Framework: We propose a pioneering framework that systematically extracts and analyzes health data from diverse offline and heterogeneous sources of wrist-wear devices. To the best of our knowledge, this is the first framework of its kind specifically designed for iOS systems. It ensures the data is forensically sound and compatible with various wrist devices, including Huawei, Amazfit, and Xiaomi.
- Application of the Framework: We demonstrate the practical application of our framework by using it to analyze a wrist-wear device dataset. By successfully applying our framework to this dataset, we highlight its capability to extract valuable insights and conduct in-depth analysis, thereby showcasing its practicality and usefulness in the field of digital forensics. This demonstration reinforces the reliability of our framework, further establishing its potential to contribute to future investigations involving wrist devices.
- Creating a Taxonomy of Wrist-Wear Digital Forensic Artifacts: We created the observed forensic artifacts discovered in the investigated wrist devices. These artifacts are categorized according to the artifact catalog structure outlined in reference (Casey et al., 2022). By providing a detailed overview of these artifacts, we ensure that investigators are well-informed about the forensic capabilities that can significantly enhance their investigations. It can mitigate the risks associated with overlooking relevant digital evidence and misinterpreting forensic findings. It also empowers practitioners to make informed decisions and draw accurate conclusions from the digital evidence they encounter, ultimately strengthening the overall integrity of their forensic investigations.
- Construction of WristSense-VendorData Dataset: We constructed a dataset that provides valuable information obtained from wrist devices, covering multiple vendors, operating systems, and data collection periods. Researchers in the digital forensics field can utilize this dataset for various investigative and analytical purposes.

Our contributions significantly strengthen the field of digital forensics by providing a robust framework for analyzing health data from wrist devices, offering practical insights through dataset analysis, and presenting a comprehensive catalog of forensic artifacts.

This article is structured as follows: Section 2 provides an overview of the related work in the field of wrist-worn devices. Section 4 presents the details of our proposed framework, WristSense. In Section 5, we evaluate the framework using five case studies from four different vendors. Subsequently, Sections 6 and 7 present the results, discussion, and future work, respectively. Finally, the conclusion is provided in Section 8.

2. Related work

In this section, we present an overview of the research conducted in the field of wrist-worn devices forensics investigation, exploring the extraction techniques and data analysis methods employed. Additionally, we discuss the operating systems utilized in wrist-worn devices, highlighting their impact on forensic procedures. Furthermore, we delve into the evidentiary data stored in wrist-worn devices, encompassing a wide range of artifacts that can be extracted for investigative purposes.

2.1. Wrist-worn devices forensics investigation

Recent studies have highlighted the importance of extracting and analyzing data from Wrist-worn devices in forensic investigations. For instance, MacDermott et al. conducted a study involving manual and logical data extraction techniques on wrist devices from three different vendors (MacDermott et al., 2019). Their aim was twofold: to extract potential data from these wrist devices and to identify data inconsistencies among the vendors. The researchers examined three fitness trackers: the Garmin Forerunner 110, Fitbit Charge HR, and a generic low-cost HETP fitness tracker. They performed multiple test runs on a subject who wore all three devices simultaneously while running a predetermined path with a one-mile distance and intentional elevation changes. The objective was to assess the accuracy and validity of the fitness bands. The findings indicated inconsistencies among the devices. Although these inaccuracies were acknowledged by the manufacturers, they have not significantly impacted court cases that utilize fitness bands as evidence, leading to convictions.

Becirovic and Mrdovic employed manual and logical extraction techniques specifically on Samsung devices. They conducted a case study using the Samsung Gear S3 Frontier smartwatch (Becirovic and Mrdovic, 2019). They followed the "event-timeline reconstruction" analysis technique by recording a three-hour sequence of watch events with the aim of restoring and analyzing the data. These events encompassed tasks like pairing the watch with an iPhone, answering calls, removing WhatsApp notifications, and activating flight mode. The study emphasized the crucial role of the data gathering timeframe in the analysis process. Due to the smartwatch's limited memory, previous data gets overwritten during regular use. To mitigate this issue, the researchers recommended that the initial step in forensic analysis involves enabling flight mode or turning off the smartwatch when not in use. These precautions minimize data tampering and improve the reliability of acquired data for forensic examination.

In their study, Williams et al. utilized logical and physical data extraction techniques on Fitbit wrist-devices paired with iOS and Android mobile devices (Williams et al., 2021). Their aim was to provide investigators with timely access to health data across various devices and forensic methods. By analyzing the Ionic smartwatch and Alta tracker, they identified recoverable data types such as private messages, feed posts, profile information, GPS data, sleep data, and heart rate data. The researchers created a test account, FitbitForensics, to simulate real-world scenarios and determine if forensic tools could successfully recover these artifacts. The results demonstrated the availability of different databases and data types through various extraction and analysis techniques, while also validating the accuracy of recorded data compared to planned test instances. Moreover, the researchers also delve into the crucial aspect of data recovery from deleted data on these wrist devices. By exploring the possibility of retrieving deleted data, the study sheds light on the potential for uncovering valuable evidence even from erased information on these devices. This finding underscores the importance of thorough forensic analysis to ensure that no relevant data is overlooked, even if it has been intentionally deleted.

Considering the same vendor, Almogbil and Alghofaili investigated Fitbits devices using the physical data extraction technique (Almogbil et al., 2020). They aimed to demonstrate that open-source digital analysis tools, such as Autopsy Sleuth Kit and Bulk Extractor Viewer, can produce results comparable to those of expensive commercial tools like Forensic Tool Kit (FTK) and EnCase, which often face resource and time limitations. In addition, Williams et al. found that open-source tools like Autopsy and BE Viewer could retrieve essential information for investigations. Although this is true, it is crucial to ensure that these tools are forensically sound and admissible in court (Williams et al., 2021).

Baggili et al. conducted case studies involving logical and physical extraction techniques on two different vendors: the Samsung Gear 2 Neo and LG G watches paired with a Samsung Galaxy S4 (Baggili et al., 2015). Their aim was to compare the artifacts present in the paired devices with those available directly on the smartwatches. The researchers followed specific usage scenarios, such as sending an email, tracking footsteps, using voice commands, and checking heart rate. The results revealed that a significant amount of digital evidence could be recovered directly from the smartwatches compared to the synced data on the phones. However, the method of physically imaging the smartwatch posed risks as it required gaining root access, potentially leading to a factory reset and permanent data deletion. The study also highlighted the difference in forensic soundness between acquiring a physical image of the Samsung Gear 2 Neo and acquiring data from the LG G watch, as the latter required a factory reset to gain root access.

2.2. Wrist-worn devices operating systems

Previous research in the field of wrist-worn devices has primarily focused on well-established companies like Apple, Fitbit, and Garmin, whose devices commonly operate on popular operating systems such as iOS (MacDermott et al., 2019; Loomis, 2019), Android (Rongen and Geradts, 2017; Kasukurti and Patil, 2018; Yoon and Karabiyik, 2020), and Tizen OS (Becirovic and Mrdovic, 2019).

However, it is worth noting that there is a category of wrist-worn devices referred to as "Others," which includes low-cost smartwatches. These affordable devices, despite being less recognized, have gained popularity among individuals seeking cost-effective options with moderate functionality. Gregorio et al. conducted an investigation specifically targeting these lesser-known low-cost smartwatches equipped with Real-Time Operating Systems (RTOS) (Gregorio et al., 2019). Their study delved into the acquisition and forensic analysis of these RTOS-based smartwatches, shedding light on an understudied area within the wrist-worn device landscape. By exploring these lesser-known devices, researchers like Gregorio et al. are expanding our understanding of the diverse range of operating systems and devices present in the wrist-worn device market.

2.3. Evidentiary data in wrist-worn devices

The information stored on wrist-worn devices, as well as other potential sources of evidence, plays a crucial role in investigations. Kasukurti and Patil have classified the artifacts found in wearables, including wrist-worn devices into seven types, including geo-location, activity log, and medical data (Kasukurti and Patil, 2018). However, further research has shown that these artifacts can be expanded upon. The literature reveals a range of extracted artifacts, including device information, geo-location information, health information, contacts, call logs, text messages, social media interactions/posts/notifications, web browsing behavior, search history, media files (pictures, videos, audios, music), connected devices, WiFi and/or Bluetooth connections, and deleted files (Rongen and Geradts, 2017; MacDermott et al., 2019; Loomis, 2019; Gregorio et al., 2019; Becirovic and Mrdovic, 2019; Kasukurti and Patil, 2018; Yoon and Karabiyik, 2020). The variation in extracted data from wrist-worn devices can be attributed to differences in the level of data extraction, sources of evidence, storage medium size, and the technological features of the devices.

Some related studies have highlighted that wrist-worn devices store information about the device itself, such as the device name, serial number, and software version (MacDermott et al., 2019; Kasukurti and Patil, 2018; Gregorio et al., 2019). Additionally, health-related information found on these devices holds significant forensic value. This data can be used to challenge a suspect's false testimony or to track a victim's behavior during an incident, as exemplified in the Richard Dabet first-degree murder case (BBC News, 2017). Researchers have successfully extracted health information from wrist-worn devices, including step counts, heart rate, calories burned, and average speed (MacDermott et al., 2019; Becirovic and Mrdovic, 2019; Kasukurti and Patil, 2018; Yoon and Karabiyik, 2020; Loomis, 2019).

Furthermore, forensic analysis of event data from vehicle applications has demonstrated the ability to reconstruct events during accidents or crime scenes (Onik et al., 2024). This method adds a new aspect to vehicle forensics, underscoring the potential for applying similar techniques in wrist-worn device investigations. By adopting these methods, forensic investigators can improve their capability to reconstruct event data from wrist-worn devices, thus providing more thorough evidence in forensic investigations.

Apart from device and health information, evidence of communication and call logs plays a vital role in numerous legal cases, providing insights into a person's social and/or professional life. Call record data can be used by investigators to determine the most frequently contacted individuals, call duration, and even the timeline of communication with specific individuals. Previous works have demonstrated the extraction of call logs and contacts from wrist-worn devices (Rongen and Geradts, 2017; Loomis, 2019; Gregorio et al., 2019; Becirovic and Mrdovic, 2019; Kasukurti and Patil, 2018). For instance, Gregorio et al. (2019) showcased the extraction of call logs from Real-Time Operating System (RTOS) smartwatches. Similarly, Rongen and Geradts (Rongen and Ger-

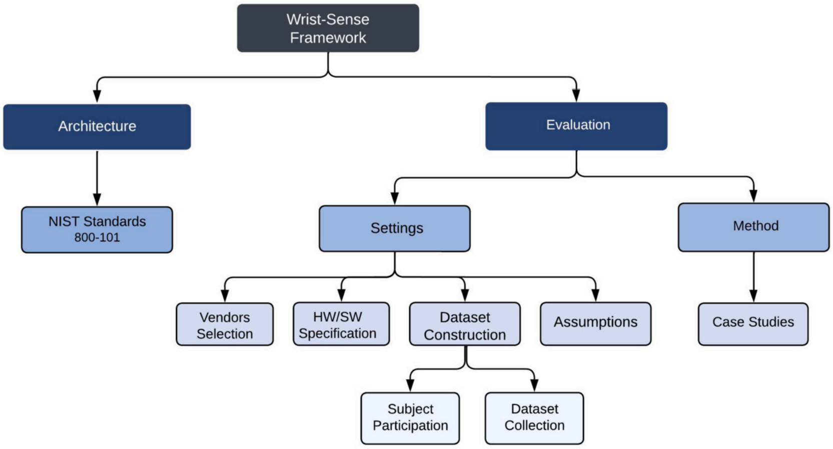


Fig. 1. Workflow Overview.

adts, 2017) were also successful in extracting phone calls made/received using Google smart glass.

3. Workflow overview

This section presents an overview of the proposed WristSense framework, combining the architectural design based on NIST 800-101 standards with the evaluation process. The framework operates through two interconnected components: architecture and evaluation through case studies (see Fig. 1 The architecture (detailed in Section 4) ensures the systematic extraction of health-related data, such as sleep patterns, heart rate, and activity logs, from wrist-worn devices. The framework employs the Sensor-Feature Cross-Reference Table (SFCRT) to map sensors to forensic artifacts, facilitating the identification of Potential Circumstantial Evidence (PCE). The evaluation component (discussed in Section 5) involves vendor selection, dataset construction, and case studies that validate the framework's compatibility across different vendors and operating systems. These evaluations demonstrate the framework's ability to adapt to diverse forensic contexts. Practical applications, such as reconstructing crime timelines, are also explored in these sections.

4. Framework architecture

This section proposes the WristSense framework for extracting health data from various wrist devices and identifying artifacts relevant to digital forensics, in accordance with NIST standards (Ayers et al., 2014). WristSense emphasizes a focus on wrist devices, highlighting the framework's ability to gather meaningful insights from these devices. The framework is designed to be independent of specific wrist-wear devices, ensuring broad applicability across different manufacturers and models. WristSense ensures the retrieval and analysis of data, including sleep patterns, heart rate, blood oxygen saturation, activities, and stress levels. These insights contribute to identifying the PCE in digital forensic investigations.

The framework architecture of WristSense is illustrated in Fig. 2, providing a visual representation of its components and their interactions.

4.1. Data source layer

The Data Source Layer serves as the initial stage in the data processing pipeline, responsible for gathering data from wrist devices and facilitating its subsequent handling by other layers. This layer includes wrist-worn devices such as smartwatches and smart bands discovered at the crime scene, along with their associated mobile devices. The mobile devices are forwarded to a digital forensics unit, where specialized tools are utilized to perform a logical extraction of stored data, decrypt encrypted application data, and extract various types of data in the SQLite format.

Given the diverse nature of the data sources involved, employing a unified and forensically sound digital forensics unit is advisable. Examples of such units include MD-RED, MD-NEXT, XRY, and EnCase. The extraction process results in a logical image comprising a substantial number of SQLite databases.

4.2. Analysis layer

The Analysis Layer consists of two primary components: an optional profiling unit and a mandatory processing unit. This layer receives the forensic image from the Data Source Layer and processes it using the Logical Analyzed Image Database Parser. The parser's primary objective is to extract health data from wrist-worn devices embedded within logical images. By employing specialized filtering mechanisms, the parser efficiently identifies and extracts relevant SQLite databases.

4.2.1. Profiling unit

The framework uses various markers to identify the likely suspect:

- **Biological Markers ("Biomarkers")**: Identify characteristics such as age, weight, body mass index, and body fat percentage.
- **Logical Markers**: Investigate connected devices, stored account credentials, and WiFi/Bluetooth connections associated with the wrist-wear device.
- **Location Markers**: Examine routes visited by the wearer. If the device contains information related to the suspect's work or home, it strengthens the likelihood of the device being linked to the suspect.

4.2.2. Processing unit

The processing unit is a fundamental component of the WristSense framework architecture, encompassing several key elements, each serving a specific purpose. Firstly, the Health-Related Database stores the health-related data obtained from the Logical Analyzed Image Database Parser, acting as a valuable resource for analysis and interpretation. Secondly, the Sensor-Feature Cross-Reference Table (SFCRT) maps sensors to their corresponding features, aiding in identifying PCE from wrist-worn devices. Thirdly, the PCE component analyzes features from the investigated devices to present factual information, such as sleep patterns (including deep sleep, light sleep, and the number of awakenings) and heart rate data (including maximum and minimum readings). Lastly, the PCE Repository organizes and stores this data, ensuring systematic management within the WristSense framework.

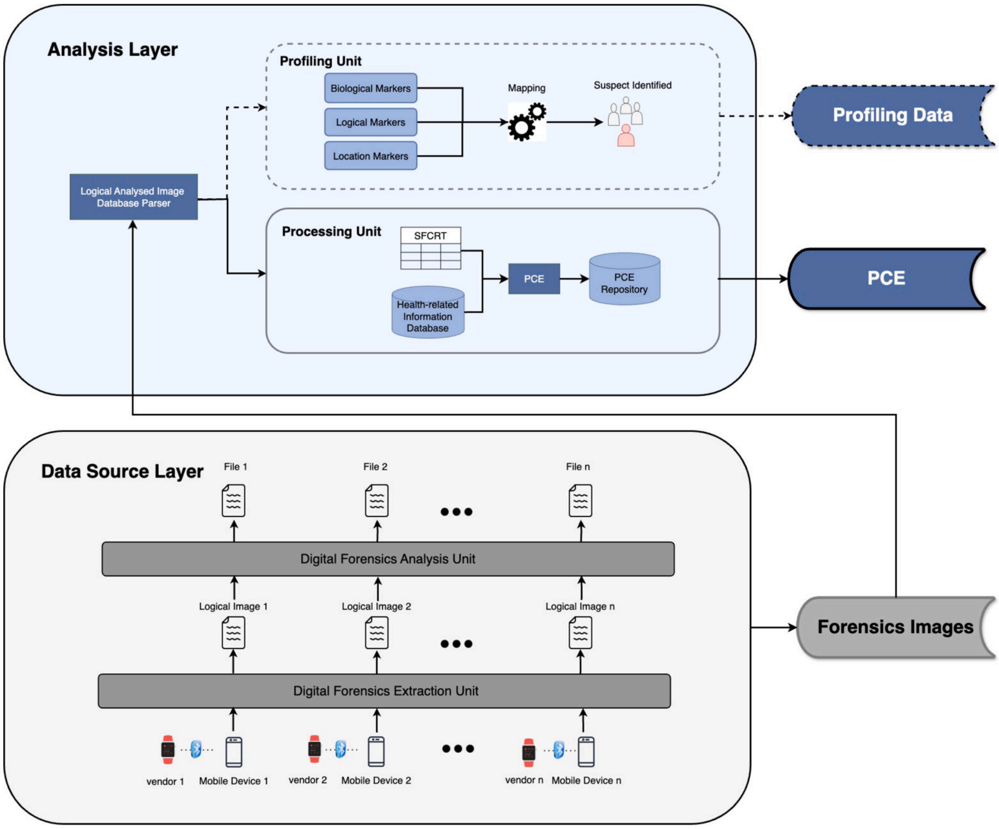


Fig. 2. WristSense Framework Architecture: **Logical Image**: Active data accessible through the file system; **Forensics Image**: A duplication process that preserves all data from the original medium without alterations, ensuring suitability for investigations and legal proceedings; **SFCRT**: Sensor-Feature Cross-Reference Table, **PCE**: Potential Circumstance Evidence, **Straight Line** ——— : Mandatory; **Dashed Line** - - - : Optional.

Sensor-Feature Cross-Reference Table(SFCRT): This component draws inspiration from the methodology proposed in Kebande et al. (2021) for developing a Digital Forensic Readiness Intelligence Repository (DFRIR), which establishes cross-referencing of potential digital evidence. In our framework, we utilize the SFCRT to capture the PCE and create a repository that can be shared among digital forensic professionals and law enforcement agencies.

We consider two key observations in building the SFCRT. First, some vendors, such as Huawei, Amazfit, Samsung, and Garmin, clearly list the embedded sensors for each wrist device on their official websites, while others, like Apple, primarily list device features with limited information about the sensors. Additionally, certain vendors provide a list of embedded sensors along with additional features that are not explicitly linked to these sensors. To address this variability, the SFCRT uses sensors and features as keys to help determine the PCE. Second, the presentation of wrist device features varies significantly among vendors, and there is no standardized list of features. Therefore, we consider a set of features that are common across wrist devices, vendor-independent, and useful for investigations

- Sensors: Wrist devices constantly monitor individuals through various sensing mechanisms, making them essential for everyday applications (King and Sarrafzadeh, 2018). These sensors provide substantial information about user activities. The list of sensors in the SFCRT is derived from two sources: (1) a review and two systematic review research papers (King and Sarrafzadeh, 2018; Morales et al., 2022; Khakurel et al., 2018); (2) five vendor websites. The sensors include: accelerometer, pedometer, GPS, gyroscope, blood pressure monitor, SpO2/oximetry, magnetometer/compass/geomagnetic, heart rate/Heart Rate Variability (HRV) monitor, temperature sensor, and electrocardiogram (ECG).
- Features: Wrist device features provide valuable information about an individual. For example, the heart rate monitoring feature can be highly useful to DFIs. In a domestic abuse case, a person may claim to be at home relaxing, but an elevated heart rate could indicate physical activity during that time, suggesting a false statement (Yoon and Karabiyik, 2020). The features considered in the SFCRT include: sleep monitoring, heart rate monitoring, SpO2 measurement, blood pressure measurement, body temperature monitoring, activity tracking, and stress measurement.

The SFCRT, illustrated in Table 1, demonstrates that a single sensor can provide information about multiple features. For example, the heart rate sensor assists in sleep monitoring, heart rate monitoring, activity tracking, and stress monitoring. Conversely, features often rely on multiple sensors; for instance, sleep monitoring utilizes accelerometers, blood pressure sensors, and heart rate sensors. To facilitate the generation of the PCE, the following key concepts are defined:

- F: Feature
- n: # Feature
- S: Sensor
- $SFCRT$: Sensor-Feature Cross-Reference Table
- PCE: Potential Circumstantial Evidence
- F_m: Existing feature based on vendor's manual
- S_m: Existing sensor based on vendor's manual
- F_s: Existing feature based on existing sensor S_m

The PCE is the sum of features; see Equation (1).

$$PCE = \sum_{i=1}^{n} F_i \quad \text{where} \quad F_i \in (F_m \cup F_s) \tag{1}$$

Table 1
Sensor-Feature Cross-Reference Table (SFCRT).

Sensor / Feature	Sl	HR	SpO2	BP	BT	AT	St
Accelerometer	✓	✓				✓	
Pedometer						✓	
GPS						✓	
Gyroscope						✓	
Blood Pressure	✓			✓			
SpO2/Oximetry			✓				✓
Magnetometer/Compass/Geomagnetic						✓	
Heart Rate/HRV	✓	✓				✓	✓
Temperature					✓	✓	✓
Electrocardiogram (ECG)		✓				✓	✓

Abbreviations:
Sl: Sleep monitoring, HR: Heart Rate monitoring, SpO2: Oxygen Saturation, BP: Blood Pressure Measurement, BT: Body Temperature Monitoring, AT: Activity Tracking, St: Stress Monitoring.
References:
✓Sl: (Yoshihi et al., 2021; Shin et al., 2019); ✓HR: (Zhao et al., 2021; Bent et al., 2020; Chow et al., 2020); ✓SpO2: (Buekers et al., 2019; Davies et al., 2020; Wackernagel et al., 2020); ✓BP: (Kumar et al., 2021; Kim et al., 2019); ✓BT: (Li et al., 2022); ✓AT: (Li et al., 2016; Zhang et al., 2022; Popleteev, 2015); ✓St: (Parlak, 2021; Han et al., 2020; Minguillon et al., 2018).

To generate a list of PCE, digital forensic investigators (DFIs) must first access the SFCRT and the manual of the investigated wrist device. The process involves the following steps:

1. Iterate through each feature listed in the SFCRT.
2. If a feature from the SFCRT is found in the device manual, it is directly added to the PCE list.
3. If the feature is not listed in the manual, the investigator then examines each sensor in the SFCRT that contributes to that feature.
4. If the examined sensor is found in the device manual and is associated with that feature, the feature is subsequently added to the PCE list.

This systematic approach ensures that all relevant features and sensors are thoroughly considered in the generation of PCE.

Apple Watch Series 9 Example

The Apple Watch Series 9 serves as a practical demonstration of how the Sensor-Feature Cross-Reference Table (SFCRT) can be used to generate Potential Circumstantial Evidence (PCE).

* **Manual Information:** The following sensors and features are identified from the Apple Watch Series 9 manual:

- **Sensors:**
  - Electrical Heart Sensor
  - Third-Generation Optical Heart Sensor
  - Temperature Sensor
  - Compass
  - Always-On Altimeter
  - High-G Accelerometer
  - High Dynamic Range Gyroscope
  - Ambient Light Sensor
- **Features:**
  - Sleep App Including Sleep Stages
  - Heart Rate App
  - High and Low Heart Rate Notifications
  - Irregular Rhythm Notifications
  - Medications App
  - Mindfulness App
  - Noise App
  - Cycle Tracking App with Retrospective Ovulation Estimates
  - ECG App
  - Activity Tracking (includes various workouts and metrics)

* **Generating PCE:**
Using the SFCRT and the manual, the following steps generate the PCE:

1. Iterate through each feature listed in the SFCRT.
2. Check if the feature is explicitly mentioned in the manual:
   - Add Sleep Monitoring (**Sl**), Heart Rate Monitoring (**HR**), and Activity Tracking (**AT**) to the PCE list.
3. For features not explicitly mentioned, check the contributing sensors:
   - Stress Monitoring (**St**) is supported by the Heart Rate Sensor and Temperature Sensor, both of which are present in the manual. Add it to the PCE list.
   - SpO2 Monitoring (**SpO2**): Typically supported by Optical Heart Sensors or dedicated SpO2 Sensors. However, neither is explicitly mentioned in the manual, so SpO2 Monitoring cannot be added to the PCE list.
   - Blood Pressure (**BP**): Commonly supported by sensors that measure vascular tension, such as dedicated Blood Pressure Sensors. As no Blood Pressure Sensor is mentioned in the manual, this feature cannot be added to the PCE list.
   - Body Temperature Monitoring (**BT**): Supported by the Temperature Sensor, which is explicitly listed in the manual. Add Body Temperature Monitoring to the PCE list.

* **Final PCE List:** Based on the analysis, the PCE for the Apple Watch Series 9 is:

$$\mathrm{PCE} = \{\mathrm{Sl}, \mathrm{HR}, \mathrm{AT}, \mathrm{St}, \mathrm{BT}\}$$

5. Framework evaluation

This section showcases the evaluation of the WristSense framework through a series of case studies. The chosen research design for these case studies was an exploratory approach, as it allows for assessing the feasibility and effectiveness of the framework (Hancock et al., 2021). Additionally, a collective case study research design was employed to contribute to the existing literature and enhance the conceptualization of the underlying theory (Hancock et al., 2021).

5.1. Evaluation settings

This subsection outlines the comprehensive setup and conditions used to evaluate the WristSense framework. It includes the selection

Table 2
Wrist-Wear Devices and Specifications.

Vendor	Huawei	Huawei	Amazfit	Xiaomi	Samsung
Investigated Device	Fit 2 Smartwatch	Band 7	Band 7	Watch 3	Watch 6
Operating System	Android Wear	Android Wear	Zepp OS	Wear OS	Wear OS
Health Applications	Huawei Health	Huawei Health	Zepp	Mi Fitness	Samsung Health
Period	Around one year	18 days	8 days	11 days	10 days
Timeframe	11 May 22-4 Apr 23	10 Jul 22-27 Jul 23	9 Jul 23-16 Jul 23	3 Sep 23-13 Sep 23	1 Oct 23-10 Oct 23

criteria for vendors, details about the dataset generation and its public accessibility, specifications of the hardware and software employed, and the assumptions underlying the evaluation. These elements ensure the robustness, reproducibility, and relevance of the evaluation process to real-world forensic applications.

5.1.1. Vendor selection

Three prominent vendors from the wearable technology market were considered: Huawei, Xiaomi, and Samsung. These vendors are recognized as market leaders in the industry (Market.us, 2023; Intelligence, New Astron). Additionally, Amazfit, a non-competitive player, was also included in the evaluation.

5.1.2. Hardware / software specifications

Table 2 presents the wrist-wear devices investigated in the study, along with their respective vendors, operating systems, periods of data collection, and timeframes. The devices include Huawei Fit 2 Smartwatch and Band 7, Amazfit Band 7, Xiaomi Watch 3, and Samsung Watch 6. These devices operate on different operating systems such as Android Wear, Zepp OS, and Wear OS. Data collection periods vary, with Huawei having the longest duration. All devices, except for the Samsung Watch 6, were connected to an iPhone 11 for data synchronization through the vendor's health applications. The Samsung Watch 6 was paired with a Galaxy device.

5.1.3. Dataset construction

The dataset was constructed using a single participant who wore various wrist-worn devices across different periods. Each device was paired with its corresponding mobile health application to ensure data synchronization. To capture diverse real-world scenarios, the participant engaged in varying activity levels, including sedentary, moderate, and active states. The resulting dataset, named "WristSense-VendorData," was generated separately for each vendor to maintain clarity and reproducibility. The dataset, publicly accessible at,[1] enables validation and supports forensic research involving wrist-worn devices.

5.1.4. Assumptions

The evaluation of the framework involves several underlying assumptions that aid digital forensic investigators in their decision-making processes. These assumptions are:

1. Profiling data is available to help identify the likely suspect from a specific group.
2. The PCE can be extracted from all features with a minimal number of variables.
3. Wrist-worn device data can offer insights into the suspect's sleep and activity data related to specific dates, such as the date of a crime.
4. Wrist-worn device data can provide insights into the suspect's average awake time duration, indicating sleep disturbances or irregular patterns.
5. There is a correlation between steps and calories extracted from wrist-worn devices.

These evaluations will provide recommendations for vendors to facilitate wrist-wear device investigations.

5.2. Evaluation method (case studies)

This subsection describes the steps involved in applying WristSense to each wrist-wear device, ensuring the reproducibility of the evaluation results.

1. **Data Source Layer**:
   - **Tools Employed**: MD-NEXT and MD-RED for data extraction and analysis.
   - **Data Extraction**: Data is extracted from paired devices (e.g., iPhone 11) using MD-NEXT and analyzed with MD-RED, which supports over 1500 mobile apps on iOS and Android platforms.[2]
   - **Output**: A logical image containing numerous SQLite files is generated for further analysis.
2. **Analysis Layer**:
   - **Profiling Unit**:
     - **Data Search**: Searches for biological (e.g., weight, birthday, height, age) and logical (e.g., device linkage) profiling data.
   - **Processing Unit**:
     - **Database Parsing**: The Logical Image Database Parser extracts health-related databases and apply SFCRT to identify PCE.
     - **PCE Identification**: Identifies potential features such as sleep monitoring, HR monitoring, oxygen saturation measurement, activity tracking, and stress measurement.
     - **Evidence Compilation**: PCE_Rep compiles circumstantial digital evidence features and corresponding data.

By detailing each step and tool used, this subsection ensures that the evaluation process is transparent, reproducible, and scientifically rigorous.

5.3. Case study results

Based on the assumptions made, the evaluation of the framework in this case study yields insightful results for digital forensics investigators. These assumptions serve as fundamental principles that shape the evaluation process, allowing investigators to derive meaningful conclusions and extract valuable insights from the data at hand. The summarized results of the case studies are presented in Table 3, providing a clear overview of profiling data availability and insights across different wearable devices. Table 4 details the specific variables used in the analysis, offering a comprehensive view of the data collected from each device. For detailed visualizations of the case study results, refer to the Appendix A.

5.3.1. There is profiling data that can help determine the probable suspect among a given set of individuals.

- **Huawei**: The Fit2 and Band7 encompass a range of biological and logical markers in the *wear.db* database, more specifically in the *HWSporetHealth_localStorage_AccountInfo_table*. This data includes weight, birthday, height, age and a username that corresponds to a

[1] https://data.mendeley.com/datasets/f7fvmmsd86/3.

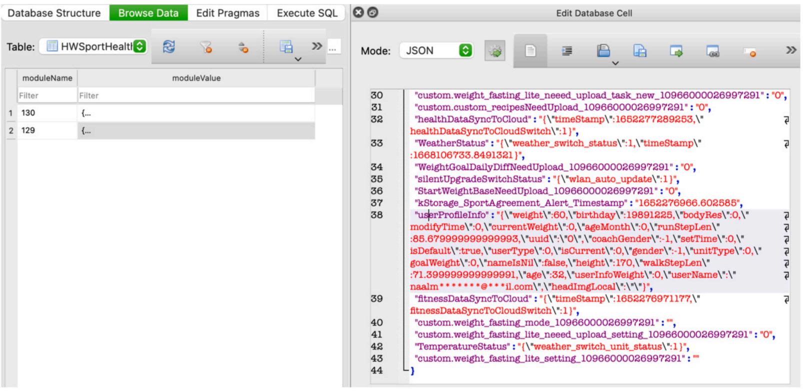
[2] https://mh-service.de/en/products/md-red/.

Table 3
Summary of Case Study Results.

Feature	Huawei Fit2	Huawei Band7	Xiaomi Watch3	Amazfit Band7	Samsung Watch6
Profiling Data Availability	Yes	Yes	No	Yes	N/A
Insights from Sleep Data (Crime Date)	Yes	Yes	Yes	Yes	N/A
Average Awake Time Insights	Yes	Yes	Yes	Yes	N/A
Correlation between Steps and Calories	High	High	High	High	N/A

Table 4
Detailed Variable-Specific Results.

Feature Variables	Huawei Fit2	Huawei Band7	Xiaomi Watch3	Amazfit Band7	Samsung Watch6
Sleep	Time stamp, light sleep, deep sleep, REM sleep, nap duration, awake duration, awake counts, fall asleep time, wake-up time				
Heart Rate	Time stamp, max HR, min HR, avg resting HR				
Blood Oxygen	Time stamps, max SpO2, min SpO2				
Stress	Time stamp, max stress, min stress, avg stress				
Activity	Time stamps, total steps, total distance, total calories				



```
 "custom.weight_fasting_lite_neeed_upload_task_new_10966000026997291" : "0",
 "custom.custom_recipesNeedUpload_10966000026997291" : "0",
 "healthDataSyncToCloud" : "{\"timeStamp\":1652277289253,\"
healthDataSyncToCloudSwitch\":1}",
 "WeatherStatus" : "{\"weather_switch_status\":1,\"timeStamp\"
:1668106733.8491321}",
 "WeightGoalDailyDiffNeedUpload_10966000026997291" : "0",
 "silentUpgradeSwitchStatus" : "{\"wlan_auto_update\":1}",
 "StartWeightBaseNeedUpload_10966000026997291" : "0",
 "kStorage_SportAgreement_Alert_Timestamp" : "1652276966.602585",
 "userProfileInfo" : "{\"weight\":60,\"birthday\":19891225,\"bodyRes\":0,\"
modifyTime\":0,\"currentWeight\":0,\"ageMonth\":0,\"runStepLen\"
:85.679999999999993,\"uuid\":\"0\",\"coachGender\":-1,\"setTime\":0,\"
isDefault\":true,\"userType\":0,\"isCurrent\":0,\"gender\":-1,\"unitType\":0,\"
goalWeight\":0,\"nameIsNil\":false,\"height\":170,\"walkStepLen\"
:71.399999999999991,\"age\":32,\"userInfoWeight\":0,\"userName\":\"
naalm*******@***il.com\",\"headImgLocal\":\"\"}",
 "fitnessDataSyncToCloud" : "{\"timeStamp\":1652276971177,\"
fitnessDataSyncToCloudSwitch\":1}",
 "custom.weight_fasting_mode_10966000026997291" : "",
 "custom.weight_fasting_lite_neeed_upload_setting_10966000026997291" : "0",
 "TemperatureStatus" : "{\"weather_switch_unit_status\":1}",
 "custom.weight_fasting_lite_setting_10966000026997291" : ""
}
```

Fig. 3. Huawei - Profiling Data (1).

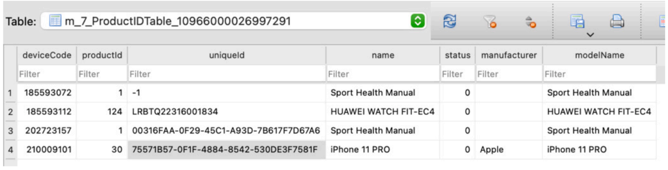


Table: m_7_ProductIDTable_10966000026997291

	deviceCode	productId	uniqueId	name	status	manufacturer	modelName
	Filter	Filter	Filter	Filter	Filter	Filter	Filter
1	185593072	1	-1	Sport Health Manual	0		Sport Health Manual
2	185593112	124	LRBTQ22316001834	HUAWEI WATCH FIT-EC4	0		HUAWEI WATCH FIT-EC4
3	202723157	1	00316FAA-0F29-45C1-A93D-7B617F7D67A6	Sport Health Manual	0		Sport Health Manual
4	210009101	30	75571B57-0F1F-4884-8542-530DE3F7581F	iPhone 11 PRO	0	Apple	iPhone 11 PRO

Fig. 4. Huawei - Profiling Data (2).

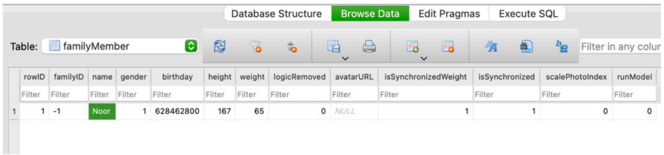


Table: familyMember

	rowID	familyID	name	gender	birthday	height	weight	logicRemoved	avatarURL	isSynchronizedWeight	isSynchronized	scalePhotoIndex	runModel
	Filter	Filter	Filter	Filter	Filter	Filter	Filter	Filter	Filter	Filter	Filter	Filter	Filter
1	1	-1	Noor	1	628462800	167	65	0	NULL	1	1	0	0

Fig. 5. Amazfit Band7 - Profiling Data (Biological) (1).

portion of the user's email address (refer to Fig. 3). Thus, DFI can establish ownership of a wearable device by examining these data. Furthermore, the investigation uncovers compelling evidence suggesting a clear linkage between the investigated wearable and an iPhone 11 Pro (see Fig. 4). This evidence is derived from the presence of a *ProductIDTable** (i.e., where ∗ matches exactly 17 digits), which establishes a definitive connection between the wearable device and the specific mobile device model mentioned, namely the iPhone 11 Pro. The existence of this table serves as a robust piece of evidence, bolstering the assertion that the wrist-wear device was deliberately paired and utilized in conjunction with the associated iPhone 11 Pro. Consequently, this further substantiates the case for ownership or possession of the investigated wearable by the identified suspect.

- **Amazfit:** The Band 7 contains biological, logical, and location data. The investigation findings indicate that the Amazfit Band 7 device stores specific biological data within its database, known as *HMCorePersistanceDatabaseV1.sqlite.db*. More specifically, this data is stored in the *familyMember* and includes information such as name, gender, birthday, height, weight (refer to Fig. 5). These data points can be crucial for DFI to establish device ownership. As for the logical markers, the investigation has uncovered compelling evidence linking the Amazfit Band 7 to a device with system version 15.6.1 (see Fig. 6). This evidence is derived from the presence of a *anonymous_context* table in the *HMStatisticsAnonymousDBV2.sqlite.db* database, which establishes a definitive connection between the Band 7 device and the iPhone with a system version. Furthermore, the data obtained from the smartwatch reveals the presence of a location identifier "SA," which symbolically represents the country "Saudi Arabia" where the device is connected, operating, or configured.
- **Xiaomi:** The Redmi Watch 3 device consists of a single database consisting of 44 tables, named: *6678634272.db*. However, upon investigation, it has been determined that this device does not store any profiling data, including logical, biological, or location-related information.
- **Samsung:**Although the data could be extracted, the encryption mechanism poses a challenge for analyzing profile data. A database called *SecureHealthData.db* and an encrypted key called *encryptedKeystore* were extracted, but they cannot be accessed without the

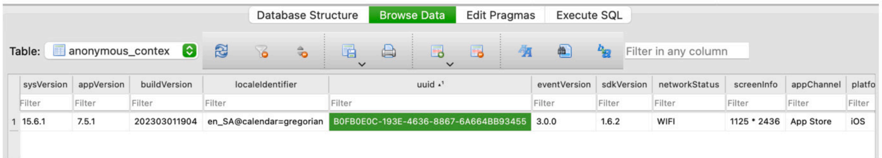


Table: anonymous_contex

	sysVersion	appVersion	buildVersion	localeIdentifier	uuid	eventVersion	sdkVersion	networkStatus	screenInfo	appChannel	platfo
	Filter	Filter	Filter	Filter	Filter	Filter	Filter	Filter	Filter	Filter	Filter
1	15.6.1	7.5.1	202303011904	en_SA@calendar=gregorian	B0FB0E0C-193E-4636-8867-6A664BB93455	3.0.0	1.6.2	WIFI	1125 * 2436	App Store	iOS

Fig. 6. Amazfit Band7 - Profiling Data (Logical - Location) (2).

decryption key to decrypt the *SecureHealthData.db*. Therefore, Samsung data is not included neither in profiling nor in the analysis.

5.3.2. *Potential Circumstantial Evidence (PCE) can be extracted from all features with a minimum number of variables*

Sleep Monitoring (SLM): The findings indicate that sleep data from wrist-band wearable devices can provide valuable insights into the wearer's sleep pattern. Several common variables have been identified that contribute to deriving the sleep pattern, including *time stamp, light sleep duration, deep sleep duration, REM sleep duration, nap duration, sleep awake duration, awake counts, fall asleep time, and wakeup time*. These variables collectively offer clues and information about the individual's sleep habits and patterns. Detailed plots and time series for these variables can be found in the appendix (Figs. 9, 10, and 11).

Heart Rate Monitoring (HRM): The variables of interest, including *time stamp, maximum heart rate, minimum heart rate, and average resting heart rate*, provide significant insights into an individual's heart rate patterns. An acceptable range for resting heart rate falls within 50 to 80 beats per minute (bpm). Research has shown that a low resting heart rate is linked to various factors such as criminal behavior, aggression, psychopathy, and conduct problems (Wilson and Scarpa, 2012). Furthermore, studies have found associations between low heart rate and different types of criminal offenses, including violent offenses, drug offenses, property offenses, and even traffic offenses (Latvala et al., 2015). Refer to the appendix for relevant plots (Fig. 12).

Blood Oxygen Measurement: Blood oxygen measurement provides valuable circumstantial evidence through variables such as *time stamps, maximum blood oxygen, and minimum blood oxygen*. In general, a lower SpO2 level indicates a higher risk. If the SpO2 falls below 90%, the wearer may be susceptible to hypoxemia, a condition associated with inadequate oxygen levels in the body (Co). Refer to the appendix for relevant plots (Figs. 13 and 14).

Stress Measurement (STM): The variables *time stamp, maximum stress, minimum stress, and average stress* can provide valuable circumstantial evidence related to stress levels. Research has indicated that stress has detrimental effects on human health and is closely associated with mental disorders, including anxiety (Tsukuda et al., 2019) and seizures (Cano-Lopez and Gonzalez-Bono, 2019). Refer to the appendix for relevant plots (Fig. 15).

Activity Tracking (AT): The variables of *time stamps, total steps, total distance, and total calories* can provide valuable information about an individual's movement patterns and activity levels from a forensic standpoint. Analyzing these variables allows investigators to understand the length of routes taken by the wearer and assess their level of physical activity, aiding in the investigation. Refer to the appendix for relevant plots (Fig. 16).

5.3.3. *The wrist-worn device data can offer insights into the suspect's sleep and activity data related to a particular date, such as the date of a crime scene*

The wrist-worn device data analysis provided valuable insights into the suspect's sleep patterns on a particular date, such as the date of a crime scene. Fig. 17 displays the relevant sleep variables recorded during the investigated period. Similarly, Fig. 18, 19, 20, and 21 present activity variables (e.g., step counts, calories burned) for specific date. This information played a crucial role in establishing a timeline of the suspect's sleep cycle and activity, thereby verifying or raising doubts about their alibis during specific time periods. By examining the sleep and activity data, investigators gained a better understanding of the suspect's behavior and were able to potentially correlate these patterns with the timeline of events under investigation.

5.3.4. *The wrist-wear device data can provide insights into the suspect's average awake sleep time duration, indicating sleep disturbances or irregular sleep patterns*

The analysis of wrist-worn wearable average awake sleep time duration yielded significant results in the investigation. The time duration in minutes provides valuable insights into sleep disturbances or irregular sleep patterns. Higher values indicate a greater occurrence of sleep disturbances. These findings contribute to a better understanding of the sleep patterns and potential disruptions experienced by the individuals under investigation. Refer to the appendix for relevant plots (Fig. 22).

5.3.5. *There is a clear correlation between steps and calories extracted from wrist-wear devices*

The analysis of data extracted from wrist-worn devices revealed a strong correlation between steps and calories. All wrist-wear devices demonstrate a high correlation between these variables, indicating that an increase in the number of steps taken is associated with a higher calorie expenditure. Refer to the appendix for relevant plots (Fig. 23).

6. Results and discussion

This section presents the key findings obtained from the evaluation of the WristSense framework. The analysis delves into the applicability of the framework in extracting and analyzing health-related data from various wrist-worn devices, providing valuable insights for digital forensic investigations.

6.1. *Wrist-wear device potential circumstantial evidence*

Given that the case study results presented in 5.3 belong to a wearer, who can be either a suspect or victim under investigation, several pieces of evidence can be obtained to draw conclusions.

6.1.1. *Huawei Fit 2*

From a forensic perspective, several facts can be extracted from sleep data. It is evident that the wearer exhibits variations in sleep time distribution based on different seasons (Fig. 10). In winter, "Deep Sleep Time" increases due to colder temperatures and longer nights, promoting deep sleep. Conversely, in summer, "Deep Sleep Time" decreases due to warmer temperatures and shorter nights. "Sleep Dream Time" follows the opposite trend.

Furthermore, Fig. 11 shows that "Light Sleep Time" occupies the largest portion of the sleep cycle, indicating significant time in this stage. "Deep Sleep Time" is substantial, suggesting considerable restorative sleep, while "Sleep Dream Time" is the shortest, emphasizing the importance of REM sleep.

The mean of "Awake Sleep Time" varies across the year (Fig. 22). In April, it peaks at 28.3 minutes, indicating more frequent awakenings, potentially due to temperature changes or allergies. In December, it drops to 1.8 minutes, suggesting more continuous sleep. This trend continues into January with 3.1 minutes of awakeness, highlighting the influence of seasonal factors on sleep quality.

Moreover, DFIs can know exactly the sleep time for a suspect at a specific crime scene. If a wearer states that he was sleeping all night, large amounts of “Awake Sleep Time” might indicate misleading statements (Fig. 17).

Regarding heart rate data, the user’s average resting heart rate falls within the acceptable range (Fig. 12). However, maximum heart rates on specific dates exceed the normal range, warranting further investigation (e.g., 4 June 2022, 6 June 2022, 29 December 2022, 31 Jan 2022 reached 152, 152, 149, and 153 bpm respectively).

For blood oxygen levels, Fig. 14 shows normal saturation levels (90-100%) with an exception on March 28, 2024, when it dropped below 90%. This day warrants further investigation. The analysis reveals consistently higher stress levels on specific dates, such as May 15, 2022, May 22, 2022, and March 28, 2023 (Fig. 15). Regarding activity, the wearer maintains a consistent step count (1,000 to 10,000) with notable variations (Fig. 16). Significant drops in activity can indicate periods of non-wear or inactivity. DFIs can determine step counts and burned calories on specific dates (Fig. 18).

6.1.2. Huawei Band 7

The wearer spends the majority of sleep time in the light sleep phase (45.3%), followed by deep sleep (33.5%) and dream phase (22.2%) (Fig. 9). The yearly calendar heat map shows minimal sleep interruptions with an average “Awake Sleep Time” of 1.5 minutes (Fig. 22).

A significant drop in sleep on July 16, 2023, is observed, followed by a nap on July 17, 2023 (Fig. 11). Heart rate peaks at 166 bpm on July 17, 2023, indicating heightened activity, and drops to 52 bpm on July 21, indicating rest (Fig. 12). Blood oxygen data shows consistent readings with variations on specific days, such as July 14 and 17 (Fig. 14). Activity levels show an average of 4182 steps with decreases on July 21 and 26, 2023.

6.1.3. Xiaomi Watch 3

The wearer spends most of the time in light sleep (Fig. 9). Average awake time is 5.1 minutes, with an awakening recorded on September 11 (Fig. 22). The wearer consistently uses the device except on September 7. Heart rate data shows deviations from the normal range on September 4 and 7 (Fig. 12). Blood oxygen saturation remains high with a drop to 85% on September 12 (Fig. 14). Unlike Huawei, Xiaomi does not automatically record stress levels, relying on user-initiated tracking. Only one instance on September 13 shows stress levels between 29 and 33 (Fig. 15). Activity levels average around 4000 steps, with a peak of over 8000 steps on September 4, 2023 (Fig. 16).

6.1.4. Amazfit Band 7

Non-REM sleep time is consistently lower than REM sleep, indicating additional variables not included (Fig. 9). Average awake time is 10.9 minutes, with an increase to 33 minutes on July 14 (Fig. 22). Amazfit offers continuous SpO2 measurement, with levels above 90 except for a drop to 84 on July 11 (Fig. 14). “Pressure rate” rather than “stress” is used, peaking on July 14 (Fig. 15).

6.2. Taxonomy of wrist-wear digital forensic artifacts

The study reveals several wrist-wear artifacts on the iOS operating system that hold forensic value, providing practitioners with significant data for investigations (Fig. 7). The taxonomy is categorized according to the artifact catalog structure suggested by Casey et al. Casey et al. (2022).

The artifact catalog includes:

1. Category: Health features (e.g., sleep, heart rate, SpO2, activities, stress).
2. Platform: Operating systems (e.g., Android Wear, Zepp OS, Wear OS on iOS).
3. Container: Full path or data structure of the container, including respective databases and tables.
4. Artifacts: Both atomic and dependent artifacts.

The presence of the artifact catalog addresses potential knowledge gaps among practitioners, ensuring awareness of forensic capabilities and enhancing investigation outcomes.

6.3. Consistency analysis of variables across vendors in forensic investigations

The consistency of data is crucial in forensic investigations. We examined variables within each vendor’s dataset to ensure analysis integrity. Fig. 8 shows the intersection of variables among Huawei, Amazfit, and Xiaomi for sleep monitoring, heart rate monitoring, blood oxygen saturation measurement, activity tracking, and stress measurement.

The Venn diagram highlights overlapping areas, indicating commonly measured and recorded variables across different devices. Sleep monitoring, activity tracking, and stress measurements show the highest overlap, suggesting these variables provide reliable insights across vendors. Heart rate monitoring and blood oxygen saturation measurements show varying degrees of overlap, indicating differences in data availability.

By focusing on consistent variables, forensic practitioners can rely on robust evidence, enhancing the credibility of their findings.

7. Future directions

This section presents some potential future directions for the WristSense framework:

1. **Extension to Other Wearables**: One promising direction is to extend the framework beyond wrist-worn devices and incorporate compatibility with other wearables, such as smart clothes. This expansion would allow for a more comprehensive analysis of health data from a wider range of devices, providing additional insights and potential evidence for digital forensic investigations.
2. **Ensuring Accuracy of Investigated Wrist-Wear Devices:** Wrist-wear devices often provide data that is prone to inaccuracies due to factors such as environmental conditions, user-specific characteristics (e.g., tattoos, scars, excessive wrist hair), and proprietary sensor algorithms. For example, Huawei has acknowledged that capillary narrowing in cold environments can lead to inaccurate heart rate measurements. Future work should focus on systematically quantifying error rates for each physiological feature (e.g., heart rate, sleep patterns, SpO2) and developing mechanisms for validating the accuracy of data collected under varying conditions. Additionally, incorporating cross-sensor or cross-device corroboration methods can help mitigate these inaccuracies and ensure more reliable forensic insights.
3. **Framework Validation**: Conducting thorough validation studies to assess the PCE generated through the WristSense framework would be a crucial step. Validation efforts can involve comparing the obtained results from different digital forensics extraction and analysis techniques to ensure reproducibility. This validation process would enhance confidence in the framework’s capabilities and support its adoption in the field.
4. **Integration with Other Digital Forensic Investigation Tools**: Recognizing the importance of collaboration and interoperability, the framework seamlessly integrates with established forensic tools, facilitating a comprehensive examination of wrist device data alongside other forms of digital evidence. This integration empowers investigators to leverage the strengths of different tools and enhance the efficiency and effectiveness of their forensic analyses.
5. **Encryption Challenges**: Addressing the challenge posed by encryption mechanisms in certain wrist-wear devices, such as Sam-

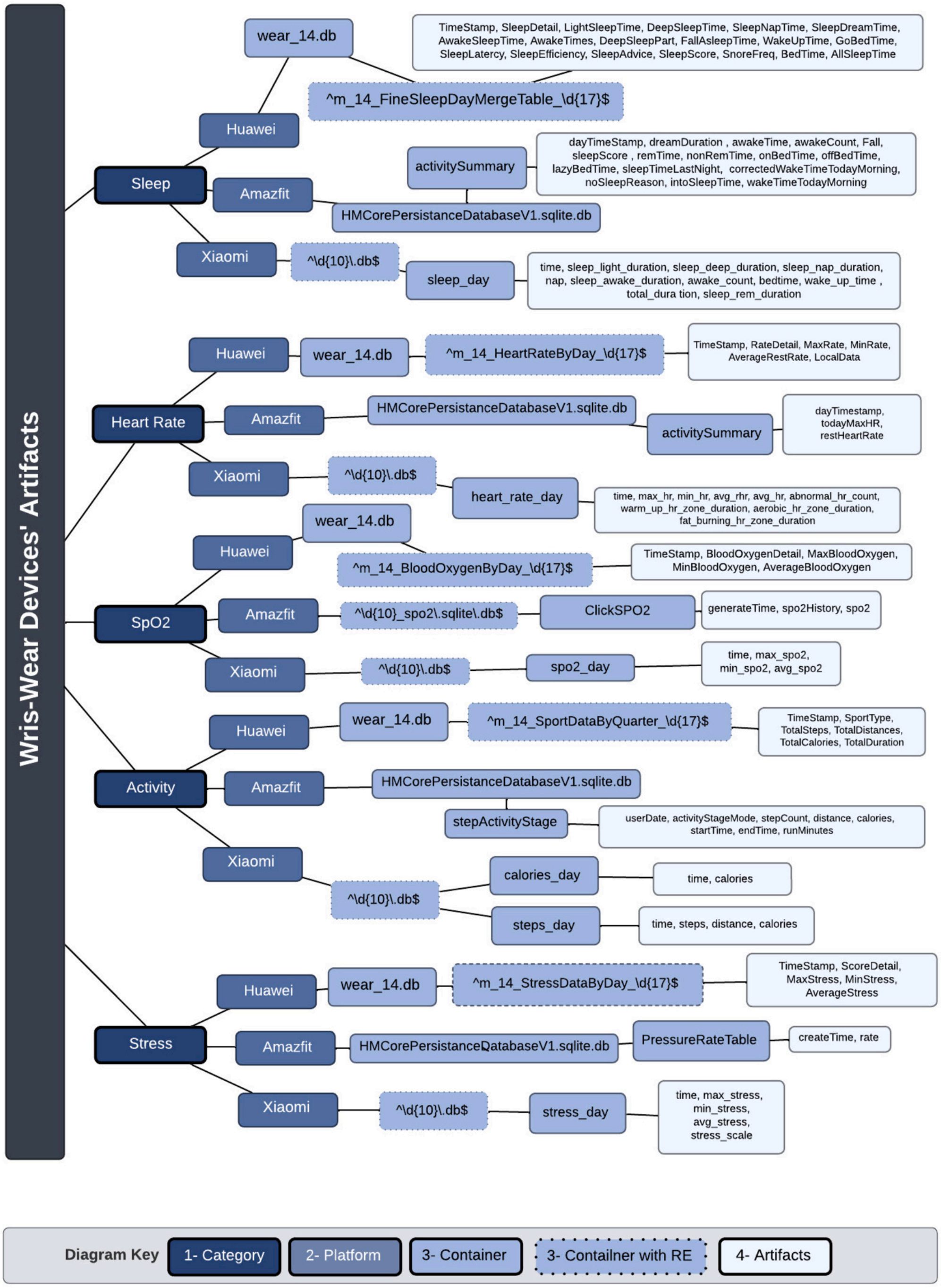

Wris-Wear Devices' Artifacts
Sleep
Huawei
wear_14.db
^m_14_FineSleepDayMergeTable_\d{17}$
TimeStamp, SleepDetail, LightSleepTime, DeepSleepTime, SleepNapTime, SleepDreamTime, AwakeSleepTime, AwakeTimes, DeepSleepPart, FallAsleepTime, WakeUpTime, GoBedTime, SleepLatercy, SleepEfficiency, SleepAdvice, SleepScore, SnoreFreq, BedTime, AllSleepTime
Amazfit
HMCorePersistanceDatabaseV1.sqlite.db
activitySummary
dayTimeStamp, dreamDuration , awakeTime, awakeCount, Fall, sleepScore , remTime, nonRemTime, onBedTime, offBedTime, lazyBedTime, sleepTimeLastNight, correctedWakeTimeTodayMorning, noSleepReason, intoSleepTime, wakeTimeTodayMorning
Xiaomi
^\d{10}\.db$
sleep_day
time, sleep_light_duration, sleep_deep_duration, sleep_nap_duration, nap, sleep_awake_duration, awake_count, bedtime, wake_up_time , total_dura tion, sleep_rem_duration
Heart Rate
Huawei
wear_14.db
^m_14_HeartRateByDay_\d{17}$
TimeStamp, RateDetail, MaxRate, MinRate, AverageRestRate, LocalData
Amazfit
HMCorePersistanceDatabaseV1.sqlite.db
activitySummary
dayTimestamp, todayMaxHR, restHeartRate
Xiaomi
^\d{10}\.db$
heart_rate_day
time, max_hr, min_hr, avg_rhr, avg_hr, abnormal_hr_count, warm_up_hr_zone_duration, aerobic_hr_zone_duration, fat_burning_hr_zone_duration
SpO2
Huawei
wear_14.db
^m_14_BloodOxygenByDay_\d{17}$
TimeStamp, BloodOxygenDetail, MaxBloodOxygen, MinBloodOxygen, AverageBloodOxygen
Amazfit
^\d{10}_spo2\.sqlite\.db$
ClickSPO2
generateTime, spo2History, spo2
Xiaomi
^\d{10}\.db$
spo2_day
time, max_spo2, min_spo2, avg_spo2
Activity
Huawei
wear_14.db
^m_14_SportDataByQuarter_\d{17}$
TimeStamp, SportType, TotalSteps, TotalDistances, TotalCalories, TotalDuration
Amazfit
HMCorePersistanceDatabaseV1.sqlite.db
stepActivityStage
userDate, activityStageMode, stepCount, distance, calories, startTime, endTime, runMinutes
Xiaomi
^\d{10}\.db$
calories_day
time, calories
steps_day
time, steps, distance, calories
Stress
Huawei
wear_14.db
^m_14_StressDataByDay_\d{17}$
TimeStamp, ScoreDetail, MaxStress, MinStress, AverageStress
Amazfit
HMCorePersistanceDatabaseV1.sqlite.db
PressureRateTable
createTime, rate
Xiaomi
^\d{10}\.db$
stress_day
time, max_stress, min_stress, avg_stress, stress_scale
Diagram Key
1- Category
2- Platform
3- Container
3- Containler with RE
4- Artifacts

Fig. 7. Taxonomy of Wrist-Wear Digital Forensic Artifacts.

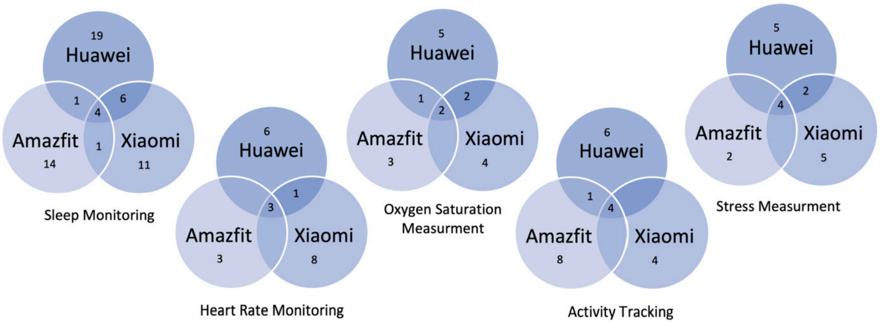


Fig. 8. Intersection of Variables among Huawei, Amazfit, and Xiaomi Vendor.

sung devices, is an important future direction. Developing techniques to overcome encryption barriers and analyze encrypted data would expand the framework's applicability and ensure a more comprehensive analysis of potential circumstantial evidence.

6. **Admissibility of Wrist-Worn Device Data in Forensics:** Future research should focus on developing standardized guidelines and methodologies to ensure the admissibility of data from wrist-wear devices in court. This involves not only addressing inaccuracies but also demonstrating how these devices can produce reliable evidence when supported by corroborative data.

By pursuing these directions, the framework can further enhance its capabilities and contribute to the advancement of digital forensic investigations involving wrist devices and other wearables.

8. Conclusion

In conclusion, the research presented in this study addresses the challenges and opportunities posed by wrist-worn devices in the field of digital forensics. The widespread adoption of wearable technology, particularly wrist devices, has created a new frontier for investigators, necessitating the exploration of their potential implications.

The study highlights the limited scope of previous research, which focused on specific operating systems while neglecting the overall market share and diverse range of vendors in the wrist device market. This oversight presents challenges for digital investigators in retrieving and analyzing data from wrist devices with different operating systems. Furthermore, the utilization of health data from wrist devices in digital investigations has been relatively unexplored.

To bridge these gaps, the WristSense framework is proposed, offering a systematic approach to extracting health-related data from heterogeneous sources of wrist devices. The framework is designed to ensure compatibility with devices from different vendors and enables the analysis of various health data, including sleep patterns, heart rate, blood oxygen saturation, activities, and stress levels. Through comprehensive case studies involving wrist devices from Huawei, Amazfit, Xiaomi, and Samsung, the effectiveness of the WristSense framework in extracting and analyzing data from various vendors is demonstrated.

The results of the case studies reveal potential circumstantial evidence that can be valuable for forensic investigations involving wrist-worn devices. The research introduces a wear-device artifact catalog, providing practitioners with a codified and leveraged forensic collective knowledge. This artifact catalog holds significance for practitioners in the field, enabling them to identify and interpret forensic artifacts from wrist devices. Additionally, the study conducts a consistency analysis of variables across vendors to ensure the integrity of the data in forensic investigations. This analysis enhances the reliability of the findings and strengthens the potential evidentiary value of the extracted data.

While the research demonstrates the effectiveness of the WristSense framework, challenges such as encryption mechanisms on certain devices are acknowledged and warrant further investigation.

In summary, this research provides a comprehensive overview of suspect or victim health data obtained from wrist-worn devices, empowering digital forensics investigators to reconstruct detailed timelines and gather crucial evidence. The WristSense framework offers a valuable toolset for extracting and analyzing data from a wide range of vendors, contributing to the advancement of digital forensic investigations in the evolving landscape of wearable technology.

CRediT authorship contribution statement

Norah Ahmed Almubairik: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology. **Fakhri Alam Khan:** Writing – review & editing, Supervision, Funding acquisition. **Rami Mustafa Mohammad:** Supervision, Writing – review & editing. **Mubarak Alshahrani:** Conceptualization, Investigation, Supervision.

Software availability

A comprehensive software framework, WristSense, was developed to systematically extract, analyze, and visualize health-related data from various wrist-worn devices. The software is designed for reproducibility and ease of use, accommodating multiple device vendors such as Huawei, Amazfit, and Redmi.

The framework consists of modular Python scripts tailored to each device, ensuring compatibility while adhering to a unified workflow. It includes separate scripts for data extraction and analysis, as well as integrated tools for certain vendors. A detailed README file is provided, outlining the usage of each script and demonstrating the overarching functionality of the framework.

The software is openly available on GitHub,[3] enabling researchers to utilize or expand upon the framework for their investigations. This repository also includes the WristSense-VendorData dataset to facilitate reproducibility.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Visualizations of case study results

This appendix provides detailed visualizations of the case study results discussed in Section 5.3 (Figs. 19–21).

Data availability

I have shared the link to my data and code in the manuscript

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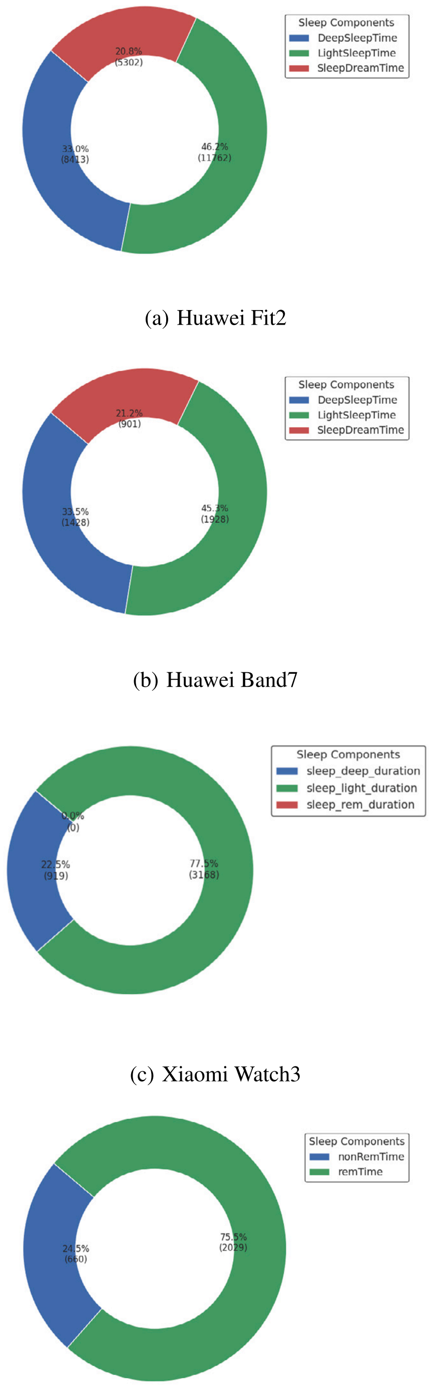
[3] https://github.com/naalmubairik/WristSense.



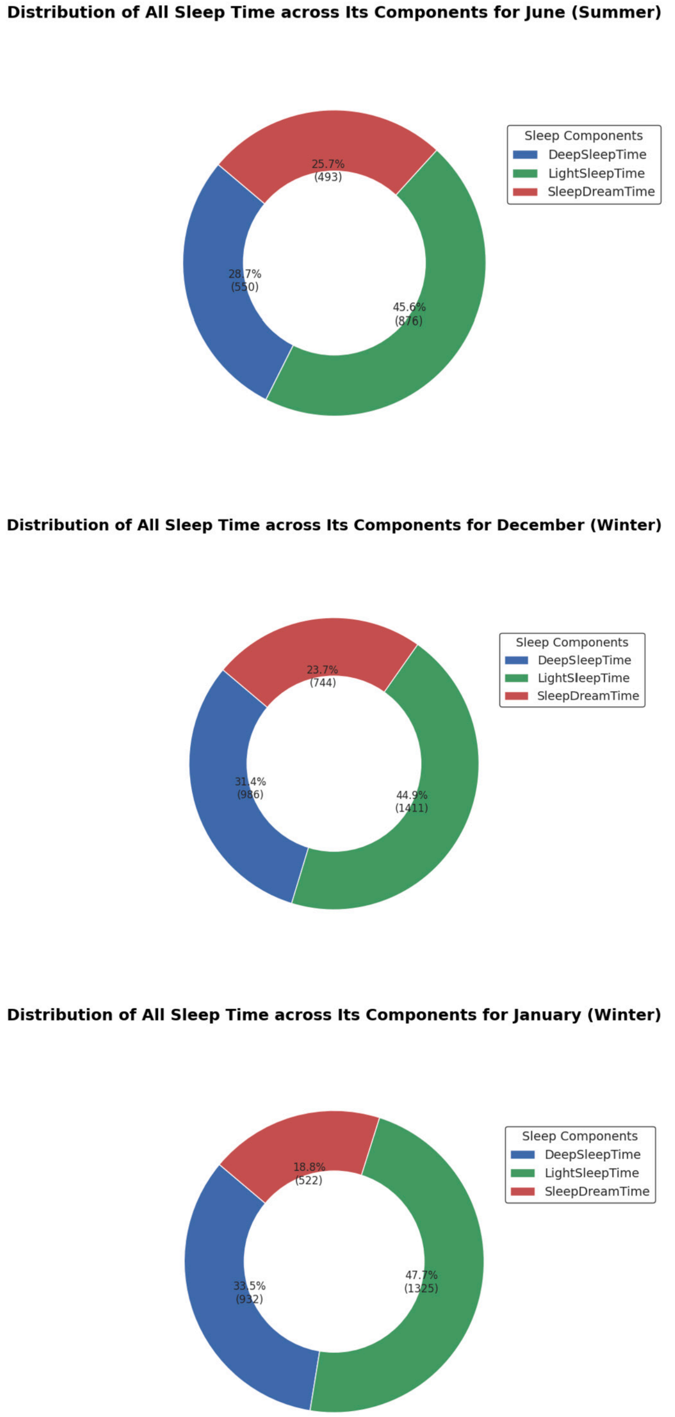
(a) Huawei Fit2

(b) Huawei Band7

(c) Xiaomi Watch3

(d) Amazfit Band7

Fig. 9. Distribution of sleep time across its variables for the Whole Dataset.


Distribution of All Sleep Time across Its Components for June (Summer)

Distribution of All Sleep Time across Its Components for December (Winter)

Distribution of All Sleep Time across Its Components for January (Winter)

Fig. 10. Huawei Fit2: Distribution of all sleep time across its components in different months.

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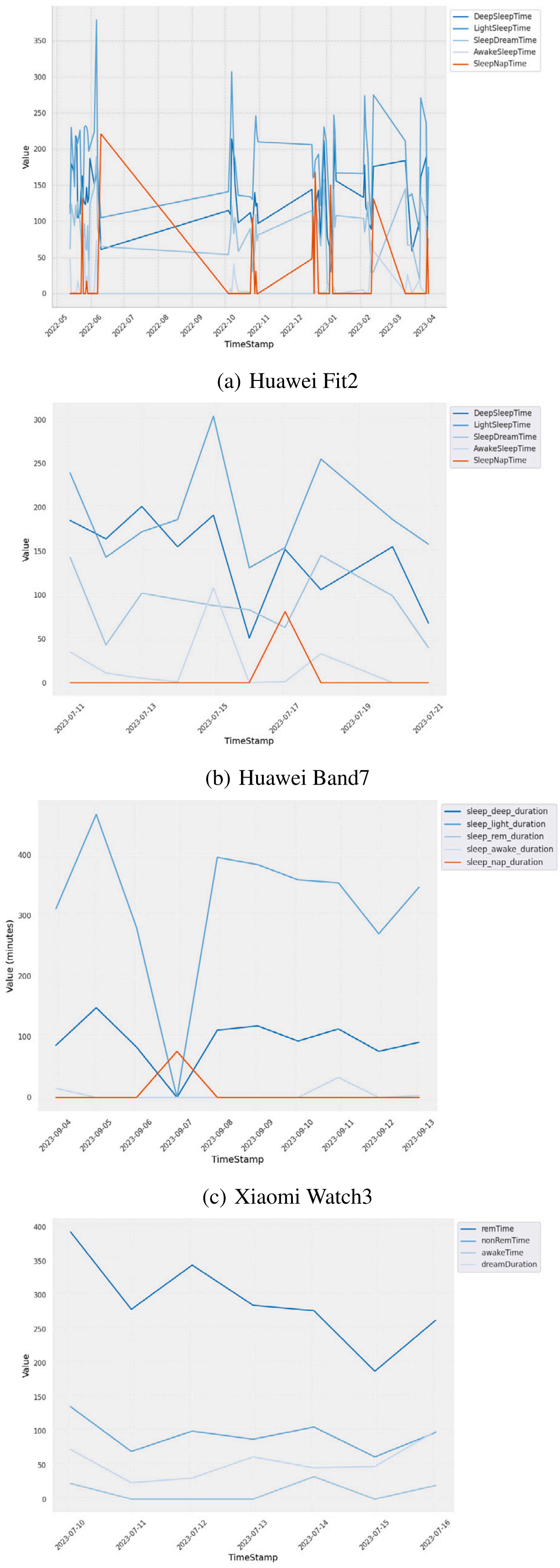


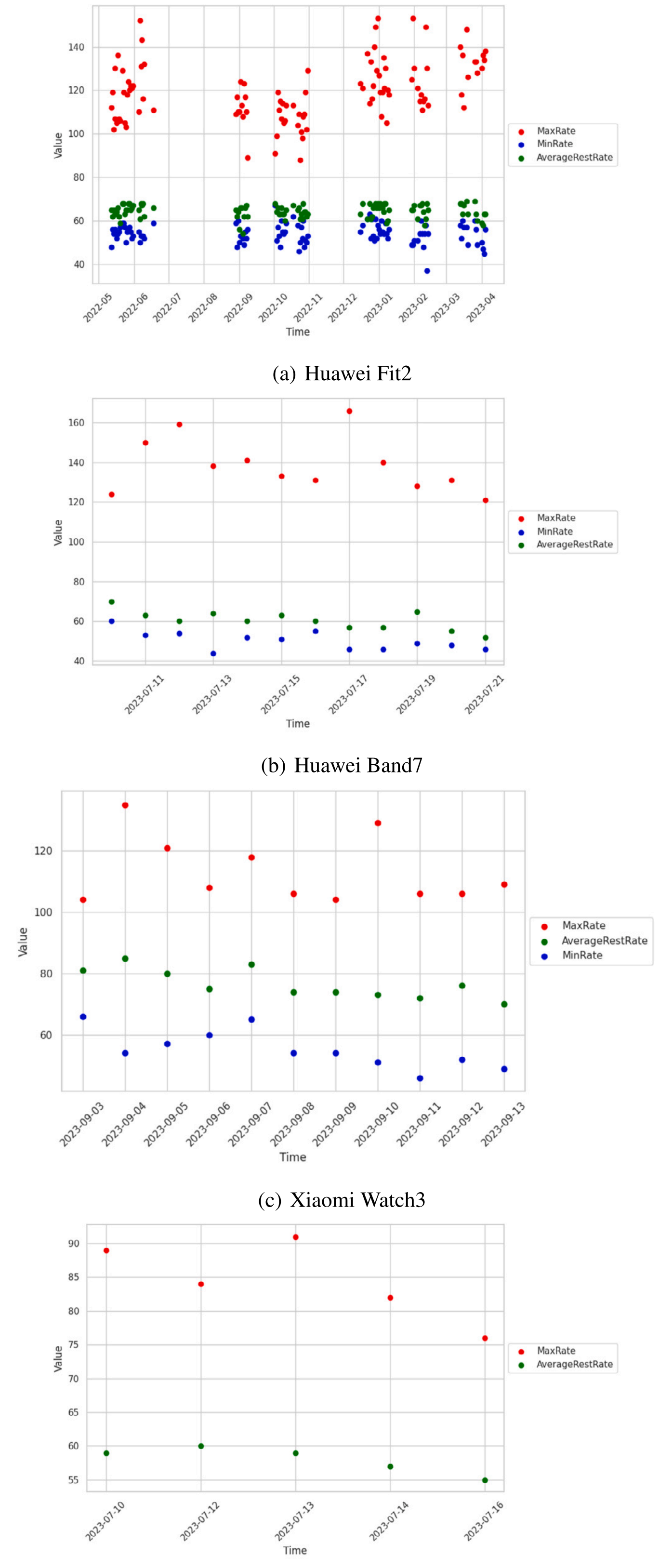
(a) Huawei Fit2

(b) Huawei Band7

(c) Xiaomi Watch3

(d) Amazfit Band7

Fig. 11. Time series for sleep variables.



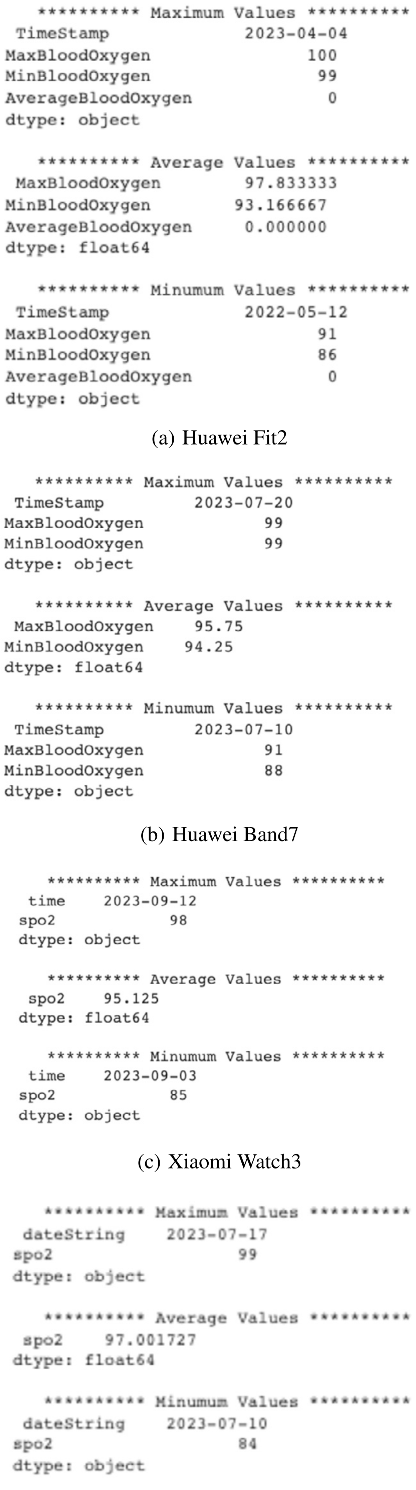
(a) Huawei Fit2

(b) Huawei Band7

(c) Xiaomi Watch3

(d) Amazfit Band7

Fig. 12. Scatter plot for heart rate variables.



```
   ********** Maximum Values **********
 TimeStamp                  2023-04-04
MaxBloodOxygen                     100
MinBloodOxygen                      99
AverageBloodOxygen                   0
dtype: object

   ********** Average Values **********
 MaxBloodOxygen             97.833333
MinBloodOxygen            93.166667
AverageBloodOxygen          0.000000
dtype: float64

   ********** Minumum Values **********
 TimeStamp                  2022-05-12
MaxBloodOxygen                      91
MinBloodOxygen                      86
AverageBloodOxygen                   0
dtype: object
```

(a) Huawei Fit2

```
   ********** Maximum Values **********
 TimeStamp           2023-07-20
MaxBloodOxygen               99
MinBloodOxygen               99
dtype: object

   ********** Average Values **********
 MaxBloodOxygen     95.75
MinBloodOxygen     94.25
dtype: float64

   ********** Minumum Values **********
 TimeStamp           2023-07-10
MaxBloodOxygen               91
MinBloodOxygen               88
dtype: object
```

(b) Huawei Band7

```
   ********** Maximum Values **********
 time     2023-09-12
spo2              98
dtype: object

   ********** Average Values **********
 spo2     95.125
dtype: float64

   ********** Minumum Values **********
 time     2023-09-03
spo2              85
dtype: object
```

(c) Xiaomi Watch3

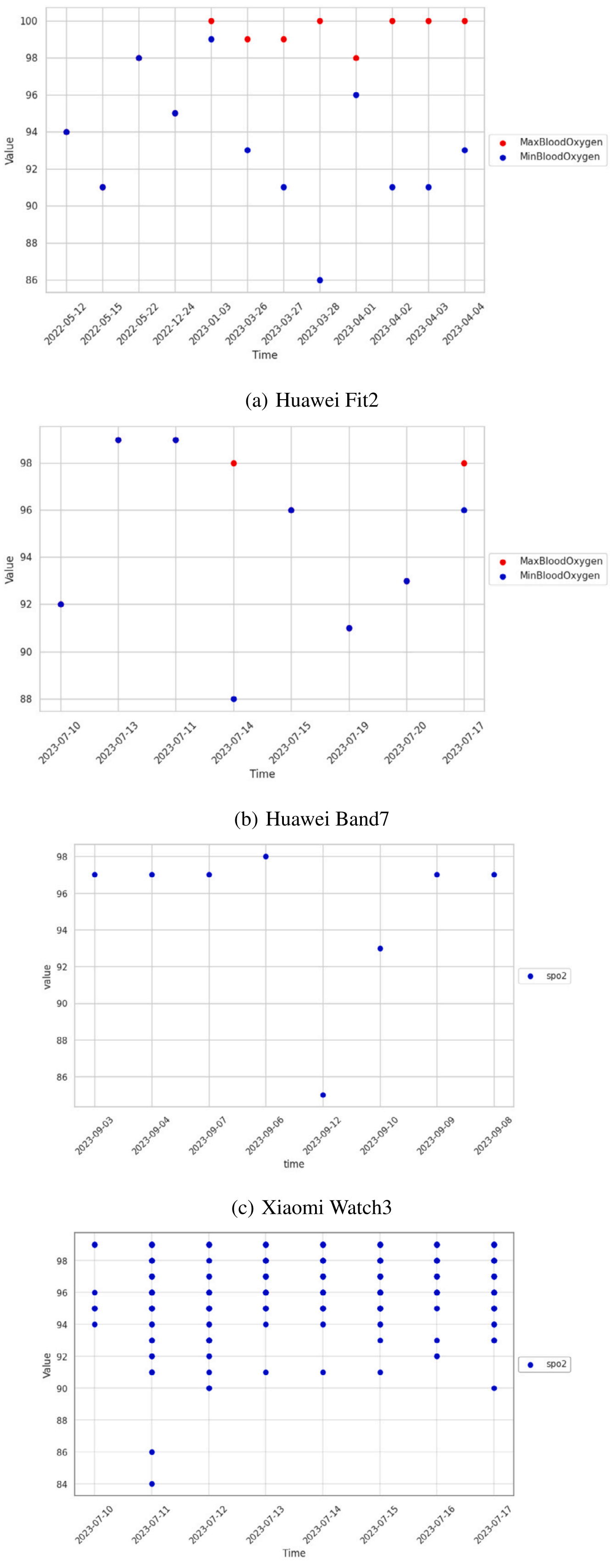
```
   ********** Maximum Values **********
 dateString     2023-07-17
spo2                   99
dtype: object

   ********** Average Values **********
 spo2     97.001727
dtype: float64

   ********** Minumum Values **********
 dateString     2023-07-10
spo2                   84
dtype: object
```

(d) Amazfit Band7

Fig. 13. Min, Max, and Average values for each variable of blood oxygen variables.



(a) Huawei Fit2

(b) Huawei Band7

(c) Xiaomi Watch3

(d) Amazfit Band7

Fig. 14. Scatter plot for blood oxygen variables.

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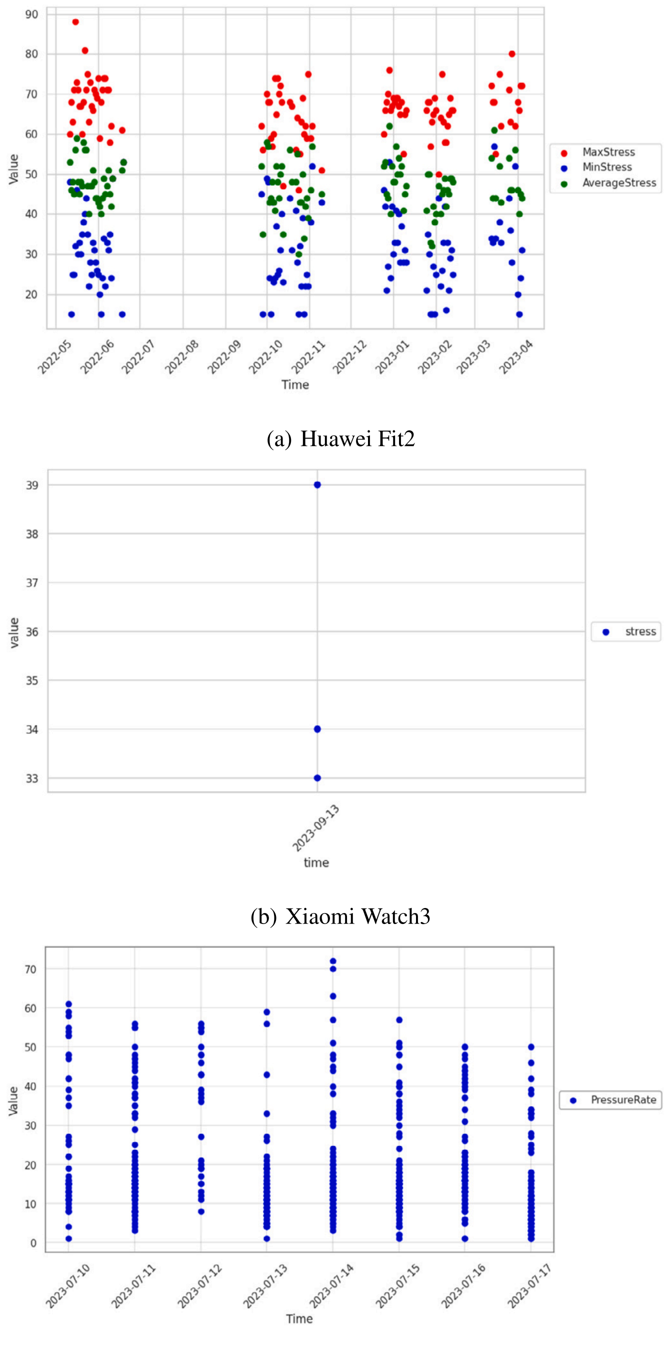
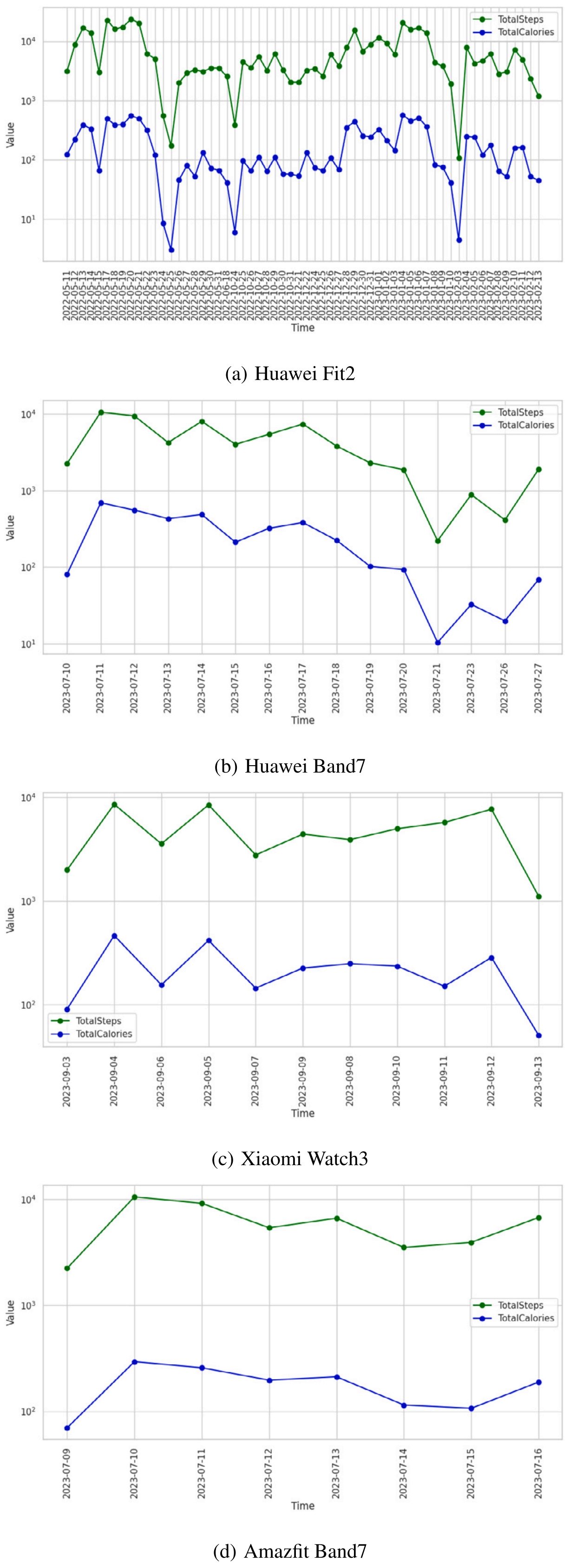


(a) Huawei Fit2

(b) Xiaomi Watch3

(c) Amazfit Band7

Fig. 15. Scatter plot for stress/pressure variables.



(a) Huawei Fit2

(b) Huawei Band7

(c) Xiaomi Watch3

(d) Amazfit Band7

Fig. 16. Time series for activity variables.

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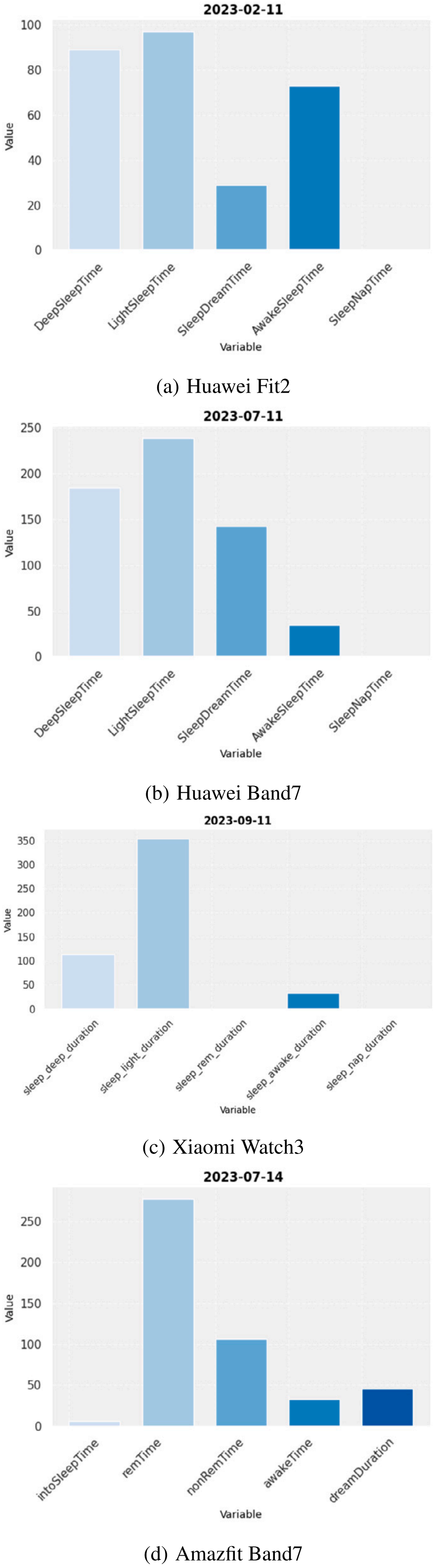

(a) Huawei Fit2

(b) Huawei Band7

(c) Xiaomi Watch3

(d) Amazfit Band7

Fig. 17. Sleep variables for specific date “crime scene date” in minutes.

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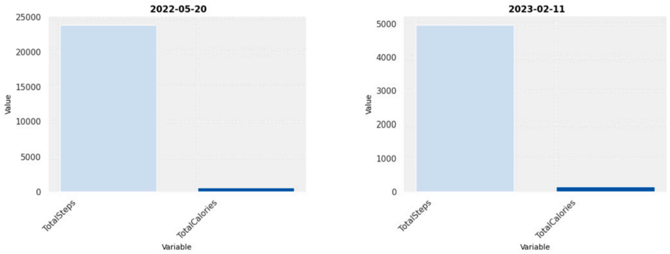

Fig. 18. Huawei Fit2 - Activity variables for specific date “crime scene date”.

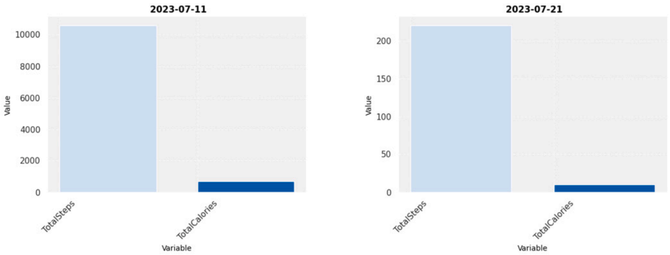

Fig. 19. Huawei Band7 - Activity variables for specific date “crime scene date”.

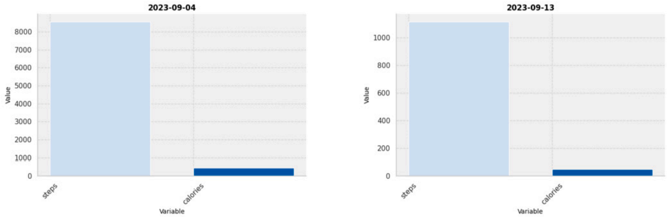

Fig. 20. Xiaomi Watch3 - Activity variables for specific date “crime scene date”.

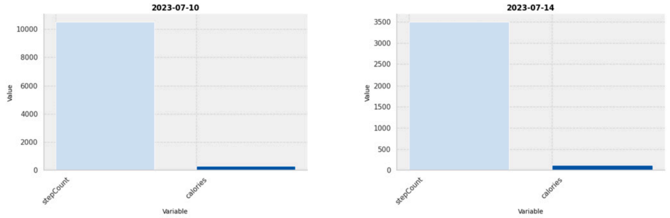

Fig. 21. Amazfit Band7 - Activity variables for specific date “crime scene date”.

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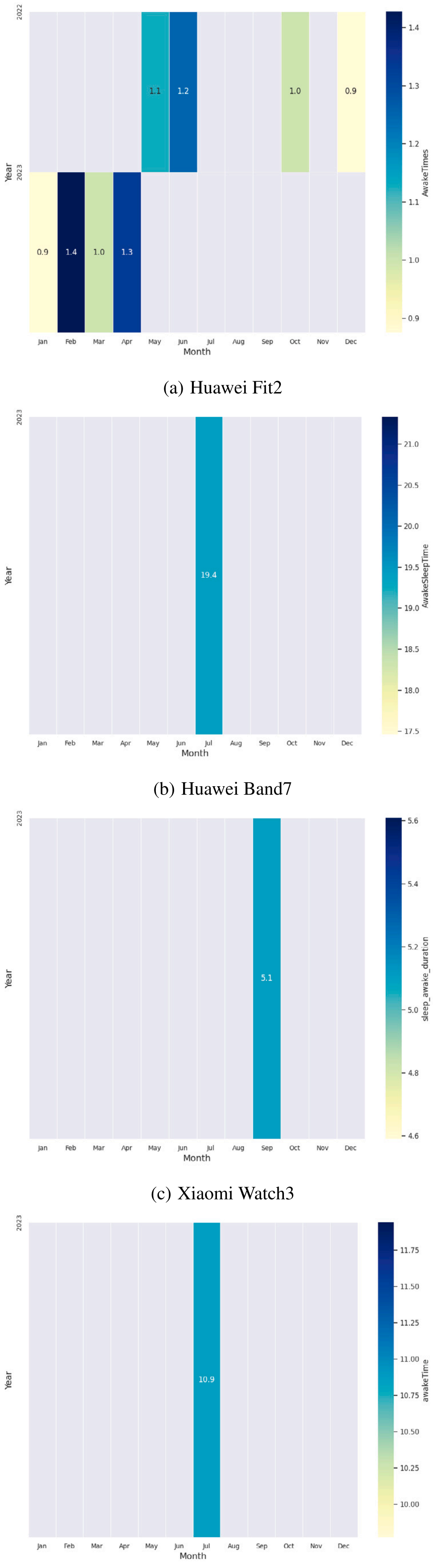


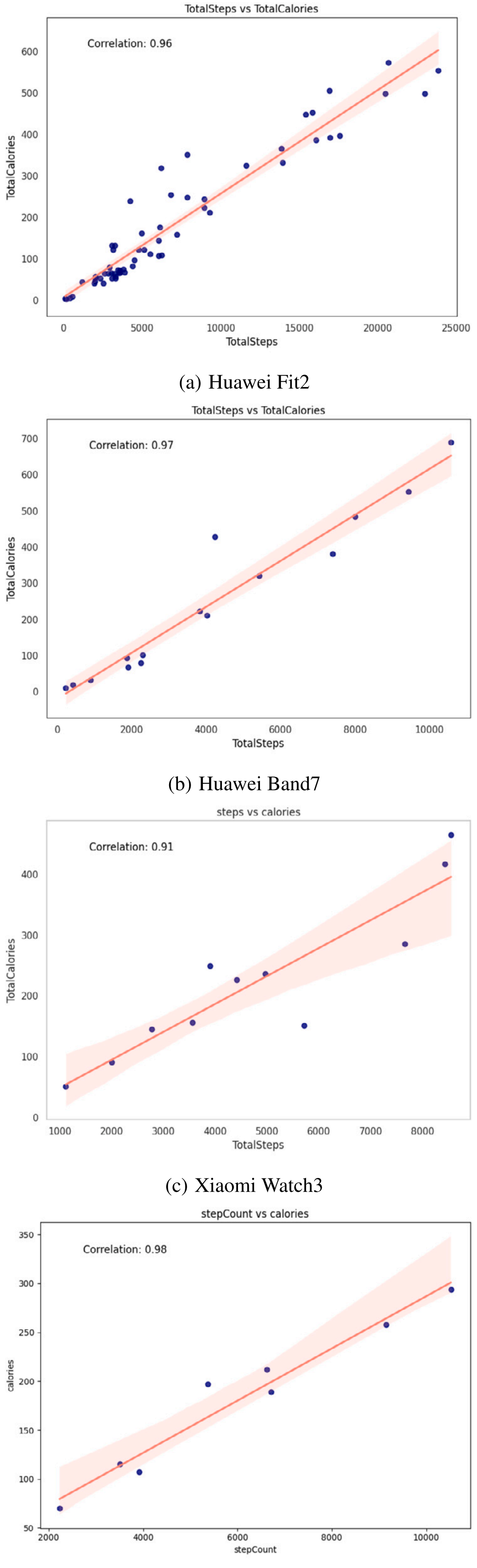
(a) Huawei Fit2

(b) Huawei Band7

(c) Xiaomi Watch3

(d) Amazfit Band7

Fig. 22. Average awake times in minutes. (For interpretation of the colors in the figure(s), the reader is referred to the web version of this article.)



(a) Huawei Fit2

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(c) Xiaomi Watch3

(d) Amazfit Band7

Fig. 23. Correlation between steps and calories.

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